AN IMPROVED ENERGY REQUIREMENT PREDICTION FOR QUEUEING APPLICATIONS OF ELECTRIC VEHICLES BASED ON PARAMETER ESTIMATION

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

BERKAY SAĞLAM

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
ELECTRICAL AND ELECTRONICS ENGINEERING

AUGUST 2022

Approval of the thesis:

AN IMPROVED ENERGY REQUIREMENT PREDICTION FOR QUEUEING APPLICATIONS OF ELECTRIC VEHICLES BASED ON PARAMETER ESTIMATION

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ABSTRACT

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August 2022, 69 pages

The use of electric vehicles has increased in recent years. Although they have many benefits to the environment such as reduced carbon emissions, charging of vehicles brings some new challenges for power systems such as overloading, reliability problems, etc. Charging of electric vehicles should be managed to overcome these problems. Queueing strategies are one of the management methods. These strategies are applied to obtain a feasible operation that depends on the decisions made considering system properties and the electricity market. Although there are several methods for queueing in the literature, there is a gap in determination of the load demand of the vehicle. The demand of a vehicle is related to the power consumption of that vehicle and can be calculated by using drivetrain models. These models help to calculate the power consumption of the vehicle by using mathematical models which are related to the vehicle parameters. The parameter values change with time due to aging effects. Therefore, they should be estimated to obtain accurate consumption information. This thesis proposes a method to estimate the parameter values and determine the load demand of a vehicle in order to make feasible queue decisions. The proposed method relies on the Least Squares Estimation method for parameters used in the uti-

lized backward simulation based drivetrain model. In addition, the conditions of the route of individuals are concerned while determining the load requirements. Finally, an optimization method is presented for queueing applications to manage the system operation.

Keywords: Parameter Estimation for Electric Vehicles, Energy Prediction for Charging Stations, Electric Vehicle Drivetrain Modelling, Vehicle to Grid Applications, Linear Programming

ÖZ

ELEKTRİKLİ ARAÇLARIN KUYRUK UYGULAMALARI İÇİN PARAMETRE KESTİRİMİNE DAYALI İYİLEŞTİRİLMİŞ ENERJİ GEREKSİNİMİ TAHMİNİ

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Ağustos 2022 , 69 sayfa

Elektrikli araçların kullanımında son yıllarda artış gözlemlenmiştir. Araçların şarj edilmesi, karbon emisyonlarının azaltılması gibi çevreye birçok faydası olmasına rağmen, güç sistemleri için aşırı yükleme, güvenilirlik sorunları vb. gibi bazı yeni zorlukları da beraberinde getirmektedir. Bu sorunların üstesinden gelmek için elektrikli araçların şarj edilmesi yönetilmelidir. Kuyruk stratejileri yönetim metodlarından biridir. Bu stratejiler, sistem özellikleri ve elektrik piyasası dikkate alınarak verilen kararlara bağlı olarak makul bir operasyon elde etmek için uygulanır. Literatürde kuyruğa alma için çeşitli yöntemler bulunmakla birlikte, aracın yük talebinin belirlenmesinde bir boşluk bulunmaktadır. Bir aracın talebi, o aracın güç tüketimi ile ilgilidir ve aktarma organları modelleri kullanılarak hesaplanabilir. Bu modeller, araç parametreleri ile ilgili matematiksel modeller kullanılarak aracın güç tüketiminin hesaplanmasına yardımcı olur. Yaşlanma etkileri nedeniyle parametre değerleri zamanla değişir. Bu nedenle, doğru tüketim bilgisi elde etmek için değerlerin kestirilmesi gerekmektedir. Bu tez, uygulanabilir kuyruk kararları vermek için bir aracın parametre değerlerini

tahmin etmek ve yük talebini belirlemek için bir yöntem önermektedir. Önerilen yöntem, kullanılan geriye dönük simülasyon tabanlı aktarma organları modelinde kullanılan parametreler için En Küçük Kareler Kestirimi yöntemine dayanmaktadır. Ayrıca yük gereksinimleri belirlenirken bireylerin güzergah koşulları da dikkate alınmaktadır. Son olarak, sistem operasyonunu yönetmek için kuyruğa alınan uygulamalar için bir optimizasyon yöntemi sunulmuştur.

Anahtar Kelimeler: Elektrikli Araçlar İçin Parametre Kestirimi, Şarj İstasyonları İçin Enerji Tahmini, Elektrikli Araç Aktarma Organları Modellenmesi, Araçtan Şebekeye Uygulamaları, Lineer Programlama

To Casper and Ghost.

ACKNOWLEDGMENTS

First, I would like to thank Dr. Murat Gol, my advisor, for guiding me through my master's degree. I was very lucky to have such an advisor during the last three years. In addition, I want to thank to my friends in E-101 for their friendship and support.

I also thank Scientific and Technological Research Council of Turkey (TUBITAK) for financially supporting me through my master's education via BIDEB 2210-A Graduate Student Scholarship and the research project I worked for under grant number 119E209.

I also thank to my family for inspiring me to become an engineer and support me in every part of my life. Also, I want to thank my biggest motivation source, Umay Acar, for her love, being my best friend and her patience. I would not come this far without her.

Lastly, I want to thank to my best friends, Casper and Ghost, for teaching me how to be happy and responsible and giving my life meaning.

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EV	Electric Vehicle
PV	Photovoltaic
ESS	Energy Storage System
V2G	Vehicle to Grid
LS	Least Squares
GPS	Global Positioning System
LP	Linear Programming

CHAPTER 1

INTRODUCTION

In recent years, Electric Vehicle (EV) usage has increased in order to reduce environmental pollution and fuel consumption [1]. In addition, the electrification of the transportation sector accelerates the wide-scale adoption of electric vehicles [2]. Conventional cars with internal combustion engines (ICE) are still a major source of air pollutants such as carbon dioxide (CO_2), nitrogen oxides (NO_x), and black carbon (BC) [3]. The increase in the air pollution levels brings environmental problems such as global warming. On the other hand, electric vehicles help to decrease air pollution level and can be considered as environmentally friendly thanks to the zero-emission property of electric vehicles. In addition, developments in drive and battery technology, the use of efficient electric motors, and safe driving increase the use of EVs [4]. In the United States, EVS annual sales increased from 34000 to almost 350000 between the years 2011 and 2019 [5].

Despite their many advantages to the environment and drivers such as decreasing air pollution levels, the increase in the usage of EVs brings some new challenges for the power grid. Simply, the load of the EVs will be added to the existing system loads. Higher peak demands and ramping requirements that the existing grid cannot manage are some of these challenges [6]. In addition, EVs are considered as mobile loads in the system rather than stationary loads [7]. The term mobile load comes from the mobility of the vehicle. In other words, the location of the load can be changed. Also, the amount of charge that is delivered to the vehicle and charging time may vary for each vehicle. As a result of that, and with the increase in the amount of load, the EV loads should be forecasted, and accordingly some actions might be taken in order to maintain the system stability. In [8] a deep learning method is used to forecast the load. On the other hand, [9] proposes a load forecast based on Monte Carlo simulations. The inadequacy of these methods is determining the accurate load demand of the vehicles. Drivetrain models offer a solution to this problem. These models help to calculate the power consumption and hence load demands.

In order to determine the amount of the load, i.e. the energy demand of a vehicle, drivetrain models are used. These models use a road trip data and calculate the power consumption of a vehicle by using mathematical models for mechanical and electrical power-consuming units. The models contain vehicle and environmental parameters, and they are set as constants in basic applications. However, this is not the case in reality because the parameters may change over time, and assuming parameters stay constant reveals inaccurate solutions. For example, the aging of mechanical parts or changes in environmental conditions due to seasonal differences cause changes in parameters. The determination of parameter values can be done by using estimation algorithms. In the literature, different estimation algorithms are proposed. In [10], electronic differential system parameters are estimated using radial basis neural network. In [11], dual Kalman filter is utilized. One of the most popular estimation methods is Least Squares (LS) method. The main advantage of the LS method is that it is easy to use and implement [12]. Moreover, it is a Best Linear Unbiased Estimator [13] in the presence of Gaussian error. In [14] and [15] estimation is implemented for tire pressure and mass respectively using LS method. This approach can be extended to determine many other parameters. The power consumption of the vehicle can be calculated based on observing the forces acting on the vehicle. These forces can be divided into three main categories. The first one of them is road friction. The friction force depends on the contact between the wheels of the vehicle and the traveled road. The manufacturing material of the tires, the material of the traveled road, and the tire pressures are some examples each of which determines the friction coefficient between the wheels and the road. Secondly, the aerodynamic properties are important in terms of aerodynamic resistance. The design of the vehicle is done by considering these properties. In addition, the aerodynamic properties may change frequently. For example, opening the windows of the vehicle or putting top carriers are some of the examples that change the aerodynamic properties of the vehicle. The last force is the well-known gravitational force (i.e. gradient force). These three main forces can be calculated by using mathematical models, and those models contain parameters related to the vehicle. Therefore, changes in parameters directly affect the power consumption of the vehicle.

Conventionally, the directional velocity of a vehicle is calculated via measuring the angular velocity of the wheel [16]. Having the rotational-longitudinal speed equation which requires vehicle parameters, the directional velocity is calculated. However, the parameters are assumed to be constant, which is not the case in reality because they change as time passes. In addition, these types of measurements do not include longitudinal and lateral slips, which generally occur during braking and steering. So the measurements may contain large errors [17]. A more accurate approach is taking Global Position System (GPS) location (or velocity) data and determining the actual velocity of the vehicle [18]. As a result, time-series velocity data can be obtained apart from vehicle parameters. In addition to that, the changes in road type can be detected by the location information coming from the GPS, and this property can be used in order to determine the road friction coefficient by determining the type of the load. The GPS data also enable to determine the road gradient. By using the altitude information of locations and the traveled distance between them, the road slope can be found accordingly. On the other hand, torque measurements are rarely used because collecting them can be hard and require effort. To overcome this challenge, torque can be estimated by using power measurements collected from the vehicle. Measuring power can be easy compared to the torque.

System operators make decisions in order to adjust their operations by considering their system conditions and market operations. With the ease of use and developments in photovoltaics and energy storage systems, systems start to be utilized together as a whole, and hence operating them together requires management. In addition, charging stations of electric vehicles have become a part of this system. The charging station is where EVs connect to the power grid. The most important feature of charging stations is having bi-directional power flows. Vehicle batteries can be considered as both loads and storage by the introduction of the vehicle to grid applications, so the management of them brings some new challenges to the system. To overcome these phenomena, scheduling strategies have been developed. The scheduling can be defined as managing the operation of a system by examining the components in terms of time, cost and reliability. The scheduling can be performed via two approaches. The first one of them is scheduling the load of the system. The load scheduling is usually done by considering the electricity market properties and to decrease the operation cost of the system by shifting the load among the operation time. The second one of them is expressed as queueing and it implies listing the vehicles by considering their presence at the charging stations and system operating conditions. There are different types of approaches to this concept and different types of queueing methods developed in the literature. In [19] and [20], the distribution of different vehicles to different charging stations is investigated. On the other hand, [21] proposes a smart power distribution algorithm. Also, [22] and [23] investigates the Markov decision process to schedule the charging stations. However, these studies do not take driver behaviors and vehicle specifications into account. The consideration of all vehicles as a same type of load would not lead to the optimal decisions for system management. The load demand of each vehicle would be different. Therefore, identification of the vehicles specifically makes approaches more realistic.

This thesis proposes a method to identify vehicle parameters by using time-series GPS data as well as measurements that can be gathered from the vehicle. The measurements taken from the vehicle include angular velocity and power, while the GPS data is used to extract the directional velocity. The first step is performing the LS state estimation algorithm and determining the unbiased estimates. After that, the parameter estimator uses those estimated state values and estimates the parameters by using the same method. After finding the parameters of vehicles, the energy demands are calculated. This calculation is based on the vehicle owners' range demand and average power consumption of each vehicle. Then, a scheduling algorithm manages the operation of the designed system by using linear programming (LP) algorithm. Lastly, a rule-based queueing strategy is developed to manage the arriving vehicles to the charging station.

1.1 Motivation

As the number of vehicles increases, the electric demand of the vehicles increases. This electric demand can be supplied by utilizing vehicle charging stations into the existing power grid. The first challenge rises from this point of view as the infrastructure of the existing grid may not be sufficient to supply the demand. The amount of electric vehicle load may be comparable to the other loads in the existing grid as the number of charging spaces for vehicles increases. This situation leads to inadequacy of the power supply, and there are two different actions that may be taken into account to solve this problem. The first one of them is upgrading the infrastructure. This solution implies that the components of the existing grid should be changed with the ones that have higher power ratings. Although it may sound sufficient, the cost of the re-installation may be too much and unfeasible. Therefore, a second solution that uses the existing grid may be considered. The second solution is based on managing the loads by using the same infrastructure and considering the system properties. If the load is managed properly, the demand can be supplied without changing the system components and the additional infrastructure cost would be eliminated. With the developments in electric storage systems and photovoltaic generation systems, power grids started to be utilized together with these elements. In addition, electric vehicle charging stations also become a part on the power grid. Therefore, management of the load becomes important as the number of elements in a grid with different behavior increases. Furthermore, the infrastructure limits should not be exceeded while managing the system load.

The daily charging behaviors of electric vehicle owners show that there are several trends of charging. The first one of them is charging the vehicle during working hours which can be observed in workplaces with charging stations. The second one of these trends is charging the vehicles individually in residential areas at night. Both of these trends are based on long charging times to fully charge the batteries of the vehicles. However, these trends may change as the vehicle and charging station technologies developed.

The motivation behind this thesis is to provide accurate information to the management strategies of the power grids by considering changes in the vehicle during time, the daily usage of the vehicles, and the behaviors of the vehicle owners. Accordingly, a commercial area, such as a shopping mall, is selected for the application as they are one of the most common places which individuals visit and have the opportunity to charge their vehicles. In addition, commercial systems are suitable for being designed by multiple grid elements which were mentioned earlier.

The determination of the load demand becomes important as the strategy suggests that charging the vehicles fully is not feasible considering the time spent in a commercial area. This determination can be done by using drivetrain models which are used to calculate the power consumption of a vehicle. The power consumption can be calculated by using a road trip data which contains velocity values and a proper model of the vehicle. This calculation is based on the forces acting on a vehicle and laws of motion. In order to increase the accuracy of the drivetrain model, two estimation methods are used. The first one of them is determining the unbiased values of the states by using a state estimation algorithm. By doing that, the errors in the measurements collected from the vehicle are eliminated. Secondly, the parameters of the vehicle can be changed as time passes and this situation leads to calculating incorrect power consumption values. A parameter estimator algorithm can be utilized to overcome this challenge. By using these estimation algorithms, an accurate drivetrain model can be obtained to be used for power consumption calculations of the vehicle. The next step is determining the load demand of a vehicle by considering the drivers' demand. This can be achieved by taking the demands of drivers' as kilometers that they want to go. The driver of a vehicle may not be well informed about the characteristics of an electric vehicle. On the other hand, they are usually aware of the distance they travel. By looking from this point of view, the demand of a driver is taken as a range in kilometers.

The range input may not be sufficient to determine the energy requirement of the vehicle by itself as the driving behaviors of the drivers may differ from each other. As a result of that, the trip data is required for the demanded range to calculate the power consumption. If the historical data of a vehicle is present, the behavior of the driver can be found and the trip data of the daily usage curve can be obtained [24]. In addition, the parameter estimation algorithm can be performed and power consumption calculation accuracy can be improved as using a generic vehicle model for each vehicle may be misleading. On the other hand, if the historical data of a vehicle is not present, then an approximation should be done to determine the trip data of that vehicle. To overcome this challenge, a second strategy is taken into account. This strategy relies on the study that states that the behaviors of individuals converge to a mean value [25]. In other words, the power consumption of a vehicle whose historical data is not present can be calculated by using the mean trip values of individuals traveling in the same location.

The management of the load in a system can be done by scheduling strategies. The scheduling enables the system owner to minimize the cost of the operation. With the dynamic electricity market and flexibility of the loads in the system, scheduling the loads in the system over time minimizes the cost of the operation. This strategy can be expressed as an optimization problem and methods such as linear programming help to solve this optimization problem. In addition, the vehicle batteries can be considered as energy storage units by the introduction of vehicle-to-grid applications and this property increases the flexibility of the operation. Lastly, the queueing algorithms help optimization to arrange the number of vehicles charging at the station. As mentioned before, there may be a limitation in delivered power at the charging stations and sometimes the amount of the demand may exceed this limit. In this situation, the queueing algorithm schedules the vehicles at the charging station to satisfy the demand by considering the system infrastructure.

1.2 The Contribution of the Thesis

The drivetrain and queueing methods in the literature take constant vehicle parameters into account. However, this situation may lead to incorrect calculation of power consumption and energy requirement prediction. This thesis proposes a methodology to obtain accurate energy requirement prediction. In addition, by taking the range demand from the drivers and determined trip route, the demanded energy amount is calculated. An optimization problem is solved to manage the load demand of the system accordingly to reveal the benefits of the proposed approach. The contributions of the thesis are as follows;

1 - Least Squares Estimation problem for the states and parameters is formulated which eliminates the effects of errors in the measurement set and then estimates the values of the parameters of the vehicle by using time-series GPS data.

2 - A drivetrain model which uses estimated parameters is utilized based on the

backward simulation method.

3 - An energy requirement prediction and queueing method which considers traffic data and individual demands to obtain feasible system operation and meet the demands of vehicle owners.

1.3 The Outline of the Thesis

The thesis is organized as follows; in Chapter 2, the necessary theoretical background on Vehicle Dynamics, Powertrain Models, State and Parameter Estimation Algorithms, and Queueing Strategies are given. In Chapter 3, the proposed drivetrain model and estimation methods are explained in detail and the results are presented. Chapter 4 presents the proposed energy requirement prediction and its results. Chapter 5 presents discussions and future work. In Chapter 6, the thesis is concluded.

CHAPTER 2

BACKGROUND INFORMATION

Introduction chapter describes the historical background of electric vehicles, the challenges they bring to the power systems, and proposed solution methods. This chapter follows with the theoretical background of vehicle dynamics, Least Squares Estimation, parameter estimation, drivetrain models, queueing strategies, and linear programming.

2.1 Vehicle Dynamics

In order to move a stationary solid body, there should be at least one force acting on it. In this thesis, the body is considered as an electric vehicle. There are several forces acting on a moving vehicle. These forces can be divided into two groups as repulsive force and resistive forces. The repulsive force of a vehicle is supplied by the engine (i.e. motor). The motor converts the electrical power to mechanical power by consuming the energy stored in the battery. Generally, the motors of commercial electric vehicles are interior permanent magnet synchronous machines and squirrel cage induction machines [26]. Acting forces are shown in Fig. 2.1. The power which moves the vehicle is called traction power. Traction power is generated by the motor, and transferred to tires by mechanical parts. This power is said to be applied power from wheels to the ground surface. The transfer equation of the generated power is given in 2.1.

$$P_{applied} = P_{motor} \times i_g \tag{2.1}$$

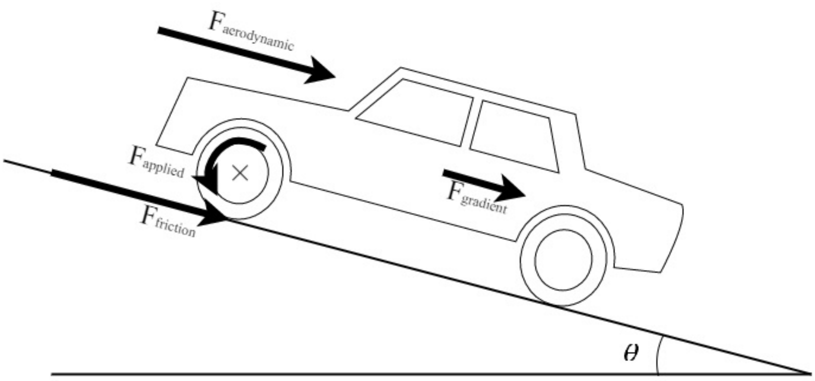


Figure 2.1: Representation of forces acting on a vehicle.

where $P_{applied}$ is the applied power from wheels to ground, P_{motor} is the generated power at the motor, and i_g is the gear ratio of the vehicle's gearbox. A gearbox is the mechanical part of a vehicle that transfers the power with its ratio.

In addition to the repulsive force, there are resistive forces. The resistive forces are due to the environmental conditions which occur by the movement and location of the vehicle. They typically act in the opposite direction of the vehicle's motion. The resistive forces can be divided into three main categories. Those are ground friction force, aerodynamic resistance force, and gradient force. These forces are caused by surface friction, the shape of the vehicle, and the slope of the road respectively.

The resistive force components can be computed as follows.

$$F_{friction} = m \times g \times f_r \times cos(\theta) \tag{2.2}$$

$$f_r = f_{rc} \times (1 + (v \times \frac{3.6}{100})) \tag{2.3}$$

$$F_{aerodynamic} = \frac{1}{2} \times \rho \times C_D \times A_f \times (v + v_{wind})^2 \tag{2.4}$$

$$F_{gradient} = m \times g \times sin(\theta) \tag{2.5}$$

$F_{friction}$: Ground friction force

$F_{aerodynamic}$: Aerodynamic resistance force

$F_{gradient}$: Gradient force

f_r : Friction coefficient which depends on the velocity and friction constant f_{rc}

f_{rc} : Friction constant which is related to the road type, and material and structure of the wheels

ρ : Air mass density

C_D : Aerodynamic drag coefficient

A_f : Frontal area of the vehicle

m : Mass of the vehicle

g : Gravitational constant

θ : Road slope angle

v : Directional velocity

v_{wind} : Wind velocity

The resistive forces can be considered as the force losses, and formulated as follows.

$$F_{loss} = F_{aerodynamic} + F_{gradient} + F_{friction} \tag{2.6}$$

When the vehicle moves, the repulsive force acts via the wheels. The force required to move the vehicle from one point to another with the desired velocity is considered as the required force, and the related torque is considered as the required torque. The relations are as follows.

$$F_{required} = \sigma \times m \times a = F_{applied} + F_{loss} \tag{2.7}$$

$$F_{required} = T_{required}/r_d \tag{2.8}$$

where σ is the rotational inertia constant, $F_{required}$ is the required force, r_d is the wheel radius, $F_{applied}$ term stands for the applied force from the motor to the wheels, and a is the acceleration.

Lastly, from the required force equation, the acceleration of the vehicle can be formulated as follows.

$$a = \frac{\dfrac{T_{applied}}{r_d} - F_{losses}}{\sigma \times m} \tag{2.9}$$

where $T_{applied}$ is the applied torque from wheels to the road.

The sign of the acceleration can be considered as a decision parameter for drivetrain models as it points out whether the vehicle is accelerating or decelerating. The importance of this decision comes from determining the direction of the force created by the engine and also the direction of power flow between the engine and the battery. Regenerative braking phenomena rises from this situation and it is the concept of charging the battery of a vehicle during the braking period.

2.2 Least Squares State Estimation

The idea of state estimation in power systems is proposed by Fred Schweppe and it broadened the capabilities of SCADA applications, leading to the establishment of the EMS [27]. The aim is to determine the optimal estimates for the system states, which are bus voltages and phase angles in basic applications. A state estimator can be considered as a filter between raw measurements received from the system and applications that require a reliable database.

One of the state estimation methods in the power system is the LS estimation method. The method is about estimating states by minimizing the squared discrepancies between the observed data and its expected value [28]. Also, it is the most commonly used method in different areas. In [29], LS method is utilized to estimate power system frequency. On the other hand, [30] proposes the LS method to estimate the distance for mobile beacon-based localization in wireless sensor networks. Furthermore, the LS method is utilized to channel estimation algorithm for underwater acoustic systems in [31].

In a simple power system state estimation algorithm, the state vector consists of voltage magnitudes and phase angles as described in 2.10. In addition, the measurement vector consists of active and reactive power measurements as described in 2.11. The power measurements may contain line flow and bus injection measurements.

$$\hat{x} = \begin{bmatrix} \hat{V} \\ \hat{\theta} \end{bmatrix} \tag{2.10}$$

$$z = \begin{bmatrix} P_{inj} \\ P_{flow} \\ Q_{inj} \\ Q_{flow} \end{bmatrix} \tag{2.11}$$

The relation between measurements and states can be defined as in 2.12

$$z = h(\hat{x}) + e \tag{2.12}$$

where z is the set of measurements, $h(\hat{x})$ is the function relating measurements to states and e is the measurement errors.

Two common assumptions below are made regarding the statistical properties of the measurement errors

1 - $E(e_i) = 0, i = 1, ..., m$

2 - $E[e_i e_j] = 0$

By using the relations between measurements and states, the measurement Jacobian matrix (H matrix) can be formed simply by taking the partial derivative of functions with respect to the states. The form of H matrix is given in 2.13

$$H = \begin{bmatrix} \frac{\delta P_{inj}}{\delta \theta} & \frac{\delta P_{inj}}{\delta V} \\ \\ \frac{\delta P_{flow}}{\delta \theta} & \frac{\delta P_{flow}}{\delta V} \\ \\ \frac{\delta Q_{inj}}{\delta \theta} & \frac{\delta Q_{inj}}{\delta V} \\ \\ \frac{\delta Q_{flow}}{\delta \theta} & \frac{\delta Q_{flow}}{\delta V} \\ \\ \end{bmatrix} \tag{2.13}$$

Then, the gain matrix (G matrix) is formed as in 2.14 by using the H matrix. The G matrix is structurally and numerically symmetric and sparse compared to the H matrix and it is built for computational efficiency.

$$G = H(\hat{x}^k)^T \times H(\hat{x}^k) \tag{2.14}$$

The steps of the iterative solution algorithm for LS state estimation is presented below.

Step 1: Start iterations, set the iteration index $k = 0$.

Step 2: Initialize the state vector $\hat{x}^k$, typically as a flat start.

Step 3: Calculate the gain matrix, $G(x^k)$

Step 4: Insert $\hat{x}^k$ to the measurement function and find Δz^k

Step 5: Find $\Delta \hat{x}^k = G(x^k)^{-1} \times H(\hat{x}^k)^T \times \Delta z^k$

Step 6: Test the convergence for e pre-set threshold, $max|\Delta \hat{x}^k| \leq \epsilon$

Step 7: If no, update $\hat{x}^{k+1} = \hat{x}^k + \Delta \hat{x}^k$, $k = k + 1$, and go to step 3. Else, stop.

2.3 Parameter Estimation

The relations between system states and measurements include system parameters. For example, the power flow equation of a power system model includes line resistance and reactance parameters. These parameter values might change in time due to aging effects or environmental conditions. If the state estimator used in this system is not updated with new parameter values, the results of the estimator will be incorrect. To overcome this problem, the parameter estimator method is used.

There are two subgroups in this method. One of them is based on residual sensitivity analysis. It is performed at the end of the state estimation process. The main advantage is that there is no need to modify the main state estimator method. The second one is augmenting the state vector. The suspected parameters are included in the state vector and they are both estimated simultaneously with the system states. The form of new state and measurement vectors are in 2.15 and 2.16 respectively. As described in 2.2, the LS estimation method can be used to estimate the parameters.

$$\hat{y} = \begin{bmatrix} \hat{x} \\ \hat{p} \end{bmatrix} \tag{2.15}$$

$$z = h(\hat{x}, \hat{p}) + e \tag{2.16}$$

2.4 Drivetrain Models

A drivetrain model can be defined as an artificial environment of a virtually designed vehicle. The aim of this model is to observe the behavior of the vehicle under given circumstances. The most common usage of it is calculating the power consumption for a predetermined trip. The model contains some vehicle specifications as follows.

1 - Mechanical and electrical efficiencies of components.

2 - Aerodynamic properties.

3 - Power consumption of components.

Consumption of power of a vehicle is calculated by using these specifications and power equations. There are several forces acting on a moving vehicle and all of them create power. The source of power which enables a vehicle to move comes from the battery for an electric vehicle. The battery power is converted to mechanical power by the engine to create the repulsive force for the vehicle. Drivetrain models aim to calculate the required power coming from the battery to move the vehicle under desired conditions.

The drivetrain models are divided into two types. One of them is the forward simulation which aims to calculate the power generated at the engine and then transfers this power to the wheel by using consumed power input data. The second type is the backward simulation which aims to calculate the net forces acting on a vehicle in the wheel-road base and then transfers it to the engine. The backward simulation method has a faster response than the forward simulation [32]. Also, the backward simulation method uses the directional velocity data as an input. This property increase the ease of use of the simulation and enables the user to try different types of trip data.

2.5 Queueing Strategies

Power system operators aim to decrease their operation costs besides reliability. The operation cost depends on the market prices of electricity and those market prices change during a day. In the literature, several methods are proposed to achieve this goal such as load shifting [33] and utilization of storage systems [34]. In addition, load scheduling methods bring another solution to this phenomenon. Load scheduling aims to distribute the load demand over time. This method can be combined with other methods such as queueing. The queueing method is used to reduce or optimize the total waiting time. The method enables mathematical analysis of several related processes, including arriving at the queue, waiting in the queue, and being served at the front of the queue [35]. This method is used in different areas. In [36], the method is used for IP networks. On the other hand, it is used for plug-in electric vehicle charging in [37].

The implementation of queueing method to a power system can be expressed as dividing the load into partitions and align them one after another to minimize the cost of operation by changing the time of power consumption. Reaching this goal requires flexibility of the system. For example, electric vehicle charging is considered as a flexible load. In other words, the charging of an electric vehicle can be done in different times of the day. Queueing strategies for electric vehicles arise from this challenge. They are performed to arrange the load of the system by considering the market prices and aim to minimize the total operation cost. This is the biggest advantage of this strategies. The second approach of these strategies aims to reduce the time of a vehicle spent on a charging station to meet the customer demands.

The aim of a queueing strategy varies for different applications. The applications for electric vehicles can be basically divided into two subgroups by system sizes. Firstly, for a system with multiple charging stations, the aim can be distributing the vehicles among stations to decrease the charging/waiting time of a vehicle [38]. Secondly, queueing strategies are done to minimize the cost of the operation for a single system with charging station. Managing the load of the system enables the system owner to make the operation more feasible as electricity market becomes more dynamic.

2.6 Linear Programming

Linear programming (LP) is a method to achieve the optimal outcome in a mathematical model whose requirements are presented by linear relationships. It is also called linear optimization and mostly used to obtain solutions to problems as maximum profit or lowest cost. LP is subject to linear equality and inequality constraints. The problem can be expressed in canonical form as below.

Find vector x that minimizes $c^T x$

Subject to $Ax \leq b$ and $x \geq 0$

where x is the variables to be determined,A, c, and b are given vectors. $c^T x$ is called the objective function to be minimized.

LP problem is also named as an optimization problem. In a basic power system application, the cost of operation is said to objective function of the problem, power demand is the optimization variable and there should be constraints related with the system capabilities. LP finds a solution to minimize the system cost by arranging the load demand considering problem constraints. In this thesis, the objective function is the operation cost for determined period of time. The optimization variables are electric vehicle and energy storage system loads.

CHAPTER 3

THE PROPOSED DRIVETRAIN AND ESTIMATION METHODS

Chapter 2 presents the background information for the proposed thesis. Vehicle dynamics, state and parameter estimation algorithms, and queueing strategies are explained. This section presents the utilized drivetrain model first. Then, the implementation of state and parameter estimation algorithms is explained. Lastly, several tests are performed and the results are shown.

3.1 Introduction

This thesis proposes a drivetrain model by using the backward simulation method. The first input of the model is the road trip data. The trip data includes time-series velocity measurements. There are two different methods to obtain the trip data from the vehicle. One of them is getting the angular velocity of the tires from the vehicle. This approach uses the relation between the angular and the directional velocity. The disadvantage of this approach is using constant parameters while converting the velocity from angular to directional. As mentioned before, the parameter values change in time due to some external or aging effects, so the calculation of the directional velocity from the angular velocity may be incorrect. The second method is taking the GPS data of the trip. This data can be obtained from different applications. The Main advantage of using GPS data for measuring velocity is that it is independent of the vehicle parameters. In other words, any changes in vehicle parameters do not bias the velocity measurements. With the improvements in GPS technology, more accurate measurements would be taken for future applications. In this thesis, the second method is used for taking the velocity measurements of trips.

The second input of the model is vehicle parameters which can be classified as interior and exterior parameters. These parameters can be considered as characteristics of a vehicle, and their values change from one vehicle to another. Especially, the calculation of power consumption depends on these parameters. The list of interior and exterior parameters used in this thesis are given in Table 3.1.

Table 3.1: Parameters used in drivetrain model.

Parameter symbol	**Variable name**
σ	Rotational inertia constant
g	Gravitational constnat
A_f	Frontal area of vehicle
C_d	Aerodynamic drag coefficient
ρ	Air mass density
i_g	Gear ratio
η_{motor}	Electric motor efficiency
$\eta_{mechanical}$	Mechanical efficiency
$\eta_{battery}$	Battery efficiency
r_d	Radius of wheels
m	Mass of vehicle

This thesis also proposes state and parameter estimation methods. They are both based on the LS estimation technique. State estimation is used to eliminate the measurement errors and obtain unbiased estimates of states which are used for the following steps. Parameters to be estimated are selected by investigating their effects on the power consumption of the vehicle.

The following sections present the proposed drivetrain and estimation processes. Lastly, several tests are performed and results are presented.

3.2 The Drivetrain Model

The drivetrain model aims to simulate the vehicle trip in a virtual environment. The model is implemented in MATLAB environment. The calculations are done on a wheel-road base and then transferred to the battery side as the backward simulation method suggests. The model works step by step for each time-series data point in the inputs. After getting the input data as a start, the first step is calculating the acceleration. As the trip data is time-series, the acceleration can be found as calculating the difference between the present state and the next step. The solution is considered as the required acceleration. In other words, the amount of acceleration needed to follow the trip data is named as required acceleration and it is formulated for a time instance i as in 3.1.

$$a_{required} = a_{i+1} - a_i \tag{3.1}$$

The sign of the $a_{required}$ is the indicator of whether the vehicle is accelerating or decelerating. The drivetrain model splits into two cases for these conditions. For the accelerating case, the next step is determining the region of the motor. Motors have two regions of operation which are the constant torque region and the constant power region. The determination of the motor region is done by checking the speed value. There is a base speed value for each motor to discriminate the regions. Motors start working in the constant torque region and then the region is changed to constant power after reaching above the base speed. Fig 3.1 demonstrates the regions of an electric motor. This figure implies that there are certain limits for motors to operate. In other words, the capability of the motor to operate can not be on the outside of the curves.

In the third step, the required torque or power to move the vehicle from the present state to the next state is calculated based on the motor operating region. The required torque can be calculated by using the equation in 2.8 and the required power can be calculated as in 3.2. Considering the difference in the magnitude of forces for different velocities in each step, calculating forces based on velocity in just one step would be inaccurate. The proposed method calculates the forces by using the mean

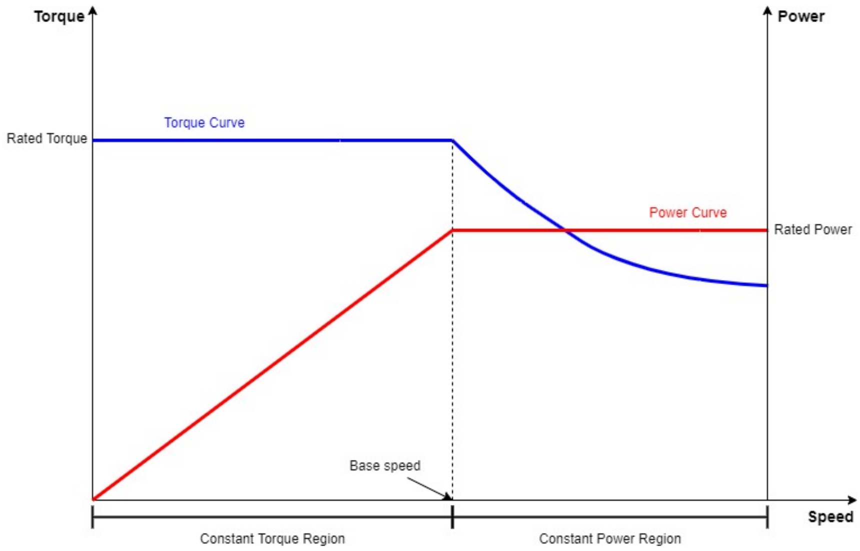


Figure 3.1: Electric motor operating regions.

value of the velocities between the present and next state of the vehicle speed. This strategy aims to increase the accuracy of the drivetrain model.

$$P_{required} = T_{required} \times \omega \tag{3.2}$$

where ω is the angular velocity of the wheels, $P_{required}$ is the required power value, and $T_{required}$ is the required torque value.

The most important part of this step is determining whether the required power/torque is within the limits of the vehicle or not. If it is inside the limits, then the vehicle is said to be following the trip data. However, if the required power/torque exceeds the limits, the maximum capability of the vehicle is applied and the next state is determined by using this information. The determination is done by calculating a new acceleration value. The last part of this step is recalculating the new power consumption if necessary.

Accelerating and decelerating parts of the model work with the same method. One additional concept was introduced to the decelerating part. It can be explained as decelerating while applying power to the wheels. For example, if the driver cuts the power from the engine by releasing the gas pedal, the vehicle starts to decelerate.

However, if the desired velocity for the next step is higher than the velocity in the no-power case, the drives should decelerate while pushing the pedal.

The next feature of the model is traction control. Traction of the vehicle can be done from rear wheels, front wheels, or both (Four Wheel Drive, FWD). When the vehicle decelerates, the distribution of total weight changes between front and rear. This situation leads to differences in applied powers from wheels to the road surface. For decelerating part, the regenerative braking power is calculated by using the information of traction control.

The last step of the model is converting the calculated power from the wheel-road base to the battery side of the vehicle. This conversion is done by using the efficiencies of the components. The equations of power conversion are as below.

$$P_{motor} = P_{applied} \times \eta_{total} \tag{3.3}$$

$$\eta_{total} = \eta_{motor} \times \eta_{mechanical} \tag{3.4}$$

$$P_{battery} = P_{motor} \times \eta_{battery} \tag{3.5}$$

where $P_{applied}$ is the applied power from wheel-road base, P_{motor} and $P_{battery}$ are the power applied by the motor and battery respectively. η_{motor}, $\eta_{mechanical}$, and $\eta_{battery}$ are the efficiencies of electric motor, mechanical parts, and battery respectively.

The overall flowchart of the drivetrain model is given in Fig 3.2. The drivetrain model works step by step. The k term in the flowchart indicates the step number.

3.3 The State Estimation

The collected measurement from devices may contain errors. State estimation aims to eliminate these errors and determine the unbiased values of the states. The method is based on the relations between measurements and states. The states to be estimated are the applied torque, the angular velocity of wheels, and the radius of the wheels as in 3.6. The measurements are selected as applied power, directional velocity, and the

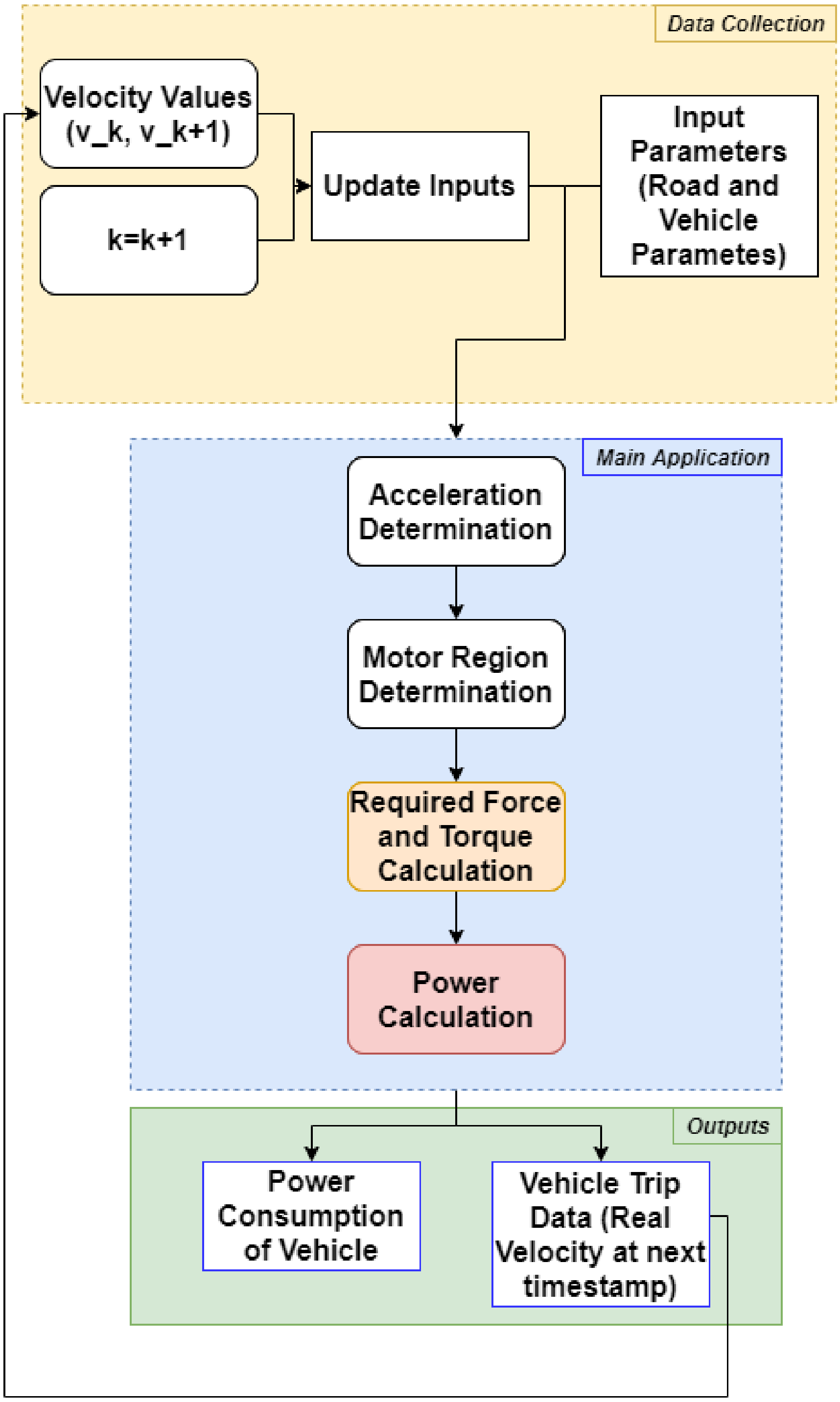


Figure 3.2: Flowchart of the proposed drivetrain model.

angular speed of wheels as in 3.7. Relations between measurements and states are given in 3.8 and 3.9.

$$\hat{x} = \begin{bmatrix} \hat{T} \\ \hat{w} \\ \hat{r_d} \end{bmatrix} \tag{3.6}$$

$$z = \begin{bmatrix} P \\ v \\ \omega \end{bmatrix} \tag{3.7}$$

$$P_{applied} = T_{applied} \times w + e_1 \tag{3.8}$$

$$v = \omega \times r_d + e_2 \tag{3.9}$$

where e_1 and e_2 are the measurement errors.

The next step is forming the measurement Jacobian matrix (H matrix). H matrix has a form of partial derivative functions of states to the measurements. The structure of the H matrix is given in 3.10.

$$H = \begin{bmatrix} \omega[t] & T_{applied}[t] & 0 \\ 0 & r_d & \omega[t] \\ 0 & 1 & 0 \end{bmatrix} \tag{3.10}$$

After forming the H matrix, the next step is performing an iterative solution. The iteration process continues until the convergence is satisfied. The determination of convergence threshold value is based on the concern of computation. It can be selected as a small value but the tradeoff will be a longer computation time. The iterative solution follows the steps in 2.2. The following equations are used in the process steps.

$$\hat{x}^{k+1} = \hat{x}^k + \Delta\hat{x}^k \tag{3.11}$$

$$\Delta\hat{x}^k = (H(\hat{x}^k)^T \times H(\hat{x}^k))^{-1} \times H(\hat{x}^k)^T \times \Delta z^k \tag{3.12}$$

$$\Delta z^k = z_1^k + \hat{z}_1^k \tag{3.13}$$

where $\hat{x}^k$ is the estimated states at iteration k, and $\hat{z}_1$ can be found by inserting an initial condition to the measurement function. The initial condition is said to be a flat start which can be selected intuitively.

3.4 The Parameter Estimation

In the drivetrain model, the values of parameters are considered as correct values. However, this is not the case in reality because parameter values change with time. This situation causes getting incorrect solutions to power consumption. To overcome this problem, the parameter estimation method is used. By using the solution of state estimation, α can be calculated as unbiased directional velocity estimates are available. The parameter estimation process uses the relations of system parameters with torque and acceleration observations given in 2.9. The selected parameters are σ , f_{rc} and f_{aero} and 3.14 shows the parameter vector. The f_{aero} term is described in 3.15. In addition, the applied torque can be expressed as in 3.16. For the sake of simplicity, parameter estimation is performed by using torque equations in the next parts.

$$\hat{p} = \begin{bmatrix} \hat{\sigma} \\ \hat{f_{rc}} \\ \hat{f_{aero}} \end{bmatrix} \tag{3.14}$$

$$f_{aero} = \rho \times C_d \times A_f \tag{3.15}$$

$$\hat{T}_{applied} = r_d[\sigma m\alpha + mgf_r cos(\theta) + \frac{1}{2}\rho C_D A_f (v + v_{wind})^2 + mgsin(\theta)] \tag{3.16}$$

The selection of parameters to be estimated can be done differently based on the application. In this thesis, the parameters which have dominant effects on power consumption are selected. The reason behind this is the power consumption characteristics of a vehicle indicate how much energy will be demanded from the grid.

Parameter estimation is done based on the state vector augmentation method. However, the state vector is omitted. The reason is that the estimation of the states is already done in 3.3. Hence, the remaining part of the process is done by using the LS algorithm. As the parameters are linearly related to the measurements, this estimation is not an iterative process. In other words, one step solution can be applied. The form of H matrix and estimation formula is given in 3.17 and 3.18 respectively.

$$H = \begin{bmatrix} \frac{\delta T_{applied}}{\delta \sigma} & \frac{\delta T_{applied}}{\delta f_{rc}} & \frac{\delta T_{applied}}{\delta f_{aero}} \end{bmatrix} \tag{3.17}$$

$$p = (H^T \times H)^{-1} \times H^T \times \hat{T} \tag{3.18}$$

where $\hat{T}$ is the estimated torque value and p is the parameter vector.

The measurements in the proposed method have different types. Therefore, their magnitude may vary significantly. Those differences may lead to ill-conditioning, and hence numerical stability should be improved. As the estimator is linear, scaling is employed, such that each row of the H matrix and corresponding measurement value are normalized with respect to the largest value of that row.

If the changes in parameter values are investigated, it can be noted that σ and f_{aero} parameters are less variable compared to the f_{rc}. In addition to that, the effective mass (m) may vary in each trip of the vehicle. So, estimation of m and f_{rc} leads more accurate solutions. By using the same torque equation in 3.16, a new H matrix can be formed as in 3.19 and the new parameter vector is in 3.20. One difference from the previous parameter estimation approach is that this should be an iterative process because there is a nonlinear relation between the measurements and m. LS estimation was performed to solve this problem as before.

$$H = \begin{bmatrix} \frac{\delta T_{app}}{\delta m} & \frac{\delta T_{app}}{\delta f_{rc}} \end{bmatrix} \tag{3.19}$$

$$\hat{p} = \begin{bmatrix} \hat{m} \\ \hat{f}_{rc} \end{bmatrix} \tag{3.20}$$

The strategy of parameter estimation is decided as performing for σ , f_{rc} and f_{aero} parameters first with the information of m, and then for f_{rc} and m only. After a dedicated period of time, the first step should be performed to update the parameters again. Therefore, the accuracy of the estimation can be improved as time passes.

Parameter estimation is utilized with the presence of described measurements. However, this may not be the case in reality. Obtaining measurements from an electric vehicle may not be always possible. This situation can be because of lack of a measuring devices or even the related data may not be reachable for users. To overcome this challenge, a second estimation algorithm is utilized.

The modified algorithm is based on considering the absence of time series power measurements. This strategy proposes that the parameter estimation can be modified to estimate the parameters by using multiple trip data and consumed energy information for each trip. The relation between power and energy is given in 3.21. Since power is related to the torque by equation 3.2 and torque is related to the parameters, the energy is related to the parameters. Then, the energy consumed for different trips becomes the new measurement for the parameter estimation process. Note that, this strategy is proposed for lack of torque measurement. Although the torque measurement may not be at present, the amount of energy spent can be easily determined by checking the remaining percentage of the battery by vehicle owners. The accuracy increases with the number of measurements in this case. The measurement vector of energy consumption is in 3.22 and the H matrix formed based on the second strategy is in 3.23.

$$E_i = \sum_{1}^{t} P_i \tag{3.21}$$

$$E = \begin{bmatrix} E_1 \\ E_2 \\ E_3 \\ . \\ . \\ . \\ E_n \end{bmatrix} \tag{3.22}$$

$$H = \begin{bmatrix} \frac{\delta E}{\delta \sigma} & \frac{\delta E}{\delta f_{rc}} & \frac{\delta E}{\delta f_{aero}} \end{bmatrix} \tag{3.23}$$

3.5 Results

In this section, tests and results of the drivetrain model and estimation processes are presented. For the drivetrain model, the reference trip data is selected as Worldwide Harmonised Light Vehicles Test Procedure (WLTP) at first. It is the common test cycle in the literature and the information on the power consumption of different vehicles is available based on this cycle [39]. Then, real measurements obtained from field tests are used to observe the model algorithm behaviors. For the estimation part, different types of data are created by using the drivetrain model.

3.5.1 The Drivetrain Model

Firstly, the drivetrain model is tested to follow the WLTP cycle. The selected vehicle for the model is the BMW i3. Fig 3.3 shows the WLTP cycle and the simulated output speed labeled as the actual speed. In addition, the difference between reference velocity and calculated velocity values is shown in Fig 3.5. It can be stated that the model accomplished to follow the input cycle. The second observation is that the operating condition of the motor does not exceed its limits. This proves that the model works accurately and Fig 3.4 shows the operating points of the motor for WLTP input data.

Secondly, the power consumption of the vehicle is calculated. During calculations,

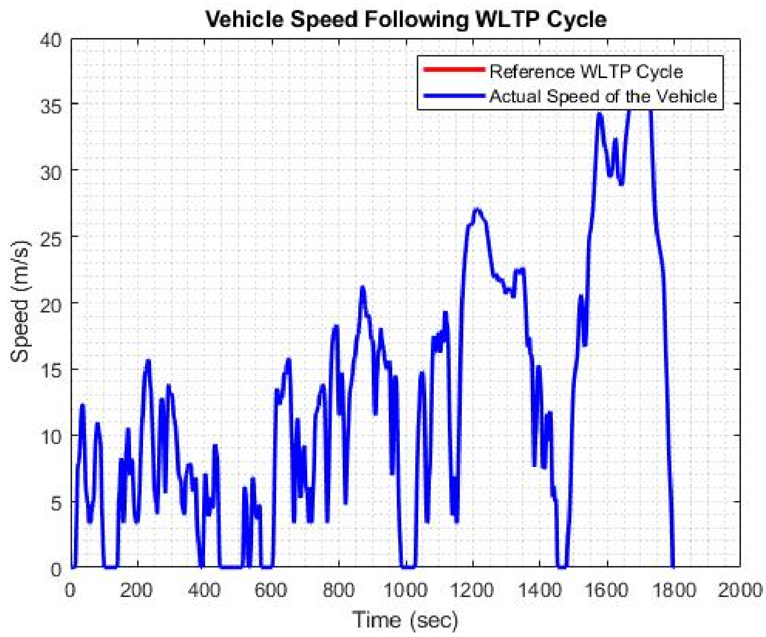


Figure 3.3: WLTP cycle and actual speed vs time graph.

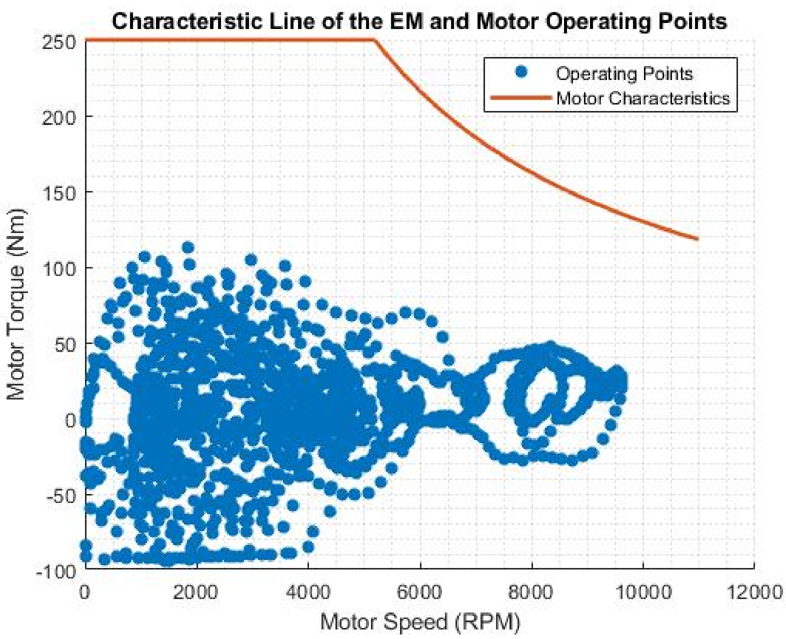


Figure 3.4: Simulation output of motor operating points.

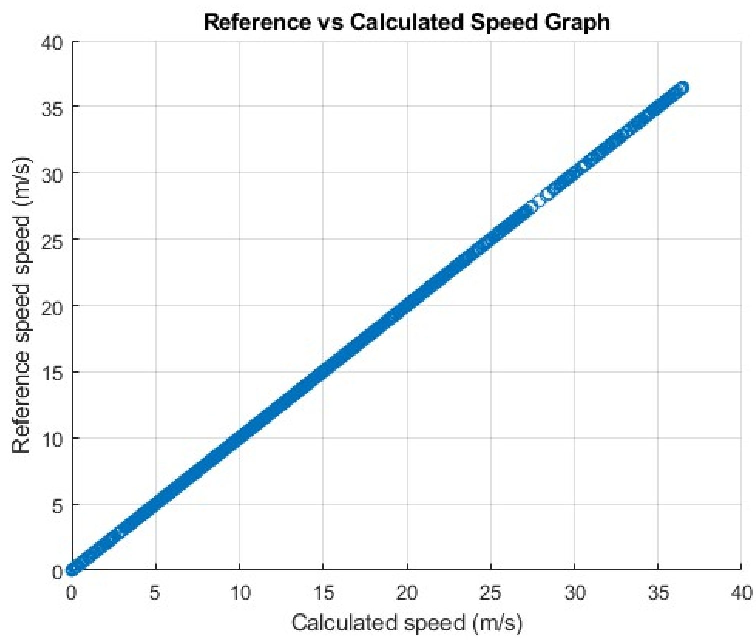


Figure 3.5: Reference vs Calculated Velocity Difference Graph

auxiliary power is added to the battery (i.e. 750W). The reason behind this is considering the power consumed by the other components of the vehicle like air conditioning, lighting system, etc. The applied power and battery powers are shown in Fig 3.6 and Fig 3.7 respectively. The sign of the power is an indicator of power flow direction. The negative sign means that power is regenerated during the braking period. The differences between these graphs prove that the implementation of traction control is done properly. In addition, efficiencies mentioned before are the second reason for the differences as expected.

Then the validation of the drivetrain model for different vehicle models is performed. The aim is to achieve at least 95% accuracy in determining the total battery power of the vehicle by comparing calculated data and the manufacturer data. As the total available battery capacity information is available, power consumption data is used to obtain the total energy. Table 3.2 shows different types of vehicles, their calculated capacity, and the difference between the manufacturer data in percentage. The vehicles selected have different types of traction control. Types of vehicle traction controls are shown in 3.3. There are three traction control types named as front-wheel drive (FWD), rear-wheel drive (RWD), and four-wheel drive (4WD). FWD and RWD terms

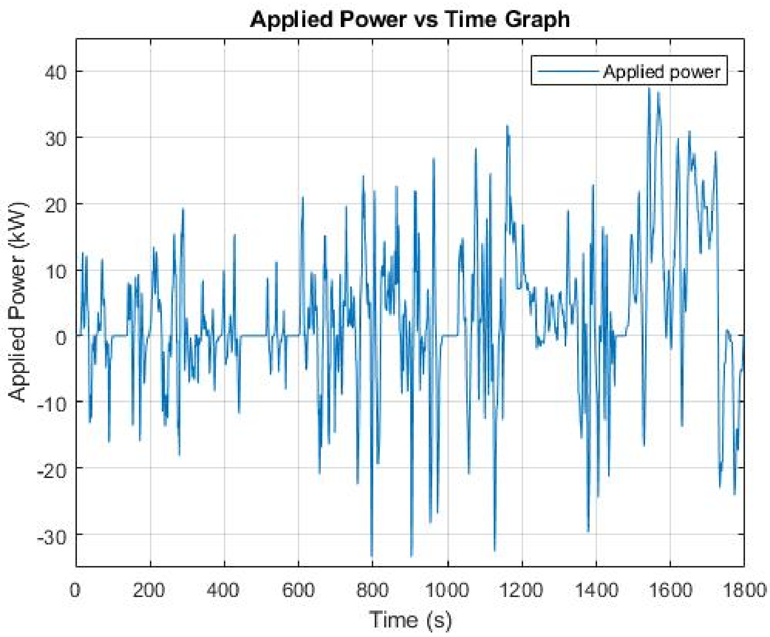


Figure 3.6: Applied power vs time graph.

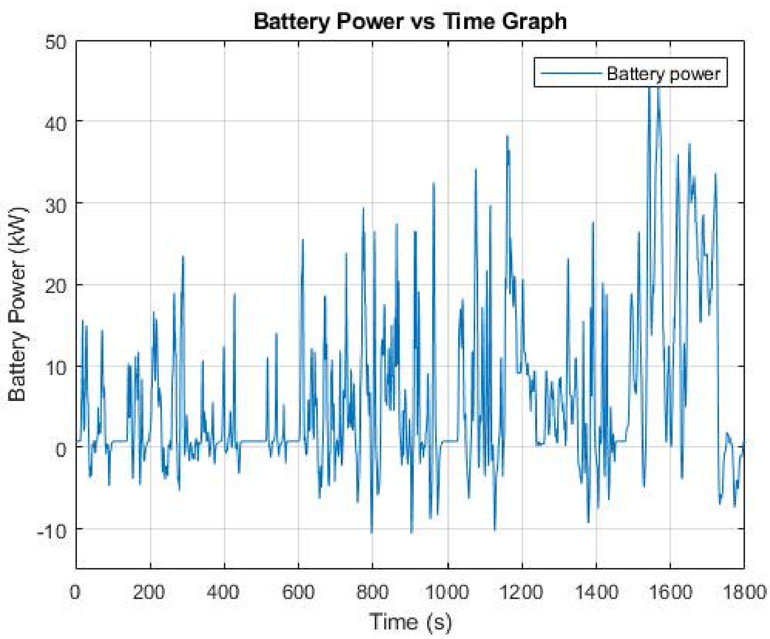


Figure 3.7: Battery power vs time graph.

imply that the traction force is applied through the front or rear wheels of the vehicle respectively. On the other hand, the 4WD term implies that the traction force is applied through all the wheels. The manufacturer data is based on the same WLTP cycle [39]. As the differences in percentage are not above the desired limit, the validation is said to be accomplished.

Table 3.2: Manufacturer and calculated values of energy of the battery.

Battery Size(kWh)	**Manufacturer Data**	**Calculated Capacity**	**Difference (%)**
BMW i3 120Ah	37.90	39.20	3.43
Renault Zoe ZE50	52.00	52.33	0.63
Nissan Leaf	36.00	37.60	4.44
Peugeot e-208	45.00	46.49	3.31
Tesla Model 3 LRP	72.50	71.60	1.24

Table 3.3: Traction control types of selected vehicle models.

Model	**Traction Type**
BMW i3 120Ah	RWD
Renault Zoe ZE50	FWD
Nissan Leaf	RWD
Peugeot e-208	RWD
Tesla Model 3 LRP	4WD

Lastly, the drivetrain model was tested with input trip data which the model can not follow. Fig 3.8 shows the velocity curves of the input and model output and Fig 3.9 shows the difference between reference and calculated velocity values. This proves that the model can work even if the input data is above the limits of the vehicle. The model always works inside the operating region.

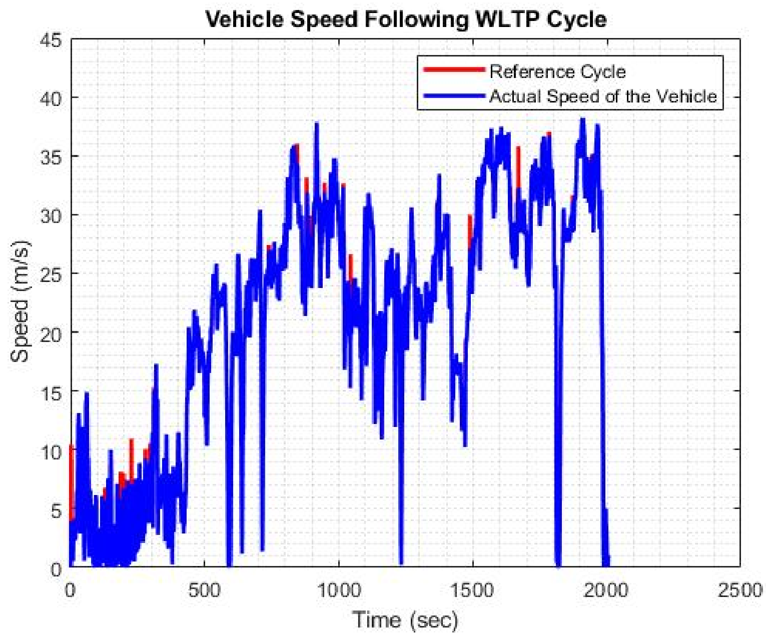


Figure 3.8: Simulation output of motor operating points.

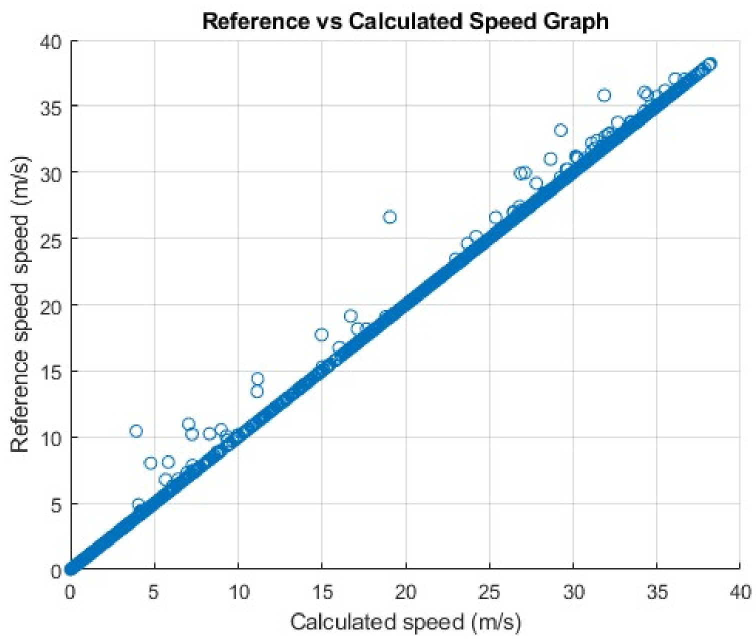


Figure 3.9: Reference vs Calculated Velocity Difference Graph

3.5.2 The State and The Parameter Estimation

State estimation is performed to determine the unbiased values of the states. The selected measurements are created by using the drivetrain model with some manipulations. The manipulations are done to obtain erroneous data. Fig 3.10 shows the graph of applied torque before and after the estimation process with respect to 100 seconds time interval and Fig 3.11 shows the differences between estimated and true states for each time step. Similarly, Fig 3.12 shows the graph of angular velocity before and after the estimation process and Fig 3.13 shows the differences between estimated and true states for each time step.

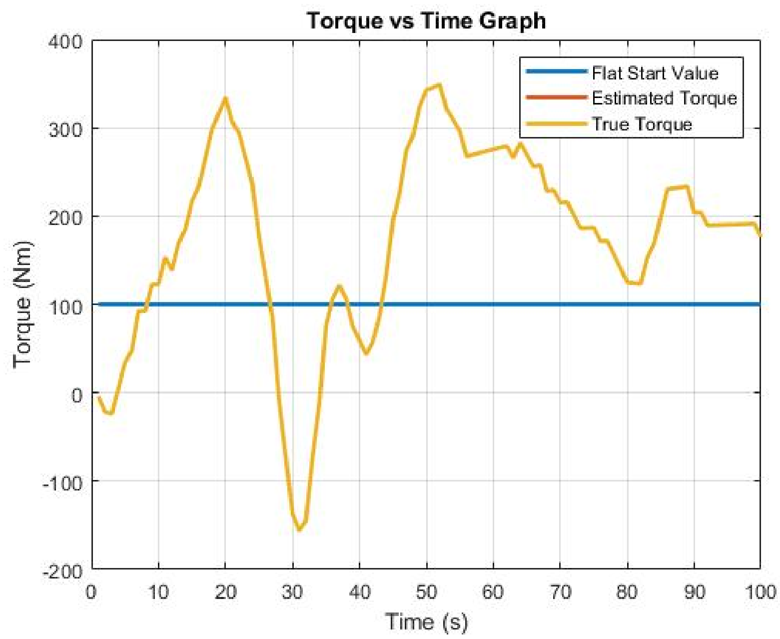


Figure 3.10: Torque vs time graph before and after the estimation.

The parameter estimation is performed firstly for σ , f_{rc} and f_{aero} parameters. Table 3.4 shows the parameters of the BMW i3 vehicle before and after the estimation process. To observe the effect of parameters on power consumption, the simulation is run for initial and estimated parameters. Fig 3.14 shows the applied power vs time graph for 100 seconds time interval. True power is obtained from the simulator by using the real values of parameters. In addition to that, power values before estimation are obtained by using erroneous parameters.

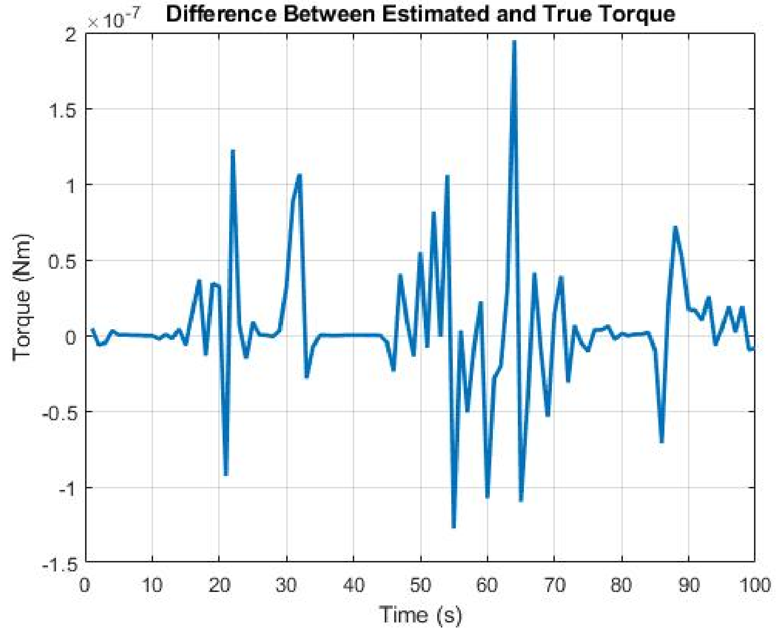


Figure 3.11: Difference of torque values before and after the estimation.

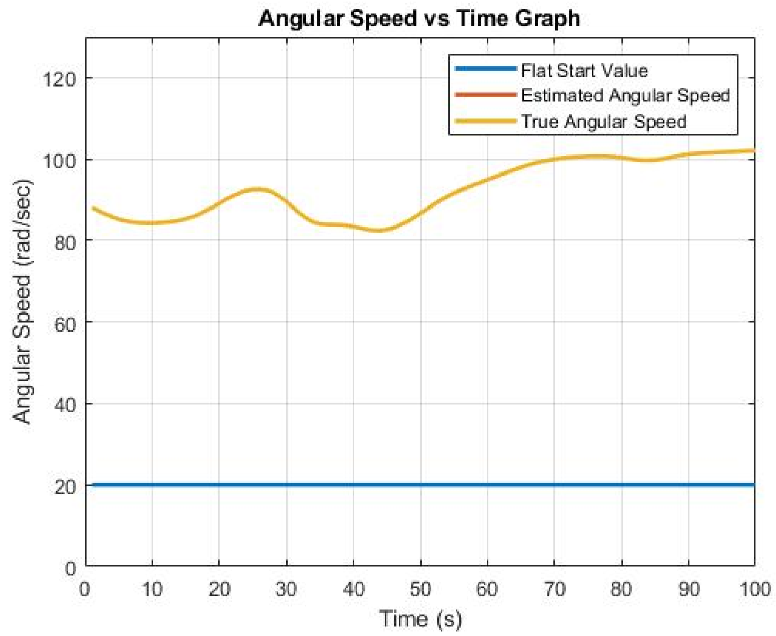


Figure 3.12: Angular velocity vs time graph before and after the estimation.

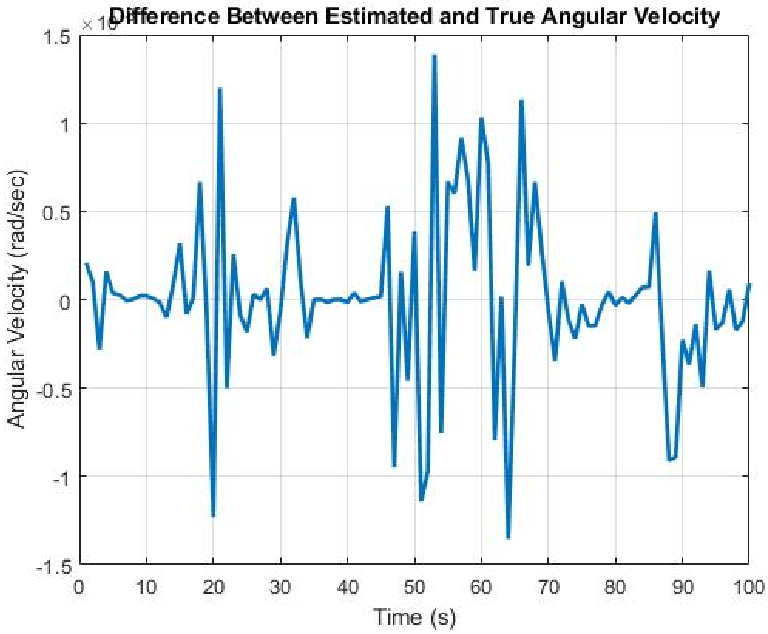


Figure 3.13: Angular velocity vs time graph before and after the estimation.

Table 3.4: Parameter values before and after the estimation.

Parameter Value	σ	f_{aero}	f_{rc}
Before Estimation	1.10000	0.73890	0.00100
After Estimation	1.11739	0.73913	0.00097

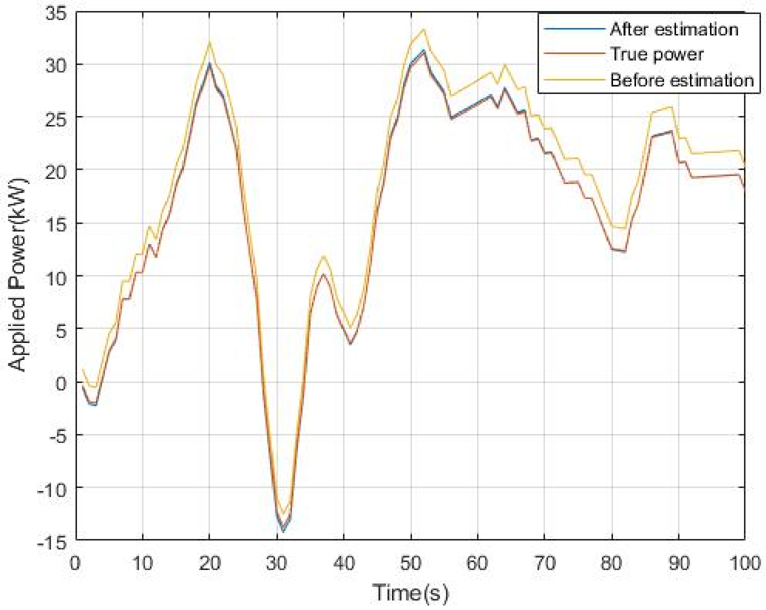


Figure 3.14: Power vs time graph before and after the estimation.

Estimation robustness has a major role as measurement errors may cause biased estimates. In the presence of gross error with a low measurement redundancy the LS estimator temp to provide biased estimates. However, the proposed method uses a high number of measurements that are collected during the trip, e.g. the resolution of the used dataset is one sample per second. Therefore, this high measurement redundancy provides robustness against bounded gross error. Fig 3.15 shows the torque estimation results after an exaggerated error (i.e. plus 500 Nm) is applied between the seconds of 44 and 50. The estimation results are close to the true values. However, as the number of biased measurements increases above some point, the estimator will eventually converge to biased estimates.

Then, parameter estimation is performed for f_{rc} and m parameters. Table 3.5 shows the parameter values and Fig 3.16 shows the power graph before and after the estimation and true state.

Lastly, the absence of related measurements is considered and parameter estimation is performed by using the energy information. The input cycles are generated by manipulating the WLTP cycle. Fig 3.17 shows 4 different created cycles used as input. The input data of energy spent in kW is presented in 3.24. The parameter

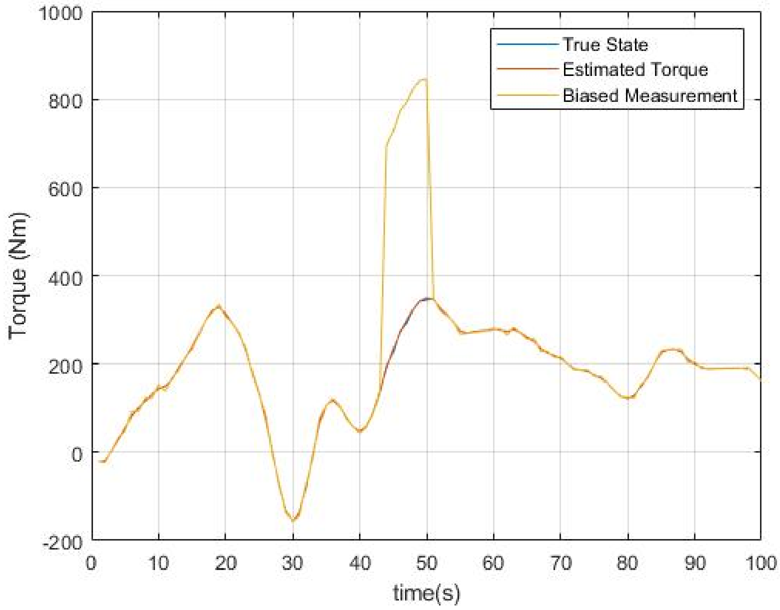


Figure 3.15: Torque vs time graph with an error, before and after the estimation.

Table 3.5: Parameter values before and after the estimation.

Parameter Value	m	f_{rc}
Before Estimation	1400.00	0.001500
After Estimation	1425.23	0.001081

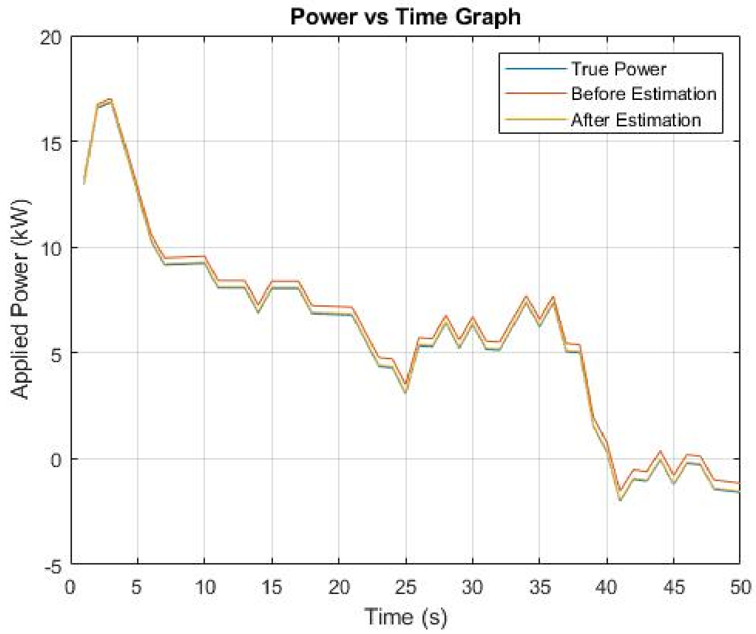


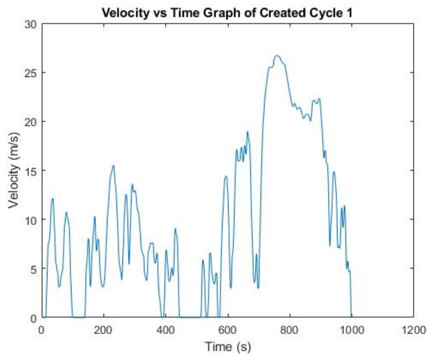
Figure 3.16: Power vs time graph before and after the estimation.

values before and after the estimation and true values are shown in Table 3.6. Note that, the true parameter values are the same as in previous tests.

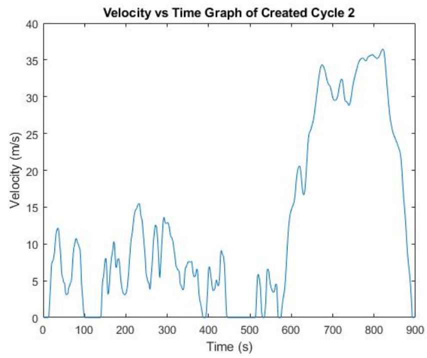
$$E = \begin{bmatrix} 149.61 \\ 184.87 \\ 933.56 \\ 134.90 \end{bmatrix} \tag{3.24}$$

Table 3.6: Parameter values before and after the estimation.

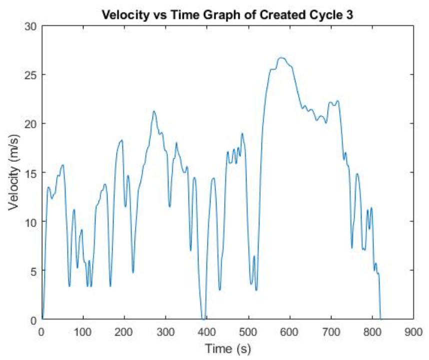
Parameter Value	σ	f_{rc}	f_{aero}
Before Estimation	1.1500	0.0015	1.7389
After Estimation	1.0900	0.0010	0.7387
True Value	1.1000	0.0010	0.7389



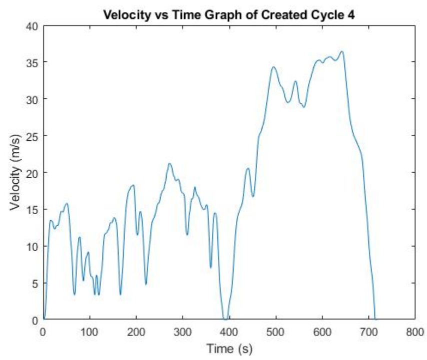
(a) Cycle 1



(b) Cycle 2



(c) Cycle 3



(d) Cycle 4

Figure 3.17: Generated cycles in the order of (a) cycle 1, (b) cycle 2, (c) cycle 3, and (d) cycle 4.

3.6 The Summary of the Chapter

Firstly, building an accurate drivetrain model with an elaborated structure is very crucial. Forces acting on a moving vehicle are not constant during a trip. The dynamic nature of the vehicle system needs proper modeling. Properties of vehicles are the determinant factor in terms of performance and hence, power consumption. The proposed drivetrain model can be considered as an accurate model in terms of given trip and manufacturer data. In addition, the model is implemented based on the backward simulation method.

Secondly, the state estimation process followed by parameter estimation is important in terms of eliminating the errors in measurements and finding the true value of vehicle parameters. The fuel of an electric vehicle is the power generated by the battery. For any application, this power should be calculated accurately to obtain a realistic solution. Power consumption calculation can be done by using several equations. These equations are all related to the measurements and parameters. Errors in the measurements or wrong parameter values diverge the results of power calculations. In this thesis, state and parameter estimation algorithms are utilized as a proper way to find the true values of the states/parameters by using the LS estimation method. The results show that the estimation process leads to finding accurate values of parameters.

Lastly, selecting parameters to be estimated has an important role. The parameters to be estimated are selected by taking their effects on power consumption into account. It is known that some of the parameter values change more frequently than others. This thesis proposes a two-stage strategy to overcome this challenge. The first stage is determining the parameters which are crucial for power calculations but change less frequently. Then, in the second stage, it aims to find parameters that change more frequently for a certain period of time. By doing this, the investigation of trip data gives more accurate information about the vehicle. In addition, a different strategy is utilized to estimate the parameters in case of the absence of related measurements.

CHAPTER 4

THE PREDICTION OF ENERGY REQUIREMENT

In previous chapters background information, utilized drivetrain model, and state/-parameter estimation algorithms are explained. In this chapter, energy requirement prediction and implementation of the LP method are presented. Lastly, tests are performed and results are shown accordingly.

4.1 Introduction

This thesis proposes an optimization solution by using linear programming followed by a queueing algorithm. The implementation of the method is done in MATLAB environment. The first step of optimization is determining the amount of load demanded by vehicle owners. The demanded load is calculated by taking input from the user and using information from historical trip data if it is available. Also, the estimated parameters are needed to obtain accurate solutions. The second step is gathering the power curves of the power system components. System load, PV generation, and battery (energy storage system) curves are considered in this proposed method. Lastly, the optimization problem is solved by linear programming. The optimization is done by setting working hours for the selected system and dividing it into determined periods.

4.2 The Determination of Load Demand

Determination of the load demand of a vehicle plays an important role in optimization and queueing algorithms. Each vehicle has its own distinct parameters even if they are produced by the same fabrication process. These parameters cause differences in the power consumption of the vehicles. So, the amount of energy required for a trip data would be different for each individual. The determination of required energy can be calculated by using different methods. For example, in [24], behaviors of drivers and their effect on power consumption are investigated. However, the vehicles are considered as having the same properties. This situation leads to inaccurate solutions in terms of not considering parameter effects on individuals. This thesis proposes a strategy to determine the load demand of each vehicle by determining its related parameters and characterizing them to get realistic solutions.

The first step of determining the load demand in the proposed strategy is taking the drivers' demands in terms of range. These demands are the number of kilometers that the drivers want to go. Then, the required loads that are sufficient to meet the demands are calculated by the input kilometer set point and average power consumption per kilometer for that each driver.

To calculate the average power consumption, the vehicle model should be well-established. The first part of the strategy relies on the presence of historical trip data. By using the proposed method in previous chapters, the parameters of the vehicle can be obtained by using those data. In addition, the daily trip route and driving behavior can also be obtained. This information helps to determine an average trip data for the driver and average power consumption can be calculated by using this trip. This calculation is done by using the utilized drivetrain model. Note that this strategy can be improved by obtaining more historical data.

The second part of the proposed strategy is based on the absence of historical trip data. In this case, an assumption is made to determine an average trip. In this thesis, a plot site is selected for which the charging station is located. Then, different trip data which are started at the location of the station are selected. The average trip data is generated by taking the mean values of velocities in each data. The reason behind this method is that the behavior of individuals converges to the mean as stated in [25].

4.3 The Optimization

An optimization algorithm can be described as finding the values of variables that minimizes/maximizes the objective function by considering determined constraints. In this thesis, optimization is utilized to minimize the cost of system operation. The cost is based on the power consumption of system elements. In the proposed system, the cost function contains 4 elements which are based on system load, PV generation, ESS, and EVs. The objective function of the problem is given in 4.1. Each of these elements has its own characteristics.

$$min \sum_{1}^{t} c_L(P_{load} + P_{EV} + P_{ESS} + P_{PV}) \tag{4.1}$$

where c_L is the market cost of electricity, P_{load} is the system power, P_{EV} is the electric vehicle charging power, P_{ESS} is the energy storage system power and P_{PV} is the photovoltaic power. The signs of P_{load} and P_{PV} are always positive and negative respectively. On the other hand, the sign of ESS changes as it can both generate or consume power. In addition, EV power has the same property as ESS with the use of the vehicle to grid applications.

Optimization is solved by using LP. The strategy starts with an initial state. The first step is listing the vehicles in the charging station and determining their load demand. Then, the optimization problem is solved for a predetermined period of time (i.e. optimization period). The result of the optimization can be added to the system load for the next process as it can be considered as the best solution for the initial state. After a short time period (i.e. restart period), this process can be repeated for the next vehicles coming to the station. The steps of the solution are presented below.

Step 1: Listing the vehicles in the station.

Step 2: Determine the load demand of the vehicles listed.

Step 3: Solve optimization problem for optimization period.

Step 4: Save the solution as load for next process.

Step 5: Go to step 1 after restart period.

The first constraint of the optimization is meeting the demanded power of the vehicles. In other words, the amount of delivered power to the vehicles should be at least the amount of demand. The second constraint is that the energy level of the battery should stay between an upper and a lower limit. This is done in order not to decrease the battery's lifetime.

Lastly, one additional feature is added to the methodology. The proposed method solves the optimization problem in a determined period of time. However, some of the vehicles may not be present during the whole period. For example, one driver may want to leave the station before the optimization period. In this case, the new method labels the vehicle and adds a new constraint to the problem to meet the driver's demand in a shorter period. In other words, the total optimization time remains the same, but the labeled demands are solved for a shorter duration.

4.4 The Queueing

The last part of the thesis is about the utilized queueing method in charging stations. The queueing is used to schedule vehicles that are waiting to be charged in present. This problem arises when the amount of power delivered to the vehicles reaches its upper limit but the demand is more. The reason behind this problem can be based on several situations such as an unexpected decrease in PV generation or an instant rise in the amount of the system load. The solution to this problem is scheduling the vehicles' charging time in a determined period of time and this method is expressed as queueing.

A rule-based strategy is utilized to overcome this challenge. The algorithm works when the power demanded is above the powering capacity of the system. Fig 4.1 shows the flowchart of the proposed queueing algorithm. The queueing algorithm starts when the total demand of electric vehicles is greater than the maximum power that can be delivered by the charging station. In this situation, the vehicles at the station are listed in terms of their energy demand. Then the number of vehicles that their total demand do not exceed the station power is listed in the charging list and started to be charged. Other vehicles are moved to a queueing list. After a vehicle is charge at the desired amount, then that vehicle is removed from the charging list and the new vehicle in the queue list is moved to the charging list. This process continues until the queue list empties.

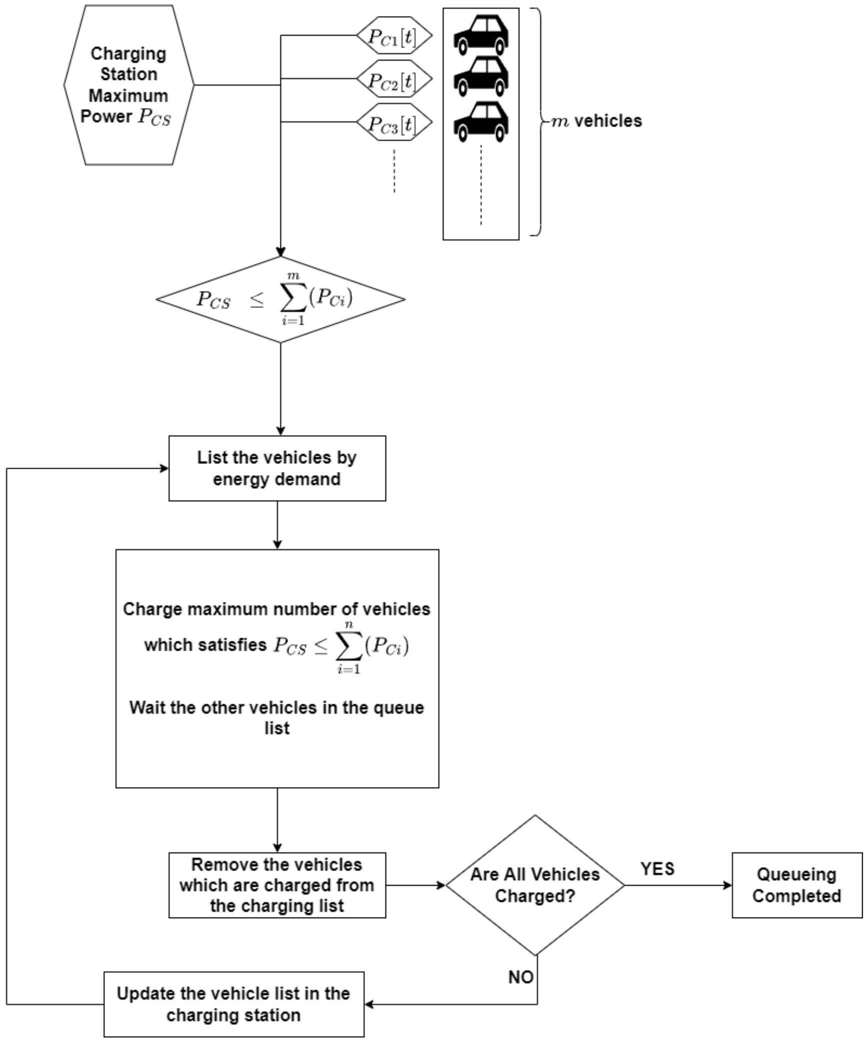


Figure 4.1: Overall Flowchart of the Proposed Queueing Algorithm

where $P_{Ci}[t]$ is the delivered power for a vehicle i at time t, and P_{CS} is the maximum capacity of the charging station power.

4.5 The Overall Workflow

The overall block diagram of the proposed methodology is shown in Fig 4.2. The first step is estimating the states determined in section 3.3. Secondly, by using the state estimates, the parameter estimation is performed to obtain the parameter values stated in section 3.4. The characterization of each vehicle is done in this step. Then, the energy requirements for individuals are calculated by using the drivetrain model. Also, the range demand and route information is taken as inputs. Lastly, the charging scheduling is performed by using the LP algorithm.

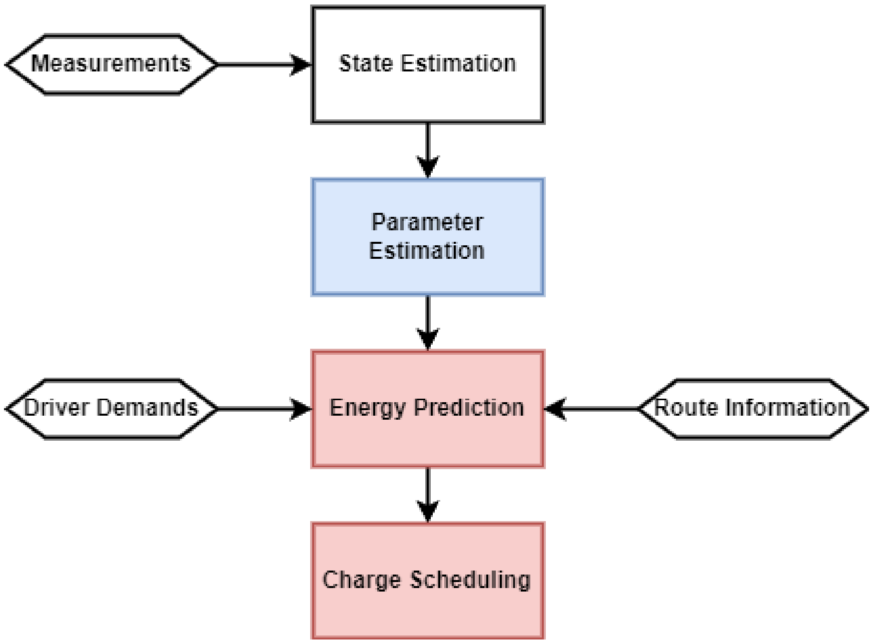


Figure 4.2: Overall Flowchart of the Proposed Methodology

The second block diagram explains the utilized parameter estimation method. The diagram is shown in Fig 4.3. The first step is checking the presence of the values of σ , f_{rc} and f_{aero} parameters. If the values of these parameters are known, the estimation of m is performed. If the values of these parameters are unknown, estimation of them is performed by using a known mass.

The next diagram shows the workflow of the energy requirement prediction method, and it is shown in Fig 4.4. The first step is taking the presence of vehicles in the charging station as an input and checking if their historical trip data is available or not. If the data is available, the required energy that meets the demand of the driver

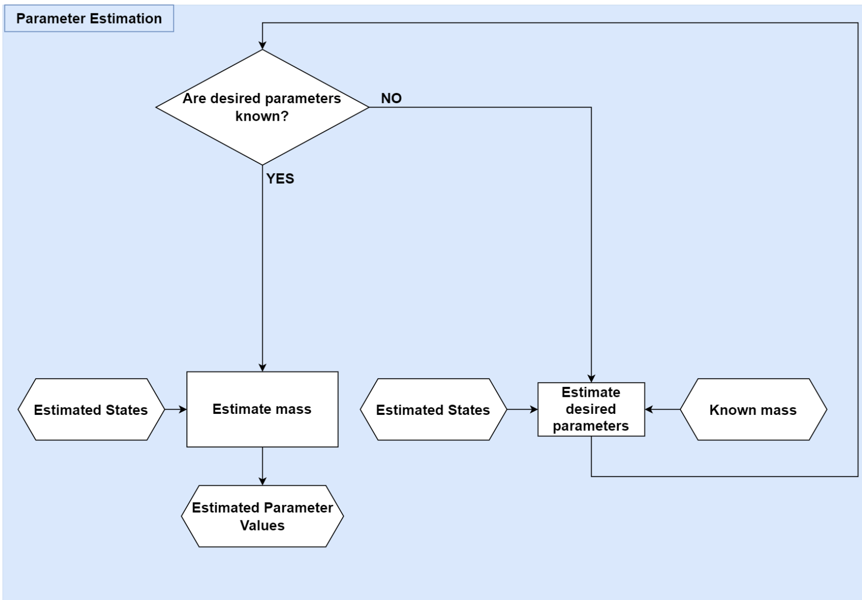


Figure 4.3: Overall Flowchart of the Parameter Estimation

is calculated by using the vehicle parameters. If the data is not available, then the required energy is calculated with the average power consumption information. Then, the calculated required energies are taken as inputs of the LP algorithm. The LP algorithm calculates the optimum operating condition by scheduling the load of the system.

The last diagram shows the workflow of the optimization process, and it is shown in Fig 4.5. The first step is determining the required energy calculation which is described above. Then, the LP algorithm takes the required energy values as an input. To solve the optimization problem which is minimizing the cost of the operation, the LP is also takes the information of the system load, market prices and optimality constraints. The output of the LP algorithm is the scheduled load. This scheduled load is fed back to the system load and added to each other. Lastly, if there is a higher demand than the system power delivery capacity, the queueing algorithm starts working. The queueing arranges the vehicles to be charged at the station. After the optimization period passed, the system is updated by checking the new vehicles at the station.

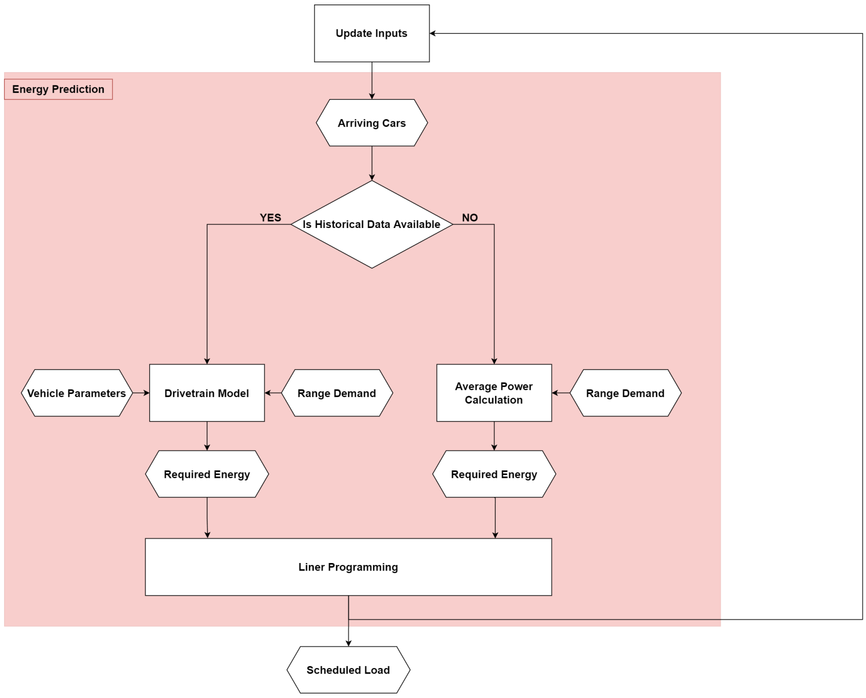


Figure 4.4: Overall Flowchart of the Energy Prediction

4.6 Results

In this section, tests and results of load determination, optimization, and queueing are presented. Real trip data obtained in the field is used in the averaging process. The implementation is done in MATLAB environment and built-in functions are used in the LP algorithm.

4.6.1 The Load Determination

Load determination for a vehicle whose data is well-known is a simple process. By using the estimation method and drivetrain model in previous chapters, the average power consumption for a determined trip can be calculated. Then, the demanded range can be multiplied by the average power consumption to calculate the total energy demand.

For the second case which is the absence of historical data, the new approach is utilized. Real trip data recorded in Ankara city is obtained and presented in Fig 4.6. The

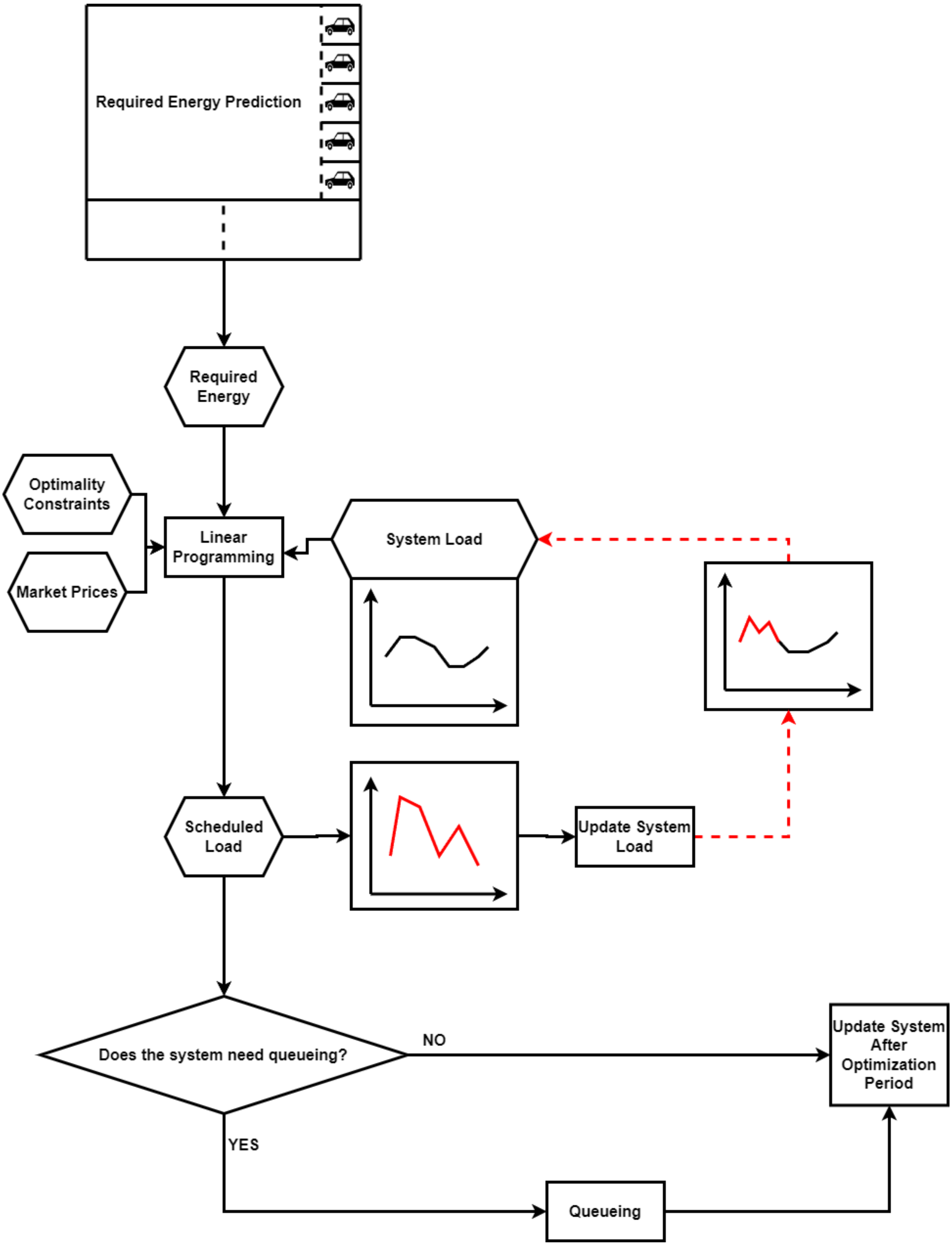
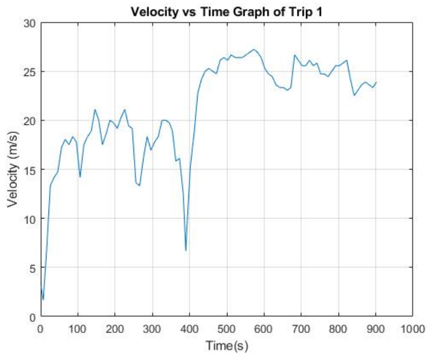
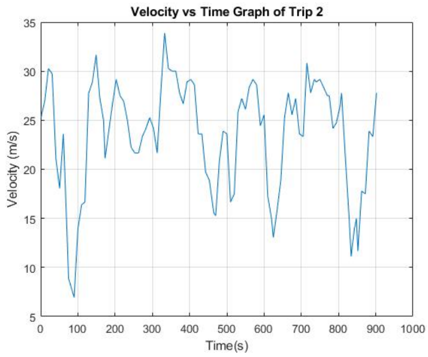


Figure 4.5: Overall Flowchart of the Optimization

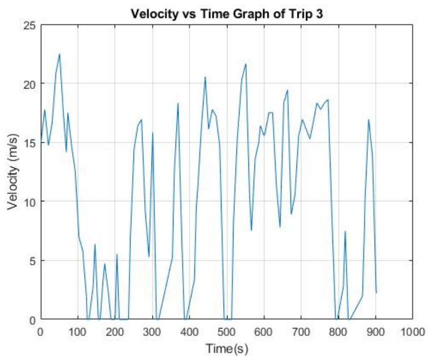
trip routes start nearly at the same location. The average power consumption is calculated based on the mean velocities of the trip data. The average speed is calculated and shown in Fig 4.7.



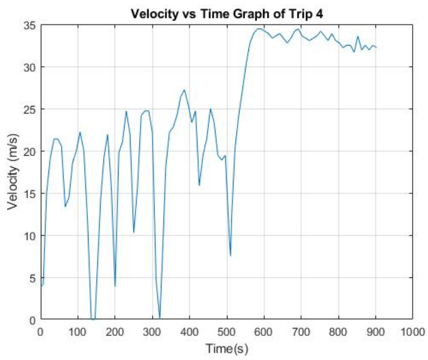
(a) Cycle 1



(b) Cycle 2



(c) Cycle 3



(d) Cycle 4

Figure 4.6: Recorded trip data in the order of (a) cycle 1, (b) cycle 2, (c) cycle 3, and (d) cycle 4.

The average power consumption value is found as 0.1275 kWh per km. For example, if the driver demands 100 kilometers as a range demand, the demanded energy is calculated as 12.75 kWh.

4.6.2 The Optimization

For the optimization part, a test setup is utilized with 4 elements which are system load, PV generation, charging station, and energy storage system. The properties of the system are given in Table 4.1. The optimization process is executed for 3 hours of

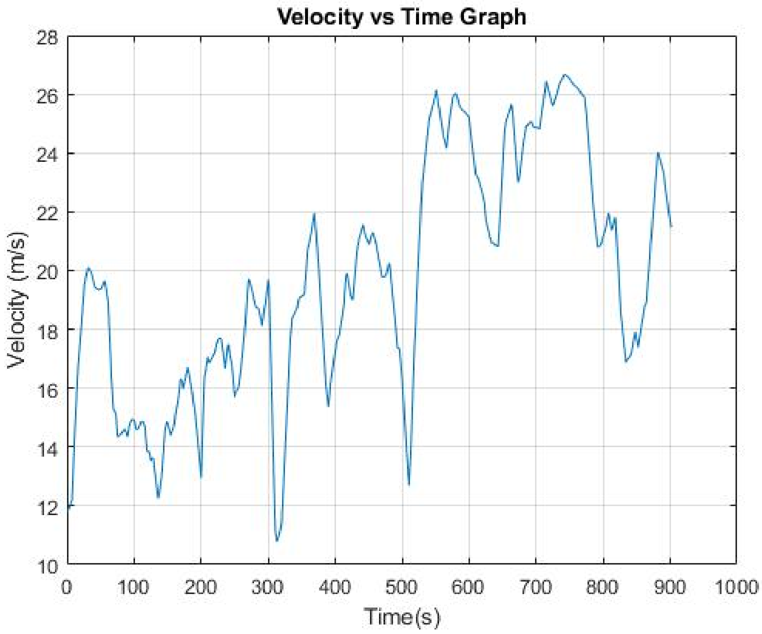


Figure 4.7: Average trip velocity vs time graph.

operation and updates its state in 30 minutes. The optimization period is determined based on the average time spent in shopping malls [40].

Table 4.1: Utilized system properties.

Number of charging slots	600
Maximum charging power of slots	7 kW
ESS capacity	500 kWh
ESS power	100 kW

The optimization is performed based on the working hours of a shopping mall which is between 09:00 and 22:00. The power graphs are plotted based on this working hours and their time axis are in minutes. As the resolution is selected by 1 minute, the power curves are plotted with respect to 780 minutes of period which defines 13 hours of working. The first element is the system load. The load curve is given in Fig 4.8. The second element is the PV generation which is shown in Fig 4.9. This PV data is obtained from the machinery lab in METU and scaled up to 100 times to be comparable to the utilized system load. In addition, the electricity market prices through a determined period of time graph are shown in Fig 4.10. This data is taken from Australian Energy Market Operator [41]. The resolution of the market price data is 5 minutes, so the graph is plotted based on the hours of the day to avoid misunderstanding. This setup is used for the following tests.

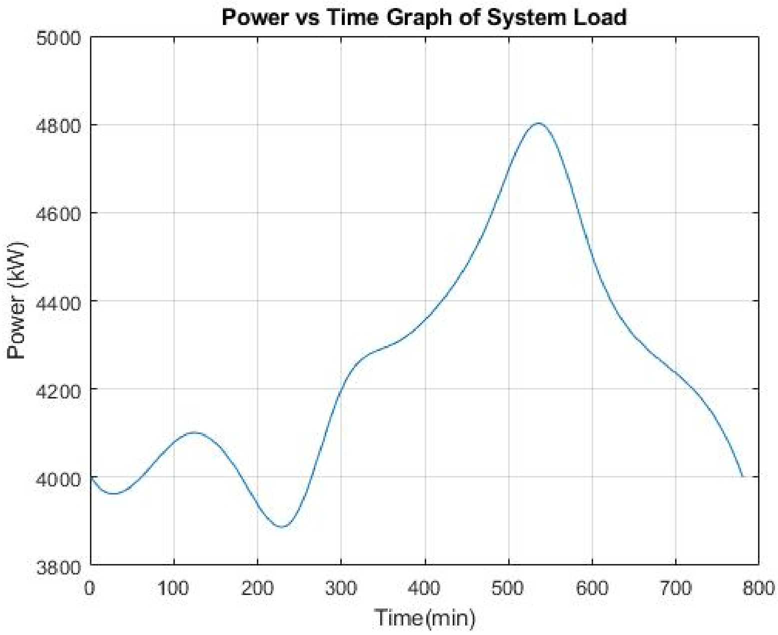


Figure 4.8: System load vs time graph.

4.6.2.1 Test 1

The first test is performed to observe the characteristics of the system without optimization. The vehicles which arrive at the station are charged instantly. In addition, V2G is not allowed for vehicles. The charging power curve is given in Fig 4.11. Then, the optimization is performed and Fig 4.12 shows the charging power curve.

In Fig 4.11, it can be seen that the vehicles are charged as they enter the station. On the other hand, the optimization method offers a schedule to charge the vehicles by taking market prices and system properties into account.

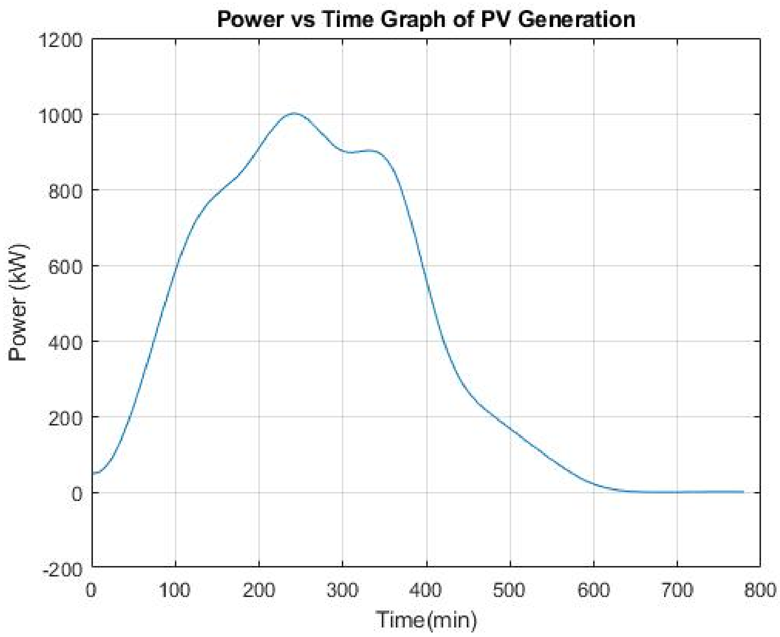


Figure 4.9: PV generation vs time graph.

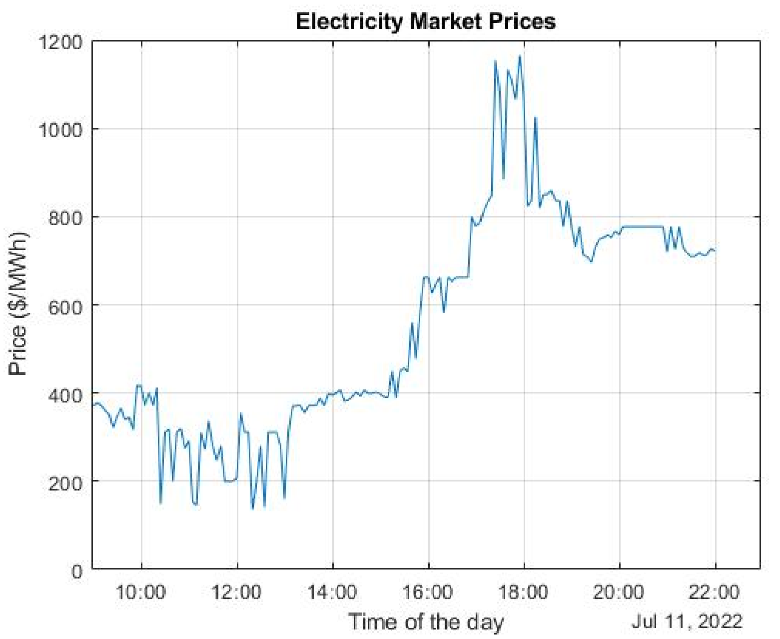


Figure 4.10: Electricity market prices graph.

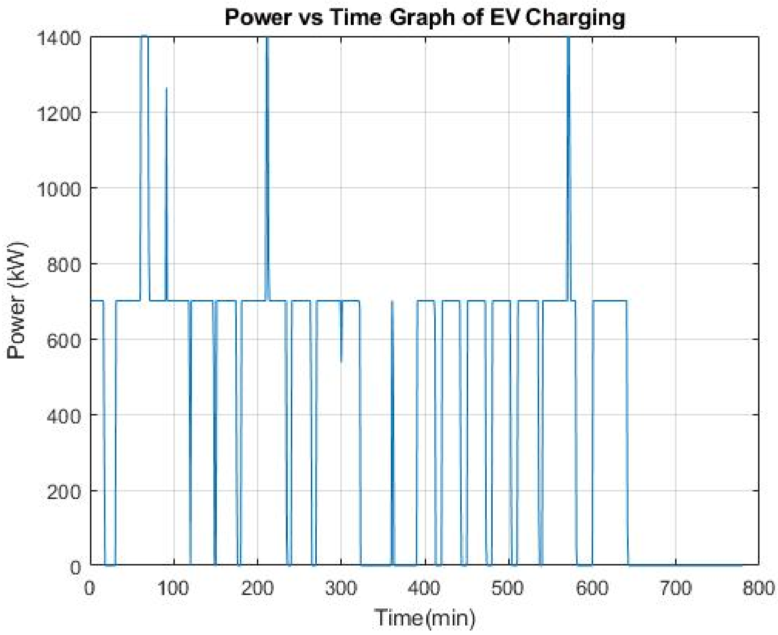


Figure 4.11: EV charging power vs time graph without optimization.

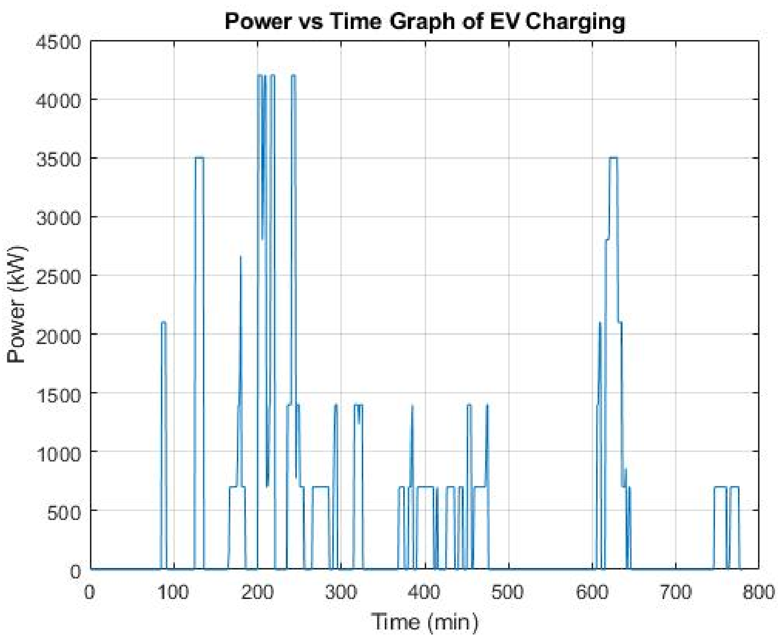


Figure 4.12: EV charging power vs time graph with optimization.

4.6.2.2 Test 2

The second test is performed to investigate the effect of the V2G application. Note that, to perform V2G, optimization is required. Otherwise, there may be a disorder in determining when the vehicle is charged or discharged. The charging curve with optimization is shown in Fig 4.13.

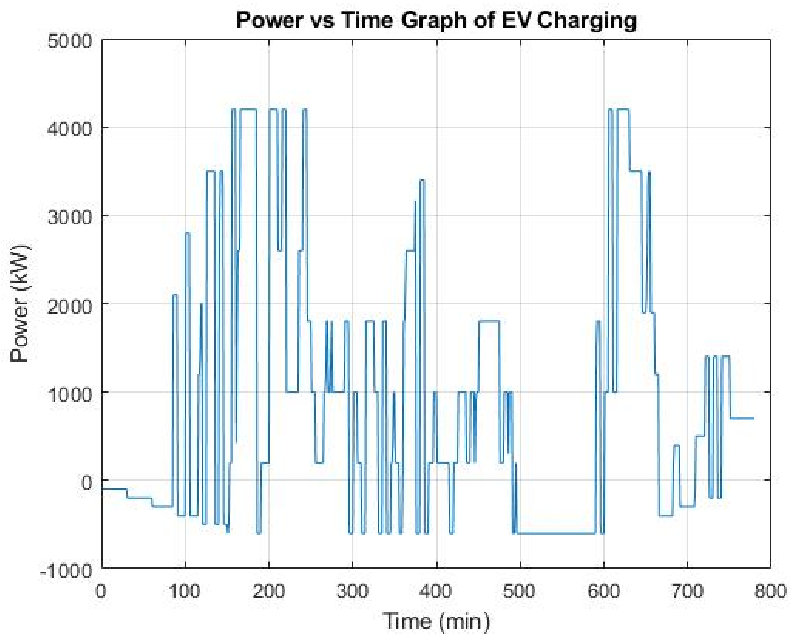


Figure 4.13: EV charging power vs time graph with optimization (V2G introduced).

4.6.2.3 Test 3

The last test is performed for the last case of the optimization. In this case, the vehicles which leave the station in 1 hour are concerned. These vehicles are said to be labeled and labeling is randomly generated among the same vehicle data. The optimization of labeled vehicles is performed for 1 hour period. The charging power curve is shown in Fig 4.14.

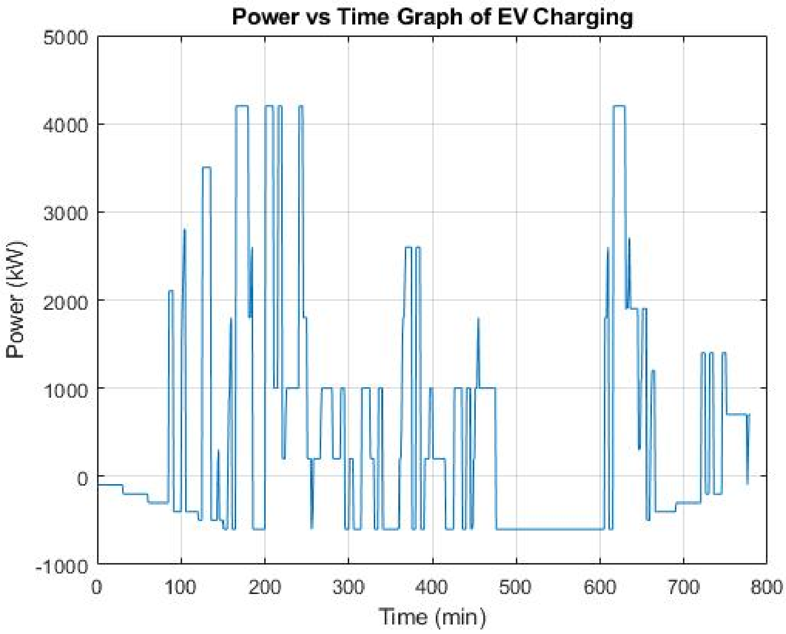


Figure 4.14: EV charging power vs time graph with optimization and labeling (V2G introduced).

4.6.2.4 Cost Analysis

The next step is performing cost analysis to observe the effect of utilized features of optimization. In Table 4.2, the performed tests are numbered and their properties are shown. Table 4.3 shows the charging cost of vehicles. It can be seen that V2G and optimization reduce the operation cost of the system. On the other hand, the labeling method increases the cost as expected.

Table 4.2: Numbering performed tests.

Performed Test Number	Labeling	V2G	Optimization
1.1	No	No	No
1.2	No	No	Yes
2.1	No	Yes	Yes
3.1	Yes	Yes	Yes

Table 4.3: Operation cost of performed tests.

Performed Test	Operation cost ($)
1.1	2888.698
1.2	2328.413
2.1	1344.330
3.1	1660.528

4.6.3 The Queueing

The last part of the results is the queueing. The queueing algorithm works with a rule-based method. The first step is taking the information of arriving cars at the present. Then, add these cars to the queue list. These vehicles are sorted in terms of their power demand and moved to the charging list if there is available space. Furthermore, if the demanded power of a vehicle is fulfilled, this vehicle is removed from the charging list. In addition, there is a priority mechanism in order not to wait the cars with a higher amount of power demand compared to other vehicles. There is a counter for each vehicle waiting in the queue list. When a vehicle waits in the queue list, it counts the waiting time and then puts the vehicle which has more counted value at top of the list.

The queueing algorithm is tested for 1000 vehicles that arrive at the station between 09:00 AM and 22:00 PM. Fig 4.15 shows the number of vehicles in the queue list.

4.7 The Summary of the Chapter

Firstly, determination of load demand of vehicles has an important role. This determination can be improved by characterizing the vehicles by their parameters. The proposed method takes the driver's range demand in kilometers and calculates the required amount of energy to fulfill the demand. The presence of historical trip data helps to calculate required energy by using proposed estimation algorithms and drive-train model. In case of absence of historical data, the averaging method may be useful

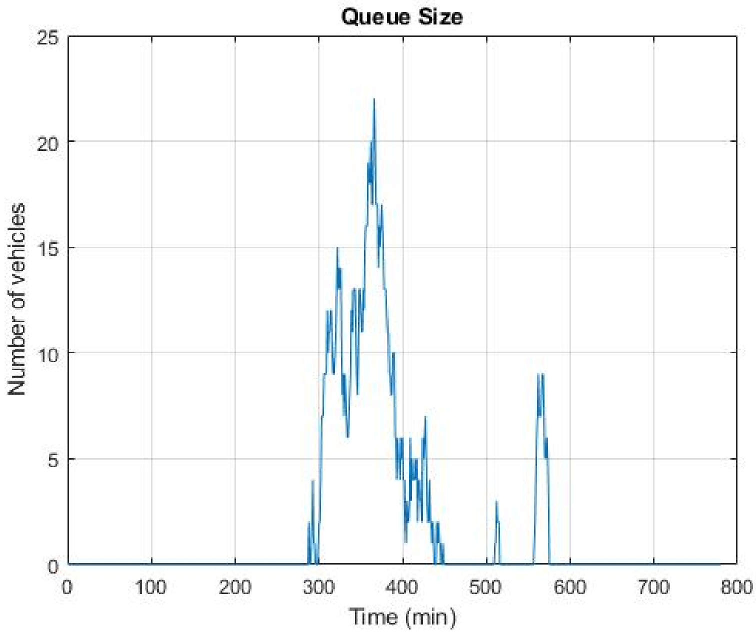


Figure 4.15: Number of vehicles in queue list vs time graph.

to calculate required energy.

Secondly, optimization is a key factor to minimize the cost of power system operations. With the introduction of dynamic market prices and electric vehicle charging, scheduling the load of a system benefits the operator in terms of operation cost. In this thesis, a power system with PV generation, ESS and EV charging is presented. The optimization is performed by using LP. The effect of optimization and V2G concept is demonstrated by testing the system in different conditions. In addition, a labeling method is proposed by considering the vehicles which are present in the charging station, but stays out of the optimization process.

Lastly, a queueing algorithm is proposed for the situations which the load demand of the vehicles exceeds the limits of the charging station. This algorithm list the vehicles until an available space exists.

CHAPTER 5

DISCUSSION

In previous chapters, the introduction of the thesis work, the proposed methodologies, and the test results are explained. The results show that this thesis work reaches its goals. Furthermore, it can be seen that there is still room for improvement. In this chapter, a discussion is made and possible future works are mentioned.

Drivetrain models are used to calculate the power consumption of electric vehicles. The model calculates the power by using force equations of motion. In this thesis, the drivetrain model takes road friction, aerodynamic drag, and gradient forces into account. The equations of forces can be improved by considering more interior or exterior effects. For example, the slips which occur between tires and surface can be added to the model to increase the accuracy of calculations. In addition, the efficiencies of the component may be considered and modeling of the components may lead this challenge to a solution.

Secondly, with the developments in the technology of measurement devices, more data can be obtained from electric vehicles during their trips. More data means more measurements to be used in power calculations and estimation processes. In addition, determining the average trip data can be improved. Traffic simulations and driving behaviors of individuals may help to determine the trip data.

Thirdly, the period of optimization can be changed by considering different approaches. The charging times of the vehicles are set as constant, but investigating the behaviors of individuals in terms of charging may be helpful to improve the optimization. In addition, the use of energy storage systems can also be improved. The charging characteristic of ESS tends to deplete its energy until it reaches its safety limits. With the information on electricity market prices, ESS charging can be further optimized considering long-term applications. Moreover, the modeling of batteries in the ESS and the vehicle may help to investigate the aging effects and performance of the batteries.

Lastly, electricity market investigations may help the optimization process. Operations in an environment that has dynamic pricing should be managed to obtain feasible operating conditions. Forecasting methods used in electricity marketing may change the solutions to optimization problems. Moreover, individual pricing may be investigated to manage the operation cost of the system.

CHAPTER 6

CONCLUSION

Drivetrain models are used to calculate the power consumption of electric vehicles. The input of these models is the trip data which consists of time series velocity measurements. The models use mechanical and electrical equations to calculate power consumption. The calculations include interior and exterior vehicle parameters. The parameter values may change in time due to aging effects and should be estimated to get better solutions.

With the developing technology, more components are integrated with the power system. These situations bring the challenge of managing the loads with them. Load management can be done by various methods and one of the most popular one is load scheduling. The load scheduling can be done by optimization methods. These methods aim to minimize the cost of the system operation. The optimization can be achieved by scheduling EV charging basically.

In this thesis, a drivetrain model is utilized to simulate the vehicle behaviors and calculate the power consumption by using input trip data and power equations. The implementation is done in MATLAB environment and the backward simulation method is used. The WLTP trip data is selected to validate the performance of the utilized model. Then, the state estimation algorithm is performed to estimate the erroneous values of the states. After finding the estimated states, the parameter estimation method is utilized to estimate the values of parameters that are used in the drivetrain model. The parameters to be estimated are selected by taking their effect on power consumption into account. The frequency of changes in parameters is considered and the estimation process is divided into two sections. One of them is for estimating parameters that change less frequently, and the other one is for parameters that change more frequently. Moreover, a second strategy is proposed in case of the absence of desired measurements. The test results show that the designed drivetrain model works properly with implemented mathematical models. Moreover, by using state and parameter estimation algorithms, the power consumption calculation is obtained accurately. Thirdly, a required energy prediction method is proposed. This method uses the utilized drivetrain model and the demands of the drivers to calculate the required energy. The historical or mean trip data approaches are suggested in this part. Lastly, an optimization strategy followed by a queueing algorithm is implemented. The optimization is solved by considering different system properties and the behaviors of individuals. Then the observation of the effects of the optimization and V2G application is done by various tests.

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