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DEVELOPMENT AND EVALUATION OF AN INTELLIGENT TRANSPORTATION SYSTEMS-BASED ARCHITECTURE FOR ELECTRIC VEHICLES

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DEVELOPMENT AND EVALUATION OF AN INTELLIGENT TRANSPORTATION SYSTEMS-BASED ARCHITECTURE FOR ELECTRIC VEHICLES

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ABSTRACT

The rapid development of increasingly complex in-vehicle electronics now offers an unprecedented level of convenience and versatility as well as accelerates the demand for connected driving experience, which can only be achieved in a comprehensive Intelligent Transportation Systems (ITS) technology based architecture. While a number of charging and range related issues continue to impede the Electric Vehicle (EV) market growth, integrating ITS technologies with EVs has the potential to address the problems and facilitate EV operations. This dissertation presents an ITS based vehicle infrastructure communication architecture in which abundant information can be exchanged in real time through vehicle-to-vehicle and vehicle-to- infrastructure communication, so that a variety of in-vehicle applications can be built to enhance the performance of EVs.

This dissertation emphasizes on developing two applications that are specifically designed for EVs. First, an Ant Colony Optimization (ACO) based routing and recharging strategy dedicated to accommodate EV trips was devised. The algorithm developed in this study seeks, in real time, the lowest cost route possible without violating the energy constraint and can quickly provide an alternate suboptimal route in the event of unexpected situations (such as traffic congestion, traffic incident and road closure). If the EV battery requires a recharge, the algorithm can be utilized to develop a charging schedule based on recharging locations, recharging cost and wait time, and to simultaneously maintain the minimum total travel time and energy consumption objectives. The author also elucidates a charge scheduling model that maximizes the net

profit for each vehicle-to-grid (V2G) enabled EV owner who participates in the grid ancillary services while the energy demands for their trips can be guaranteed as well. By applying ITS technologies, the charge scheduling model can rapidly adapt to changes of variables or coefficients within the model for the purpose of developing the latest optimal charge/discharge schedule.

The performance of EVs involved in the architecture was validated by a series of simulations. A roadway network in Charleston, SC was created in the simulator and a comparison between ordinary EVs and connected EVs was performed with a series of simulation experiments. Analysis revealed that the vehicle-to-vehicle and vehicle-to-infrastructure communication technology resulted in not only a reduction of the total travel time and energy consumption, but also in the reduction of the amount of the recharged electricity and corresponding cost, thus significantly relieving the concerns of range anxiety. The routing and recharging strategy also potentially allows for a reduction in the EV battery capacity, in turn reducing the cost of the energy storage system to a reasonable level. The efficiency of the charge scheduling model was validated by estimating optimal annual financial benefits and leveling the additional load from EV charging to maintain a reliable and robust power grid system. The analysis showed that the scheduling model can indeed optimize the profit which substantially offsets the annual energy cost for EV owners and that EV participants can even make a positive net profit with a higher power of the electrical circuit. In addition, the extra load distribution from the optimized EV charging operations was more balanced than that from the unmanaged EV operations. Grid operators can monitor and ease the load in real time by adjusting the prices should the load exceed the capacity.

The ITS supported architecture presented in this dissertation can be used in the evolution of a new generation of EVs with new features and benefits for prospective owners. This study suggests a great promise for the integration of EVs with ITS technologies for purpose of promoting sustainable transportation system development.

DEDICATION

This dissertation is dedicated to my Family.

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LIST OF ABBREVIATIONS

Abbreviation	Meaning
ACO	Ant Colony Optimization
BEV	Battery electric vehicle
EV	Electric vehicle
GHG	Greenhouse gas
ISO	Independent system operators
ITS	Intelligent Transportation Systems
PHEV	Plug-in hybrid vehicle
QoS	Quality of service
RFID	Radio-frequency identification
RSP	Restricted shortest path
RTO	Regional transmission organizations
SOC	State of Charge
TOU	Time of use
V2G	Vehicle to grid
VRP	Vehicle routing problem

CHAPTER ONE

INTRODUCTION

Conventional transportation operations may need urgent changes to address main issues that have adversely impacted the development of a sustainable society. According to the 2012 Annual Energy Outlook published by the U.S. Energy Information Administration, of the total amount of fuel imported, 70% was consumed by the transportation sector in 2010 (Energy Information Administration 2012). The automobiles that are consuming the preponderance of this oil have the lowest energy efficiency among all energy market sectors, at a dismal 20% (Tulpule et al. 2009). In addition to the US transportation sector being heavily dependent upon the overseas oil imports, the US transportation industry accounts for one-third of all energy-related carbon dioxide emissions (Energy Information Administration 2012). Although these issues remain critical, an increasing number of measures have been implemented to break this oil dependency and reduce the associated environmental footprint. As the transportation sector is moving towards a sustainable transportation system, Electric Vehicles (EVs) have been recognized as promising alternative fuel vehicles and have drawn more attention in recent years. Indeed, EVs fueled by electricity from renewable energy sources can clearly result in a drop in overall gasoline consumption and substantially reduce life cycle Greenhouse Gas (GHG) emissions over the entire road network. Even if they were in widespread use and powered with coal-generated electricity (Samaras and Meisterling 2008), the direct development of a sustainable transportation system would nonetheless occur.

Many predictions on the number of the EVs in the future automobile market have been made. It is envisioned that one million EVs, including Plug-In Hybrid Vehicles (PHEVs), Extended Range Electric Vehicles (EREVs) and Battery Electric Vehicles (BEVs), will be on the road by 2015 (Department of Energy 2011). A study by the Center for Entrepreneurship & Technology from University of California, Berkeley seems to validate such predictions, suggesting a market share of 3 million Electric Cars on the road by 2020 (Becker 2009). It is also expected that EVs will achieve a 24%-46% market share by 2030 if strong incentives are provided, resulting in a decrease in oil imports by 2.0-3.7 million barrels a day (Becker 2009). Statistics, however, do not appear to reflect such a trend. Data from the Electric Drive Transportation Association in Figure 1 shows that only 70,915 EVs were sold by 2012, and while multiple incentives are granted to EV customers, the sales numbers are still growing slowly (Electric Drive Transportation Association 2013).

1.1 RESEARCH BACKGROUND AND MOTIVATIONS

1.1.1 EV CHARGING

Several major deficiencies that currently hinder the commercial adoption of EVs may explain this phenomenon. The most significant challenge concerns the

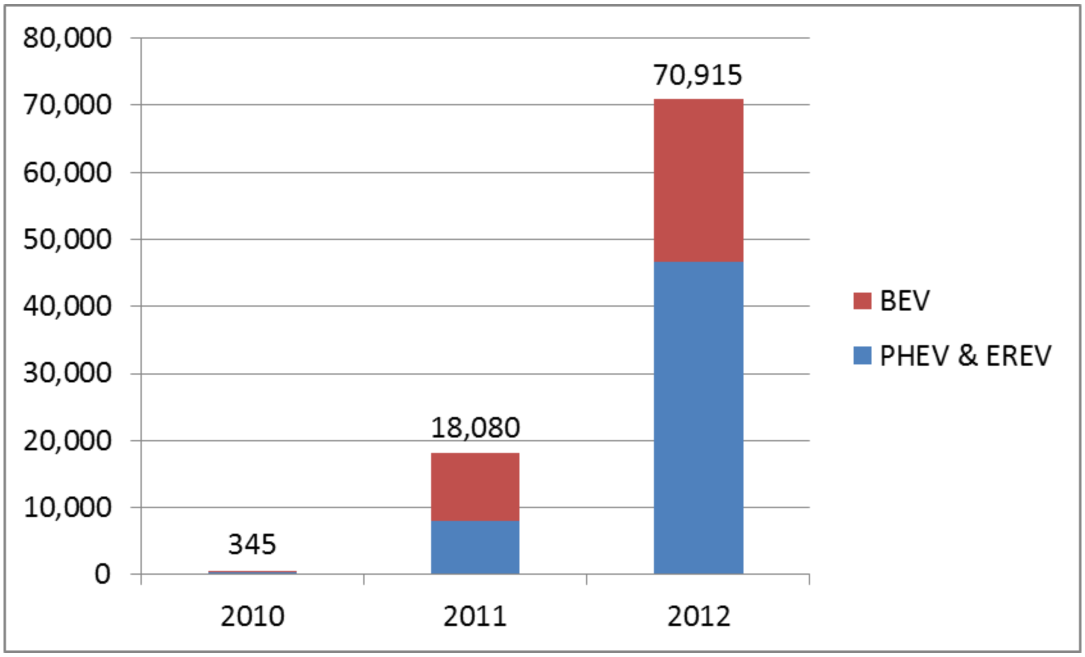


Figure 1. Cumulative U.S. EV sales by 2012 (Electric Drive Transportation Association 2013)

Table 1. Battery features of popular BEV models in the market

BEV model	Nissan Leaf	Ford Focus Electric	Honda Fit EV	Mitsubishi i-MiEV
Battery Type	lithium-ion	lithium-ion	lithium-ion	lithium-ion
Battery Capacity (kWh)	24	23	20	16
EPA Label Range (miles)	73	76	82	62
EPA Combined (kWh/100 mi)	34	32	29	30
EPA Combined MPGe Rating	99	105	118	112
On-board charger (kW)	3.3	6.6	6.6	3.3

charging of these vehicles. Table 1 shows the battery features of several popular BEV models in the EV market (Department of Energy 2012, Federal Highway Administration 2009). While the Environmental Protection Agency's (EPA's) certified all-electric falls within the range of 62-82 miles, the U.S. weighted average daily driven distance of 39.5 miles (Federal Highway Administration 2009) indicates that BEV owners are likely to recharge their vehicles frequently in order to meet their daily driving demands. Unlike gasoline refueling, however, recharging BEVs takes much more time, often as much as 7 hours for a Nissan Leaf BEV to reach a full charge using a level two home charging dock with a 240-volt supply, and 3.5 hours for a Ford Focus Electric using a similar charging station. Furthermore, the high initial manufacturing cost of BEVs, mostly due to the high battery cost, offsets any advantages of the inexpensive electrical energy used to power them. The vehicular battery life is typically defined as the cycle in which a battery can be fully charged and discharged before the battery capacity is degraded to 80% of its initial full charge capacity (Element Energy Limited 2012). Currently the average price of an EV lithium-ion battery pack is $800/kWh with a lifetime of approximately 1000 complete charge-discharge cycles (Element Energy Limited 2012), which is equivalent to a capital cost of approximately $19,200 for a Nissan Leaf battery. Therefore, replacing the battery before the end of the service life of the vehicle, should that be required, would greatly increase the total cost of ownership.

A variety of federal and state incentives (i.e. tax credits, rebates, free parking and access to the HOV lanes) for EVs and charging stations have been introduced to reduce their prohibitive costs. For example, consumers purchasing EVs after December 31, 2008 are eligible for a $2,500 to $7,500 tax credit depending upon battery size, and with an accompanying BV infrastructure tax credit of 30%, up to $1,000 (Department of Energy 2013). Also, new research on the integration of BEV energy storage systems with vehicle-to-grid (V2G) technology has determined the feasibility of rerouting excess electricity from this V2G technology back into the grid. A V2G-enabled BEV can not only draw the electricity from the grid to recharge the battery but also reverse the flow and provide a variety of ancillary services to ease the grid imbalance. With such technology, BEV owners stand to profit quite nicely when the vehicle is connected to the bi-directional charger to provide ancillary services to the power industry. However, estimates on how much profit BEV owners may earn from the surplus power are unclear based upon simple assumptions that disregard driving plans and other personalized user inputs. Though scattered BEVs in a certain area must be aggregated to enter the ancillary service market with sufficient power, very little research has been conducted to develop methods to efficiently control and manage those mobile storage resources, and little research has attempted to optimize the profit margins from V2G programs through scheduling of a sound charge and discharge plan encompassing smart grid technologies. Consequently, a comprehensive charge/discharge system in which BEV participants may maximize their V2G profits while ensuring adequate battery supply for driving demands is important for the viability of the system. Such a charge/discharge system is also required to communicate and coordinate with grid operators in order to maintain reliable grid operations.

1.1.2 EV RANGE

Driver worries regarding the likelihood of possible stranding from a dead battery given limited range per single charge is another predominant hindrance to higher EV market penetration. Though EVs are primarily recharged overnight at home, the public adoption of a publically available fast charging system is an absolute necessity, as EV drivers may have to recharge their vehicles in the middle of their long-distance trips and possibly more than once due to battery capacity limitations. The Society of Automotive Engineers (SAE) defines three levels of charging power, as shown in Table 2 (Society of Automotive Engineers 2011). So far efforts to extend EV ranges are mainly focused on developing and deploying more Level 3 charging structures that can refuel up to 200 miles for every hour of charging. Although EVs have the potential to rapidly recharge, an efficient recharging plan for an EV during a trip is difficult to arrange. For example, though EV drivers may well know the locations of the nearest charging stations, they will nonetheless have to detour for charging, thus increasing driving time and energy consumption. In the worst case, they would drain their battery on their way and thusly fail to reach the charging station. Furthermore, when there is more than one charging station en route, how to choose an appropriate one or an appropriate combination so that the overall travel time and energy consumption can be minimized becomes another problem.

TABLE 2. SAE Charging Classification

Level	AC Charging (on-board charger)	AC Estimated Charge Time	DC Charging (off-board charger)	DC Estimated Charge Time
Level 1	120 V AC ≤ 16 Amps ≤ 1.9kW	PHEV: 7hrs (SOC: 0% to full) BEV: 17hrs (SOC: 20% to full)	200-450 V ≤ 80 Amps ≤ 36kW	20kW charger: PHEV: 22 min (SOC: 0% to 80%) BEV: 1.2hrs (SOC: 20% to full)
Level 2	240 V AC ≤ 80 Amps ≤ 19.2kW	PEV: 22 min Max (SOC: 0% to full) BEV: 1.2hrs Max (SOC: 20% to full)	200-450 V ≤ 200 Amps ≤ 90kW	45kW charger: PHEV: 10 min (SOC: 0% to 80%) BEV: 20 min (SOC: 20% to 80%)
Level 3	>20kW Proposed	To be decided.	Up to 240kW Proposed	45kW charger: BEV: < 10 min (SOC: 0% to 80%)

Existing routing strategies generally fail to consider refueling problems because of the ubiquity of common gas stations, while electricity charging stations are much scarcer and it takes much more time for EVs to recharge their batteries even with fast charging facilities. In order to address the range issues, it’s critical to develop a routing strategy that is specifically designed to accommodate EV trips.

1.1.3 EVS INTEGRATED WITH INTELLIGENT TRANSPORTATION SYSTEMS (ITS) TECHNOLOGIES

Despite the fact that the EV technology is still in its nascent stage, this can be turned into a great opportunity to fully integrate advanced intelligent transportation systems (ITS) technologies with EVs in terms of relevant standards and policies. ITS, which is a broad concept, refers to any tools that can be applied to improve the efficiency, mobility and safety in transportation system operations (Chowdhury and Sadek 2003). Some of the tools, such as the on-board navigation system and the automatic crash response system, have already been placed not only in conventional internal combustion engine (ICE) vehicles but also in EVs, and interest in the concept of Connected Vehicle has surged dramatically over the past few years. Connected Vehicle technology, formerly known as Vehicle Infrastructure Integration (VII), seeks to deploy and enable interoperable wireless communication that supports vehicle-to-vehicle and vehicle-to-infrastructure connectivity for numerous transportation operations (Stephen Ezell 2010). As envisioned in this concept, transportation system components will be able to intelligently communicate and coordinate with each other in real time through wireless communication networks, delivering and extracting a wealth of useful information in efforts to provide driver assistance and other potential services.

Connected-vehicle-equipped EVs, or connected EVs, have several unique advantages over current ordinary automobiles and EVs. As traffic conditions change constantly, it’s difficult for motorists to find the best route based on previous experience. They cannot obtain information regarding traffic incidents, road closures and other situations causing traffic congestions before being notified, and should that happen, they will get stuck in the congestion or have to search for detour routes raising risks of consuming much more travel time and energy. Connected EV drivers, however, can be diverted from congested areas through an on-board routing guidance service, which exchanges a variety of real-time data with roadside infrastructure in order to adapt each trip with the best route based upon drivers’ preferences, either the one with the shortest distance, the lowest travel time, or the lowest energy cost. As the overall energy consumption for a trip can be estimated by the on-board routing system, should recharge activity be required, drivers will be navigated to a proper charging station before the battery is depleted while the overall time and cost can simultaneously be optimized. Through interaction with public charging stations, the battery’s State of Charge (SOC) can be monitored and managed in a timely matter so as to alleviate the concerns of range anxiety. Furthermore, the evolution of smart grid technologies permits the sharing of grid information between grid operators and EVs using Information and Communication Technologies (ICT) (Erol-Kantarci and Mouftah 2010). V2G-enabled EV owners are allowed to appropriately allocate time slots to recharge their vehicles when the electricity time-of-use (TOU) price is relatively low and provide grid ancillary services when the selling prices are more attractive once the dynamic price of each item is provided. Such a connected driving experience is expected to improve the safety, comfort and convenience of EV drivers and passengers in an effort to enhance the EV market share.

A sophisticated and comprehensive communication platform will play a key role in creating the vehicle-to-vehicle and vehicle-to-infrastructure connectivity together with more innovative in-vehicle applications. It’s essential to develop a seamlessly connected EV-infrastructure network with requisite components when very little research has been undertaken in this area.

1.2 RESEARCH OBJECTIVES

This research aims to develop an ITS-based architecture that integrates multiple cutting edge technologies and in-vehicle applications with EVs in order to address EV-related issues and improve EV performance. To build the architecture three major tasks need to be completed corresponding to the three objectives of this dissertation:

1) Develop a routing strategy that is dedicated to accommodate EV trips. With Connected Vehicle technologies, the routing strategy is expected to find the best path with minimum overall travel time and energy consumption. When unusual situations (i.e. traffic congestion, traffic incident, road closure etc.) are detected, the routing strategy is able to quickly provide an alternative route that avoids traffic delays and remains optimal. If the EV battery needs to be recharged, the routing strategy should develop an optimal

charging plan based on recharging cost and wait time while ensuring the minimum travel time and energy consumption in the scenario.

2) Develop a scheduling model for V2G-enabled EVs that appropriately arranges charge and ancillary service activities so that the potential net profits can be maximized and the energy demand for driving can be met simultaneously. The scheduling model can also help grid operators leverage the additional load from EV charging by adjusting dynamic TOU electricity prices and ancillary service prices to prevent violations of the peak hour restrictions.

3) Develop a vehicle-infrastructure communication network that seamlessly connects a slew of introduced system components through wireless technologies. The in-vehicle applications and server side software should also benefit from such a communication network by sending and obtaining data in real time.

While this research primarily focuses on facilitating EV adoptions and EV market growth, the ITS-based architecture will also be built in support of maintaining a reliable and robust power grid system.

1.3 ORGANIZATION OF THE DISSERTATION

This dissertation contains five additional chapters for presentation and elaboration. In addition to the first chapter that presents current EV-related issues and the objectives of this research, the second chapter demonstrates a review of relevant research in the fields of vehicle routing and refueling problems, grid ancillary services for EVs, and strategies for optimizing V2G implementations as well as vehicle infrastructure communication technologies. In the third chapter, the author introduces all the theories and methods behind the integrated architecture, and devotes the fourth and fifth chapter to the EV routing and recharging strategy and the charge scheduling model, respectively, through simulation and analysis. The author then concludes with contributions and directions for future research in the sixth chapter. The scripts and simulation data are also provided in the appendices.

CHAPTER TWO

RELATED WORK

Connected Vehicle technologies and alternative fuel vehicles are expected to have a significant impact across all sectors of the society in reducing dependence on fossil fuel use. A number of studies have focused on these topics, such as the routing and refueling strategies, V2G implementation for BEVs and Vehicle Infrastructure Integration. This chapter summarizes previous work on vehicle routing, V2G and Connected Vehicle technologies as they relate to the focus of this dissertation.

2.1 VEHICLE ROUTING PROBLEM (VRP)

The vehicle routing problem (VRP) is a classical optimization problem seeking to find the optimal route and schedule for passengers and goods mobility based on specified demands. In most cases VRP is formulated as an integer or mixed-integer linear programming model (Chabrier 2006; Omidvar and Tavakkoli-Moghaddam 2012; Erdoğan and Miller-Hooks 2012) and always augmented by various constraints from complex real world applications. Since VRP belongs to the category of NP-hard combinatorial optimization problems (Lenstra and Kan 1981) indicating that the computational complexity for exact solutions grows exponentially as the size of the problem increases, only small instances of the problem can be solved with exact solutions. For large instances in practice, exact approaches are too time consuming to be considered as viable while researches have emphasized on developing approximation algorithms with constructive metaheuristics which yield acceptable results within polynomial time although the optimality cannot be guaranteed. Given the ability to tighten the feasible solution domain and guide the search toward a suboptimal solution quickly, metaheuristic methods have evolved as the most promising direction of research for the VRPs (Caric and Gold 2008).

The fear of running out of electricity due to the constraints of limited range and scarce recharging infrastructure makes routing strategies more important to EV drivers when it comes to long distance travels. A significant amount of work has been done to tackle the linear integer programming problems in the field of VRP, in particular the local search based meta-heuristic techniques regarding the routing of Alternative Fuel Vehicles (AFVs) have been growing rapidly over the past few years. Carić et al. presented a modeling and optimization framework for solving VRPs with a list of available constructive heuristics for capacitated VRPs in which the uniform capacity of vehicles must service customer demands, including the heuristics of nearest neighbor, nearest addition, sweep and Clark & Wright (Carić et al. 2008). Erdogan and Miller-Hooks addressed a routing and refueling problem for AFV fleets considering limited fueling capacity and limited fuel station availability (Erdoğan and Miller-Hooks 2012). The problem was formulated as a mixed-integer linear program and solved by constructing two heuristics, the Modified Clarke and Wright Savings heuristic, assuming all the depots were served as refueling stations as well. The heuristics were performed well in minimizing the total traveled distances in the case studies. Nevertheless, sometimes drivers seem more concerned about the total travel time, fuel cost and perhaps GHG emissions for common vehicles rather than the minimal total travel distance which is usually set as the only objective in classical VRPs, and apparently the minimization of distance does not imply minimization of other factors. As a result, Bektaş and Laporte extended the problem to employ a more comprehensive objective function considering fuel consumption and GHG emissions for the "environmental-friendly" routing (Bektaş and Laporte 2011). Similarly, Omidvar and Tavakkoli-Moghaddam introduced a routing model for AFVs to minimize the total cost of vehicles in terms of travelled distance, travel time and GHG emissions (Omidvar and Tavakkoli-Moghaddam 2012), and the intermediate depots were assumed to be alternative fuel stations. Both of the problems were treated as time-dependent VRPs that took different departure times with different travel times into consideration, nevertheless, the desired time-dependent travel time can become less accurate should any unexpected situations occur (e.g. incidents and closed lanes), and unlike fleet vehicles, EV charging stations may not be located along the travel route or even nearby. One EV may have to detour to recharge the battery and very little research has been undertaken to find the restricted optimal route when the reroute activity is needed. What's more, traffic conditions change constantly. With the support of ITS technologies, real-time vehicle routing becomes possible. By continuously exchanging data with roadside infrastructure, the optimal route can always be updated when approaching a decision node where there is more than one ongoing route, and the accuracy of the routing strategy will be significantly enhanced compared to the time-dependent routing approaches. Under this circumstance, however, the routing problem may have to be adjusted and reformulated as a new one for the next iteration due to the changes on variables, coefficients and corresponding constraints, which would exponentially increase the complexity of the problem, especially for computer programming. In addition, most heuristics are only designed to solve specific VRPs and may not be applicable for other scenarios, while the distinction of traffic conditions over time can possibly violate the viability of the heuristics. Therefore, in efforts to solve real-time VRPs with robust and general approaches, a number of researches have been conducted with regard to Artificial Intelligence (AI) algorithms other than conventional mathematical programming models. In the following sections, the author provides a review on the real-time vehicle routing problem, the vehicle refueling problem and the Ant Colony Optimization (ACO).

2.1.1 REAL-TIME VEHICLE ROUTING PROBLEM

Real-time vehicle routing with sufficient information can improve the accuracy of departure time and travel time prediction by quickly responding to uncertainties caused by accidents, congestions, and lane closures. Once the real-time communication capability among vehicles and infrastructure is enabled using ITS technologies, the optimal path will be built in an ongoing fashion at each time when a vehicle is approaching a decision node with more than one route to follow. To give the recurring updates real-world relevance, real-time vehicle routing must incorporate a fast and efficient algorithm to obtain the optimal result within a limited time.

Before traffic data can be collected in real time, dynamic vehicle routing problems are studied in a time-dependent context and uncertain variables are typically modeled as random variables with time-dependent distributions in a stochastic network. Gao and Chabini proposed four approximations to solve the time-dependent stochastic shortest path problem (Gao and Chabini 2002). It is assumed that the next move for one traveler is uncertain and the probability of all possible moves is determined by realizations of link travel times which vary from full to no knowledge of information. In their examination of the value of real-time traffic information for determining optimal routing policies and departure times in a nonstationary stochastic network, Kim et al. collected real traffic data in Southeast Michigan and implemented a Markov chain model for simulating real-time average travel speed (Kim et al. 2005). The vehicle also has the probability to choose an alternate adjacent link in case of an accident or unexpected road block. They concluded that using real-time information can significantly save total costs and improve delivery service level. Though these studies are of particular relevance to the real-time EV routing optimization classical shortest path algorithms cannot exactly solve the problem because the EV routing and recharging problem is NP-hard, especially when the recharging process is incorporated. In addition, vehicle-infrastructure communication contributes to the transition of the real-time VRPs from a stochastic to a deterministic problem because all the required data are known for calculation at a given time. In that only one least-cost route can be found at that particular time, it is then unnecessary to estimate the transition probability to choose an alternate path in the event of accidents. Nevertheless, transition probability is an essential component that can be integrated into the process of searching for the feasible solution in the constrained shortest path problems.

2.1.2 EV RECHARGING PROBLEM

Unlike regular gas stations that are ubiquitous and convenient for use, the lack of charging infrastructure in both accessibility and usability makes EV routing an essential function to prevent battery drain. Previous studies were mainly conducted on refueling fleet vehicles and the refueling stations were always along the fixed route because only visited depots were assumed to have charging facilities (Omidvar and Tavakkoli-Moghaddam 2012; Hong Lin et al. 2007). For common EVs, should the rerouting and recharging activity be required on the way to ensure adequate battery storage level for the entire trip, the location and selection of a proper charging station while maintaining an optimal route becomes a primary concern. In graph theory, a least-cost path from an origin node to a destination node over a network where each arc has its associated costs is typically determined by classical shortest path algorithms. Computer network and transportation related analyses (e.g. the Floyd-Warshall algorithm, the Bellman-Ford algorithm and the Dijkstra's Algorithm) have been used to study least-cost pathway. An EV recharging problem, nevertheless, can be described as a shortest path problem with additional constraints that an EV must maintain adequate energy at any time and consider passing through certain nodes before arriving at the destination. This is defined as a restricted shortest path (RSP) problem and belongs to the class of NP-hard problems in combinatorial optimization (Hassin, 1992).

Modern refueling problems for gasoline-powered vehicles mainly deal with minimizing total refueling cost with fuel stations located on the given path (Lin 2008; Suzuki 2008), while only little research has been undertaken on non-fixed-route vehicle refueling problems in the academic literature, let alone EV recharging problems. Khuller et al. developed four different refueling scenarios and solved the NP-hard problems with approximation algorithms (Khuller et al. 2011). One of the models was developed to find the shortest and cheapest path that visits a collection of cities while ensure the vehicle never runs out of gas. Regrettably, it was assumed that every city has a gas station within certain distance, which can simply be reduced to the well-known Traveling Salesman Problem. Another closely related piece of work is done by Sweda and Klabjan who formulated a recharging model to find the minimum-cost path for EVs (Sweda and Klabjan 2012). Since recharging capability was enabled at every node in the directed network, the optimal recharging policy was converted into a fairly simple one regardless of the routing issue and could solve the problem by an exact solution method. As a matter of fact charging stations are scarce, charging time and location become uncertain factors in finding the shortest path for EVs, as a result, few approaches in the vehicle routing and refueling problems in the past can be appropriately applied in this situation.

Although it seems unnecessary to deal with the shortest path problems in which charging stations are not located on or near the route, RSP methods have been regarded as one of the key components in the Quality of Service (QoS) routing problems for the wireless network since 1980s. As each link in the wireless network is associated with multiple parameters (e.g. delay, bandwidth and loss probability) , an essential challenging issue for QoS routing is to determine a feasible path that is subject to a set of QoS constraints while simultaneously achieve high utilization of network resources (Korkmaz and Krunz 2001). An EV recharging problem resembles the QoS routing problem because it has to deal with dynamic information with respect to link parameters (e.g. link average speed, energy consumption and cost) as well, and they both aim at identifying an optimal path that satisfies multi-parameter constraints.

A number of heuristics and approximation algorithms were proposed to address RSP problems for QoS routing. Hassin described two fully polynomial approximation schemes that were both solved by e-approximation algorithms, the principles of which are close to those of Warburton's algorithm, using the basic rules of rounding and scaling (Hassin 1992). Widyono presented a constrained Bellman-Ford algorithm for RSP problems using a breadth-first search by discovering paths of monotonically increasing delay while updating the lowest cost paths (Widyono 1994). Dynamic routing with minimum bandwidth guarantee was also considered and formulated as an integer programming problem (Kodialam and Lakshman 2000). Another effective approach is the k-shortest path algorithm which computes k shortest paths based on weighted average cost of each link in increasing order and expects the k-th one is feasible (Skiscim and Golden 1989; Eppstein 1998). Other similar heuristics and improved works that cope with this NP-hard problem were also proposed (Blokh and Gutin 1996; Chen and Nahrstedt 1998; Chong et al. 1995). However, despite that the above algorithms can possibly solve the RSP problems, they only exhibit good performance at the expense of excessive computational efforts. The running time grows exponentially as the size of the network increases, and they are still deemed impractical for real-time operations in large networks due to excessive computational complexities.

Other than building conventional mathematical programming models, Artificial Intelligence (AI) algorithms are considered as promising approaches to solve RSP problems as well. The author gives a detailed review on the Ant Colony Optimization (ACO) which belongs to the category of swarm intelligence in the next section.

2.1.3 ANT SEARCH ALGORITHM

As a relative new search technique in the Swarm Intelligence family, Ant Colony Optimization (ACO) has drawn wide attention after first introduced by Marco Dorigo in his Ph.D. dissertation in 1992 (Dorigo 1992), and has been successfully applied across a plethora of domains, including traveling salesman problem, vehicle routing and scheduling, QoS routing in wireless networks and graph coloring. ACO is a widely recognized metaheuristic approach inspired by the behavior of real ants which have the ability to find the shortest path between the food source and their colony. Each ant acts as a mobile agent that individually and iteratively seeks the feasible path while a colony of ants cooperate by depositing a chemical substance called pheromone, which can be recognized by all the ants, on the trail (Dorigo and Gambardella 1997).

To elaborate this behavior, consider a set of asynchronous agents wandering randomly from the starting node while laying down a certain amount of pheromone along the path, as shown in Figure 2. When arriving at a decision node to choose the next path segment (Figure 2(a)), each ant will move stochastically since they have no clue which route is the shortest one (Figure 2(b)). Assuming all ants move at the same speed, it can be expected that more pheromone will be left on the shorter link as they proceed back and forth within a shorter time, even though pheromone evaporates at a certain rate over time as well. Given that more pheromone on the path increases the probability of being followed, after a number of ants finish their tours, the choice of the following ants when they reach the decision node will be influenced by the pheromone concentration that they are more likely to select the way with higher accumulated pheromone (Figure 2(c)). Figure 2(d) illustrates that stimulated by the attractions of pheromone, some ants will end up sucessfully finding out the food source. Every finished tour becomes a feasible solution to the problem and the ant colony will eventually determine the shortest path possible if they iteratively exploit the graph. The convergence properties of the ACO algorithm have been proven (Onwubolu and Babu, 2004).

Ants must follow the constructive decision policy when iteratively build their routes, including the state transition rule at the decision nodes and the pheromone updating rule after all ants have completed their tours in one iteration (Dorigo and Gambardella 1997). The state transition rule that computes the probability of moving to each adjacent node can be given by (Onwubolu and Babu, 2004):

$$P_{ij}^{k}(u) = \frac{\tau_{ij}(u)^{\alpha} * \eta_{ij}{}^{\beta}}{\sum_{l \epsilon N_i^k}(\tau_{il}(u)^{\alpha} * \eta_{il}{}^{\beta})} \quad if\ j \epsilon N_i^k$$

where k represents the increasing order number of the ants in one iteration u and N_i^k is the feasible neighborhood of node i. In this equation, $\tau_{ij}(u)$ denotes the accumulated pheromone intensity on edge ij, indicating a posteriori desirability of the move, while η_{ij} is the attractiveness of that move represented by priori heuristic information, and α, β are parameters reflecting the relative importance of $\tau_{ij}(u)$ and η_{ij}.

All the feasible solutions can be determined after iteration u and according to the pheromone updating rule, the pheromone value on each edge for the next iteration should be updated using the equation (Onwubolu and Babu, 2004):

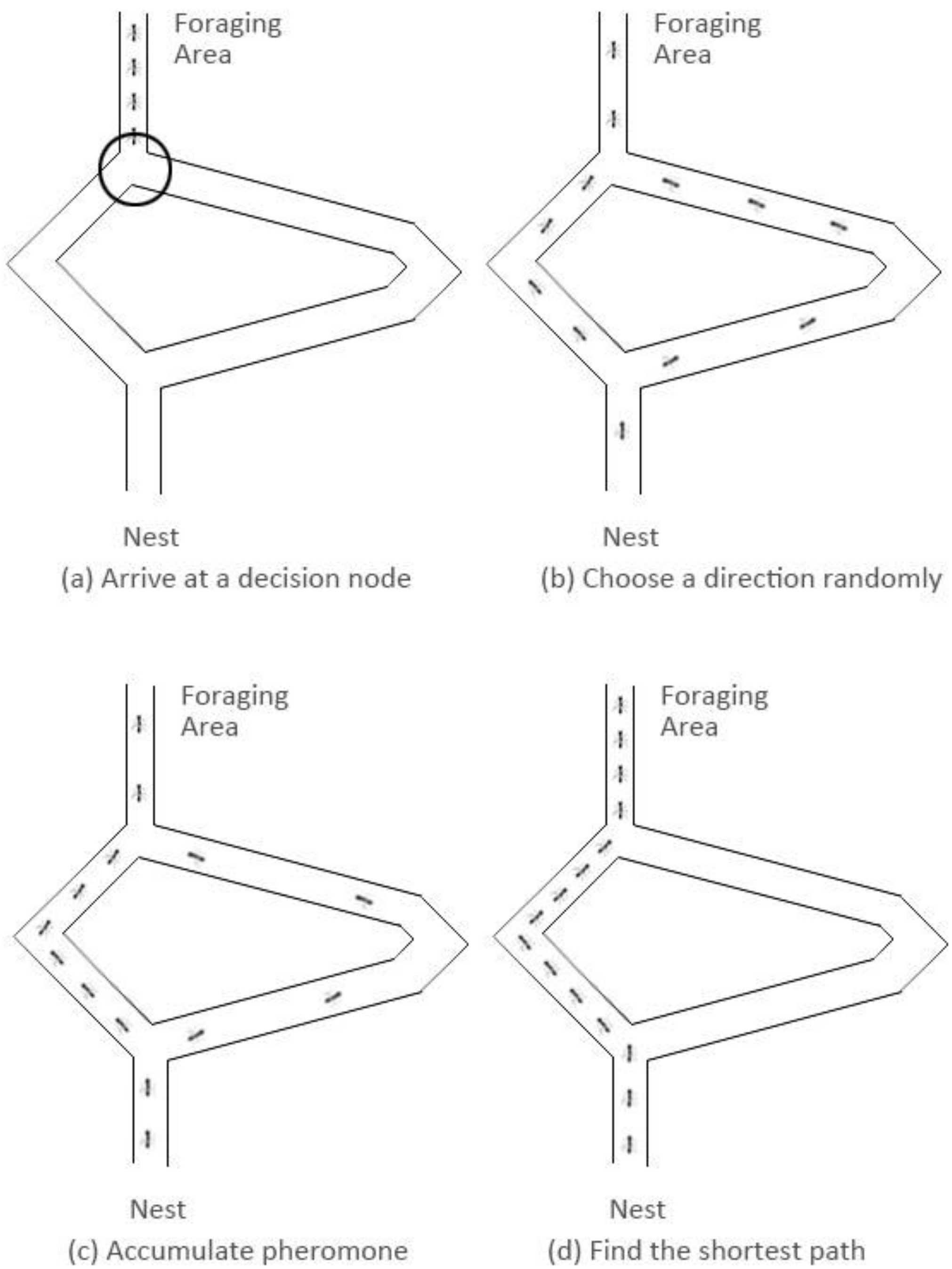


Figure 2. Description of the ACO principle

$$\tau_{ij}(u+1) = \rho * \tau_{ij}(u) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(u) \qquad \forall(i,j)$$

where $0 \leq \rho \leq 1$ is the pheromone evaporation coefficient, which implies that the pheromone value reduces over time to avoid falling into a local optimum, and $\Delta\tau_{ij}^{k}(u)$ represents the amount of the pheromone contributions of the ants that used edge ij to build their solutions. Subsequently, each ant incrementally moves towards those nodes corresponding to its partial solution. The outline of the ACO algorithm in pseudo-code is presented in Figure 3.

The ACO algorithm distinguishes itself with numerous features that differ from traditional RSP solving methods. The essential characteristic of ACO lies in the fact that every single agent in the colony can construct a possible solution by considering both heuristic and stochastic information exchange between the ants and the surroundings. More importantly, previous empirical studies from the ant colony allow the agent to evolve its search behavior iteratively and thus elucidate the most promising solution (Dorigo and Stützle 2003). As a probabilistic search technique, ACO is capable of solving a general class of path finding problems using problem specific heuristics in that parameters in the probabilistic decision and pheromone update equations can be adjusted accordingly to enhance the search efficiency. Unlike mathematical path searching methods whose computational complexity grows exponentially with the increase of the problem instance size, ACO algorithms are less sensitive to the scale of the problem and runs faster in large networks, which is of great importance to dynamic vehicle routing and refueling problems. For example, van Hemert and Solnon compared ACO with constraint programming, a complete tree-search approach, for solving binary constraint satisfaction problems (van Hemert and Solnon 2004). They found that constraint programming is faster when the number of variables is low, whereas ACO becomes faster as the number of variables increases. Although it's extremely difficult for artificial intelligence algorithms to perform a theoretical analysis, i.e. the result is empirical rather than theoretical, the feature of making random decisions based on empirical analysis renders ACO algorithms easy to program and quite efficient in discovering feasible solutions in a short time.

ACO algorithms have been successfully applied in the QoS routing problems which are also classified into RSP problems (Liang and Smith 2004, Roy et al. 2011). However, since the state transition rule and pheromone updating rule in the ACO algorithm are highly problem-specific, further research needs to be done to determine the appropriate heuristic for the emerging EV routing and recharging problems. The efficiency of the ACO algorithms as well as the sensitivity analysis of parameters should also be evaluated.

```
function ACO (initial, target)
initialize pheromone values on each edge of the graph
for each ant colony as iteration number
    for each ant in one colony as agent number
        var open = node queue from initial
        var closed = empty set
        var current = remove the starting node from open
        while an adjacent link exists
            choose the next node using probabilistic equation
            add current to closed
            replace current with selected node
        loop
    end for
    store feasible routes and other information
    update pheromone values
end for
return path
```

Figure 3. The outline of the ACO algorithm in pseudo-code

2.2 V2G IMPLEMENTATIONS

Vehicle electrification is envisioned to seamlessly integrate electric power systems with EVs, including fast charging infrastructure and the vehicle to grid (V2G) technology. EVs are expected to provide assistance for grid stability by charging and discharging EV batteries, while EV owners can obtain economic benefits from providing V2G services. This section gives a review on the development of the V2G implementations.

2.2.1 ANCILLARY SERVICES FOR V2G-EQUIPPED BEVS

Independent system operators (ISOs) and Regional Transmission Organizations (RTOs) deploy a variety of energy resources to provide ancillary services in an effort to maintain reliable and secure grid operations. BEVs can be treated as distributed mobile storage resources and would be competitive for the following four ancillary services (Kempton et al. 2008). Frequency regulation is the first service, which is responsible for rapidly correcting frequency deviations that can adversely affect electric equipment and appliances. Such control can be accessed as often as hundreds of times per day with a response time of no more than five minutes. Spinning reserve is the second service, which activates the backup energy resources to deliver electricity back in response to major outrages. The frequency of this service request ranges between 20-50 times yearly and can provide supply within 10 minutes of request. Peak load leveling is the third service, which typically occurs within a single hour of the day at peak demand times, finally with backup supply the fourth service, which engages during power outages. Of these four ancillary services, frequency regulation appears to be the most appropriately suited for V2G-enabled BEVs (Kempton et al., 2008; Brooks, 2002; De Los Rios et al., 2012) because unlike spinning reserve and peak load leveling, frequency regulation requires no high battery capacity and allows for a shallow charge/discharge cycling instead of deep depth of discharge (DoD) that is likely to degrade the lifecycle of the battery. The number of cycles of a lithium-ion battery can be estimated as a function of DoD, making it obvious that lowering DoD can extend the life cycle of the battery (De Los Rios et al. 2012). Therefore, providing frequency regulation services with low DoD will only minimally affect the battery cycle lifetime. While the power fluctuations of frequency regulation may change the battery's state of charge (SOC) in a short time, the energy storage level is nonetheless retained over a certain period as opposed to other ancillary services that could drain the battery. Statistics also show that the frequency regulation is much more economically viable compared to other forms of V2G ancillary services. In the United States, ancillary services account for 5-10% of total electricity cost as $12 billion/year, 80% of which are for regulation and spinning reserve with an average value of $30-$45/MW per hour and $10/MW per hour respectively (Kempton et al., 2008).

A vehicle can be V2G available for the majority of the day. A previous study shows that in the US typically only 4% to 5% of the vehicles are on the road with at least 90% of vehicles parked and available for plug in even during peak hours (Tomic and Kempton, 2007). Although the uncertainty of a BEV's battery SOC and plug-in duration may adversely affect the reliability of a BEV that is supposed to augment regulation resources, a group of BEVs in the same region can constantly provide an adequate energy level to enter the frequency regulation market. In this paper, we use frequency regulation for their V2G ancillary service studies and analysis of the architecture.

Currently frequency regulation is largely provided by generators specifically designed for this purpose. Replacing these generators with V2G-enabled BEVs as energy storage resources could save ISO/RTO a large amount of expenses. Since V2G-equipped BEVs can transmit the power flow bi-directionally, both “regulation up” and “regulation down” services representing power delivery to and from the grid respectively can be accessed as necessary. The gross revenue of frequency regulation consists of two main parts: the capacity value and the energy value. The capacity value is contracted based upon the vehicle’s available power capacity and the energy value is the sum of the hourly regulation up and regulation down prices. Though regulation up and regulation down can be procured separately, ISO may call for equal quantities of both services in a certain time to prevent discharge of EV batteries (Kempton et al. 2008). The architecture assumes that the amount of energies for both regulation up and regulation down at hourly intervals would yield a zero net energy delivered to the grid.

Several studies were undertaken to calculate the potential revenue of offering ancillary services for EVs and PHEVs when V2G power transfer is enabled. A report from the California Air Resources Board and the California Environmental Protection Agency shows that frequency regulation results in an annualized gross value of $967 to $5038 to BEV owners when a BEV is assumed as plugged in 94.2% of the day (Brooks 2002). Tomic and Kempton (Tomic and Kempton 2007) found that the annual net profit of 252 Toyota RAV4 fleets ranged from $135,000 to $450,000 when both up and down regulation services are provided, assuming they are available for V2G power delivery from 3PM to 8AM, or either 17 hours per day. Similarly, in their investigation of the maximum average revenue for individual PHEVs in Sweden and Germany, Andersson et al. found that each PHEV in the German market generated 30 to 80 euros per month while the Swedish market provided no profit via grid ancillary services (Andersson et al., 2010). All of these studies, however, considered neither the driving demands nor the dynamic regulation pricing, and they oversimplified available V2G hours as a consecutive time frame. Indeed, the BEV charging process must consider a real-time variation of regulation prices so they may provide the regulation services when the prices are relatively high and recharge the battery otherwise, thereby maximizing the profits. We explore the potential benefits and costs of V2G-equipped BEVs in the United States by intelligently arranging charging events (charging, regulation, driving and do nothing) through real-time communication with grid operators.

2.2.2 APPROACHES FOR OPTIMIZING THE V2G IMPLEMENTATION

Though the grid scheduling problem, which includes V2G-enabled vehicles, was the subject of recent studies, it has been done so only from the perspective of power systems. In their particle swarm optimization based approach for the distribution network scheduling problem, Soares et al. minimized the total generation cost for the power generators (Soares et al., 2011). Though they considered the V2G resources and driving pattern impacts on the smart grid, BEVs were only treated as discharge resources and they did not explore the potential of BEVs to act as ancillary service resources. Guille and Gross proposed a conceptual framework to integrate the aggregated battery vehicles which acted as distributed energy resources within the power grid (Guille and Gross, 2009). Though they developed strategies to construct the information layer and design an incentive program for V2G implementation, they did not validate the performance of the conceptual framework, nor did they consider the charge/discharge scheduling problem for aggregators and the management of customized BEV input. Clearly, much more research must be undertaken to accommodate individual BEVs. In that regard, Mal et al. presented a charge scheduling system to optimize charge/V2G activities in a parking garage using the own profiles of the vehicles (Mal et al., 2012). Regrettably, however, they only optimized the charge scheduling between the arrival and the departure times, not vehicles that may have been possibly plugged and unplugged multiple times a day. Such a scheduling optimized for the next couple hours may not be the best solution, particularly when compared to the optimal scheduling on a 24-hour basis.

In an effort to fully explore the potential of V2G-equipped BEVs to enhance their performance, we developed a comprehensive smart charging architecture that is specifically designed for BEV owners in the distributed energy network. Under such a scheme, BEV owners are expected to become more motivated to participate in such V2G programs if they see the benefits of such participation. A communication network was developed to effectively enhance real-time communication and coordination among BEVs, aggregation servers and the ISO/RTO together with an optimal scheduling model for rapidly arranging the charge and ancillary service activities over a 24 period. A detailed description of the architecture is described in the next section.

2.3 CONNECTED VEHICLE TECHNOLOGIES

In-vehicle electronics are growing fast both in quantity and complexity, offering an unprecedented level of convenience and versatility as well as accelerating the demand for connected driving experience, which can be achieved in a comprehensive ITS technology based architecture. A variety of technologies with regard to building the architecture are reviewed in the following sections.

2.3.1 WIRELESS TECHNOLOGIES FOR MOVING VEHICLES

Heterogeneous communication technologies must be integrated to support diverse services and functionalities in a sophisticated transportation communication infrastructure. A variety of wireless communication technologies are deemed viable under high vehicle speed mobility conditions. For example, Dedicated Short-Range Communications (DSRC) which links between the vehicles and the roadside infrastructure is specifically established for ITS applications and assigned 75 MHz of spectrum in the 5.9 GHz band (U.S. DOT, 2013). DSRC are designed to support a plethora of transportation applications, including collision avoidance, advanced vehicle control and electronic toll collection. Wi-Fi and WiMAX wireless protocols can also provide vehicle-vehicle and vehicle-infrastructure connectivity. Wi-Fi technology has been widely used on mobile devices but primarily covers a relatively short range using local area network (LAN) for Internet access. Since moving vehicles are likely to experience poor connectivity between two WiFi basestations, Wi-Fi technology is not deemed reliable for communication between moving vehicles and infrastructure. In contrast, WiMAX technology has the ability to provide broadband connectivity services that a large number of end users can get access simultaneously at high speed within a range up to 30 miles. Unlike the Wi-Fi environment in which users may have to compete to get connected through a specified access point, WiMAX network supports Quality of Service (QoS) routing as mobile devices can be automatically allocated to different WiMAX stations. A few studies have evaluated the feasibility of the WiMAX technology for vehicular networks. The mobile WiMAX-based Vehicle-to-Infrastructure (V2I) communication networks was tested through simulation by Msadaa et al. (Msadaa et al., 2010). Obtained results revealed that the mobile WiMAX technology will become a competitive solution in the context of V2I communications. In addition, as the cellular data usage has been soaring dramatically over the past years, there is a unique demand to connect in-vehicle applications and smartphone software platforms. The vehicle smartphone communication allows the smartphone to function as a remote control device so that the passengers can take full advantage of cellular data services, and as a result, the rapid evolution of cellular data networks has attracted a tremendous attention. The third generation (3G) and fourth generation (4G) standards have significantly increased the speed of mobile data transmission, which is expected to reach to the same speed as modern computer networks. Other than the familiar communication protocols above, the evolving Ethernet technology has increasingly been considered for automotive applications. Currently, Ethernet is restricted to onboard diagnostic access and camera-based driver assistance systems while further efforts must be made for Ethernet to be used for other in-vehicle applications, such as the electromagnetic compatibility and the automotive industry standard.

2.3.2 VEHICLE INFRASTRUCTURE COMMUNICATION FRAMEWORK

Vehicle infrastructure communication is generally divided into two parts: the vehicle-vehicle communication and the vehicle-infrastructure communication. The rapid development of ITS technologies will have a significant influence on the transportation infrastructure in order to support transportation safety, efficiency and mobility, and the connected vehicles must collaborate with intelligent infrastructure to facilitate information and energy transfer. The trend of transportation electrification to replace traditional gasoline fuel stations with modern charging stations will urge the development of new standards to support power and data transfer through communication interfaces between EVs and charging facilities. A communication protocol is designed that the Electric Vehicle Supply Equipment (EVSE) will provide the bi-directional connection between the EV's battery and the grid service infrastructure, which requires specific access and management tools.

2.3.3 IN-VEHICLE APPLICATIONS

The practical interest of the ITS has spawn a number of studies. More and more vehicle corporations are trying to build integrated in-vehicle platforms so that the driver assistant functions and vehicle enhancement services can be embedded into onboard applications to facilitate EV usage. Large auto companies like Toyota and Ford are all engaged in developing mobile applications and releasing them onto cell phone app stores. Take MyFord Mobile App as an example. All the Ford PHEV and EV owners are allowed to download and install this application on their smart phones by which EV owners are able to access this application and remotely control their vehicles, such as monitoring the remaining SOC, the charging settings and status as well as planning trips (Ford Automobile, 2013). In fact, mobile applications are capable of performing functions that are compatible to all the vehicle models, like providing parking and tolling information, entertainment services and location technologies.

Nevertheless, such applications need to be downloaded and installed on the smart phones, which is responsible for running all the programs. Due to hardware requirements, mobile applications always fail to perform large-scale tasks at a time, making Software as a Service (SaaS) more attractive as applications become more and more data-intensive. SaaS, newly referred to as Cloud Computing, can provide infinite computing resources on demand through web browsers which are universally compatible on different mobile devices. A number of large companies like Amazon, Apple and Google have become major cloud providers. SaaS can assist Connected EVs in remotely running complicated programs in a timely manner to improve efficiency and safety of EVs.

CHAPTER THREE

METHOD

This chapter provides the detailed methodology adopted for this research. The author starts with a description of the ITS-based architecture, followed by two major applications; the routing application and the V2G-equipped ancillary service application which are used to facilitate EV operations. The corresponding algorithms for these applications are elaborated in this chapter.

3. 1 THE ITS-BASED ARCHITECTURE

It is essential to define the communication interface associated with the key components among vehicles and between vehicles and the roadside infrastructure supported by wireless protocols. Figure 4 shows the interconnections among the components under the ITS-based architecture. Vehicles as the data transmission center can communicate with other vehicles and roadside units using the DSRC technology and also send and receive GPS signals. A cloud based server side architecture can also be built, under which a variety of ITS applications can be embedded, while the open interface also permits the compatibility and expandability of the architecture so that any application that is considered as a useful tool for EVs can be created in the future. Other than vehicles and transportation infrastructure, mobile devices, traffic management centers and other stakeholders can also get access to the cloud based server center to obtain valuable information and remote control the devices. As a result, drivers, vehicles and infrastructure in this architecture are inter-connected.

The proposed communication architecture is expected to fulfill the following tasks:

1. Connect vehicles to the cloud based server side to retrieve information, such as the speed data and the accident records. The server which collects and stores a plethora of information should also have the ability to process complex models and return the results to the vehicle side.

2. Connect other Internet accessible devices to the cloud based server to allow data flow between infrastructures. Authorized devices can exchange data with the server and acquire valuable collected information for their own use.

3. Connect vehicles to each other so that they can share and exchange data among each other, and most importantly, avoid incidents and instantly response to emergencies through the DSRC communication.

4. Connect mobile devices to the vehicle in order to take full advantage of the cellular data services and all the applications from the smartphones. The smartphone can also be regarded as a remote control so that the vehicle owners can monitor the status of vehicles at anytime, anywhere.

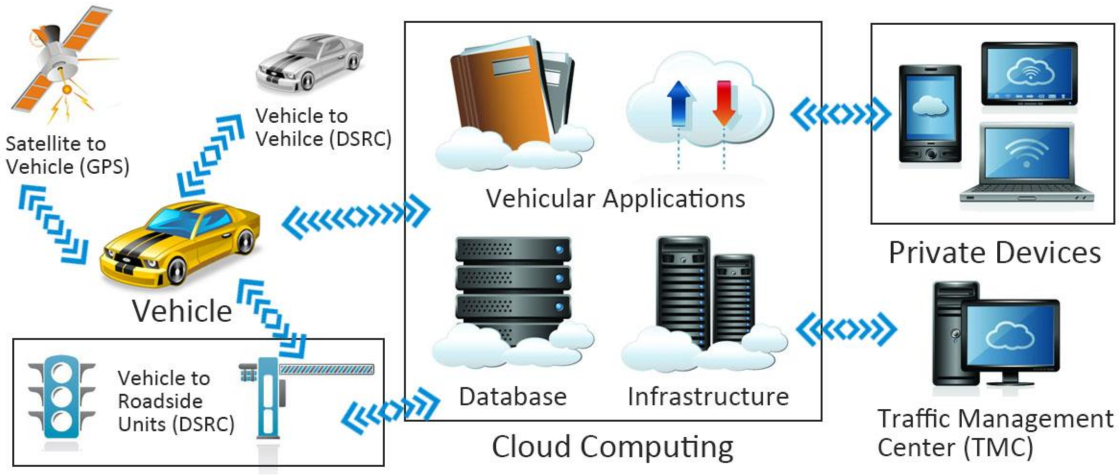


Figure 4. Interconnections among architecture components

3.2 THE ACO BASED ROUTING AND RECHARGING STRATEGY

Let the entire network be a directed graph G = (V, E), where V is a set of vertices representing junctions in the traffic network and E is a set of edges representing road segments in the traffic network. Each edge has an associated cost and delay, which are average travel time and energy consumption through this road, respectively in this context. This multi-objective integer programming problem can be described as follows:

Minimize

$$\sum_{i \in I} (t_i + c_i) y_i$$

$$\sum_{j \in J} f_j r_{j,t} x_j$$

Subject to

$$c_{ini} - \sum_{a \in A} e_a > c_{lim}, \forall\, a$$

$$x_j, y_i \in \{0, 1\}\ \forall\ i, j$$

Where

i = index of selected edges

I = set of all O-D edges

t_i = travel time consumed at edge i

c_i = recharge time consumed at edge i

$$y_i = \begin{cases} 1 & \text{if edge } i \text{ is selected} \\ 0 & \text{otherwise} \end{cases}$$

j = index of recharge edges

J = set of all O-D recharge edges

f_j = amount of recharged electricity at recharge edge j

$r_{j,t}$ = electricity pricing of time point t at recharge edge j

$$x_j = \begin{cases} 1 & \text{if edge } j \text{ is selected} \\ 0 & \text{otherwise} \end{cases}$$

c_{ini} = initial energy storage level in battery

c_{lim} = lower limit of energy storage in battery

a = index of edges from origination to current edge

A = set of edges from origination to current edge

e_a = overall energy consumption at edge a, can be negative at some edges where EVs can get recharged

Note that the total delay, or total energy consumption in this context, cannot exceed the given bound $(C_{lim} - C_{ini})$, indicating the unlimited shortest travel time path may not be feasible as the EV battery may run out before reaching the destination unless it is recharged halfway. In order to efficiently assist EV drivers, a routing algorithm based on ACO is presented in this paper for path selection.

The routing approach will be recursively called at every decision node with more than one ongoing route to continuously provide up-to-date EV driver assistance. Through Connected Vehicle technology, all the information needed in the process can be acquired from VII components. This acquisition involves a four step process:

1. Initialization: information includes allowed maximum energy consumption, adjacency matrices of cost and delay, colony number and ant number in each colony, initial trail level, and the coefficient of pheromone and evaporation.
2. Select proper heuristics and corresponding probability distribution function. Since EVs are not allowed to exceed the maximum energy consumption, the remaining delay should be considered as one of the heuristics. If the least total travel time is set as the first priority for optimization in this multi-objective problem, the Ant Colony Optimization algorithm can be implemented with the probability distribution below:

$$P_{ij}^{k}(u) = \frac{\tau_{ij}(u)^{\alpha} * \mathrm{c_{ij}}^{\beta} * \mathrm{d_{ij}}^{\gamma}}{\sum_{l \epsilon N_i^k} (\tau_{il}(u)^{\alpha} * \mathrm{c_{il}}^{\beta} * \mathrm{d_{il}}^{\gamma})} \quad if\ j \epsilon N_i^k$$

This probability distribution is the result of trade-off among previous learning experience, estimated remaining cost and remaining delay. The heuristics contain the shortest remaining travel time $\mathrm{c_{ij}}$ and lowest remaining energy consumption $\mathrm{d_{ij}}$ from the current point to the destination with their influence coefficients β and γ respectively. A number of shortest path algorithms can be used to calculate $\mathrm{c_{ij}}$ and $\mathrm{d_{ij}}$, such as Dijkstra's algorithm and Floyd's algorithm.

3. Store feasible solutions in each iteration, the delays of which are always within the limit. Update pheromone values using the formula mentioned above and iterate through the loop.

4. Output the best feasible path with the least travel time and/or the lowest recharge cost among all the feasible solutions according to users' optimization preference.

3.3 THE ANCILLARY SERVICE OPTIMIZATION

Figure 5 depicts the components and communication flow of the smart charging architecture in which BEVs get to control and switch the charging status automatically at optimal times by monitoring both the time varying pricing data and the ISO/RTO dispatch signals. BEVs can be plugged in either at home or public charging stations with each belonging to a single aggregation server that is connected through a wireless network. To provide a greater power-on-demand reserve for use in the ancillary service market, BEVs in a certain area are aggregated as a centralized resource so that the ISO/RTO can interact with aggregation servers representing BEVs rather than thousands of individual vehicles. An aggregation server is responsible for collecting, storing and processing all the data regarding BEV charging activities as well as communicating with the ISO/RTO. The dynamic ancillary service pricing can make ancillary services more attractive when the demand is high, while the time-of-use (TOU) electricity rates that are released by ISO/RTO can ease the load during peak hours. Aggregation servers acquire the day-ahead and real-time price for electricity and ancillary services to support the bidding and scheduling strategies. After determining the aggregated available capacity in a given time frame, each aggregation server submits its ancillary service bid with the rate per MWh and the total capacity it offers to the ISO/RTO which controls all electrical transmission in a region. Once the bid is accepted, all the involved BEVs are placed on standby to respond automatically to dispatch signals sent by the ISO/RTO through aggregation servers.

Since multiple BEVs are likely to share home and public charging systems, the communication architecture should encompass an ID authentication sub-system for personal configuration and billing purposes. In this architecture, an onboard radio-frequency identification (RFID) tag is mounted where each BEV is assigned a unique vehicle identification when connected with the power grid system. The aggregation server then retrieves specific information (e.g. the user profile, scheduling preference, trip plan and billing history) from the database using the RFID reader. A corresponding optimal charge/regulation schedule is determined for each BEV based on the associated information on the server side. Once all the schedules are updated, the aggregation server calculates the total available capacity for the next time interval and submits the bid offer to the ISO/RTO ancillary service market. The detailed components and connections between aggregation servers and BEVs are illustrated in Figure 6.

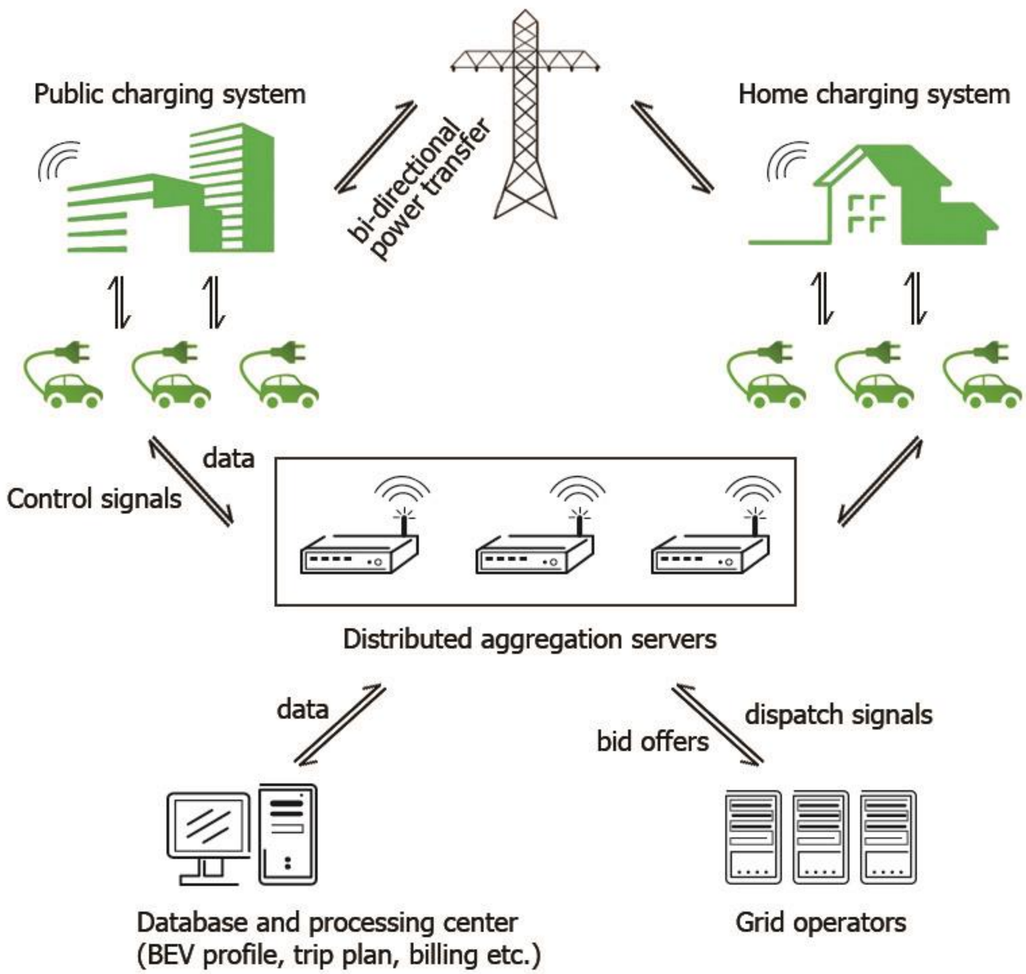


Figure 5. Components and communication flow in the smart charging architecture

In this architecture, all the aggregation servers are Internet-accessible. BEV owners are provided continuous access to the information management system from which they can monitor the battery status, update BEV settings and upcoming trip plans, and access charging and billing histories via web browsers and mobile devices. The user interface as depicted in Figure 7 encompasses a variety of modules, including the management of BEV profiles, personal settings, upcoming trip plans, billing histories associated with the information of electric metering, optimal scheduling and bidding offers. Should any of the changes affect the coefficients or variables in the scheduling model, the aggregation server instantly updates the optimal scheduling to ensure a constant accuracy of the total available capacity.

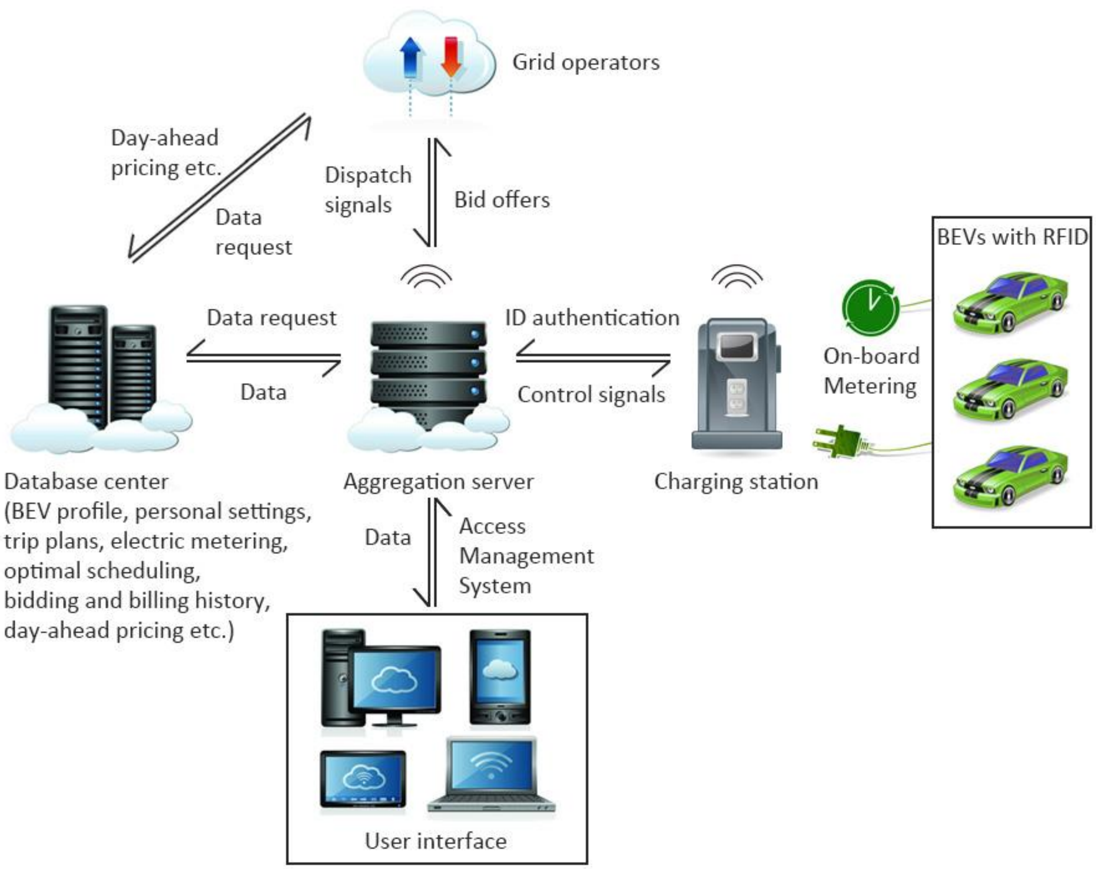
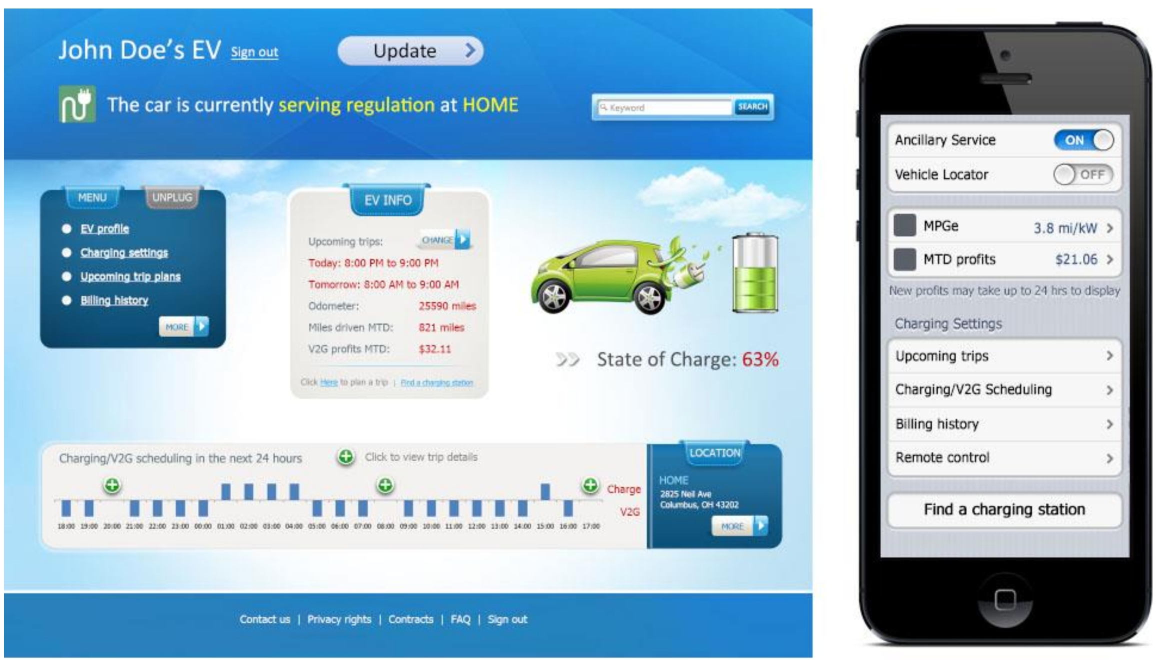


Figure 6. Detailed components and connections between aggregation servers and BEVs

To help BEV owners maximize their potential benefits and simultaneously satisfy driving energy demands, a charge/regulation scheduling model that optimizes and updates the schedule in a timely manner based on the time varying data is necessary. Since last-minute trip changes are always likely, aggregation servers must have the capability to update the charge/regulation schedule right before the start of each time interval. In this way, both aggregated servers and BEV participants can benefit from acquiring accurate optimal charge/regulation scheduling information.



Web browser Mobile device

Figure 7. Interfaces of the charging management system on the web browser and mobile device

In the scheduling model of this architecture, the charge/regulation plan of an individual BEV is optimized for the next 24 hours. Every hour is defined as a time interval (i.e. in which one BEV is sitting idle, in use, being recharged or providing regulation services) when parked and plugged in. Although the objective is to maximize the net profit for BEV owners by providing regulation services, several constraints impede unlimited regulation supply in that BEVs will lose energy after driving and must recharge to prevent a battery drain. Optimizing the BEV charging schedule is considered as a binary linear programming problem. The objective is described as:

$$\text{Maximize} \quad \sum_{j=1}^{24}\left(P_l * R_{cj} * X_{2j} + E * P_l * (R_{uj} + R_{dj}) * X_{2j}/2 - P_v * R_{sj} * X_{1j}\right) \qquad (1)$$

Where j: index of time intervals. j = 1, 2, …, 24

$$x_{1j} = \begin{cases} 1 & \text{if the BEV is charging at time interval j} \\ 0 & \text{otherwise} \end{cases}$$

$$x_{2j} = \begin{cases} 1 & \text{if the BEV is providing regulation service at time interval j} \\ 0 & \text{otherwise} \end{cases}$$

P_v: Power of vehicle in kW

R_{cj}: Regulation capacity price at the time interval j in \$/kW-h

P_l: Power of line in kW

R_{uj}: Regulation up price at the time interval j in \$/kWh

R_{dj}: Regulation down price at the time interval j in \$/kWh

R_{sj}: Electricity selling price at the time interval j in \$/kWh

E: Dispatched energy ratio

In this binary problem, the net profit in the next 24 hours is defined as the total ancillary service profit subtracted from the charging cost. The first item of the objective function is the capacity value of frequency regulation while the second item is the energy value of frequency regulation. The dispatched energy ratio in the energy value portion is defined as the ratio of the dispatched energy for regulation to the contracted power and time. As mentioned in the previous section, the energy delivered for regulation up and from regulation down in each hour is assumed as equal. Therefore, the energy value is projected as the sum of the 30-minute regulation up rate and the 30-minute regulation down rate in each time interval.

The constraints of this problem are expressed as:

$$X_{1j} + X_{2j} \leq 1 \ \forall j \tag{2}$$

$$X_{1k} + X_{2k} = 0 \ \forall k \tag{3}$$

$$\sum_{i=1}^{j} DIS_i * M/Bat - \sum_{i=1}^{j} X_{1i} * \mu * P_v/Bat \leq SOC_i - SOC_b \ \forall j \tag{4}$$

$$\sum_{i=1}^{j} X_{1i} * \mu * P_v/Bat - \sum_{i=1}^{j} DIS_i * M/Bat \leq SOC_t - SOC_i \ \forall j \tag{5}$$

Where k: index of unavailable time intervals. $k \in j$

DIS_i: Driving distance at the time interval j in mile

μ: Charging efficiency

M: MPGe in kWh/mile

Bat: Battery capacity in kWh

SOC_i: Initial SOC

SOC_b: SOC window minimum

SOC_t: SOC window maximum

Constraints (2-3) indicate that a single BEV might be unavailable to plug in during several time intervals (e.g. in use with no equipment in proximity for grid connection). Both the charging binary value and regulation binary value are projected as zero under the circumstances. Constraints (4-5) suggest the SOC of the battery must fall in the allowed SOC window at any time, the lower limit of which is typically more than 20% and the upper limit up to 90%. We do not suggest 0% to 100% availability, however, as a complete charge-discharge cycle will slightly diminish the battery capacity and a valid SOC window can extend the potential lifetime of the battery as mentioned in the previous section. BEV participants may then determine both the lower and upper limits of the SOC window through the information management system with additional constraints that are applicable based upon the user configurations.

The scheduling model can adapt to various changes. For example, in the Great Britain, grid balancing market data is released every 30 minutes, for which the scheduling model can split each day into 48 time intervals instead for optimization. Similarly, the coefficients of this binary integer programming problem may vary over time as the TOU rates and dynamic ancillary service market prices can be measured hourly. The problem will be updated and solved iteratively at the beginning of each time interval to provide the latest optimal charge/regulation schedule according to the user preferences, driving plans and other information in the next 24 hours. If the solution cannot be determined, the aggregation server sends an alert to the participant who is responsible for changing associated settings to make the schedule possible, such as adjusting excessive driving mileages or trying to connect to the charging station before the trip. It's also beneficial for BEV participants to be aware whether or not their driving plan can be satisfied so as to relieve the concerns of range anxiety.

The event sequence diagram in Figure 8 shows the processes by which the architecture works. BEVs become cash-back cars and can support the power grid system stability in this architecture.

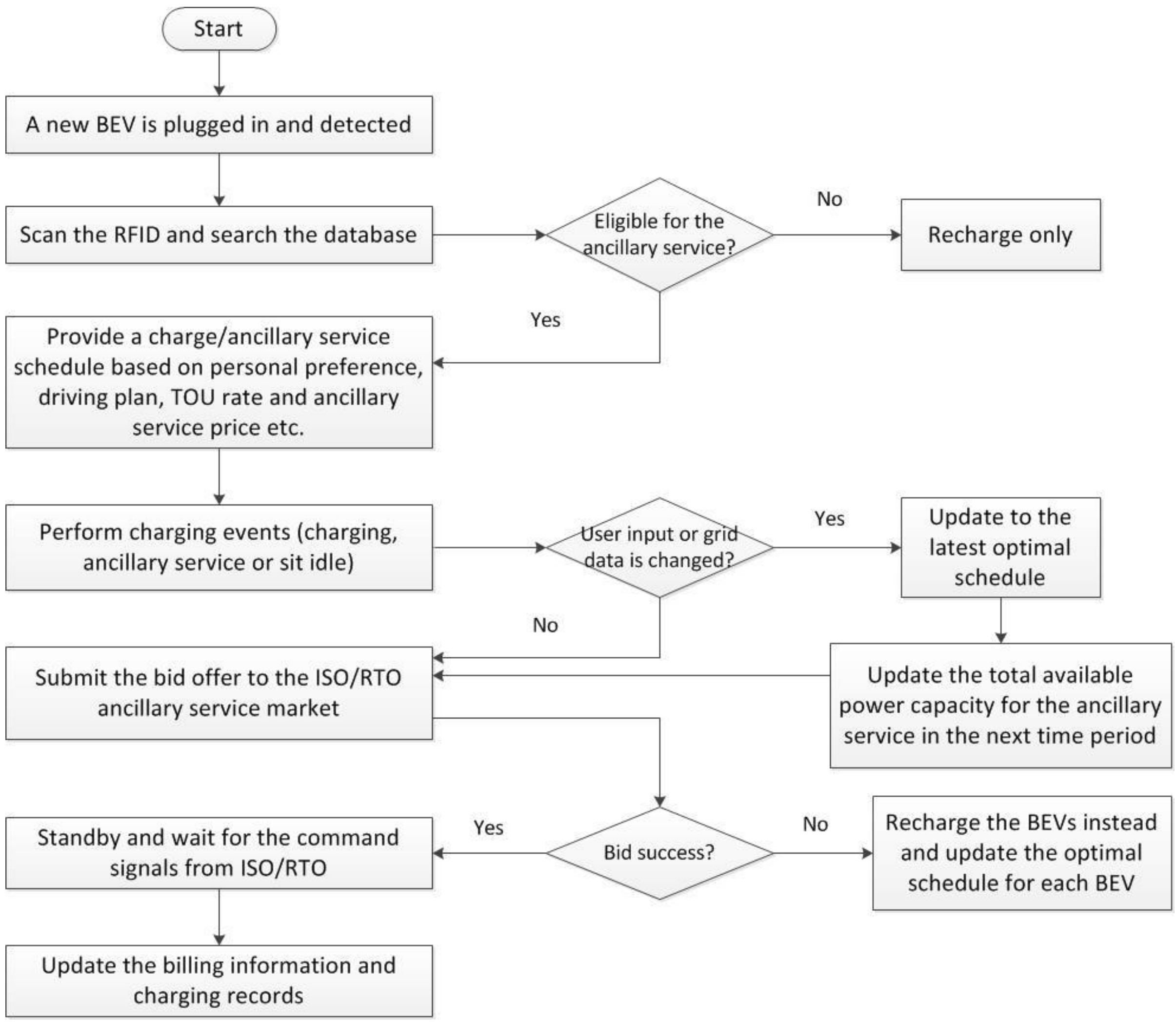


Figure 8. Event sequence diagram of how the system works

CHAPTER FOUR

ROUTING AND RECHARGING APPLICATIONS

A roadway network in Charleston, SC area was selected to evaluate the performance of the approach discussed in the earlier chapter, and the PARAMICS simulator was used to model the Charleston network. Figure 9 presents an overview of the entire network and a detailed simulated roadway in PARAMICS.

Figure 9. Simulated Charleston, SC traffic network.

4.1 SIMULATION CONFIGURATIONS

The Electric Vehicle model for the simulation experiment was constructed using a simulation platform in Matlab-Simulink. To simplify the problem, it was assumed that vehicles precisely followed the driving cycle input to the model. The power request was first calculated through vehicle dynamic with the parameters of the EV model shown in Table 3, and then sent to the Motor/Generator (MG). The MG power in this model was set to 80kW, which satisfied the power request in all driving tasks considered in this study. Under normal driving conditions, MG works as an electric motor, transforming electric power from the battery into mechanical power to yield vehicle power supply, while during braking it becomes a generator to recharge the battery, converting mechanical power from the wheel back to electric power. The range capacity of an EV battery is most important to EV operation, which is currently quite limited. For this study, the SOC of the battery was set between 30% and 90% with all electric range (AER) of approximately 100 miles in urban driving (UDDS cycle).

TABLE 3. EV Model Specifications

Total weight	1500 kg
Projected frontal area	2.16 m^2
Aerodynamic drag coefficient	0.26
Rolling friction coefficient	0.007
Transmission efficiency	0.98
Final gear ratio	4.11
Motor/Generator (MG) power	80kW
Battery construction	192 cells of 13-Ah lithium-ion battery
Battery packs	4
SOC window	30% ~ 90% (99.91mile for UDDS)

50 base EVs together with 50 connected EVs were deployed with the same origin-destination (OD) were randomly released over time in the simulation experiments. All the VII components were allowed to communicate with each other. Traffic information was updated and transmitted to EVs in real time. Current average speed of vehicles on the link was utilized as the predicted link speed at a certain time step, with a conservative coefficient to offset the forecasting errors. The user-specified lower bound of SOC was set to 40%, indicating the SOC of battery is expected to be above 40% anytime driving towards the destination. When the connected EV is approaching a decision point where there are more than one adjacent path in the same direction, the onboard routing

application will be triggered that helps drivers find the best routing and recharging plan in real time. A conservative adjustment strategy can be used to recharge for more energy in the event of an emergency, such as the involvement in an incident or unwanted forecasting errors.

The dynamic electricity rates were also applied in this study and changed every 30 minutes. Due to lack of proper data in South Carolina, the dynamic national electricity sell price in UK was used according to the real-time data on the Balancing Mechanism Reporting System website. The author selected dynamic IPT charging facilities over static charging stations in this study. For appropriately testing the proposed routing approach, six dynamic IPT tracks were evenly buried under the major roadway surface in the simulated network, each with a 30kW power supply. The length of the tracks was approximately 4000 feet. Moreover, the recharge efficiency was assumed to be 80% on average. Because of the high initial cost, we intended to minimize the length of the IPT tracks while offering an acceptable recharge capacity. Consequently, IPT tracks were placed under the roadway links where the average speed of vehicles passing by in the simulation is relatively low to maximize the valid recharge time and recharge volume.

4.2 ANALYSIS

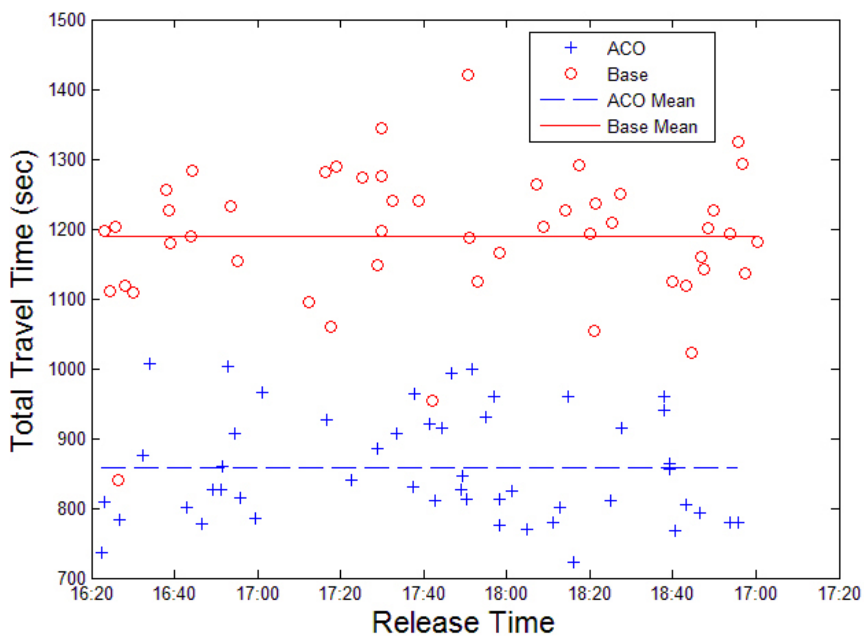
We performed the simulation for the rush hour traffic which begins at 4 PM and lasts for 3 hours and 20 minutes, and the EVs were released from 4:20 PM. To evaluate the new approach in a comprehensive way, we intentionally created an incident on one six-lane highway, two southbound lanes of which were blocked from 4:30 PM to 6:30 PM. Each EV starts at some point of time with a random initial SOC of battery between

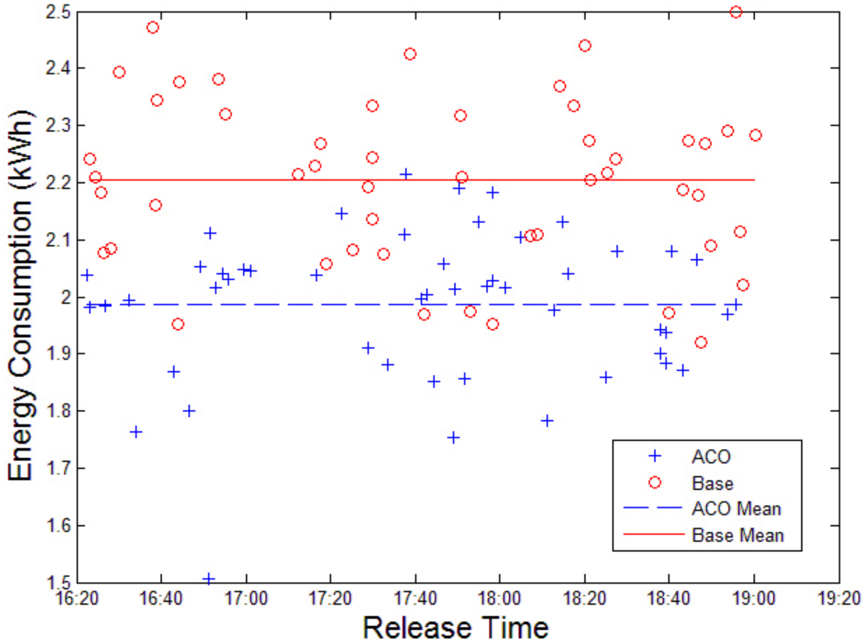
43% and 44%. In addition, in order to appropriately weigh the effects of the Connected Vehicle-based new approach, 50 base EVs were leaded with a conventional navigation strategy for comparison, the logic of which is to guide EVs along the route with the shortest distance. Since the VII interaction is not available for base EVs, a fixed speed limit was used as an independent variable to predict the travel time and associated energy consumption. Considering the range anxiety, drivers were continuously detoured to the nearest charging tracks to obtain more energy if the SOC of battery was projected to drop below 40% in the end. The overall results of the simulation are shown in Table 4.

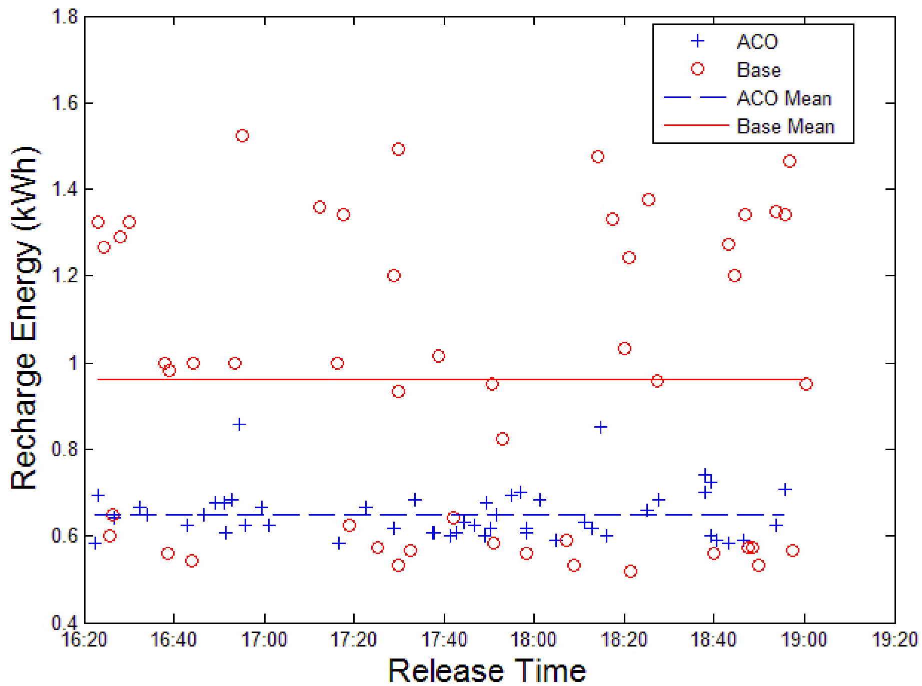
TABLE 4. Comparative Simulator generated data of base EVs and Connected EVs in First Simulation

Strategy	Base	Connected	(Base-Connected)/Base
Average Travel Distance (mile)	4.092	3.763	8.04%
Standard Deviation of Travel Distance	0.197	0.119	
Average Travel Time (sec)	1188.94	857.11	27.90%
Standard Deviation of Travel Time	98.37	77.21	
Average Consumed Energy (kWh)	2.206	1.986	9.97%
Standard Deviation of Consumed Energy	0.146	0.130	
Average Recharge Volume (kWh)	0.961	0.650	32.36%
Standard Deviation of Recharge Volume	0.346	0.058	
Average Recharge Cost (cent)	61.98	41.70	32.73%
Standard Deviation of Recharge Cost	28.078	11.406	
Average Starting SOC	43.41%	43.46%	
Average Final SOC	41.35%	41.05%	

Although base EVs used the shortest distance approach, they drove even longer than connected EVs because detours for recharging. Connected EVs also saved 27.90% of average travel time, 9.97% of average energy consumption, 32.7% of recharge energy and 32.73% of recharge cost. The detailed comparisons of performances between the two types of EVs from 4:20 PM to 7:20 PM are represented graphically in Figure 10. From the scatter plots, it is evident that the total travel time and energy cost of connected EVs were generally lower than base EVs at each released time step. Also, the recharge electricity along with the recharge cost of connected EVs has a relatively tight range of values while the corresponding values of base EVs are widely dispersed, revealing a more consistent and reliable recharge navigation against base EVs'. Indeed, though base EVs were unable to control the recharge volume since it will only locate the nearest track and refuel, the nearest charging station did not always have the best charging capacity and charging price. As the deviation between predicted and actual energy consumption always exists, it was deemed prudent to charge more than required.




Energy Consumption (kWh)
2.5
2.4
2.3
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
16:20
16:40
17:00
17:20
17:40
18:00
18:20
18:40
19:00
19:20
Release Time
ACO
Base
ACO Mean
Base Mean


Recharge Energy (kWh)
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
16:20
16:40
17:00
17:20
17:40
18:00
18:20
18:40
19:00
19:20
Release Time
ACO
Base
ACO Mean
Base Mean

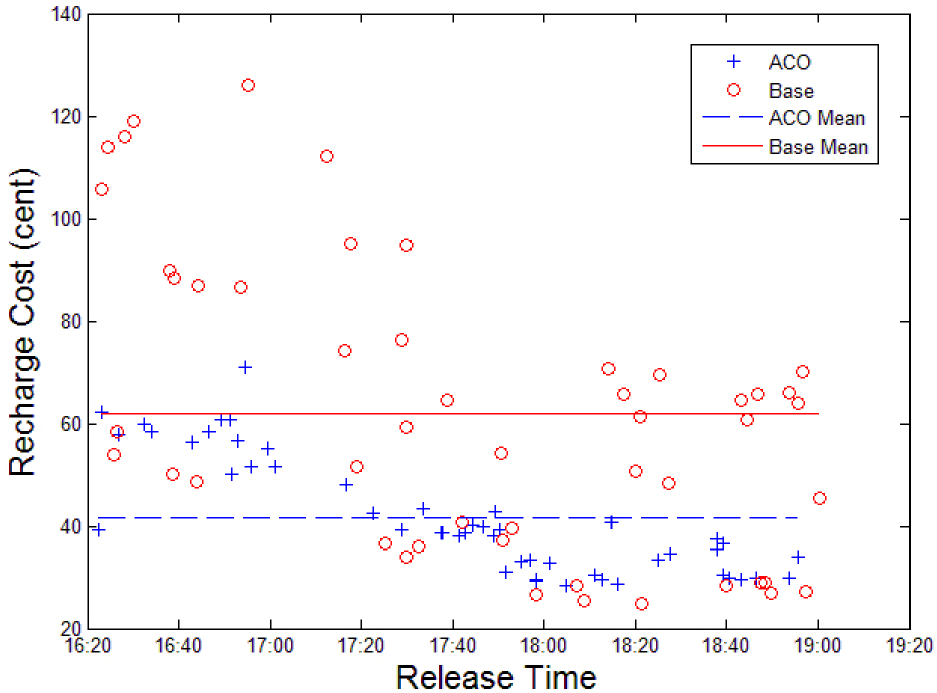


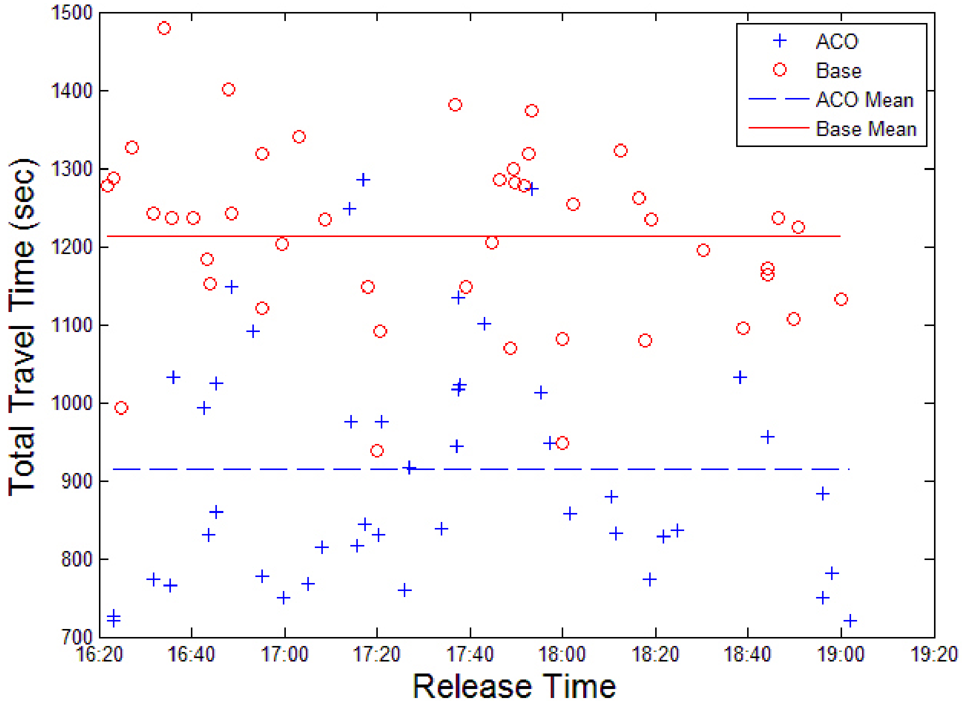
FIGURE 10 Performances of connected EVs vs. ordinary EVs from 4:20 PM to 7:20 PM in the first simulation.

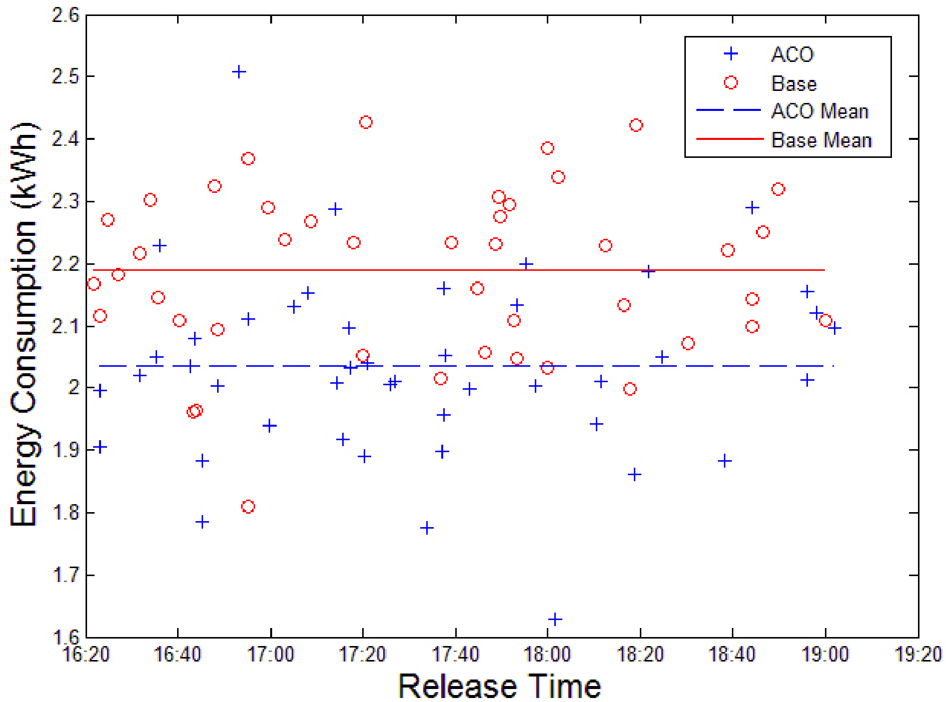
On the second round, the author again conducted simulations in which only the lower bound of SOC was set to 40.5% which is 0.5% higher than the setting on the first simulation. Results from the simulation experiments are in Table 5 and Figure 11.

TABLE 5 Overall Results of Base EVs and Connected EVs in Second Simulation

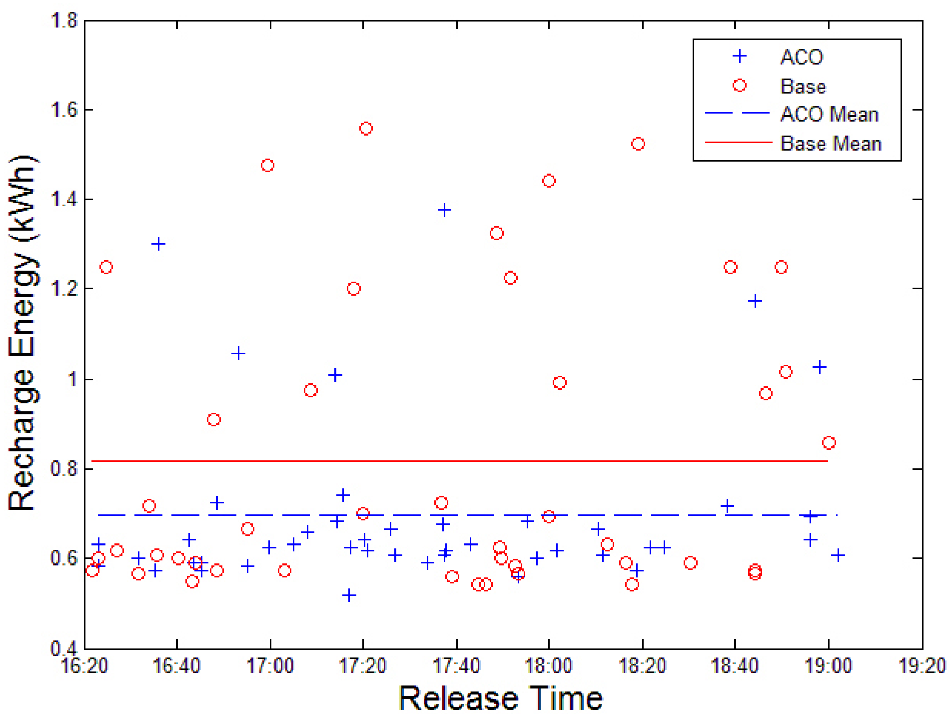
Strategy	Base	Connected	(Base-Connected)/Base
Average Travel Distance (mile)	3.994	3.868	3.15%
Standard Deviation of Travel Distance	0.183	0.161	
Average Travel Time (sec)	1213.26	914.39	24.63%
Standard Deviation of Travel Time	115.400	151.839	
Average Consumed Energy (kWh)	2.193	2.069	5.65%
Standard Deviation of Consumed Energy	0.135	0.130	
Average Recharge Volume (kWh)	0.817	0.698	14.57%

Standard Deviation of Recharge Volume	0.321	0.194	
Average Recharge Cost (cent)	53.52	48.15	10.03%
Standard Deviation of Recharge Cost	22.604	17.994	
Average Starting SOC	43.5%	43.39%	
Average Final SOC	41.12%	40.93%	





ACO
Base
ACO Mean
Base Mean
Energy Consumption (kWh)
Release Time
2.6
2.5
2.4
2.3
2.2
2.1
2
1.9
1.8
1.7
1.6
16:20
16:40
17:00
17:20
17:40
18:00
18:20
18:40
19:00
19:20



ACO
Base
ACO Mean
Base Mean
Recharge Energy (kWh)
Release Time
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
16:20
16:40
17:00
17:20
17:40
18:00
18:20
18:40
19:00
19:20

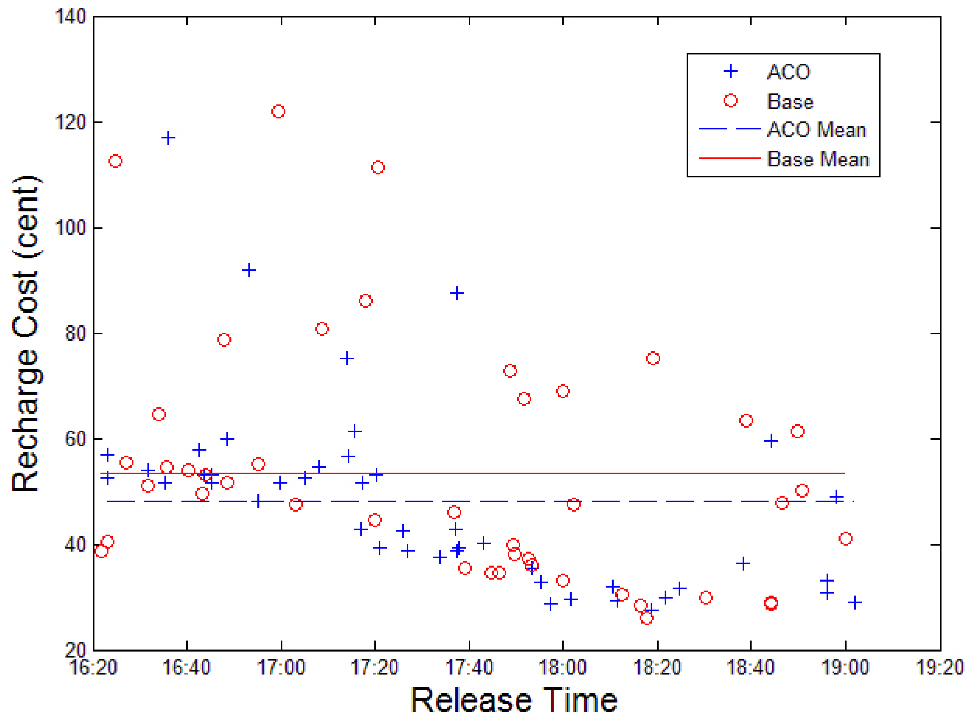


Figure 11. Performances of connected EVs vs. base EVs from 4:20 PM to 7:20 PM in the second simulation

Although the maximum allowable energy consumption was reduced by 14%, the routing strategy still managed to yield an appropriate route together with a recharging plan for connected EVs, indicating the possibility of shrinking the battery size to some extent while extending EV ranges by offering more access to charging facilities. In this case, ACO routing strategy still excels in all aspects against the base strategy. The author also observed a reduction in the average gap of recharge electricity volume and recharge cost between the conventional method and the ITS-based routing and recharging method, since both EV types went through more charging routes and were charged for more energy to satisfy the SOC threshold.

CHAPTER FIVE

CHARGE SCHEDULING APPLICATIONS

5.1 SIMULATION SETUP

To evaluate the performance of the BEVs within the architecture presented in this dissertation, the Nissan Leaf model was chosen as a study case for this dissertation, the Nissan Leaf model was chosen as the study case , the specifications of which are illustrated in Table 6. The scheduling model has to retrieve associated information, such as the TOU electricity rate, the regulation capacity price and the regulation up/down prices, from the database before yielding the optimal charge/regulation plan through the aggregation server. Here the author performed a number of simulations using the data of Electric Reliability Council of Texas (ERCOT) market for the year of 2009 (Electric Reliability Council of Texas, 2013).

Table 6. Nissan Leaf Model Specification

Base total weight	3385 lbs
Maximum speed	90 mph
Maximum torque	210 ft łb
Battery size	24 kWh lithium-ion battery
Miles per gallon equivalent (MPGe)	34 kWh/100 miles
Maximum range	73 miles
Electric motor	80kW
On-board charger	3.3 kW
Lithium battery modules	48

In the experiments, the author assumed that on a typical work day, a Nissan Leaf is plugged in a public charging station and connected to the aggregation server that will derive a new charge/regulation schedule for the BEV. The driver uses the vehicle twice in a subsequent 24 hour period; the vehicle is disconnected from the power system between 5:00 PM and 7:00 PM for a trip of 22 miles, and again between 8 a.m. and 9 a.m. the following day for another trip of 18 miles. Total driving distance in that 24-hour period is 40 miles, quite close to the U.S. average daily driven distance of 39.5 miles. The total available plug-in parking time is 21 hours with a 240V and 30 Amps, i.e. 7.2 kW power of electrical circuit. The SOC window lies between 20% and 90% with an initial SOC of 50%, and the charging efficiency is set at 90%. A value of 0.10 is applied for the dispatched energy ratio that came from a study using the data released by the California ISO (CAISO) (Kempton and Tomić, 2005). The hourly market prices for both the capacity and the ancillary service energy of our experiments are shown in Table 7 with the solver yielding an optimal solution as shown in Figure 12. For purposes of comparison, another V2G-equipped BEV with the same setting is parked and plugged in simultaneously. We assume that it is not involved in the proposed architecture and that it follows a fixed charge/regulation schedule which involves recharging the battery to full status (90% SOC) after the TOU pricing of the nighttime hours starts at 10:00 PM, and then serves as the regulation resource for the remainder of the available time intervals. This fixed charge/regulation schedule is shown in Figure 13, with the overall result of the two charging schemes shown in Table 8. Note that all the information can be accessed and clearly displayed with a user-friendly interface in the architecture.

Table 7. Hourly market clearing prices for capacity and frequency regulation (Electric Reliability Council of Texas, 2013)

Time	12:00	13:00	14:00	15:00	16:00	17:00
Capacity ($/MW-h)	9.85	8.82	9.73	8.50	8.79	13.01
Regulation Up ($/MWh)	8.79	7.75	9.56	11.00	9.56	20.02
Regulation Down ($/MWh)	10.9	9.89	9.89	6.00	8.01	6.00
Time	18:00	19:00	20:00	21:00	22:00	23:00
Capacity ($/MW-h)	25.39	40.61	23.01	17.88	11.12	20.00
Regulation Up ($/MWh)	35.02	51.22	30.02	25.00	9.09	20.00
Regulation Down ($/MWh)	15.76	30.00	16.00	10.75	13.15	20.00
Time	00:00	01:00	02:00	03:00	04:00	05:00
Capacity ($/MW-h)	16.01	8.46	6.05	6.00	7.07	9.47
Regulation Up ($/MWh)	14.99	8.12	6.89	6.00	5.02	4.84
Regulation Down ($/MWh)	17.02	8.80	5.20	5.99	9.12	14.10
Time	06:00	07:00	08:00	09:00	10:00	11:00
Capacity ($/MW-h)	26.02	29.35	21.70	18.10	11.76	9.05
Regulation Up ($/MWh)	11.60	40.00	22.69	20.00	8.62	5.00
Regulation Down ($/MWh)	40.43	18.70	20.70	16.20	14.89	13.10

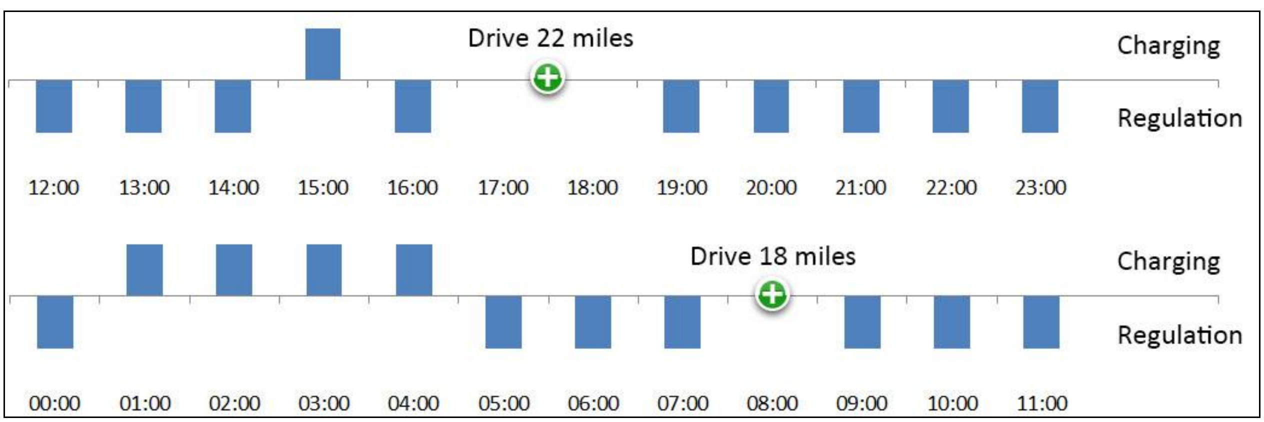


Figure 12. Optimized charge/regulation schedule in the next 24 hours

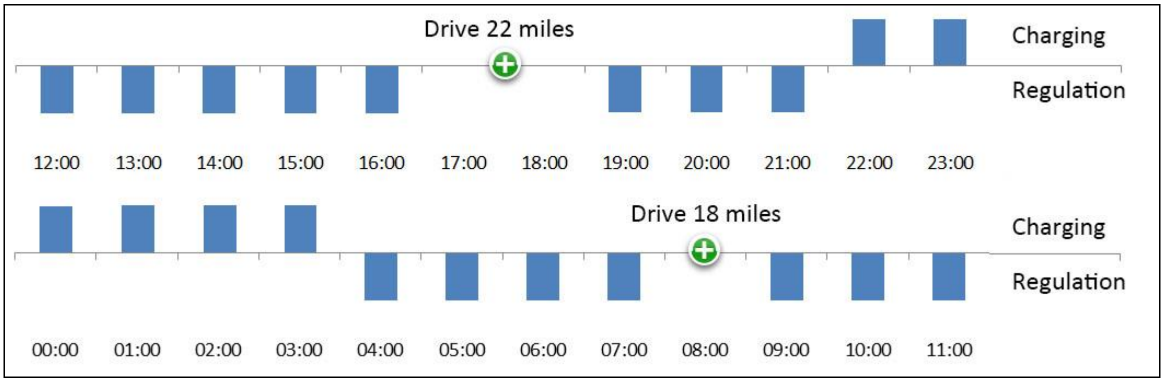


Figure 13. Fixed charge/regulation schedule in the next 24 hours

5.2 ANALYSIS

As Table 8 indicates, it is clear that although the regulation hours and charging hours of both schedules are very close, the fixed charge/regulation schedule renders a net profit of $0.54 in the next 24 hours without paying for the energy consumed by driving. The net profit based on the optimized schedule is almost twice as much as that of the fixed schedule, however, which appropriately allocates time slots by charging the vehicle when the electricity TOU price is relatively low and providing the regulation service when the up and down regulation prices are more attractive. Indeed, while the nighttime TOU pricing is the lowest of the entire day, it is sometimes unnecessary to require that the EV battery be fully recharged to meet the driving demand. It is also likely that BEV participants will increase their earnings if they choose to deploy the frequency regulation service during the nighttime hours rather than recharge the vehicles. In fact, the charge/regulation scheduling model integrated in this architecture is always the best option in that the optimization approach always yields an optimal solution. The optimized charge/regulation schedule also ensures a sufficient SOC of battery for driving demands to mitigate any concerns of range anxiety.

Table 8. An overall result of the optimized vs. fixed schedule

Charge/regulation schedule (from 12:00 PM 01/05/2009 to 12:00 PM 01/06/2009)	Optimized	Fixed
Regulation profit ($)	2.13	1.89
Charging cost ($)	1.20	1.35
Net profit ($)	0.93	0.54
Regulation hours (h)	16	15
Charging hours (h)	5	6
Unavailable hours (h)	3	3

We then calculated the annual profits and costs of popular BEV models in Table 1 assuming an average daily driving distance of 40 miles associated with 20 available plug-in hours each day using 7.2 kW as the power capacity of the line in a level two charging station. Here, as our results in Figure 14 indicate, the annual charging expense falls between $356.20 and $387.02, which is much less than conventional internal combustion engine (ICE) vehicles. The regulation service completely compensates for the energy cost with an annual driving distance of approximately 15,000 miles and all BEV models make a positive net profit through the application of the scheduling strategy. The regulation profit earned by V2G-enabled BEVs with 3.3 kW on-board chargers just offsets the energy payment for driving, while BEVs with 6.6 kW chargers earn approximately 7% more profits from regulation services since less time is required for battery recharge, thusly increasing the availability for deploying frequency regulation services.

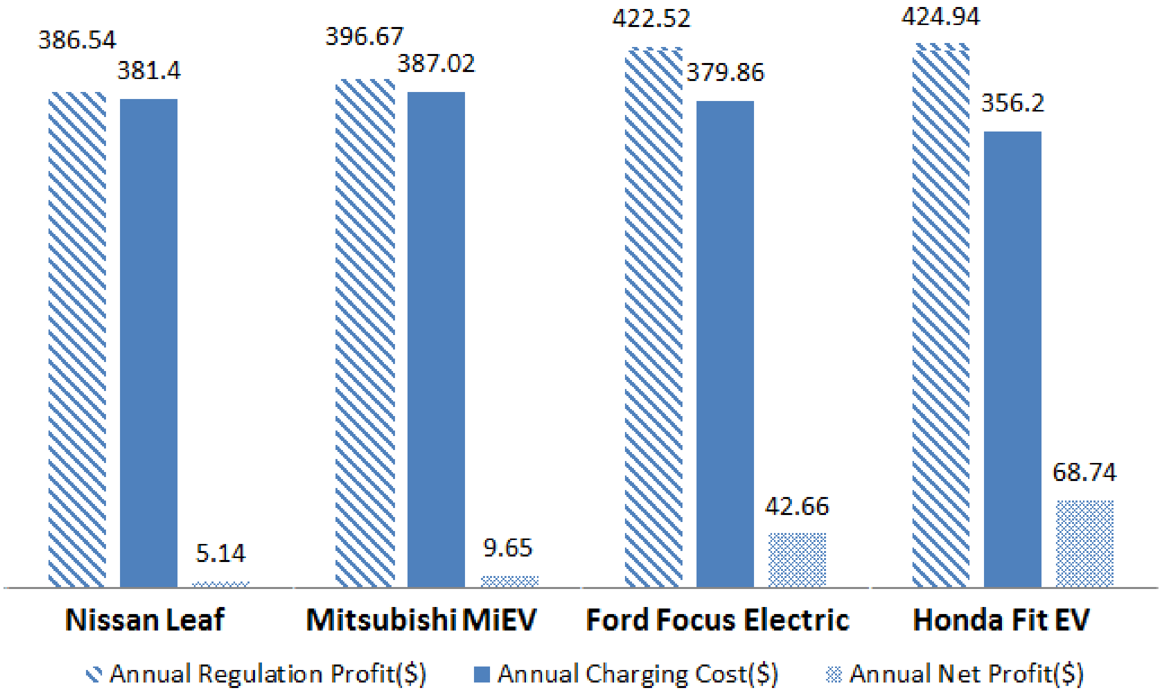


Figure 14. Annual charging profits and costs of BEV models with 7.2 kW power

As the power capacity of the electrical circuit is another important coefficient that affects objective profits, we doubled the circuit's ampere capacity to 60 Amps (i.e. increased the electrical circuit power capacity to 14.4 kW) which is close to the battery capacity of a Mitsubishi i-MiEV, to estimate the potential benefits under the circumstances. The annual profits and costs of the same BEV models under the same conditions are shown in Figure 15. As is evident, BEVs plugged in with a higher electrical circuit power capacity generate much greater profits than BEVs with a lower capacity. All the BEV models compensate the energy cost to generate a positive annual net profit between $393.57 and $493.68.

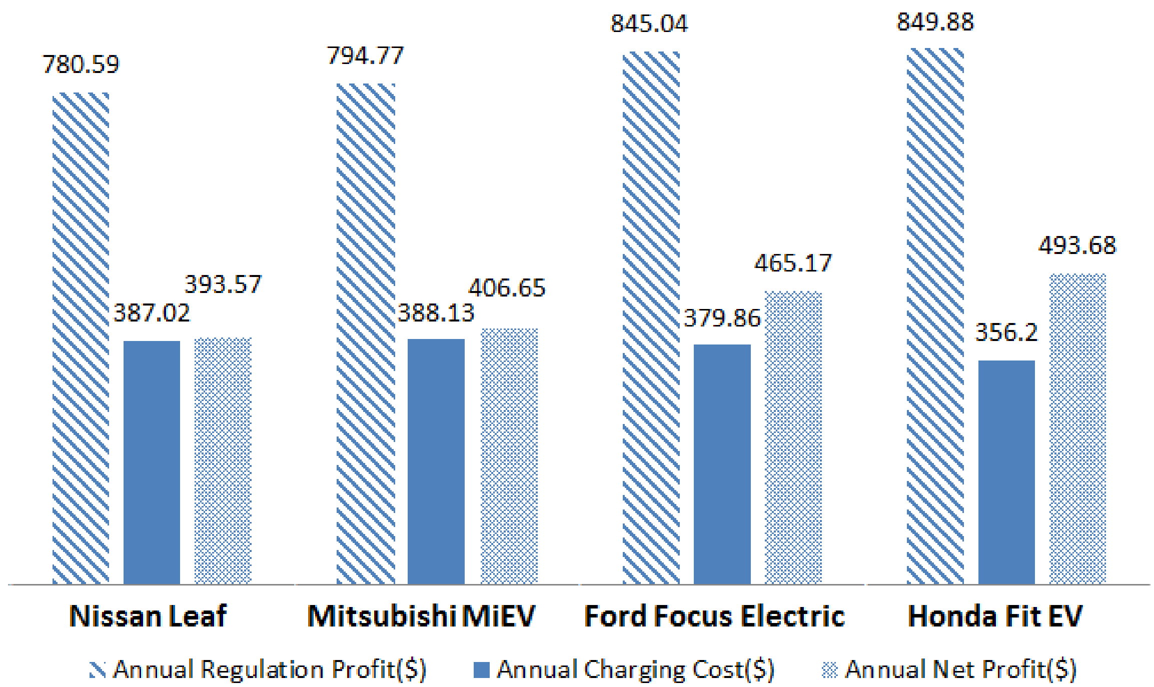


Figure 15. Annual charging profits and costs of BEV models with 14.4 kW power

On the other hand, balancing the additional load from BEV charging can be challenging, while the smart charging architecture is also designed to support the ISO/RTO with load leveling by adjusting prices through real-time communication and coordination among BEVs, aggregation servers and the ISO/RTO. To elucidate the merits of the architecture under load management, we conducted a simulation that continued using 2009 ERCOT data for Texas, most particularly in our determination that 21.4 million vehicles were registered in the state in 2009 (Texas Department of Motor Vehicles, 2010). The hourly trend of the ratio of the projected BEV regulation up and down capacity to the total regulation up and down demand in a typical day with an average power capacity of 7.2 kW and 14.4 kW is illustrated in Figure 16. This trend assumes a V2G-enabled BEV market penetration rate of 10% with an average of 80% of BEVs plugged in at one time interval.

Here, the aggregated regulation up and down capacity provided by BEVs with 7.2kW power accounts for approximately 10%-17% of total regulation demand if 80% of 2.14 million BEVs are deployed as regulation service resources in each hour interval. If the average power capacity of electrical circuits increases to 14.4kW, this supply share is doubled. As clearly indicate in Figure 16, there is a great demand for frequency regulation services in Texas. In our analysis, BEVs become a major regulation service supplier given a market penetration rate of 10%. As that number of BEVs expands, the ISO/RTO can anticipate saving more money on building frequency regulation generators by encouraging more BEVs to participate in the ancillary service program.

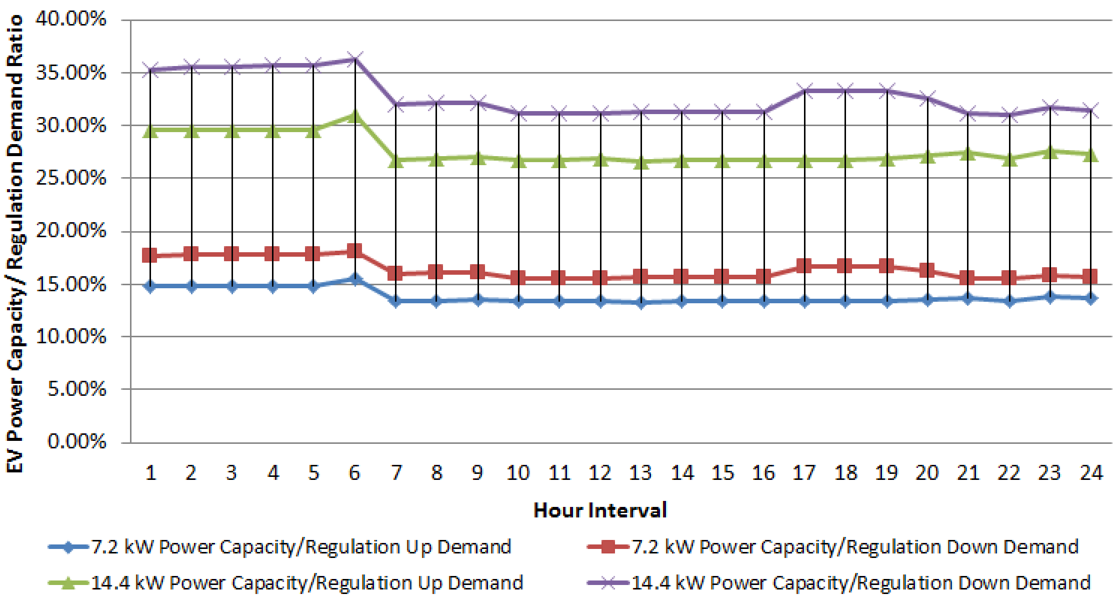


Figure 16. The hourly trend of the ratio of EV power capacity/total regulation demand

We simulated two scenarios, unmanaged BEVs without performing optimized schedules and managed BEVs following the optimized charge/regulation schedules, and added the additional load from BEV charging to the grid system assuming all chargers deliver 7.2 kW and the BEV penetration is 10%. The load distribution is presented in Figure 17.

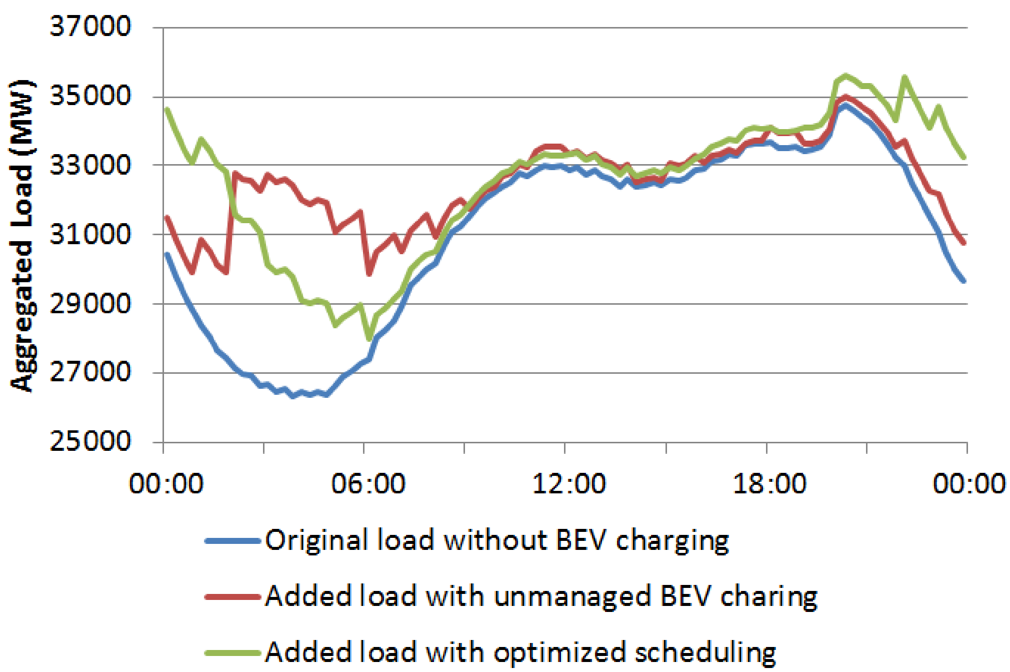


Figure 17. A comparison of added load distribution between unmanaged BEVs verses managed BEVs

In the figure above, the added load under the managed scenario is particularly concentrated and the overall distribution is more balanced than that of the unmanaged distribution. BEV owners without the charging guidance prefer to recharge their vehicles during off-peak hours when the TOU electricity pricing is the lowest of the day, but this may give rise to excessive load from 8 p.m. to midnight and hence violate the peak hour restrictions. Aggregation servers in charge of the BEVs within the region appear more sensitive to the hourly changes of the TOU electricity price and the regulation up/down prices given that most additional load is allocated between 2 a.m. and 6 a.m. to fill the grid valley. The unique variance can help ISO/RTOs monitor and ease the load in real-time by adjusting the prices should the load exceed the capacity.

5.3 INCREMENTAL COST ESTIMATE

From an economic perspective it is essential to determine if the benefits of integrating V2G technology are worth the extra cost of building a smart charging system. In addition to the energy costs already considered in the charge/regulation scheduling model considered in this study, costs for both equipment and battery are the major extra expenses BEV owners will incur to enable V2G capabilities. Key equipment components that must be installed are a power connection and an on-board inverter for V2G flow, an accurate on-board metering, and a communication system among vehicles, charging stations, aggregation servers and the ISO/RTO to receive and respond to the signals. The incremental cost of the on-board power electronics system and the on-board electric metering system designed for this purpose can be estimated as $400 and $50, respectively (Tomic and Kempton, 2007). In order to provide 1 MW of power on demand, assuming an average plug-in connection power of 10 kW with 80% of BEVs available, 125 BEVs with an estimated value of $150 for each are required to share a single aggregation server associated with other communication components, such as the RFID reader and the wireless network deployment (De Los Rios et al., 2012; Tomic and Kempton, 2007). Thus the fixed total incremental cost for V2G support is equal to $600, while BEV owners can expect less extra cost as grid operators are likely to offer either price incentives or financial subsidies to encourage V2G solutions due to the savings on the ancillary-service-specific utilities.

The extra cycling of an EV battery as a storage device for the regulation service will adversely affect the battery life and result in additional depreciation cost. The capacity loss of an EV battery for a combined driving and V2G usage can be quite low, however, regardless of the DoD window experienced. Statistical analyses from a related study indicate that participating in the V2G application will lose 2.7x10^{-3}% of the capacity per normalized Wh or Ah processed compared to the loss of 6.0x10^{-3}% for the rapid cycling encountered while driving, and one year of driving/V2G incurs only 1% capacity loss no matter how much is used for V2G support (Peterson et al., 2010). Though our simulation results show that approximately one-third of the total capacity loss is from V2G usage, it is not necessary to replace the battery before the vehicle breaks down. The annual depreciation cost of a battery with the capacity of 24 kWh therefore can be estimated as $64 for V2G support. Although current battery pack cost appears expensive, we predict a price decline from $800 per kWh to approximately $300 per kWh by 2020 given scaled production and improved technologies (Element Energy Limited, 2012) further decreasing the depreciation cost by more than 50%.

The annual average cost of enabling V2G capacities would be approximately $124 if a BEV can last for ten years. Since the profits earned by providing frequency regulation services range from $386.54 to $424.94 for the 7.2 kW power and almost doubled for the 14.4 kW, V2G technologies are deemed beneficial for bringing a positive net profit to each BEV participant.

CHAPTER SIX

CONCLUSIONS AND FUTURE WORK

In this dissertation, an ITS-based architecture that integrates communication and coordination interfaces among vehicle and infrastructure is designed and evaluated for EVs. This dissertation primarily explores the effectiveness of routing and recharging applications on EV routing policies and charging schedules. This chapter also includes concluding remarks and proposed follow-up work.

6.1 IMPACTS OF THE EV ROUTING AND RECHARGING APPLICATION

The author presents an ACO based real-time routing and recharging approach supported by Connected Vehicle technology for the purpose of assisting EV drivers to find the lowest travel time or the lowest cost path without violating the energy constraint. Compared to conventional mathematical programming methods, the ACO based approach is more efficient in finding initial feasible solutions as it does not require an increase in the number of variables with the increase in the complexity of a network. The author also found that the ACO algorithm is efficient, in terms of minimizing travel time and energy consumption, to generate approximate solutions to multi-objective routing problem for connected vehicle supported EVs. EVs once tethered to short ranges could now travel greater distances without consideration of recharge delays, thus significantly reducing the range anxiety issue. Furthermore, it was determined that, given more access to charging infrastructure, the battery pack size can be reduced, thereby the batteries could be more reasonably priced. The smart grid system permits dynamic pricing benefits to both utilities and consumers in that it reduces critical peak demands and the expense of EV operations, thusly improving EV operational efficiency.

6.2 IMPACTS OF THE CHARGING SCHEDULING APPLICATION

The author presents a smart charging architecture that can boost the performance of V2G-enabled BEVs when a bi-directional power flow is available and in which each BEV is providing the ancillary service for the grid system. BEVs in the architecture are controlled and managed by an aggregation server and are eligible to bid their aggregated capacity into the ancillary service market. Through the real-time communication interface, the aggregation server obtained a variety of dynamic data in a timely manner in order to develop the latest and optimized charge/regulation schedule for BEVs so that BEV owners can simply park, plug in and control the charge/discharge process of the EV automatically. The scheduling model involved in the architecture always yielded an optimal solution by solving the binary integer programming problem and thusly the net profit can be maximized while the energy demand for driving can be guaranteed in the meantime. The aggregation server generates an optimal charge/regulation schedule for each BEV when plugged in, and responds to changes in the variables or coefficients of the scheduling model, such as the time-varying electricity price and the bidding rate of the regulation service, in real time and updates with a new optimal solution so as to constantly maximize dividends and ensure an accurate aggregated power capacity for bidding and billing purposes. The author evaluated the performance of BEVs by estimating potential annual profit of a single BEV upon optimization of the scheduling. Through a series of simulation analyses, the author concluded that the profit could substantially offset the annual energy costs for EV owners and that BEV owners could even make a positive net profit with a high power of the electrical circuit.

The ISO/RTO will also benefit from this architecture in that they can save substantial revenue on investment in utilities specifically equipped for regulation services by authorizing and encouraging BEVs as ancillary service providers. With the availability of BEVs as an additional power regulation resource, the ISO/RTO can leverage the additional load from BEV charging by adjusting TOU electricity prices and frequency regulation prices to enhance both the reliability and robustness of the power grid system. Policy makers can utilize the findings from this research to evaluate BEV related laws and incentives to help generate more interests in BEVs.

6.3 RESEARCH CONTRIBUTIONS

This dissertation develops a routing and recharging algorithm that is dedicated to enhance EV trips. The algorithm developed in this dissertation is able to reduce not only the total travel time and the energy consumption, but also the amount of charging required and corresponding cost, thus significantly relieving the concerns of range anxiety. This routing approach also potentially allows for a reduction in the EV battery capacity, in turn reducing the cost of energy storage systems to a reasonable level.

It also involves developing a scheduling optimization approach to generate a charge/regulation schedule for BEVs so that these vehicles can automatically plan a charging schedule for maximizing the net profit for EV owners. The strategy presented in this dissertation can rapidly respond to changes of the scheduling model, adjust the plan accordingly in real time, and always yields a global optimal solution under various circumstances which has rarely been considered before. The charging optimization approach presented in this dissertation can also help to enhance the reliability and robustness of the electricity grid as it is designed to avoid BEV charging during high-priced and high-demand peak hours.

A Connected Vehicle architecture to support EV operations is developed in this dissertation This architecture is designed to support the communication and coordination of a variety of EV applications in real time. Applications under this architecture are able to solve EV charging related problems rapidly without the need to consider hardware limitations, thus improving the performance of Connected EV applications.

APPENDICES

Appendix A

ROUTING APPLICATION SCRIPTS AND DATA

A.1 SCRIPTS OF THE ROUTING API IN THE SIMULATION TOOL OF PARAMICS

Plugin.c

```
#include <stdlib.h>

#include <stdio.h>

#include <string.h>

#include <math.h>


#include "programmer.h"

#include "route_p.h"

#include "engine.h" // MATLAB header files


/* ---------------------------------------------------------------------

 * link nodes in function qpx_NET_second

 * check points in function qpx_VHC_transfer need to change if a new network is applied

 * --------------------------------------------------------------------- */


char linklist[111], finalroute[111], vehicledata[111], linkinput[111];

float timesteps;
```

```
int v = 1;


void qpx_NET_postOpen(void)
{
   errno_t  err;
   FILE     *kfile;


   qps_VHC_recycle(FALSE);
   err = fopen_s(&kfile,"J:\\Data\\Claire\\app\\files.txt","r");
         if (err==0)
         {
                  while (!feof(kfile))
                  {
                           fscanf_s(kfile,"%s\n", linklist, _countof(linklist));
                           fscanf_s(kfile,"%s\n", finalroute, _countof(finalroute));
                           fscanf_s(kfile,"%s\n", vehicledata, _countof(vehicledata));
                           fscanf_s(kfile,"%s\n", linkinput, _countof(linkinput));
                  }
         }
         else
         {
                  qps_GUI_printf("File is not open, Check for Errors\n");
```

```
            qps_SIM_close();
        }
        err= fclose(kfile);
}

void qpx_VHC_release(VEHICLE* vehicle)
{
  int vtype;
        timesteps = qpg_CFG_simulationTime();
        if ((int)timesteps >= TIMEPOINT)
        {
            vtype=qpg_VHC_type(vehicle);
            if (vtype==VEHTYPE)
            {
                qps_VHC_destination(vehicle, DEST, DEST);
                qps_VHC_usertag(vehicle,TRUE);
                v++;
            }
        }
}

void qpx_VHC_transfer(VEHICLE* vehicle, LINK* link1, LINK* link2)
```

```
{
    errno_t err;
    FILE    *kfile;
    NODE    *nodetemp;
    char    *snode, *endnode;
            int     vid;
            float   llength, ffs;

            if(qpg_VHC_usertag(vehicle)==TRUE)
            {
                        err = fopen_s(&kfile,vehicledata,"a+");
                if (err==0)
                {
                                    timesteps = qpg_CFG_simulationTime();
                                    vid = qpg_VHC_uniqueID(vehicle);
                            nodetemp = qpg_LNK_nodeStart(link1);
                            snode=qpg_NDE_name(nodetemp);
                            nodetemp = qpg_LNK_nodeEnd(link1);
                            endnode = qpg_NDE_name(nodetemp);
                            llength = qpg_LNK_length(link1); // get length of the link
                            ffs = qpg_VHC_speed(vehicle); // get speed of the link
```

```
			fprintf_s(kfile,"%d %9.2f %s %s %6.2f %9.5f\n", vid, timesteps, snode,
endnode, llength, ffs);
		}
		else
		{
			qps_GUI_printf("Vehicle Data File is not open or Missing, Check for
Errors.. stoped before Maltab module\n");
			qps_SIM_close();
		}
		err= fclose(kfile);
	}
}



// called to set the exit number for vehicle (Vp) on link (linkp). Return
// 0 to use defualt code in modeller or an index between 1 - No of exit
// links, to specificaly set the exit link the vehicle should use.
int qpo_RTM_decision(LINK *linkp, VEHICLE *Vp)
{
   ROUTE*   routes = NULL;
	VEHICLE* trueV;
   NODE*    nodetemp;
```

```
char     *snode;
int      vid, arriveTime;
char     buffer[BUFSIZE+1];
char     varitemp[111];
        char     chknode[10];
float    llength, ffs;
Engine*  ep; // matlab engine
mxArray* result = NULL;
double*  presult, trigger;
char     *chkpoint = "|569|431|571|64|517|13|10|590|611|99|471|";

if(qpg_VHC_usertag(Vp)==TRUE)
        {
                nodetemp = qpg_LNK_nodeStart(linkp);
                snode = qpg_NDE_name(nodetemp);
                sprintf_s(chknode, _countof(chknode), "|%s|", snode);
                trueV = qpg_VHC_original(Vp);
                vid= qpg_VHC_uniqueID(trueV);

                if (strstr(chkpoint,chknode) && (!isRecord(vid, snode)))
                {
                        timesteps = qpg_CFG_simulationTime();
```

```
            arriveTime = (int)(timesteps - TIMEPOINT) / 60;

        //  //Matlab code starts
        //  qps_SIM_running(FALSE);
        //  qps_GUI_printf("*****Simulation paused*****\n");
        //  if (!(ep = engOpen("matlab")))
        //  {
                //  qps_GUI_printf("\nCan't start MATLAB engine Check errors
and logs\n");
        //  }
        //  buffer[BUFSIZE] = '\0';
        //  engOutputBuffer(ep, buffer, BUFSIZE);
        //  engEvalString(ep, "cd('J:/Data/Claire/EV');path(pathdef);");
        //  sprintf_s(varitemp, _countof(varitemp), "[soc, stnode]=current(%d);",
vid);
        //  engEvalString(ep, varitemp);
                //sprintf_s(varitemp, _countof(varitemp), "xchk = shortest(%d,
stnode, %d, soc);", arriveTime, vid);
                //qps_GUI_printf("%s %s", varitemp, snode);
        //  engEvalString(ep, varitemp);
        //  if ((result = engGetVariable(ep,"xchk")) == NULL)
        //  {
```

```
//    qps_GUI_printf("\r\nOops! You didn't create a variable to
check (xchk)\n\n");
//    }
//    else
//    {
//        result = engGetVariable(ep,"xchk");
//        presult=mxGetData(result);
//        trigger=presult[0];
//    }

//    engEvalString(ep, "clear all;");
//    mxDestroyArray(result);
//    engClose(ep);
//    if (trigger==218)
//    {
//        qps_GUI_printf("Route is updated. Building Route
information... \n");
//            qps_VHC_userdata(trueV, NULL);
//            sprintf_s(varitemp, _countof(varitemp), "%s_%d.txt",
finalroute, vid);
//            routes = buildRouteInformation(varitemp);
//            qps_VHC_userdata(trueV,(VHC_USERDATA*)routes);
```

```
                    //          buildRouteRecord(vid, snode);
                    //    qps_SIM_running(TRUE);
               //   }
               //   else if (trigger<218)
               //   {
                    //    qps_GUI_printf("Reroute failed %5.2f\n",trigger);
               //   }
               //   else
               //   {
                    //    qps_GUI_printf("something wrong with MATLAB, check
errors, trigger is wrong \n");
                    //    qps_SIM_close();
               //   }
    }
               return checkForcedRouteChoice(linkp, Vp);
  }
       return ROUTE_DEFAULT; // any vehicle
}



// called only once, return TRUE to enable calls to 'routing_decision'
```

```
Bool qpo_RTM_enable(void)

{

        return TRUE;

}


void qpx_NET_second(void)

{

   char varitemp[111], linkline[100], *onelink, *startlink, *endlink, templnk[100],
*templink;

   int     sec, llane, slimit, u = 1, vehtemp = 0, i = 0, j = 0, tstation = 0;

   errno_t err, errs;

   FILE    *kfile, *kv;

   LINK    *tlink;

   float   llength, ffs = 0, ffstemp = 0, ffstore = 0, tlength = 0, tffs = 0, tlimit = 0;


   timesteps = qpg_CFG_simulationTime();

   sec = (int)timesteps % 60;

        if((int)timesteps>=TIMEPOINT)

        {

                sprintf_s(varitemp, _countof(varitemp), "%s_%d.txt", linkinput,sec);

                err = fopen_s(&kfile,varitemp,"w");// open link input file

                if (err==0)
```

```
{
    errs = fopen_s(&kv, linklist,"r");// open link list file
    if (errs==0)
    {
        while(!feof(kv))
        {
            fscanf_s(kv,"%s\n", linkline, _countof(linkline)); //
read link list
            memcpy(templnk, linkline, sizeof(linkline));
            onelink = strtok(templnk, ",");
            tlength = 0;
            tffs = 0;
            tlimit = 0;
            i = 0;
            j = 0;
            while (onelink!=NULL)
            {
                tlink = qpg_NET_link(onelink);
                llength = qpg_LNK_length(tlink);//get
length of the link
                llane = qpg_LNK_lanes(tlink);//get number
of lane for the link
```

```
slimit = qpg_LNK_speedlimit(tlink); //
speed limit

ffs = 0;
for (u=1;u<=llane;u++)
{
	ffstemp = qpg_STA_speed(tlink,u);
	vehtemp =
qpg_LNK_vehicles(tlink,u);
	if (ffstemp<=0 && vehtemp<=0)
	{
		ffs = ffs+slimit;
	}
	else
	{
		ffs = ffs+ffstemp;
	}
}
ffs = ffs/llane;
if(ffs<1){ffs=1;}
tlength = tlength + llength;
tffs = tffs + ffs;
tlimit = tlimit + llane*slimit;
```

```
                onelink = strtok(NULL, ",");
                i++;
                j = j + llane;
            }
            templink = strtok(linkline, ":");
            startlink = templink;
            while (templink!=NULL)
            {
                endlink = templink;
                templink = strtok(NULL, ":");
            }
            tffs = tffs / i;
            if (tffs<1) {tffs=1;}
            tlimit = tlimit / j;
            if (strcmp(startlink,"623")==0 &&
strcmp(endlink,"81")==0) {tstation = 250;}
            else if (strcmp(startlink,"638")==0 &&
strcmp(endlink,"665")==0) {tstation = 251;}
            else if (strcmp(startlink,"62")==0 &&
strcmp(endlink,"357")==0) {tstation = 252;}
            else if (strcmp(startlink,"67")==0 &&
strcmp(endlink,"503")==0) {tstation = 253;}
```

```
                    else {tstation = 0;}
                    fprintf_s(kfile,"%s %s %7.2f %5.2f 5.2f %d\n",
startlink, endlink, tlength, tffs, tlimit, tstation);
                }
            }
            else
            {
                qps_GUI_printf("Error opening Link list file..terminated
before Maltab\n");
                qps_SIM_close();
            }
            errs=fclose(kv);
        }
        else
        {
            qps_GUI_printf("Linkinput File is not open, Check for
Errors..terminated before Maltab module\n");
            qps_SIM_close();
        }
        err= fclose(kfile);
    }
}
```

Routing.c

```
/*---------------------------------------------------------------------
 * function needed to change when it applies to another network
 * buildRouteInformation
 * --------------------------------------------------------------------- */

#include <stdlib.h>
#include <stdio.h>
#include <string.h>
#include <math.h>

#include "programmer.h"

#include "route_p.h"
#include "route_s.h"


static ROUTE*  SampleRouteList = NULL;
static RECORD* rec = NULL;

// fill up the re routing information
ROUTE* buildRouteInformation(char flnm[111])
```

```
{
    char fn[21];// to read start node from route file
            FILE *rfile;
            errno_t err;
            LINK *link;
    ROUTE* newLink = NULL;
            ROUTE* route = NULL;
            int i = 1;

            SampleRouteList = NULL;
            newLink = malloc(sizeof(ROUTE));
            err = fopen_s(&rfile,flnm,"r");
            if (err==0)
            {
                    while (!feof(rfile))
                    {
                            fscanf_s(rfile,"%s\n", fn, _countof(fn));
                            link = qpg_NET_link(fn);
                            newLink->link = link;
                            newLink->next = NULL;

                            if (i==1)
```

```
                {
                        route = SampleRouteList = newLink;
                        i++;
                }
                else
                {
                        route->next = newLink;
                        route = newLink;
                }
                newLink = malloc(sizeof(ROUTE));
                strcpy_s(fn,_countof(fn),"");
        }
        free(newLink);
    }
    else
    {
        qps_GUI_printf("Route File is not open, build route function, Check for
Errors, %s\n", flnm);
    }
    err = fclose(rfile);
    return SampleRouteList;
}
```

```
// find the next link on the vehicles fixed route, if any?
int checkForcedRouteChoice(LINK *link, VEHICLE *vehicle)
{
   int          exitI = 0;
   int          i = 0;
   int          n_connected_links = 0;
         int       vid = 0;
   Bool   turn_found = FALSE;
   LINK*        target;
   VEHICLE*  trueV = NULL;
   ROUTE*       route = NULL;
   Bool   dummyV = FALSE;
         NODE*     nodetemp;
         char      *snode, *endnode;


   // first, find out if the vehicle should be using a user defined route or not
   // this complicated because during route choice the vehicle pased into this
   // fucntion  - from qpo_RTM_decision() - *could* be a dummy vehicle.....
```

```
    // OK, so a dummy vehicle is a vehicle that is created from a parent source
    // vehilce and projected foreward along the parent vehicles path in order to
    // make choices on lane usage on links further along the path of the origional
    // parent vehicle, confused?

    // API makes it easy
    trueV = qpg_VHC_original(vehicle);
        vid= qpg_VHC_uniqueID(trueV);
        nodetemp = qpg_LNK_nodeStart(link);
        snode=qpg_NDE_name(nodetemp);
        nodetemp = qpg_LNK_nodeEnd(link);
        endnode=qpg_NDE_name(nodetemp);

    if(trueV != vehicle) dummyV = TRUE;

    // get back the vehicle data structure and cast to our structure
    route = (ROUTE*)qpg_VHC_userdata(trueV);
    // if the route in NULL then there is no data, and no route to follow
        if(route==NULL)     {
                    qps_GUI_printf("Vehicle Route does not exist, %d, %s, %s\n",
vid, snode, endnode);
                    return ROUTE_DEFAULT;
```

```
        }
    else
    {
            // are we on the fixed route
            if(!isOnFixedReRoute(link, route)) {
                qps_GUI_printf("Not on fixed route, %d, %s, %s\n", vid, snode,
endnode);
                return ROUTE_DEFAULT;
            }

            // the next link on route
            target = nextFixedReRouteLink(link, route);

            if(!target) {
                qps_GUI_printf("No next route, %d, %s, %s\n", vid, snode,
endnode);
                return ROUTE_DEFAULT;
            }

            n_connected_links = qpg_LNK_links(link);

            // exit links in the range 1 - n_conected_links
```

```
        i = 1;

        while ((i <= n_connected_links) && (!turn_found))
        {
            // compare the target against the next exit option
            if (target == qpg_LNK_link(link, i))
            {
            turn_found = TRUE;
            exitI = i;
            break;
            }
            else
            {
            // move to next exit link
            i++;
            }
        }

        if(turn_found) return exitI;
}

    qps_GUI_printf("Still Default, %d, %s\n", vid, snode);
```

```
    return ROUTE_DEFAULT;
}



// is the given link at the *start* of a re-routing section
Bool isStartOfFixedReRoute(LINK* link, ROUTE* route)
{
    if(!link)           return FALSE;
    if(!route)    return FALSE;

    if(route->link != link) return FALSE;

    return TRUE;
}

// is the given link at the *end* of a re-routing section
Bool isEndOfFixedReRoute(LINK* link, ROUTE* route)
{
    ROUTE* routes;

    if(!link)           return FALSE;
    if(!route)    return FALSE;
```

```
    // go to end
    for (routes = route; routes != NULL && routes->next != NULL; routes = routes->next)
    {
    }

    if(routes->link != link)
    {
        return FALSE;
    }
    else
    {
        return TRUE;
    }
}

// is the given link part of a re-routing section
Bool isOnFixedReRoute(LINK* link, ROUTE* route)
{
    ROUTE* routes;
        NODE*    nodetemp;
        char     *snode, *endnode;
```

```
        LINK* links;

    if(!link)       return FALSE;
    if(!route)      return FALSE;

    for (routes = route; routes != NULL && routes->next != NULL; routes = routes->next)
    {
                if(routes->link == link)
                {
                        return TRUE;
                }
    }

        qps_GUI_printf("Cannot find it on the fixed route.");
        for (routes = route; routes != NULL && routes->next != NULL; routes = routes-
>next)
    {
                links = routes->link;
                nodetemp = qpg_LNK_nodeStart(links);
                snode=qpg_NDE_name(nodetemp);
                nodetemp = qpg_LNK_nodeEnd(links);
                endnode=qpg_NDE_name(nodetemp);
```

```
                qps_GUI_printf("The fixed route should be %s %s.\n", snode, endnode);
        }
    return FALSE;
    // It is changed. The original code was always returning TRUE;
}

// find the *next* link on the route following the given link
LINK* nextFixedReRouteLink(LINK* link, ROUTE* route)
{
    ROUTE* routes;
        NODE*    nodetemp;
        char     *snode, *endnode;
        LINK* links;

    if(!link)       return FALSE;
    if(!route)      return FALSE;

    for (routes = route; routes != NULL && routes->next != NULL; routes = routes->next)
    {
        if(routes->link != link) continue;

        // found link, what about the next one
```

```
        if(!routes->next)       continue;
        if(!routes->next->link)         continue;

        return routes->next->link;
    }

        qps_GUI_printf("Cannot find the next fixed route.");
        for (routes = route; routes != NULL && routes->next != NULL; routes = routes-
>next)
    {
                links = routes->link;
                nodetemp = qpg_LNK_nodeStart(links);
                snode=qpg_NDE_name(nodetemp);
                nodetemp = qpg_LNK_nodeEnd(links);
                endnode=qpg_NDE_name(nodetemp);
                qps_GUI_printf("The fixed route should be %s %s.\n", snode, endnode);
        }
    return NULL;
}

void buildRouteRecord(int vid, char* snode)
{
```

```
RECORD* allRec = NULL;

RECORD* newRec = NULL;

int i = 1;


newRec = malloc(sizeof(RECORD));

newRec->vid = vid;

newRec->node = snode;

newRec->next = NULL;


if (rec == NULL)

{

	rec = newRec;

}

else

{

	for (allRec = rec; allRec != NULL; allRec = allRec->next)

	{

		if (allRec->vid == vid)

		{

			allRec->node = snode;

			i++;

			break;
```

```
                }
            }

            if (i==1)
            {
                for (allRec = rec; allRec != NULL && allRec->next != NULL;
allRec = allRec->next)
                {
                }
                allRec->next = newRec;
            }
    }
}

Bool isRecord(int vid, char* snode)
{
    RECORD* allRec;

    for (allRec = rec; allRec != NULL; allRec = allRec->next)
    {
        if(allRec->vid == vid && allRec->node == snode)
        {
```

```
                return TRUE;
            }
        }
        return FALSE;
}
```

A.2 THE SCIRPTS OF THE ANT COLONY ALOGRITHM IN MATLAB

Aca.m

```
function xchk=aca(arrive, S, VID, soc)
%% Ant Colony Algorithm for Restricted Shortest Path
%% Created by Claire Zhiyun Li
%% Input Parameters
%  C          linkcost matrix (NxN)
%  D          energy consumption matrix (NxN)
%  S          start point
%  E          end point
%  VID        vehicle ID
%  arrive     arrive time (minute)
%  Dmax       maximum energy consumption
%  K          loop times (the number of groups of ants)
%  M          the number of ants in each group
%  Alpha      history coefficient
%  Beta       heuristic coefficient (linkcost)
```

```
%  Gamma       heuristic coefficient (energy consumption)
%  Rho         decay factor
%  Q           greediness factor
%% Output Parameters
%  MRT         optimum route (0/1 matrix)
%  EDGES       optimum route with links
%  cost        optimum linkcost
%%
%% Step 1: Initialization
%  soc.SOC0 = 0.43;
%  soc.T_amb = 20;
%  arrive = 15;
%  S = 23;
%  VID = 10088;
dataa = dlmread('linkinput.txt');
data = [];
exchange = [12 23 62 63 67 81 107 357 432 466 487 503 563 591 604 613 623 638 659
661 665];
for i=1:size(dataa,1)
    data(size(data,1)+1,1) = find(exchange(1,:)==dataa(i,1));
    data(end,2) = find(exchange(1,:)==dataa(i,2));
    data(end,3:5) = dataa(i,3:5);
```

```
    data(end,6) = dataa(i,6)-220;
end
mx=max(max(data(:,1:2)))+12;
mx_cost=inf*ones(mx,mx); % cost matrix
mx_delay=inf*ones(mx,mx); % delay matrix
cost_type = 2;
predict_co = 1.1;

for i=1:size(data,1)
    [linkcosts,ttime] = linkcost(data(i,1),data(i,2),data,soc,cost_type);
    mx_cost(data(i,1),data(i,2))=linkcosts;
    [elet,end_state,chg_elet] = vehicle(data(i,4),data(i,3),soc,0);
    mx_delay(data(i,1),data(i,2))=soc.SOC0-end_state.SOC0;
    if data(i,6)>0
        [elet,end_state,chg_elet] = vehicle(data(i,4),data(i,3),soc,1);
        mx_delay(data(i,1),data(i,6))=(soc.SOC0-end_state.SOC0)/2;
        mx_delay(data(i,6),data(i,2))=(soc.SOC0-end_state.SOC0)/2;
        mx_cost(data(i,1),data(i,6))=linkcosts/2;
        mx_cost(data(i,6),data(i,2))=linkcosts/2;
    end
end
```

```
C = mx_cost; % cost matrix

D = mx_delay; % delay matrix (energy)

% S = 23; % start point

E = 613; % end point

SS = find(exchange(1,:)==S);

EE = find(exchange(1,:)==E);

Dmax = soc.SOC0-0.4; % maximum restricted delay

K = 20; % loop time

M = 200; % ant number in each loop

Alpha = 1; % attractive coefficient

Beta = 2; % heuristic coefficient for cost

Gamma = 1; % heuristic coefficient for delay

Rho = 0.02; % decay factor

Q = 20; % strength factor


N=size(C,1); % number of nodes

MRT=zeros(N,N);

cost=inf;

ROUTES=cell(K,M); % crawl route for each ant stored in the cell structure

DELAYS=inf*ones(K,M);

COSTS=inf*ones(K,M);

Tau=ones(N,N); % initial matrix
```

```
ran=[];

for i=1:size(data,1)
    num = length(find(data(:,1)==data(i,1)));
    if (num>1 || data(i,6)>0)
        [aa,plength] = dijkstra(C,data(i,2),EE);
        elength = floyd(D,data(i,2),EE);
        ran(size(ran,1)+1,1) = data(i,1);
        ran(size(ran,1),2) = data(i,2);
        ran(size(ran,1),3) = plength + C(data(i,1),data(i,2));
        ran(size(ran,1),4) = elength + D(data(i,1),data(i,2));
    end
    if data(i,6)>0
        ran(size(ran,1)+1,1) = data(i,1);
        ran(size(ran,1),2) = data(i,6);
        ran(size(ran,1),3) = ran(ran(:,1)==data(i,1) & ran(:,2)==data(i,2),3);
        ran(size(ran,1),4) = ran(ran(:,1)==data(i,1) & ran(:,2)==data(i,2),4) -
D(data(i,1),data(i,2)) + 2*D(data(i,1),data(i,6));
    end
end

%% Step 2: start
```

```
for k=1:K
    for m=1:M
%% Step 3: status initialization
        W=SS; % node
        Path=SS; % path
        PD=0; % energy consumption
        PC=0; % link cost
        CC=C; % backup
        DD=D;
%%      step 4: next available nodes
        LJD=find(DD(W,:)<inf); % available nodes
        Len_LJD=length(LJD);
%%      when to stop: not able to find food or cannot reach the end point
        while (W~=EE)&&(Len_LJD>=1)
%%          step 5: choose which way to go
            kk=0;
            PP=[];
            if (Len_LJD>1)
                kk = find(ran(:,1)==W);
                for i=1:Len_LJD
                    j = find(ran(:,1)==W & ran(:,2)==LJD(i));
```

```
            PP(i)=(Tau(W,LJD(i))^Alpha)*(((2*max(ran(kk,3))-
ran(j,3))/max(ran(kk,3)))^Beta)*(((1-ran(j,4)*50)/sum(1-ran(kk,4)*50))^Gamma);
          end
          PP=PP/(sum(PP)); % probability distribution
          Pcum=cumsum(PP);
          Select=find(Pcum>=rand);
          to_visit=LJD(Select(1)); % next visiting point
        else
          to_visit=LJD;
        end
%%      step 6: update and record status
        Path=[Path,to_visit]; % add the path
        PD=PD+DD(W,to_visit);
        PC=PC+CC(W,to_visit);
        W=to_visit; % move to the next point
        LJD=find(DD(W,:)<inf);
        Len_LJD=length(LJD);
      end
%%    step 7: record the route for each ant
      ROUTES{k,m}=Path;
      if Path(end)==EE&&PD<=Dmax
        DELAYS(k,m)=PD;
```

```
            COSTS(k,m)=PC;
        else
            DELAYS(k,m)=inf;
            COSTS(k,m)=inf;
        end
    end
%%  step 8: update the information
    Delta_Tau=zeros(N,N); % initialize
    for m=1:M
        if COSTS(k,m)<inf && DELAYS(k,m)<Dmax
            ROUT=ROUTES{k,m};
            TS=length(ROUT)-1;
            Cpkm=COSTS(k,m);
            for s=1:TS
                x=ROUT(s);
                y=ROUT(s+1);
                Delta_Tau(x,y)=Delta_Tau(x,y)+Q/Cpkm;
            end
        end
    end
    Tau=(1-Rho).*Tau+Delta_Tau; % info strength updated
end
```

```
%% step 9: result
MINCOSTS=NaN*ones(1,K);
allcost=zeros(1,0);
for k=1:K
    for m=1:M
        COSTkm=COSTS(k,m);
        DELAYkm=DELAYS(k,m);
        if sum(COSTkm)<inf && sum(DELAYkm)<inf
            Tree=zeros(N,N);
            path=ROUTES{k,m};
            RLen=length(path);
            for i=1:(RLen-1)
                Tree(path(i),path(i+1))=1;
            end
            TC=Tree.*C;
            TD=Tree.*D;
            for ii=1:N
                for jj=1:N
                    if isnan(TC(ii,jj))
                        TC(ii,jj)=0;
                        TD(ii,jj)=0;
```

```
                end
            end
        end
        mincost=sum(sum(TC));
        thedelay=sum(sum(TD));
        if mincost<cost
            MINCOSTS(1,k)=mincost;
            MRT=Tree;
            cost=mincost;
            delay=thedelay;
        end
        allcost=[allcost,cost];
    end
end
end

o = dlmread('iteration.txt');
u = find(o(:,1)==VID);
if u>=1
    i = o(u,2);
    o(u,2) = o(u,2)+1;
else
```

```
    o = [o;VID 2];
    i = 1;
end

if delay<Dmax
    fid = fopen('iteration.txt','w');
    for j = 1:size(o,1)
        fprintf(fid,'%d %d\r\n',o(j,:));
    end
    fclose(fid);

    T1=SS;
    total_t=arrive;
    initial=soc;
    soc_file = [];
    adjust = [];
    while (T1~=EE)
        soc_file(size(soc_file,1)+1,1) = exchange(1, T1);
        T2=find(MRT(T1,:)==1);
        if (floor((T2+220)/10)==25)
            T2 = find(MRT(T2,:)==1);
            soc_file(end,7) = 1;
```

```
    else
        soc_file(end,7) = 0;
    end
    soc_file(end,2) = exchange(1, T2);
    soc_file(end,3) = mx_cost(T1,T2);
    soc_file(end,4) = data(T1==data(:,1) & T2==data(:,2), 3); % length
    soc_file(end,5) = data(T1==data(:,1) & T2==data(:,2), 4); % speed
    [elet,end_state,chg_elet] =
vehicle(soc_file(end,5),soc_file(end,4),initial,soc_file(end,7));
    ttime = soc_file(end,4) * 60 / soc_file(end,5) / 5280; % minutes
    soc_file(end,6) = end_state.SOC0;
    if (soc_file(end,7)==1)
        soc_file(end,8) = chg_elet;
        soc_file(end,9) = total_t;
        soc_file(end,10) = soc_file(end,8)*pricing(floor(soc_file(end,9)));
        adj = find(data(:,6)>0 & data(:,2)==T2);
        adjust = [adjust; data(adj,1) data(adj,2) data(adj,6) (mx_delay(T1,data(adj,6))*2-
mx_delay(T1,T2)) soc_file(end,10)];
    else
        soc_file(end,8) = 0;
        soc_file(end,9) = 0;
        soc_file(end,10) = 0;
```

```
    end
    total_t = total_t + ttime;
    initial=end_state;
    T1=T2;
end

if (isempty(adjust)==0)
    adjust = sortrows(adjust,-5);
    Dleft = Dmax - delay;
    for j = 1:size(adjust,1)
        if (Dleft + adjust(j,4))>=0.002
            Dleft = Dleft + adjust(j,4);
            soc_file(soc_file(:,1)==adjust(j,1) & soc_file(:,2)==adjust(j,2),7)=0;
        end
    end
end

fid = fopen(strcat('SOC_',num2str(VID),'_',num2str(i),'.txt'),'w');
initial=soc;
for j = 1:size(soc_file,1)
    [elet,end_state,chg_elet] = vehicle(soc_file(j,5),soc_file(j,4),initial,soc_file(j,7));
    soc_file(j,6) = end_state.SOC0;
```

```
        soc_file(j,8) = chg_elet;
        soc_file(j,10) = soc_file(j,8)*pricing(floor(soc_file(j,9)));
        initial = end_state;
        fprintf(fid,'%d:%d %6.3f %6.3f %6.3f %7.4f %d %6.3f %6.3f
%6.3f\r\n',soc_file(j,:));
    end
    fprintf(fid,'\r\nInitial SOC: %7.4f and T_amb: %6.3f',soc.SOC0,soc.T_amb);
    fprintf(fid,'\r\nFinal SOC: %7.4f and T_amb:
%6.3f',end_state.SOC0,end_state.T_amb);
    fprintf(fid,'\r\nCost: %6.3f and Delay: %6.3f',sum(soc_file(:,3)),(soc.SOC0-
end_state.SOC0));
    fclose(fid);

    fid = fopen(strcat('charging_',num2str(VID),'.txt'),'a');
        if (i==1)
            fprintf(fid,'0 1 2 %7.4f %7.4f\r\n', soc.SOC0, soc.T_amb);
        end
        charges = soc_file(soc_file(:,7)==1,:);
        for j = 1:size(charges,1)
            fprintf(fid,'%d %d %d\r\n',i,charges(j,1),charges(j,2));
        end
    fclose(fid);
```

```
finalroute = {};
fid = fopen('linklist.txt','r');
for k = 1:31
    tline = fgetl(fid);
    S = regexp(tline, ':', 'split');
    finalroute{k,1}=S{1};
    finalroute{k,2}=S{end};
    finalroute{k,3}=tline;
end
fclose(fid);
fid = fopen(strcat('finalroute_',num2str(VID),'.txt'),'w');
for j = 1:size(soc_file,1)
    for k = 1:31
        if (strcmp(num2str(soc_file(j,1)),finalroute{k,1}) &&
strcmp(num2str(soc_file(j,2)),finalroute{k,2}))
            S = regexp(finalroute{k,3}, ',', 'split');
            for m = 1: size(S,2)
                fprintf(fid,'%s\r\n',S{1,m});
                m=m+1;
            end
        break;
```

```
            end
        end
    end
    fclose(fid);
    xchk=218;
else
    fid = fopen(strcat('SOC__',num2str(VID),'_',num2str(i),'.txt'),'w');
        fprintf(fid,'fail to get a route, please recharge before you leave.');
    fclose(fid);
    xchk=222;
end
copyfile('linkinput.txt',strcat('linkinput__',num2str(arrive),'.txt'),'f');
```

dijkstra.m

```
function [path,short]=dijkstra(input_weight,startpoint,endpoint)

row=size(input_weight,1);
s_path = startpoint;
distance=inf*ones(1,row);
distance(startpoint)=0;
flag = zeros(700,1);
flag(startpoint)=startpoint;
temp=startpoint;
```

```
if (startpoint==endpoint)
    path=startpoint;
    short=0;
else
    while length(s_path)<row
        pos=find(input_weight(temp,:)~=inf);
        for i=1:length(pos)
            if (isempty(find(s_path==pos(i),1)) &&
distance(pos(i))>(distance(temp)+input_weight(temp,pos(i))))
                distance(pos(i))=distance(temp)+input_weight(temp,pos(i));
                flag(pos(i))=temp;
            end
        end
        k=inf;
        for i=1:row
            if (isempty(find(s_path==i,1)) && k>distance(i))
                k=distance(i);
                temp_2=i;
            end
        end
        s_path=[s_path,temp_2];
```

```
        temp=temp_2;
    end


    path(1)=endpoint;
    i=1;
    short = 0;
    while path(i)~=startpoint
        path(i+1)=flag(path(i));
        if (path(i+1)==0)
            short=-1;
            break;
        end
        i=i+1;
    end
    path(i)=startpoint;
    path=path(end:-1:1);
    if short~=-1
        short=distance(endpoint);
    end
end
```

Floyd.m

```
function d=floyd(a,sp,ep)
```

```
n=size(a,1);
D=a;
path=zeros(n,n);
if (sp==ep)
   d=0;
else
   for i=1:n
      for j=1:n
         if D(i,j)~=inf
            path(i,j)=j;
         end
      end
   end

   for k=1:n
      for i=1:n
         for j=1:n
            if D(i,j)>D(i,k)+D(k,j)
               D(i,j)=D(i,k)+D(k,j);
               path(i,j)=path(i,k);
            end
         end
```

```
    end
  end


  % p=sp;
  % mp=sp;
  % for k=1:n
  %    if (mp~=ep && mp~=0)
  %        d=path(mp,ep);
  %        p=[p,d];
  %        mp=d;
  %    end
  % end
  d=D(sp,ep);
  % path=p;
End
```

Vehicle.m

```
function [elet,end_state,chg_elet] = vehicle(avg_speed,tlt,initial,chg_switch)
%VEHICLE function is to calculate the consumption of eletricity
% avg_speed: average speed in the given link, in mph
% tlt      : total length of travel, length of the link, in ft
% chg_switch: Boolean for charging, 1 is charging, 0 is no charging
% elet     : the eletricity used for the given speed profile, in kwh
```

```
% initial and end_stat are the system states for the initial condition and
% the end condition correspondingly. The structure is as follow:
%
% structure.old_data = system status
% structure.SOC0 = start SOC
% structure.T_amb = temperature

%% Important parameters
% For the very beginning, the initial state:
% initial.SOC0 = 0.90;
% initial.T_amb = 20;

% range:    speed: 0 ~ 80 ft/s
% segment length: 0~3.9338e+004 ft

%% initialization
load test1
ceffi = 0.8; % IPT efficiency between 0 and 90%
chg_power = 30000 * ceffi;   %power of charger, 30000w

% match the average speed and driving cycle
% 1ft =  0.3048 m
```

```
avg_speed = avg_speed * 1609.344 / 3600; %mph -> m/s
tlt = tlt * 0.3048; % ft -> m
time_est = ceil(tlt/avg_speed);
avg_speed = tlt/time_est;
acc = 1.4752*(rand(time_est,1)-0.5);
diff_speed = zeros(time_est,1);
for i = 2:time_est
   diff_speed(i) = diff_speed(i-1) + acc(i);
end
speed_p = avg_speed + diff_speed;
speed_p = speed_p - mean(speed_p) + avg_speed;

% load udds % use udds cycle
% l = length(V_z);
% temp1 = avg_speed * ones(l) - avg_spd;
% temp2 = tlt * ones(l) - tot_dist;
% error = temp1.*temp1 + temp2.*temp2;
%
% [temp,start_p] = min(error);
% [temp,end_p] = min(min(error));
% start_p = start_p(end_p);
```

```
% speed_p = V_z(start_p:end_p);

tot_t = length(speed_p);   % get the total time of the cycle
T_z = [1:tot_t]';
V_z = speed_p;
GR = zeros(tot_t,1);
G_z = 4* ones(tot_t,1);

next = initial;


%% run the model
opts = simset('SrcWorkspace','current');
sim('EV',tot_t ,opts)

end_state.SOC0 = SOC(end);
end_state.T_amb = T(end);

SOC_b = SOC(1);
SOC_e = SOC(end);

sim('battery', inf, opts)
```

```
elet = electricity;

if chg_switch ==1

    chg_elet = chg_power / ceffi * tlt / avg_speed / 3600 / 1000; % charging electricity

else

    chg_elet = 0;

end

end
```

A.3 DATA OF THE FIRST SIMULATION

ID	ARRIVE TIME MINUTE	TRAVEL LENGTH	TRAVEL TIME	ENERGY COST	START SOC	END SOC	CHARGE ENERGY	CHARGE COST
9771	1.83	3.8912	1277.111	2.1672	0.4371	0.4078	0.575	77.2973
10257	3.17	3.8912	1286.29	2.1148	0.4357	0.4083	0.6	80.658
10903	4.87	4.1719	993.7613	2.2692	0.4303	0.4156	1.25	224.725
11869	7.18	3.8912	1325.608	2.1817	0.4369	0.4085	0.6167	110.8643
13679	11.86	3.8912	1241.866	2.2163	0.4379	0.4076	0.5667	101.8753
14471	14.01	3.8912	1479.553	2.3014	0.4371	0.4085	0.7167	128.8423
15167	15.77	3.8912	1236.79	2.1465	0.4367	0.4085	0.6083	109.3662
16955	20.35	3.8912	1236.925	2.1078	0.4355	0.408	0.6	107.868
18155	23.2	3.8912	1183.243	1.9605	0.4355	0.4098	0.55	98.879
18459	23.96	3.8912	1151.473	1.9649	0.4359	0.4109	0.5917	106.3698
20047	27.99	4.3574	1400.891	2.3236	0.4347	0.4104	0.9083	157.5282
20277	28.56	3.8912	1243.008	2.0932	0.4377	0.4101	0.575	103.3735
22893	35.22	3.763	1120.02	1.8098	0.4393	0.4195	0.6667	110.2333
22943	35.31	3.8912	1319.248	2.3695	0.4343	0.403	0.6667	110.2333
24507	39.47	4.1719	1202.894	2.2908	0.4307	0.4211	1.475	243.8912
25967	42.97	3.8912	1340.108	2.238	0.4367	0.4062	0.575	95.0763
28241	48.77	4.3574	1234.288	2.2685	0.4341	0.4123	0.975	161.2163
32027	58.05	4.1719	1148.899	2.2331	0.4327	0.4178	1.2	171.9776
32785	59.88	3.763	937.5537	2.0519	0.4385	0.4147	0.7	88.984
33107	60.64	4.1719	1090.446	2.4268	0.4307	0.4202	1.5583	222.6262
39565	76.8	3.8912	1380.973	2.0166	0.4365	0.4141	0.725	92.162
40451	78.98	3.8912	1148.74	2.2348	0.4351	0.4038	0.5583	70.9753
42773	84.74	3.8912	1204.352	2.1611	0.4373	0.4073	0.5417	68.8567
43465	86.47	3.8912	1285.218	2.0566	0.4365	0.4086	0.5417	68.8567

44405	88.73	4.1719	1069.322	2.2323	0.4305	0.4184	1.325	145.4293
44743	89.46	3.8912	1298.845	2.3077	0.4343	0.4033	0.625	79.45
44857	89.77	3.8912	1280.429	2.2764	0.4357	0.405	0.6	76.272
45613	91.53	4.1719	1276.487	2.2951	0.4313	0.4153	1.225	135.0701
45967	92.5	3.8912	1318.233	2.1083	0.4367	0.4089	0.5833	74.1533
46259	93.15	3.8912	1373.861	2.0478	0.4359	0.409	0.5667	72.0347
48903	99.87	4.1719	1080.473	2.3852	0.4303	0.4182	1.4417	138.0396
48981	100.03	3.763	947.9726	2.0333	0.4381	0.4144	0.6917	66.2271
49731	102.33	4.3574	1254.471	2.3389	0.4331	0.4103	0.9917	94.9521
52959	112.37	3.8912	1323.262	2.2286	0.4359	0.407	0.6333	60.6417
54243	116.43	3.8912	1262.531	2.1332	0.4343	0.4059	0.5917	56.6521
54667	117.72	3.8912	1079.035	1.9993	0.4367	0.4101	0.5417	51.8646
55123	119.13	4.1719	1235.003	2.4214	0.4323	0.4217	1.525	150.3707
58661	130.24	3.8912	1195.361	2.0726	0.4361	0.4093	0.5917	59.8708
61439	138.91	4.1719	1095.926	2.2222	0.4339	0.4201	1.25	126.4875
63047	144.21	3.8912	1164.352	2.142	0.4347	0.4057	0.5667	57.341
63069	144.28	3.8912	1171.361	2.0998	0.4369	0.4091	0.575	58.1843
63735	146.38	4.3574	1236.594	2.2502	0.4335	0.4122	0.9667	95.4503
64805	149.84	4.1719	1107.493	2.3195	0.4305	0.4148	1.25	122.7482
65125	150.91	4.3574	1224.321	2.5388	0.4325	0.4065	1.0167	100.4152
67983	160.03	3.763	1132.285	2.1075	0.4383	0.4174	0.8583	81.9794

A.4 DATA OF THE SECOND SIMULATION

ID	ARRIVE TIME MINUTE	TRAVEL LENGTH	TRAVEL TIME	ENERGY COST	START SOC	END SOC	CHARGE ENERGY	CHARGE COST
10168	3	3.763	721.4203	1.997	0.4368	0.4107	0.5833	104.8717
10216	3.1	3.763	726.2994	1.9045	0.4316	0.4087	0.6333	113.8607
13608	11.75	3.763	773.852	2.0198	0.4308	0.4047	0.6	107.868
14982	15.31	3.763	764.7478	2.0502	0.4382	0.4107	0.575	103.3735
15200	15.93	4.173	1032.087	2.2277	0.43	0.417	1.3	233.714
17998	22.77	3.763	992.4253	2.0343	0.4398	0.4148	0.6417	115.3588
18230	23.45	3.763	829.7928	2.0786	0.433	0.4057	0.5917	106.3698
18908	25.16	3.763	860.2051	1.884	0.4308	0.4065	0.575	103.3735
18914	25.18	3.763	1024.738	1.7857	0.4314	0.4098	0.5917	106.3698
20190	28.45	3.763	1147.925	2.0026	0.439	0.4168	0.725	119.8788
22104	33.27	4.3607	1090.276	2.5092	0.4304	0.4059	1.0583	184.0142
22862	35.13	3.9507	777.7428	2.1114	0.4362	0.4076	0.5833	96.4542
24644	39.76	3.763	749.7394	1.9404	0.4344	0.4106	0.625	103.3438
26796	45.11	3.9507	767.264	2.1308	0.4396	0.4123	0.6333	104.7217
28014	48.14	3.9507	814.1023	2.1515	0.4314	0.4039	0.6583	108.8554
30422	54.03	4.3574	1247.127	2.288	0.4322	0.411	1.0083	150.1616
30580	54.37	3.763	974.6177	2.0084	0.438	0.4146	0.6833	112.9892
31010	55.54	3.763	816.8039	1.9173	0.431	0.4106	0.7417	122.6346

31590	56.88	3.8912	1284.788	2.096	0.439	0.4099	0.5167	85.4308
31760	57.39	3.9507	844.5286	2.0315	0.436	0.4104	0.625	103.3438
32940	60.18	3.763	831.1659	1.8893	0.434	0.4119	0.6417	106.0996
33248	60.94	3.763	974.9395	2.0396	0.4348	0.4089	0.6167	78.3907
35216	65.85	3.763	759.3619	2.0048	0.4316	0.4077	0.6667	84.7467
35652	66.89	3.763	917.4511	2.0111	0.4352	0.4096	0.6083	77.3313
38406	73.91	3.763	838.7884	1.7756	0.4306	0.4094	0.5917	75.2127
39646	77.08	3.763	945.0349	1.8987	0.4346	0.413	0.675	85.806
39802	77.38	4.173	1134.048	2.1606	0.4302	0.4209	1.375	174.79
39826	77.47	3.763	1017.582	1.9571	0.4326	0.4083	0.6083	77.3313
39948	77.71	3.763	1021.973	2.0534	0.4348	0.4083	0.6167	78.3907
42152	83.11	3.763	1100.085	1.999	0.4352	0.4106	0.6333	80.5093
46272	93.24	3.8912	1273.552	2.1339	0.4372	0.408	0.5583	70.9753
47060	95.32	3.9507	1011.79	2.1999	0.436	0.4086	0.6833	65.4292
47816	97.28	3.9507	947.4928	2.0032	0.4316	0.4059	0.6	57.45
49516	101.63	3.763	858.7884	1.6286	0.4316	0.4139	0.6167	59.0458
52328	110.39	3.763	878.9084	1.9408	0.4328	0.4103	0.6667	63.8333
52668	111.47	3.9507	832.5229	2.0116	0.4368	0.411	0.6083	58.2479
55002	118.77	3.9507	773.6271	1.8606	0.4302	0.4064	0.575	55.0562
55956	121.72	3.763	829.0756	2.1872	0.4356	0.406	0.625	59.8438
56818	124.61	3.763	837.2389	2.0488	0.4318	0.4053	0.625	63.2437
61140	138.06	3.763	1032.29	1.8829	0.434	0.4137	0.7167	72.5195
63020	144.15	4.173	955.6941	2.2889	0.432	0.4149	1.175	118.8982
66720	155.92	3.763	749.8818	2.0141	0.432	0.4072	0.6417	61.2856
66766	156.07	3.9507	883.0579	2.1547	0.4366	0.4102	0.6917	66.0611
67418	158.13	3.9507	781.352	2.1201	0.4318	0.4133	1.025	97.8978
68410	161.99	3.9507	721.3039	2.0963	0.431	0.4028	0.6083	58.1019

Appendix B

ANCILLARY SERVICE APPLICATION SCRIPTS AND DATA

B.1 SCRIPTS FOR THE SCHEDULING MODEL IN LINGO

```
model:
data:
      CHAC = 7.2; SOCB = 0.2; SOCC = 0.5; SOCT = 0.9; E = 0.1; U = 0.9;
M = 2; N = 24; !CHAC;
enddata
sets:
      NUM/1..M/:CHARGING;
      PRD/1..N/:PERIOD,DIS,CAP,PRICE,ELEC;
      LINKS(NUM,PRD):COST,CHOICE,COMPARE;
      AVAN(PRD);
      AVAS(PRD)|#NOT# @in(AVAN,&1);
endsets
data:
      CHAV, BATT, ENEC = @OLE('final.xlsm', 'HONDA'); !NISSAN;
      AVAN = @OLE('final.xlsm', 'AVAN');
      DIS = @OLE('final.xlsm', 'DIST');
      CAP = @OLE('final.xlsm', 'CAP');
      PRICE = @OLE('final.xlsm', 'CAP');
      ELEC = @OLE('final.xlsm', 'ELEC');
      SOCI = @OLE('final.xlsm', 'SOCI');
      @OLE('final.xlsm', 'RES') = @WRITE( @sum(LINKS: -COST*CHOICE),
@sum(PRD(I):CHOICE(1,I)*ELEC(I)), @sum(PRD(I): -
ENEC/BATT*DIS(I)+U*CHAV/BATT*CHOICE(1,I))+SOCI);
      !AVAN = 6 7 21;
      !DIS = 0 0 0 0 0 11 11 0 0 0 0 0 0 0 0 0 0 0 0 0 18 0 0 0;
      !COMPARE = 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0 0 0 0 0 0 0
                 1 1 1 1 1 0 0 1 1 1 0 0 0 0 0 0 1 1 1 1 0 1 1 1;
      !COMPARE = 0 0 0 0 0 0 0 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0
                 1 1 1 1 1 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 0 1 1 1;
      !@TEXT() = @WRITE( 'Several Output', @NEWLINE(1));
      !@TEXT() = @WRITE( @sum(LINKS: COST*COMPARE), @NEWLINE(1));
      !@TEXT() = @WRITE( @sum(PRD(I): -
ENEC/BATT*DIS(I)+U*CHAV/BATT*CHOICE(1,I))+SOCI, @NEWLINE(1));
enddata
      @for(LINKS:
            @bin(CHOICE); @free(COST));
      @for(LINKS(I,J):
            COST(I,J)=@if(I #eq# 1, CHAV*ELEC(J), -CHAC*CAP(J)-
CHAC*E*PRICE(J)));
      min=@sum(LINKS: COST*CHOICE);
      @for(AVAS(I):
            @sum(NUM(J):CHOICE(J,I))<=1);
      @for(AVAN(I):
            @sum(NUM(J):CHOICE(J,I))=0);
      @for(PRD(J):
```

```
            @sum(PRD(I)|I #le# J: ENEC/BATT*DIS-
U*CHAV/BATT*CHOICE(1,I))<=SOCI-SOCB);
      @for(PRD(J):
            @sum(PRD(I)|I #le# J: -
ENEC/BATT*DIS+U*CHAV/BATT*CHOICE(1,I))<=SOCT-SOCI);
      @sum(PRD(I): ENEC/BATT*DIS(I)-U*CHAV/BATT*CHOICE(1,I))<=SOCI-
SOCC;
end
```

B.2 DATA ON ANNUAL ANCILLARY SERVICE PROFIT

NISSAN LEAF ANCILLARY	NISSAN LEAF CHARGING	END OF SOC
657.756	252	0.718261
994.3296	160	0.678261
1178.866	136	0.638261
1367.045	136	0.598261
1349.462	136	0.558261
874.1436	136	0.518261
143.946	228	0.736522
604.6656	160	0.696522
668.382	160	0.656522
741.3648	136	0.616522
745.998	136	0.576522
910.734	136	0.536522
270.3492	228	0.754783
556.2744	160	0.714783
231.792	160	0.674783
454.6608	136	0.634783
331.4256	136	0.594783
434.742	136	0.554783
596.0724	136	0.514783
155.9844	228	0.733043
512.556	160	0.693043
430.5048	160	0.653043
656.8584	136	0.613043
669.8868	136	0.573043
630.4056	136	0.533043
-183.506	228	0.751304
435.93	160	0.711304
334.9896	160	0.671304
289.3308	136	0.631304
355.2648	136	0.591304
896.0424	136	0.551304

938.3352	136	0.511304
-96.3072	228	0.729565
206.7252	160	0.689565
389.202	136	0.649565
571.8768	136	0.609565
922.2576	136	0.569565
1799.992	136	0.529565
1284.664	228	0.747826
1056.898	160	0.707826
922.218	160	0.667826
392.4492	136	0.627826
283.2324	136	0.587826
223.3968	136	0.547826
380.49	136	0.507826
-276.844	228	0.726087
153.8988	160	0.686087
262.1256	136	0.646087
168.8676	136	0.606087
83.1732	136	0.566087
51.0972	136	0.526087
-504.821	228	0.744348
-72.6528	160	0.704348
19.0212	160	0.664348
133.782	136	0.624348
303.5472	136	0.584348
61.1952	136	0.544348
81.3516	136	0.504348
-782.456	252	0.722609
118.338	160	0.682609
258.8388	136	0.642609
322.674	136	0.602609
350.8692	136	0.562609
160.71	136	0.522609
-499	228	0.74087
259.1952	160	0.70087
371.382	160	0.66087
387.3804	136	0.62087
376.332	136	0.58087
239.514	136	0.54087
265.4124	136	0.50087
-274.23	252	0.71913
134.6136	160	0.67913
177.936	160	0.63913

535.4448	136	0.59913
522.1392	136	0.55913
594.726	136	0.51913
-95.5152	228	0.737391
828.3264	160	0.697391
933.306	160	0.657391
1112.734	136	0.617391
929.6628	136	0.577391
992.2308	136	0.537391
116.8596	228	0.755652
516.8724	160	0.715652
417.4368	160	0.675652
618.6444	136	0.635652
541.6224	136	0.595652
507.5268	136	0.555652
427.218	136	0.515652
-223.661	228	0.733913
134.6928	160	0.693913
177.6192	160	0.653913
363.7392	136	0.613913
312.6948	136	0.573913
426.0696	136	0.533913
-372.596	228	0.752174
33.4356	160	0.712174
19.9716	160	0.672174
291.4296	136	0.632174
385.5984	136	0.592174
236.9796	136	0.552174
164.6304	136	0.512174
-536.224	228	0.730435
-80.4936	160	0.690435
-200.838	160	0.650435
19.536	136	0.610435
-3.7488	136	0.570435
-76.9692	136	0.530435
-625.046	228	0.748696
91.4892	160	0.708696
34.782	160	0.668696
34.8216	136	0.628696
-55.308	136	0.588696
39.732	136	0.548696
161.5416	136	0.508696
-327.69	228	0.726957

-44.418	160	0.686957
60.2448	136	0.646957
-157.04	136	0.606957
-189.156	136	0.566957
-187.255	136	0.526957
-805.464	228	0.745217
-314.807	160	0.705217
-338.844	160	0.665217
-46.3188	136	0.625217
-115.936	136	0.585217
-68.9304	136	0.545217
-53.0904	136	0.505217
-586.238	228	0.723478
-66.594	160	0.683478
300.5376	136	0.643478
453.9876	136	0.603478
148.5132	136	0.563478
89.628	136	0.523478
-587.506	228	0.741739
-72.4152	160	0.701739
-129.083	160	0.661739
108.24	136	0.621739
102.9732	136	0.581739
37.554	136	0.541739
27.5748	136	0.501739
-711.454	252	0.72
-119.42	160	0.68
-79.8204	136	0.64
-72.8508	136	0.6
-124.925	136	0.56
-112.926	136	0.52
-666.666	228	0.738261
-51.942	160	0.698261
-104.848	160	0.658261
229.6536	136	0.618261
128.2776	136	0.578261
23.3376	136	0.538261
-647.104	228	0.756522
-168.604	160	0.716522
-157.357	160	0.676522
-235.171	160	0.636522
-127.499	136	0.596522
-95.1456	136	0.556522

-147.418	136	0.516522
-631.739	228	0.734783
-196.522	160	0.694783
-215.53	160	0.654783
66.858	136	0.614783
-22.3212	136	0.574783
-55.506	136	0.534783
-571.309	228	0.753043
-81.84	160	0.713043
-137.834	160	0.673043
50.7012	136	0.633043
55.6116	136	0.593043
-3.1548	136	0.553043
29.3964	136	0.513043
-375.17	228	0.731304
556.2348	160	0.691304
2001.278	160	0.651304
1237.315	136	0.611304
1217.634	136	0.571304
914.1396	136	0.531304
92.1888	228	0.749565
-44.7744	160	0.709565
16.7244	160	0.669565
138.6924	136	0.629565
86.3016	136	0.589565
219.0804	136	0.549565
170.61	136	0.509565
-613.404	228	0.727826
147.1668	160	0.687826
1476.697	136	0.647826
1605.912	136	0.607826
255.156	136	0.567826
564.5508	136	0.527826
242.2728	228	0.746087
363.5412	160	0.706087
478.1436	160	0.666087
289.4496	136	0.626087
123.5256	136	0.586087
67.0164	136	0.546087
47.7708	136	0.506087
-586.199	228	0.724348
-180.167	160	0.684348
-103.105	136	0.644348

-136.646	136	0.604348
-121.004	136	0.564348
-119.381	136	0.524348
-631.937	228	0.742609
-144.685	160	0.702609
-266.772	160	0.662609
118.734	136	0.622609
28.2876	136	0.582609
-181.79	136	0.542609
-137.438	136	0.502609
-782.377	228	0.72087
-281.266	160	0.68087
-129.479	136	0.64087
-27.4296	136	0.60087
374.7084	136	0.56087
19.734	136	0.52087
-666.824	228	0.73913
-161.159	160	0.69913
-197.987	160	0.65913
61.1952	136	0.61913
-44.6556	136	0.57913
-113.599	136	0.53913
-864.151	228	0.757391
-189.077	160	0.717391
-342.21	160	0.677391
47.1768	136	0.637391
-93.522	136	0.597391
-166.98	136	0.557391
-0.7788	136	0.517391
-840.827	228	0.735652
-340.745	160	0.695652
-406.243	160	0.655652
-23.0736	136	0.615652
-150.467	136	0.575652
-228.162	136	0.535652
-966.082	228	0.753913
-497.006	160	0.713913
-545.12	160	0.673913
-539.537	160	0.633913
-315.361	136	0.593913
-331.558	136	0.553913
-400.976	136	0.513913
-1029.4	228	0.732174

-605.352	160	0.692174
-632.201	160	0.652174
-443.903	136	0.612174
-244.24	136	0.572174
-269.386	136	0.532174
-940.025	228	0.750435
-547.694	160	0.710435
-545.754	160	0.670435
-416.302	136	0.630435
-436.3	136	0.590435
-423.232	136	0.550435
-333.934	136	0.510435
-813.503	228	0.728696
-353.338	160	0.688696
-278.296	136	0.648696
-412.856	136	0.608696
-277.266	136	0.568696
-273.504	136	0.528696
-935.827	228	0.746957
-496.056	160	0.706957
-472.534	160	0.666957
-328.706	136	0.626957
-242.616	136	0.586957
164.7888	136	0.546957
-119.064	136	0.506957
-810.533	228	0.725217
-376.86	160	0.685217
-79.464	136	0.645217
-163.97	136	0.605217
-59.07	136	0.565217
-206.54	136	0.525217
-784.357	228	0.743478
-317.262	160	0.703478
-368.267	160	0.663478
-109.283	136	0.623478
-0.3828	136	0.583478
42.2664	136	0.543478
-17.49	136	0.503478
-1774.3	379	0.721739
872.0052	160	0.681739
20.8428	136	0.641739
106.1412	136	0.601739
355.542	136	0.561739

621.5748	136	0.521739
459.5184	228	0.74
173.3028	160	0.7
142.89	160	0.66
278.0448	136	0.62
197.0628	136	0.58
413.754	136	0.54
560.1948	136	0.5
962.478	228	0.718261
91.41	160	0.678261
136.6728	136	0.638261
101.8644	136	0.598261
24.6444	136	0.558261
344.1372	136	0.518261
-292.644	228	0.736522
330.8712	160	0.696522
237.138	160	0.656522
530.6928	136	0.616522
312.774	136	0.576522
583.044	136	0.536522
-426.532	228	0.754783
385.242	160	0.714783
667.6692	160	0.674783
475.8072	136	0.634783
676.2228	136	0.594783
715.4268	136	0.554783
220.7436	136	0.514783
-510.8	228	0.733043
-7.2732	160	0.693043
167.1648	160	0.653043
130.416	136	0.613043
74.8176	136	0.573043
181.9752	136	0.533043
-441.58	228	0.751304
78.5004	160	0.711304
115.0908	160	0.671304
70.8576	160	0.631304
592.7064	136	0.591304
121.6248	136	0.551304
199.9536	136	0.511304
-312.088	228	0.729565
108.1608	160	0.689565
579.5592	136	0.649565

734.3952	136	0.609565
391.8156	136	0.569565
259.8684	136	0.529565
-427.759	228	0.747826
-7.6296	160	0.707826
195.0036	160	0.667826
169.9368	136	0.627826
175.2432	136	0.587826
996.7056	136	0.547826
797.1612	136	0.507826
-100.782	228	0.726087
284.1828	160	0.686087
466.818	136	0.646087
816.486	136	0.606087
1077.727	136	0.566087
725.01	136	0.526087
-123.196	228	0.744348
208.8636	160	0.704348
44.2068	160	0.664348
394.2312	136	0.624348
583.242	136	0.584348
652.9776	136	0.544348
1036.028	136	0.504348
354.1428	252	0.722609
656.898	160	0.682609
701.6856	136	0.642609
741.8796	136	0.602609
737.3256	136	0.562609
618.882	136	0.522609
124.7004	228	0.74087
884.9544	160	0.70087
808.2492	160	0.66087
869.352	136	0.62087

MITSUBISHI I-MIEV ANCILLARY	MITSUBISHI I-MIEV CHARGING	END OF SOC
1338.454	160	0.514
1000.547	160	0.528
1178.866	136	0.542
1367.045	136	0.556
1349.462	136	0.57
874.1436	136	0.584

814.902	136	0.598
779.1432	136	0.612
842.622	136	0.626
566.4516	160	0.64
570.174	160	0.654
717.6048	160	0.668
752.928	160	0.682
556.2744	160	0.696
231.792	160	0.71
274.4808	160	0.724
163.9572	160	0.738
268.1844	160	0.752
411.4968	160	0.766
644.7408	160	0.78
512.556	160	0.794
1091.917	68	0.511
494.4192	160	0.525
669.8868	136	0.539
630.4056	136	0.553
475.2132	136	0.567
613.734	136	0.581
515.0904	136	0.595
289.3308	136	0.609
355.2648	136	0.623
896.0424	136	0.637
788.964	160	0.651
401.676	160	0.665
206.7252	160	0.679
225.5352	160	0.693
440.1672	160	0.707
744.612	160	0.721
1520.336	160	0.735
1777.142	160	0.749
1056.898	160	0.763
922.218	160	0.777
234.6432	160	0.791
767.6724	68	0.508
77.352	160	0.522
380.49	136	0.536
365.4816	136	0.55
318.318	136	0.564
262.1256	136	0.578
168.8676	136	0.592

83.1732	136	0.606
51.0972	136	0.62
209.2992	136	0.634
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19.0212	160	0.662
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148.4736	160	0.69
-100.373	160	0.704
-77.1672	160	0.718
-151.496	160	0.732
118.338	160	0.746
55.77	160	0.76
127.3668	160	0.774
160.0368	160	0.788
637.6656	68	0.505
30.5052	160	0.519
423.0204	136	0.533
564.9864	136	0.547
387.3804	136	0.561
376.332	136	0.575
239.514	136	0.589
265.4124	136	0.603
617.0208	136	0.617
351.186	136	0.631
177.936	160	0.645
349.2456	160	0.659
364.9668	160	0.673
422.9412	160	0.687
403.1808	160	0.701
828.3264	160	0.715
933.306	160	0.729
895.6068	160	0.743
733.7616	160	0.757
812.8824	160	0.771
618.09	160	0.785
1198.679	68	0.502
442.7808	160	0.516
494.538	160	0.53
541.6224	136	0.544
507.5268	136	0.558
427.218	136	0.572
448.8	136	0.586
308.418	136	0.6

339.7416	136	0.614
363.7392	136	0.628
128.7924	160	0.642
254.9184	160	0.656
111.8436	160	0.67
33.4356	160	0.684
19.9716	160	0.698
117.9024	160	0.712
190.5684	160	0.726
43.3752	160	0.74
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30.7824	136	0.555
271.1544	136	0.569
209.022	136	0.583
34.8216	136	0.597
-55.308	136	0.611
39.732	136	0.625
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152.3148	160	0.653
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-356.03	160	0.709
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407.5104	68	0.51
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94.6176	136	0.552
300.5376	136	0.566
453.9876	136	0.58
148.5132	136	0.594
89.628	136	0.608

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64.0464	136	0.535
229.6536	136	0.549
128.2776	136	0.563
23.3376	136	0.577
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4.29	136	0.619
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-103.541	160	0.731
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29.3964	136	0.56
258.6408	136	0.574
720.3372	136	0.588
2188.468	136	0.602
1237.315	136	0.616

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147.1668	160	0.77
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58.344	160	0.515
564.5508	136	0.529
873.1932	136	0.543
525.3864	136	0.557
640.464	136	0.571
289.4496	136	0.585
123.5256	136	0.599
67.0164	136	0.613
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-348.15	160	0.795
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-111.223	136	0.54
-129.479	136	0.554
-27.4296	136	0.568
374.7084	136	0.582
19.734	136	0.596
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-396.304	160	0.694
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-23.0736	136	0.537
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-228.162	136	0.565
-339.438	136	0.579
-335.201	136	0.593
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-632.201	160	0.705
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-545.754	160	0.789
50.556	68	0.506
-436.3	136	0.52
-423.232	136	0.534
-333.934	136	0.548
-175.93	136	0.562
-192.086	136	0.576
-278.296	136	0.59
-412.856	136	0.604
-433.132	160	0.618
-273.504	136	0.632

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-496.056	160	0.66
-472.534	160	0.674
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3.6168	160	0.716
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-109.283	136	0.573
-0.3828	136	0.587
42.2664	136	0.601
-184.166	160	0.615
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872.0052	160	0.643
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191.0436	160	0.685
443.1768	160	0.699
962.2536	160	0.713
173.3028	160	0.727
142.89	160	0.741
116.7936	160	0.755
38.7024	160	0.769
236.742	160	0.783
1043.843	68	0.5
1621.079	136	0.514
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136.6728	136	0.542
101.8644	136	0.556
24.6444	136	0.57
344.1372	136	0.584
350.988	136	0.598
330.8712	160	0.612
388.6476	136	0.626
386.7864	160	0.64

154.8096	160	0.654
453.4728	160	0.668
78.5796	160	0.682
385.242	160	0.696
667.6692	160	0.71
338.6328	160	0.724
537.8208	160	0.738
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69.8676	160	0.766
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813.2916	68	0.511
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74.8176	136	0.539
181.9752	136	0.553
193.4592	136	0.567
244.3452	136	0.581
281.5692	136	0.595
239.6724	136	0.609
592.7064	136	0.623
121.6248	136	0.637
59.0964	160	0.651
183.9948	160	0.665
108.1608	160	0.679
422.07	160	0.693
597.1416	160	0.707
244.1868	160	0.721
96.2016	160	0.735
67.65	160	0.749
-7.6296	160	0.763
195.0036	160	0.777
-12.4212	160	0.791
663.762	68	0.508
863.412	160	0.522
797.1612	136	0.536
567.5604	136	0.55
488.3208	136	0.564
466.818	136	0.578
816.486	136	0.592
1077.727	136	0.606
725.01	136	0.62
543.3648	136	0.634
208.8636	160	0.648

44.2068	160	0.662
237.0192	160	0.676
406.5864	160	0.69
500.676	160	0.704
869.6292	160	0.718
1026.208	160	0.732
656.898	160	0.746
548.5524	160	0.76
581.46	160	0.774
560.7096	160	0.788
1127.518	68	0.505
663.2736	160	0.519
1057.888	136	0.533
972.0744	136	0.547
869.352	136	0.561

FORD FOCUS ELECTRIC ANCILLARY	FORD FOCUS ELECTRIC CHARGING	END OF SOC
3104.191	364	0.552083
2529.12	340	0.604167
2955.48	272	0.5325
2902.31	340	0.584583
3350.53	272	0.512917
2061.365	340	0.565
1942.802	340	0.617083
2207.674	272	0.545417
1909.934	364	0.5975
2151.996	272	0.525833
1839.446	340	0.577917
2511.406	272	0.50625
2224.279	364	0.558333
1842.06	340	0.610417
1557.362	272	0.53875
1262.554	340	0.590833
1360.471	272	0.519167
1243.704	340	0.57125
1576.898	340	0.623333
2324.177	272	0.551667
1686.511	340	0.60375
1896.18	272	0.532083
1653.802	340	0.584167
2028.682	272	0.5125

1660.138	340	0.564583
1322.587	340	0.616667
1963.579	272	0.545
1511.4	340	0.597083
1329.742	272	0.525417
1041.19	340	0.5775
2340.334	296	0.505833
2118.547	340	0.557917
1446.139	340	0.61
1436.741	272	0.538333
1153.733	340	0.590417
1770.965	344	0.51875
2159.81	436	0.570833
3692.014	364	0.622917
4505.978	296	0.55125
2634.218	436	0.603333
2771.34	368	0.531667
1180.106	364	0.58375
1313.426	272	0.512083
847.5456	364	0.564167
1125.221	364	0.61625
1464.223	272	0.544583
1045.387	364	0.596667
1287.29	272	0.525
750.7632	340	0.577083
934.4544	272	0.505417
534.864	364	0.5575
892.9272	340	0.609583
981.8952	272	0.537917
846.9912	340	0.59
1053.492	272	0.518333
988.7592	340	0.570417
528.528	340	0.6225
932.1576	272	0.550833
542.4672	340	0.602917
1368.233	272	0.53125
1043.486	340	0.583333
1442.285	272	0.511667
1075.087	340	0.56375
783.156	340	0.615833
1159.066	272	0.544167
1263.583	364	0.59625
1906.397	272	0.524583

1201.094	340	0.576667
1509.922	272	0.505
873.3648	364	0.557083
944.4072	340	0.609167
1976.41	272	0.5375
1115.796	340	0.589583
1489.092	272	0.517917
1455.564	340	0.57
1347.139	388	0.622083
1838.206	296	0.550417
1482.888	388	0.6025
2657.213	320	0.530833
2507.34	364	0.582917
2834.7	296	0.51125
2089.639	364	0.563333
2193.391	388	0.615417
2260.421	296	0.54375
1705.519	364	0.595833
1823.712	272	0.524167
1532.309	388	0.57625
1764.233	272	0.504583
1371.374	364	0.556667
1215.43	364	0.60875
1597.358	272	0.537083
988.5216	364	0.589167
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1107.48	340	0.569583
921.6768	364	0.621667
1562.51	272	0.55
951.2976	340	0.602083
1145.285	272	0.530417
840.6552	340	0.5825
1352.155	272	0.510833
1175.909	364	0.562917
886.6704	364	0.615
1065.055	272	0.543333
655.248	340	0.595417
912.1992	272	0.52375
415.7472	340	0.575833
831.4152	272	0.504167
417.3312	364	0.55625
323.2416	340	0.608333
836.88	272	0.536667

998.5008	340	0.58875
1126.91	272	0.517083
507.2232	340	0.569167
374.484	340	0.62125
863.9664	272	0.549583
776.9784	340	0.601667
1432.781	272	0.53
751.0008	340	0.582083
917.8224	272	0.510417
145.2792	364	0.5625
148.764	340	0.614583
435.0192	272	0.542917
166.98	340	0.595
499.3296	272	0.523333
185.3544	340	0.575417
702.4776	272	0.50375
205.3128	364	0.555833
340.5072	340	0.607917
658.9968	272	0.53625
537.7944	340	0.588333
962.016	272	0.516667
954.9408	340	0.56875
1293.046	340	0.620833
1085.014	272	0.549167
652.1592	340	0.60125
891.0528	272	0.529583
490.7496	340	0.581667
776.688	272	0.51
112.9128	491	0.562083
602.58	340	0.614167
843.216	272	0.5425
552.8424	340	0.594583
891.4488	272	0.522917
509.124	340	0.575
635.4744	272	0.503333
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241.1112	340	0.6075
556.9872	272	0.535833
468.8112	340	0.587917
1040.424	272	0.51625
608.6784	340	0.568333
905.7576	340	0.620417
1054.205	272	0.54875

521.2416	340	0.600833
788.172	272	0.529167
520.2912	340	0.58125
802.5864	272	0.509583
367.1184	340	0.561667
272.9496	340	0.61375
624.0696	272	0.542083
228.1224	340	0.594167
800.448	272	0.5225
446.952	340	0.574583
678.9552	272	0.502917
626.0232	340	0.555
465.168	340	0.607083
686.004	272	0.535417
634.4184	340	0.5875
948.7896	272	0.515833
521.4792	340	0.567917
588.0072	340	0.62
913.5456	272	0.548333
509.6784	340	0.600417
872.9952	272	0.52875
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2248.224	272	0.509167
4579.687	364	0.56125
2959.176	340	0.613333
3215.969	272	0.541667
2320.111	340	0.59375
2265.014	272	0.522083
739.0416	340	0.574167
1165.56	272	0.5025
636.7152	364	0.554583
698.8872	340	0.606667
1240.087	272	0.535
855.228	340	0.587083
848.1264	272	0.515417
1143.912	340	0.5675
3490.054	340	0.619583
4018.344	272	0.547917
1035.725	340	0.6
1938.235	272	0.528333
2289.54	340	0.580417
1858.243	272	0.50875
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1042.008	272	0.54125
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323.9544	340	0.619167
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574.5432	340	0.599583
429.396	272	0.527917
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654.456	340	0.605833
723.8616	272	0.534167
316.9056	340	0.58625
361.2048	272	0.514583
484.0176	340	0.566667
105.2832	364	0.61875
911.1696	272	0.547083
349.14	340	0.599167
481.5888	272	0.5275
542.4672	340	0.579583
406.7448	272	0.507917
86.592	364	0.56
60.6936	340	0.612083
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190.3704	272	0.53375
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-311.15	340	0.618333
-108.847	272	0.546667
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344.9688	272	0.527083
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-149.503	340	0.617917
170.412	272	0.54625
-143.722	340	0.598333
292.0632	272	0.526667
818.1624	340	0.57875
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54.516	340	0.61125
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691.6272	272	0.52
116.6088	340	0.572083
497.9832	272	0.500417
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115.2624	340	0.604583
561.7392	272	0.532917
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850.6608	272	0.513333
454.5552	340	0.565417
254.892	340	0.6175
2835.65	272	0.545833
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989.4192	272	0.52625
1096.313	340	0.578333
1941.799	272	0.506667
2544.802	364	0.55875
954.228	340	0.610833
1253.947	272	0.539167
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1157.059	340	0.571667
1823.95	272	0.5
3542.484	340	0.552083
821.3304	340	0.604167
1023.396	272	0.5325
595.1352	340	0.584583
797.5176	272	0.512917
1132.982	340	0.565
985.9872	388	0.617083
1564.015	320	0.545417
1045.15	412	0.5975
1654.541	296	0.525833
897.4416	364	0.577917
1772.39	296	0.50625
674.652	364	0.558333
1332.17	388	0.610417
2192.467	344	0.53875
1188.818	412	0.590833
1995.655	272	0.519167
1596.698	364	0.57125
719.004	364	0.623333
915.684	272	0.551667
584.9184	340	0.60375
1293.072	272	0.532083
673.068	340	0.584167
915.288	272	0.5125
649.9416	364	0.564583
711.48	340	0.616667
1155.977	272	0.545
886.8288	340	0.597083

1170.708	272	0.525417
1395.926	388	0.5775
961.9368	272	0.505833
711.5592	364	0.557917
977.4336	340	0.61
1155.185	272	0.538333
1410.341	388	0.590417
2070.578	296	0.51875
1107.559	340	0.570833
899.6592	340	0.622917
1139.978	272	0.55125
690.3336	340	0.603333
1476.42	272	0.531667
756.1488	340	0.58375
1071.629	272	0.512083
2193.312	388	0.564167
1788.917	340	0.61625
1820.702	272	0.544583
1400.124	340	0.596667
1628.959	272	0.525
1873.265	388	0.577083
2760.569	296	0.505417
1698.55	364	0.5575
1433.467	340	0.609583
1481.568	272	0.537917
796.3032	340	0.59
1470.638	272	0.518333
1492.867	340	0.570417
1545.773	364	0.6225
2638.442	296	0.550833
2382.046	388	0.602917
2251.392	272	0.53125
1654.039	340	0.583333
2089.824	272	0.511667
1743.931	340	0.56375
1501.738	340	0.615833
2252.342	272	0.544167
2359.474	340	0.59625
2557.025	272	0.524583
1958.642	340	0.576667

HONDA FIT ANCILLARY	HONDA FIT CHARGING	END OF SOC
3054.691	388	0.678125
2860.757	296	0.670625
2825.671	296	0.663125
3211.296	296	0.655625
3261.984	296	0.648125
2331.226	296	0.640625
2209.02	296	0.633125
2145.343	296	0.625625
2263.114	296	0.618125
2067.41	296	0.610625
2081.033	296	0.603125
2338.195	320	0.595625
2391.418	320	0.588125
1996.843	320	0.580625
1391.834	320	0.573125
1446.245	320	0.565625
1324.039	296	0.558125
1431.593	320	0.550625
1844.858	296	0.543125
2242.759	296	0.535625
1996.051	296	0.528125
1847.63	296	0.520625
1950.274	296	0.513125
1987.498	296	0.505625
1488.907	388	0.68375
1570.351	296	0.67625
1855.471	296	0.66875
1690.735	296	0.66125
1240.404	296	0.65375
1307.17	296	0.64625
2263.034	320	0.63875
2465.39	296	0.63125
1738.097	296	0.62375
1374.173	296	0.61625
1416.149	296	0.60875
1737.384	344	0.60125
2358.312	344	0.59375
3803.633	320	0.58625
4505.978	296	0.57875
2991.595	344	0.57125
2771.34	368	0.56375

1482.518	296	0.55625
1262.422	296	0.54875
1153.205	296	0.54125
1436.662	296	0.53375
1335.602	320	0.52625
1348.987	296	0.51875
1233.83	296	0.51125
1037.414	296	0.50375
500.2536	388	0.681875
805.0416	296	0.674375
961.9368	296	0.666875
885.0336	296	0.659375
1065.134	296	0.651875
976.0344	296	0.644375
1314.298	296	0.636875
825.4752	296	0.629375
866.3424	296	0.621875
741.6816	296	0.614375
1281.667	296	0.606875
1087.944	320	0.599375
1219.97	320	0.591875
1260.204	320	0.584375
922.5744	320	0.576875
910.2192	320	0.569375
1563.778	296	0.561875
1692.478	320	0.554375
1487.666	296	0.546875
1453.452	296	0.539375
1173.163	296	0.531875
1226.227	296	0.524375
1944.73	296	0.516875
1419	296	0.509375
1475.945	296	0.501875
1355.693	388	0.68
1634.741	320	0.6725
1761.54	296	0.665
1711.882	320	0.6575
2498.575	320	0.65
2759.539	296	0.6425
2657.134	320	0.635
2346.907	296	0.6275
2498.417	296	0.62
2140.512	296	0.6125

1975.855	296	0.605
1721.544	320	0.5975
1782.528	320	0.59
1627.534	296	0.5825
1585.478	320	0.575
1444.106	320	0.5675
1574.866	296	0.56
1307.249	296	0.5525
1345.74	296	0.545
1404.823	296	0.5375
1188.766	320	0.53
1515.307	296	0.5225
1230.979	296	0.515
1094.359	296	0.5075
1099.428	296	0.5
883.1064	388	0.678125
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880.3608	296	0.648125
840.84	296	0.640625
628.3464	296	0.633125
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682.6776	296	0.618125
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987.36	296	0.543125
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416.4864	296	0.528125
342.5928	296	0.520625
351.9384	296	0.513125
371.0256	296	0.505625
-354.13	515	0.68375
375.144	296	0.67625
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485.7072	296	0.66125

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584.4696	296	0.64625
782.5488	296	0.63875
886.776	296	0.63125
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1572.727	296	0.61625
989.736	296	0.60875
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699.3888	320	0.59375
788.964	296	0.58625
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413.7408	447	0.56375
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764.1744	296	0.54875
838.5432	296	0.54125
707.4672	320	0.53375
129.492	423	0.52625
153.1728	423	0.51875
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490.8552	296	0.50375
294.4128	388	0.681875
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834.504	296	0.666875
1136.652	296	0.659375
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698.9136	296	0.636875
719.1888	296	0.629375
734.4744	296	0.621875
579.084	296	0.614375
472.2432	296	0.606875
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577.7376	320	0.584375
531.168	320	0.576875
472.3224	320	0.569375
702.3984	320	0.561875
174.0024	423	0.554375
122.364	423	0.546875
361.152	423	0.539375
815.0208	296	0.531875
720.9312	296	0.524375

781.5192	296	0.516875
791.8152	296	0.509375
232.6104	423	0.501875
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1241.117	296	0.6725
2164.906	296	0.665
5040.578	296	0.6575
3168.607	296	0.65
3089.17	296	0.6425
2539.442	296	0.635
2173.618	296	0.6275
952.5912	296	0.62
1083.509	296	0.6125
994.1712	296	0.605
720.2184	320	0.5975
1153.363	296	0.59
455.4	447	0.5825
188.892	447	0.575
741.0744	447	0.5675
3617.75	296	0.56
3818.522	296	0.5525
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1688.755	320	0.5375
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1247.638	423	0.5225
1454.983	423	0.515
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814.7832	296	0.663125
689.8056	296	0.655625
511.6056	296	0.648125
443.8104	296	0.640625
472.0848	296	0.633125
474.6984	296	0.625625
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761.0064	296	0.610625
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333.168	320	0.565625
82.4472	423	0.558125
39.9168	423	0.550625
235.8576	423	0.543125
1399.913	296	0.535625
697.6464	296	0.528125
634.92	296	0.520625
699.6264	296	0.513125
210.8304	423	0.505625
16.6056	515	0.68375
639.276	296	0.67625
485.7864	296	0.66875
266.1648	296	0.66125
678.7968	296	0.65375
373.0056	296	0.64625
818.5848	296	0.63875
534.732	296	0.63125
393.2808	296	0.62375
709.1304	296	0.61625
312.4968	296	0.60875
266.3232	320	0.60125
247.4736	296	0.59375
154.3608	447	0.58625
-89.496	447	0.57875
-229.522	447	0.57125
-25.9248	320	0.56375
57.552	296	0.55625
-30.0432	296	0.54875
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-329.155	423	0.53375
-373.19	423	0.52625
-496.188	423	0.51875
-59.8224	296	0.51125
-138.864	296	0.50375
-524.515	388	0.681875
-123.816	296	0.674375
274.7976	296	0.666875
218.8032	296	0.659375
117.0312	296	0.651875
-34.2408	296	0.644375
-34.5576	296	0.636875
-91.344	296	0.629375
-126.826	296	0.621875

-101.957	296	0.614375
66.66	296	0.606875
-139.946	447	0.599375
266.7192	320	0.591875
84.1632	320	0.584375
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190.0536	296	0.569375
-243.936	423	0.561875
-289.397	423	0.554375
-381.982	423	0.546875
100.3992	296	0.539375
62.7	296	0.531875
224.1888	296	0.524375
985.1424	296	0.516875
51.48	423	0.509375
-63.5184	423	0.501875
-497.402	515	0.68
560.9472	296	0.6725
396.6864	296	0.665
610.2888	296	0.6575
322.6344	296	0.65
419.496	296	0.6425
412.8432	296	0.635
316.4568	296	0.6275
467.3328	296	0.62
710.7144	296	0.6125
760.848	296	0.605
666.6792	296	0.5975
-68.8248	447	0.59
2278.822	447	0.5825
234.432	447	0.575
837.1176	320	0.5675
1385.419	296	0.56
1872.737	296	0.5525
2815.138	320	0.545
864.468	423	0.5375
782.6544	423	0.53
787.9608	423	0.5225
1037.969	296	0.515
1464.065	296	0.5075
1732.711	296	0.5
3450.295	388	0.678125
1142.75	296	0.670625

931.92	296	0.663125
880.2816	296	0.655625
740.256	296	0.648125
1362.372	296	0.640625
1322.138	320	0.633125
1564.015	320	0.625625
1353.264	320	0.618125
1643.532	296	0.610625
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1941.166	296	0.558125
1987.656	296	0.550625
1073.609	296	0.543125
890.4192	296	0.535625
923.4456	296	0.528125
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932.7912	296	0.513125
841.3152	296	0.505625
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1168.649	296	0.66125
1081.766	296	0.65375
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910.932	296	0.63875
1054.838	296	0.63125
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1113.684	296	0.61625
1753.303	296	0.60875
2070.578	296	0.60125
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2169.974	296	0.53375

1773.737	296	0.52625
1655.095	296	0.51875
1592.923	296	0.51125
2250.125	296	0.50375
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1999.694	296	0.674375
1698.022	296	0.666875
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1043.513	296	0.651875
1400.863	296	0.644375
1735.404	296	0.636875
1904.813	296	0.629375
2615.554	296	0.621875
2815.375	296	0.614375
2194.606	296	0.606875
1922.395	320	0.599375
1997.002	320	0.591875
1960.332	320	0.584375
1803.754	296	0.576875
2101.308	320	0.569375
2675.825	296	0.561875
2477.508	296	0.554375
2303.268	296	0.546875

REFERENCES

Andersson, S. L., Elofsson, A., Galus, M., Göransson, L., Karlsson, S., Johnsson, F., et al. (2010). Plug-in hybrid electric vehicles as regulating power providers: Case studies of sweden and germany.Energy Policy, 38(6), 2751-2762.

Becker, T. A. (2009). Electric vehicles in the United States: A new model with forecasts to 2030. Center for Entrepreneurship and Technology Technical Brief,

Bektaş, T., & Laporte, G. (2011). The pollution-routing problem. Transportation Research Part B: Methodological, 45(8), 1232-1250.

Blokh, D., & Gutin, G. (1996). An approximate algorithm for combinatorial optimization problems with two parameters. Australasian Journal of Combinatorics, 14, 157-164.

Boulanger, A. G., Chu, A. C., Maxx, S., & Waltz, D. L. (2011). Vehicle electrification: Status and issues. Proceedings of the IEEE, 99(6), 1116-38. doi:10.1109/JPROC.2011.2112750

Brooks, A. N. (2002). Vehicle-to-grid demonstration project: Grid regulation ancillary service with a battery electric vehicle California Environmental Protection Agency, Air Resources Board, Research Division.

Carić, T., Galić, A., Fosin, J., Gold, H., & Reinholz, A. (2008). A modelling and optimization framework for real-world vehicle routing problems. Vehicle Routing Problem, , 15.

Chabrier, A. (2006). Vehicle routing problem with elementary shortest path based column generation. Computers & Operations Research, 33(10), 2972-2990.

Chen, S., & Nahrstedt, K. (1998). On finding multi-constrained paths. Paper presented at the Communications, 1998. ICC 98. Conference Record. 1998 IEEE International Conference on, , 2. pp. 874-879.

Chong, E. I., Maddila, S., & Morley, S. (1995). On finding single-source single-destination k shortest paths. Paper presented at the The Seventh International Conference on Computing and Information (ICCI'95), pp. 40-47.

Chowdhury, M. A., & Sadek, A. W. (2003). Fundamentals of intelligent transportation systems planning Artech House Publishers.

Covic, G. A., Elliott, G., Stielau, O. H., Green, R. M., & Boys, J. T. (2000). The design of a contact-less energy transfer system for a people mover system. Paper presented at the Proceedings of International Conference on Power System Technology (POWERCON 2000), 1. pp. 79-84. Retrieved from http://dx.doi.org/10.1109/ICPST.2000.900035

Cuenca, R., Gaines, L., & Vyas, A. (2000). Evaluation of electric vehicle production and operating costs No. ANL/ESD-41) Argonne National Lab., IL (US).

De Los Rios, A., Goentzel, J., Nordstrom, K. E., & Siegert, C. W. (2012). Economic analysis of vehicle-to-grid (V2G)-enabled fleets participating in the regulation service market. Paper presented at the Innovative Smart Grid Technologies (ISGT), 2012 IEEE PES, pp. 1-8.

Department of Energy. (2011). One million electric vehicles by 2015.

Department of Energy. (2013). 2012 fuel economy guide. Retrieved March 31, 2013, from http://www.fueleconomy.gov/feg/download.shtml

Department of Energy. (2013). Federal and state laws and incentives for alternative fuels and vehicles. Retrieved March 31, 2013, from http://www.afdc.energy.gov/laws/

Dorigo, M., & Stützle, T. (2003). The ant colony optimization metaheuristic: Algorithms, applications, and advances. Handbook of Metaheuristics, , 250-285.

Dorigo, M. (1992). Optimization, learning and natural algorithms. Ph.D.Thesis, Politecnico Di Milano, Italy,

Dorigo, M., & Gambardella, L. M. (1997). Ant colony system: A cooperative learning approach to the traveling salesman problem. Evolutionary Computation, IEEE Transactions on, 1(1), 53-66.

Electric Drive Transportation Association. (2013). Electric drive vehicle sales figures (U.S. market) - EV sales. Retrieved March 31, 2013, from http://www.electricdrive.org/index.php?ht=d/sp/i/20952/pid/20952

Electric Reliability Council of Texas. (2013). The electric reliability council of texas (ERCOT) market information. Retrieved March 31, 2013, from http://www.ercot.com/mktinfo

Energy Information Administration. (June 2012). Annual energy outlook 2012 No. DOE/EIA-0383). Washington, DC:

Eppstein, D. (1998). Finding the k shortest paths. SIAM Journal on Computing, 28(2), 652-673.

Erdoğan, S., & Miller-Hooks, E. (2012). A green vehicle routing problem. Transportation Research Part E: Logistics and Transportation Review, 48(1), 100-114.

Erol-Kantarci, M., & Mouftah, H. T. (2010). Prediction-based charging of PHEVs from the smart grid with dynamic pricing. Paper presented at the Local Computer Networks (LCN), 2010 IEEE 35th Conference on, pp. 1032-1039.

Federal Highway Administration. (2009). 2009 national household travel survey. Retrieved March 31, 2013, from http://nhts.ornl.gov/index.shtml

Fri, R. W. (2003). U.S. oil dependence remains a problem. Issues in Science and Technology, 19(4), 53-54.

Gao, S., & Chabini, I. (2002). Best routing policy problem in stochastic time-dependent networks. Transportation Research Record: Journal of the Transportation Research Board, 1783(1), 188-196.

Garey, M. R., & Johnson, D. S. (1979). Computers and intractability. A guide to the theory of NP-completeness. Oxford, UK: Freeman.

Guille, C., & Gross, G. (2009). A conceptual framework for the vehicle-to-grid (V2G) implementation. Energy Policy, 37(11), 4379-4390.

Hassin, R. (1992). Approximation schemes for the restricted shortest path problem. Mathematics of Operations Research, 17(1), 36-42.

Hong Lin, S., Gertsch, N., & Russell, J. R. (2007). A linear-time algorithm for finding optimal vehicle refueling policies. Operations Research Letters, 35(3), 290-296.

Kempton, W., & Tomić, J. (2005). Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy. Journal of Power Sources, 144(1), 280-294.

Kempton, W., Udo, V., Huber, K., Komara, K., Letendre, S., Baker, S., et al. (2008). A test of vehicle-to-grid (V2G) for energy storage and frequency regulation in the PJM system. University of Delaware, Pepco Holdings, Inc PJM Interconnect, and Green Mountain College,

Khuller, S., Malekian, A., & Mestre, J. (2011). To fill or not to fill: The gas station problem. ACM Transactions on Algorithms (TALG), 7(3), 36.

Kim, S., Lewis, M. E., & White III, C. C. (2005). Optimal vehicle routing with real-time traffic information. Intelligent Transportation Systems, IEEE Transactions on, 6(2), 178-188.

Kodialam, M., & Lakshman, T. (2000). Dynamic routing of bandwidth guaranteed tunnels with restoration. Paper presented at the INFOCOM 2000. Nineteenth

Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE, , 2. pp. 902-911.

Korkmaz, T., & Krunz, M. (2001). Multi-constrained optimal path selection. Paper presented at the INFOCOM 2001. Twentieth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE, , 2. pp. 834-843.

Kuby, M., & Lim, S. (2005). The flow-refueling location problem for alternative-fuel vehicles. Socio-Economic Planning Sciences, 39(2), 125-145.

Kuipers, F., Van Mieghem, P., Korkmaz, T., & Krunz, M. (2002). An overview of constraint-based path selection algorithms for QoS routing. IEEE Communications Magazine, 40(12), 50-5. doi:10.1109/MCOM.2002.1106159

Lenstra, J. K., & Kan, A. (1981). Complexity of vehicle routing and scheduling problems. Networks, 11(2), 221-227.

Letendre, S. E., & Kempton, W. (2001). The V2G concept: A new model for power? Public Utilities Fortnightly, 140(4), 16-27.

Liang, Y., & Smith, A. E. (2004). An ant colony optimization algorithm for the redundancy allocation problem (RAP). Reliability, IEEE Transactions on, 53(3), 417-423.

Lin, S. (2008). Finding optimal refueling policies in transportation networks. Algorithmic aspects in information and management (pp. 280-291) Springer.

Mal, S., Chattopadhyay, A., Yang, A., & Gadh, R. (2012). Electric vehicle smart charging and vehicle-to-grid operation. International Journal of Parallel, Emergent and Distributed Systems, 27(3).

Msadaa, I. C., Cataldi, P., & Filali, F. (2010). A comparative study between 802.11 p and mobile WiMAX-based V2I communication networks. Paper presented at the Next Generation Mobile Applications, Services and Technologies (NGMAST), 2010 Fourth International Conference on, pp. 186-191.

Omidvar, A., & Tavakkoli-Moghaddam, R. (2012). Sustainable vehicle routing: Strategies for congestion management and refueling scheduling. Paper presented at the Energy Conference and Exhibition (ENERGYCON), 2012 IEEE International, pp. 1089-1094.

Onwubolu, G. C., & Babu, B. (2004). New optimization techniques in engineering Springer Verlag.

Pantic, Z., Bai, S., & Lukic, S. M. (2009). Inductively coupled power transfer for continuously powered electric vehicles. Paper presented at the 2009 IEEE Vehicle Power and Propulsion Conference (VPPC), pp. 1271-8. Retrieved from http://dx.doi.org/10.1109/VPPC.2009.5289705

Peterson, S. B., Apt, J., & Whitacre, J. (2010). Lithium-ion battery cell degradation resulting from realistic vehicle and vehicle-to-grid utilization. Journal of Power Sources, 195(8), 2385-2392.

Roy, B., Banik, S., Dey, P., Sanyal, S., & Chaki, N. (2011). Ant colony based routing for mobile ad-hoc networks towards improved quality of services. Journal of Emerging Trends in Computing and Information Sciences, 3(1), 10-14.

Samaras, C., & Meisterling, K. (2008). Life cycle assessment of greenhouse gas emissions from plug-in hybrid vehicles: Implications for policy. Environmental Science & Technology, 42(9), 3170-3176.

Skiscim, C. C., & Golden, B. L. (1989). Solving k-shortest and constrained shortest path problems efficiently. Annals of Operations Research, 20(1), 249-282.

Soares, J., Sousa, T., Morais, H., Vale, Z., & Faria, P. (2011). An optimal scheduling problem in distribution networks considering V2G. Paper presented at the Computational Intelligence Applications in Smart Grid (CIASG), 2011 IEEE Symposium on, pp. 1-8.

Society of Automotive Engineers. (2011). SAE charging configurations and ratings terminology. Retrieved March 31, 2013, from http://www.sae.org/smartgrid/chargingspeeds.pdf

Stephen Ezell. (2010). Explaining international IT application Leadership: Intelligent transportation systems, information technology and innovation foundationThe Information Technology & Innovation Foundation.

Suzuki, Y. (2008). A generic model of motor-carrier fuel optimization. Naval Research Logistics (NRL), 55(8), 737-746.

Sweda, T. M., & Klabjan, D. (2012). Finding minimum-cost paths for electric vehicles. Paper presented at the Electric Vehicle Conference (IEVC), 2012 IEEE International, pp. 1-4.

Vehicle sales, registration and titling fee information: House Committee on Transportation, Senate Committee on Transportation & Homeland Security, Vehicle sales, registration and titling fee information: (2010).

Tomic, J., & Kempton, W. (2007). Using fleets of electric-drive vehicles for grid support. Journal of Power Sources, 168(2), 459-468.

Tulpule, P., Marano, V., & Rizzoni, G. (2009). Effects of different PHEV control strategies on vehicle performance. Paper presented at the American Control Conference, 2009. ACC'09. pp. 3950-3955.

van Hemert, J., & Solnon, C. (2004). A study into ant colony optimisation, evolutionary computation and constraint programming on binary constraint satisfaction problems. Evolutionary Computation in Combinatorial Optimization, , 114-123.

Wang, Y. W., & Lin, C. C. (2009). Locating road-vehicle refueling stations. Transportation Research Part E: Logistics and Transportation Review, 45(5), 821-829.

Widyono, R. (1994). The design and evaluation of routing algorithms for real-time channels International Computer Science Institute Berkeley.