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Resilience and Operational Benefits of Electric Vehicle and Grid Integration

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Resilience and Operational Benefits of Electric Vehicle and Grid Integration

by
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Thesis

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Master Science in Engineering

The University of Texas at Austin
December 2023

Acknowledgments

I would like to express my gratitude to my undergraduate advisors Dr. Michael Levin and Dr. John Hourdos who inspired me to attend graduate school and pursue research in this area. I would also like to thank my advisor Dr. Stephen D. Boyles for his guidance and encouragement throughout this project and Dr. Javad Mohammadi specifically for his support in developing a more thorough analysis of the electric side of the problem. Finally, I would like to thank the other members of my research group: Dr. Lu Xu, Kyle Bathgate, Shidong Pan, Abigail Crocker, Diego Robalino Muñoz, and Debojjal Bagchi for their suggestions and support throughout the project.

Abstract

Resilience and Operational Benefits of Electric Vehicle and Grid Integration

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The University of Texas at Austin, 2023

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Shared autonomous electric vehicles (SAEVs) present new opportunities to control and optimize vehicle movements. Future deployment of these vehicles may reduce the need for individuals to own a personal vehicle and can have traffic flow and environmental benefits. However, to fully realize the benefits of this technology, vehicle dispatch needs to be optimized. Fleet operators will want to own and operate as few vehicles as possible while still maintaining a reasonable level of service for passengers. SAEVs can also be used for many purposes beyond moving individual passengers across the system. They could also be used to deliver food, provide last-mile delivery for packages, and interact with the electric grid. These services must be balanced to ensure that as many people are served as possible.

SAEV dispatch can be of particular interest in the aftermath of a natural disaster when there may be failures in the electric grid. In this case, vehicles can be used to transport power across broken lines to power critical facilities or reduce the number of blackouts. However, this important service must be weighed against the continued need to provide transportation to critical workers and vulnerable populations that may be reliant on SAEV service. We develop a dispatch policy that is proven to serve all demands (for both electricity and transportation service) if any policy can serve those demand. This maximum throughput policy also enables an analytical characterization of the minimum fleet size (or minimum

cost fleet if it can be heterogeneous) such that queues of passengers and energy will remain bounded in the long run.

Based on the stable dispatch policy we relax some assumptions and develop a policy that is more realistic for implementation. We pay particular attention to constraints on power flow in the electric grid to ensure realistic charging and discharging behavior (which is important for distribution system service restoration). The analysis and simulation also distinguishes between several potential objective functions which have important equity and stability impacts. We demonstrate how serving passengers from the longest queues first (a technique based on the 'pressure' from maximum stability dispatch) can lead to more equitable outcomes for passengers. Finally, we examine the impact of the time horizon needed for the model predictive control algorithm. A long time horizon is needed to incorporate charging and discharging as well as longer term trends in electric demand. We suggest that future research should examine heuristics to solve this problem more quickly than commercial solvers to enable real-time implementation.

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Chapter 1: Introduction

1.1 Background

Major developments in shared mobility-on-demand services, vehicle automation, and electrification are causing widespread changes to the transportation industry. Electric vehicles (EVs) are becoming more efficient and popular, and innovations such as smart charging and vehicle to grid (V2G) charging are creating new links between the electric grid and transportation networks (Unterluggauer et al., 2022). EVs have the potential to reduce electricity demand and voltage fluctuation and improve reliability and resilience in the electric grid if charging is optimized (Yao et al., 2019; Lei et al., 2018; Amini et al., 2019; Mohammadi et al., 2023). At the same time, advances in autonomous vehicle (AV) technologies are predicted to cause major disruptions to travel patterns (Dannemiller et al., 2021). As AVs are still a new and actively developing technology, it is predicted that their first widespread applications will be as shared autonomous vehicles (SAVs) – often called autonomous mobility-on-demand (AMoD) systems (Fagnant and Kockelman, 2015). Combining automation with mobility-on-demand services can make AVs cost competitive with privately owned vehicles in the long run (Hörl et al., 2019), can reduce the total fleet size necessary to serve demand (Boesch et al., 2016), and can improve roadway operations and control (Narayanan et al., 2020; Zhang and Guhathakurta, 2017; Chen et al., 2020).

The combination of EV and SAV technology enables a fleet of shared autonomous electric vehicles (SAEVs). Such vehicles can be dispatched to serve passenger demand and can collaboratively optimize charging and discharging schemes (Li et al., 2021b). As the fleet size must be large to serve peak hour demand, the incorporation of constraints related to the energy grid can enable additional uses for these vehicles when they are not needed for transportation. In particular, the combined battery storage of the fleet represents a important resource for peak shaving if charging and discharging behavior is coordinated (Amini et al., 2019; Chukwu and Mahajan, 2011; Mohammadi et al., 2023). However, such a system requires an optimization of both the fleet dispatch policy and the charging behavior in order to best leverage the resources of the entire fleet.

In addition to incorporating electric grid constraints into the normal operations of the SAEV fleet, there are additional resilience benefits when strains are put on the electric grid (Amirioun et al., 2023). Natural disasters can endanger the electric distribution system, causing equipment failures, blackouts, and even larger scale propagation of failures throughout the network (Neumayer and Modiano, 2013; Watson et al., 2014). In the event of electric outages, the electric resources of the SAEV fleet can be leveraged to continue providing power to affected areas (particularly critical facilities such as hospitals and shelters). In extreme cases, groups of EVs could be routed back and forth across outages to provide continuous power for long periods until repairs can be made. Previous research has examined transportable energy storage systems (which would require grid operators or government agencies to own and operator a fleet of dedicated vehicles) which would not need to transport passengers, but could be costly (Yao et al., 2019). When SAEVs are used, the benefits to electric consumers must be weighed against the continued needs of transportation passengers who may continue be reliant on the SAEV fleet after the disaster. Thus, the dispatch policy must continue to include both networks and must prioritize between these competing objectives. We will demonstrate that examining these problems in an integrated framework can have significant benefits compared with examining them each individually, as is commonly done in existing research (Li et al., 2021b; Yao et al., 2019). In particular, this research will examine how including only part of this interconnected system can lead to incorrect estimates of passenger waiting times, electric loads restored, and necessary fleet size.

The literature review in Chapter 2 summarizes existing previous research into SAV dispatch. This well studied topic has been examined from many perspectives with goals including determining the minimum fleet size, reducing passenger wait times using rebalancing strategies, determining parking needs and curb allocation, and studying the impact of increased vehicle miles traveled on congestion (Narayanan et al., 2020). Similarly, researchers have examined EV routing, charging and discharging optimization, and how behavior will impact vehicle availability at charging stations. However, the integration of these two research topics is less common. In particular, dispatch policies for SAEVs often assume unlimited power will be available at charging stations which may not necessarily be true as batteries become larger and fast chargers become more common (Weiss et al., 2017).

1.2 Problem Statements

In order to integrate electricity constraints into SAEV dispatch we start with a dispatch policy built on a queuing model using a model predictive control algorithm. This approach is beneficial because it allows us to prove that the policy can maximize throughput. We then relax some of the assumptions of that model to integrate other behaviors such as the flow of power through the electric network. Though we do not prove maximum throughput in the updated model, we discuss how relationships between the models (as well as other models from the literature) can demonstrate beneficial properties. The models below were developed to answer the following questions:

- ***Can EV discharging be incorporated into a maximum-stability dispatch framework to promote resilience of the electric grid while maintaining stability?*** One major reason for vehicles to discharge energy back to the grid is in the event of a power outage. This could become more common due to increasing frequencies of natural disasters. Luckily, it is possible to leverage the battery capacity of EVs to provide power to critical infrastructure such as hospitals or other emergency services.
  - ***What will be the impacts on fleet size?*** As demands on SAEVs grow beyond the just serving passenger demands, larger fleet sizes may be necessary. It is beneficial to have an analytical characterization of the minimum fleet size needed to serve all demand. In contrast, it would be possible to determine how much demand could be served with a given fleet size (for example if some subset

of SAEVs are providing power to a blackout by discharging, how much of the average demand could the remaining SAEVs still serve?)

- ***How can power flow constraints be integrated into a model of SAEV dispatch?*** As mentioned above, many authors have assumed that unlimited power can be taken from charging stations. If this assumption were to be relaxed, it might lead to a different spatial or temporal distribution of vehicles which could affect vehicle miles traveled, passenger waiting times, and the minimum fleet size.

- ***How does joint optimization of SAEV dispatch and power flow affect revenue, and how might pricing affect waiting times, grid stability, and equity?*** It is likely that a realistic SAEV dispatch policy will have an objective to maximize revenue or profit. However, with competing objectives it is not clear how this will affect passengers or charging/discharging behavior.

1.3 Organization

In this thesis we develop a SAEV dispatch policy which is able to take into account constraints based on both the electric and transportation networks to provide benefits of both. Chapter 2 examines previous literature on SAVs and EVs. We focus specifically on the development of dispatch policies for SAVs and the benefits that EVs and other transportable energy storage systems (TESS) can bring to the electric grid. Chapter 3 uses Lyapunov drift techniques to develop a dispatch policy for SAEVs which is proven to keep queues of passengers and energy demand stable were possible. This section extends previous research into maximum throughput dispatch by optimizing the movements of a (potentially) heterogeneous fleet of vehicles to serve multi-commodity demands. Based on the framework developed in Chapter 3, Chapter 4 develops a more realistic set of constraints for the dispatch of the SAEV fleet. This modified policy relaxes the typical assumption that unlimited power is available at charging stations and ensures that the supply of energy meets demand wherever possible. This section also includes detailed information on the operations of the electric grid in response to changing electric demands. Section 4.2.5 provides the objective of the dispatch policy, mixed integer linear program which is controlled by a series of cost functions. Section 4.3 provides additional insights into the effects of different cost functions and notes how some simple assumptions can allow this dispatch policy to simplify down to some more limited SAV and TESS policies from the literature. Chapter 5 demonstrates some of the benefits of this policy with a simulation of a large urban network. Finally, the paper ends with brief conclusions and recommendations for future extensions.

Chapter 2: Literature Review

2.1 Introduction

We split the literature review into four sections. First, we discuss recent work on SAVs, paying particular attention to benefits and dispatch policies. Though most of this work is agent-based, we discuss the importance of optimal control algorithms. Second, we focus on max-pressure control which is a particular class of SAV dispatch algorithms that have been proven to maximize throughput where possible. This approach provides some insights about the policy proposed in this paper. Third, we discuss the ways in which electric vehicles can be integrated with the electric grid. Though this is a very broad topic, we focus on recent developments of vehicle to grid (V2G) technology and the algorithms developed to leverage those benefits. We also discuss efforts to evaluate user behavior to predict EV availability at charging stations, a concern that is alleviated with an SAEV fleet. Finally, we discuss resilience and electric grid restoration. The SAV dispatch policy developed in this paper was developed with resilience in mind and is informed by past work on using distributed energy resources to improve electric grid resilience.

2.2 Shared Autonomous Vehicles

SAVs are an emerging and disruptive technology combining vehicle automation with advances in ride-hailing technologies. Past studies have come to different conclusions about the impacts of SAVs based on modeling frameworks, dispatch strategies, behavioral changes, and adoption rates (Narayanan et al., 2020). However, recent studies have shown that SAVs have the potential to reduce travel costs, congestion, parking needs, and emissions (Gurumurthy et al., 2019; Hyland and Mahmassani, 2020; Fagnant and Kockelman, 2018; Li et al., 2021b; Liu et al., 2017; Zhang et al., 2015; Narayanan et al., 2020). Many of these benefits, particularly those associated with costs and emissions, are amplified when SAV technology is combined with electrification (Weiss et al., 2017; Sprei, 2018). Though widespread adoption of such technologies is still distant, effective means of control of these vehicles is necessary.

The SAV dispatch problem is a type of vehicle routing problem, specifically a dial-a-ride problem. This problem involves assigning vehicles to pick up nearby passengers and take them to their destination (Cordeau and Laporte, 2007; Eksioglu et al., 2009; Seow et al., 2010; Maciejewski and Nagel, 2013). Though fundamentally the same problem, SAV dispatch is typically assumed to encompass a much larger fleet size and have stochastic demand. Zhao and Malikopoulos (2022) note that there are two major types of SAV modeling seen in the literature. The majority of research has produced agent-based models which examine the system behavior when each individual and vehicle follow simple rules. This approach is easy to implement and simulate for different scenarios but may produce very different results based on heuristic rules. The other area of research is analytical modeling which examines the SAV system as a queuing system and optimizes the dispatch.

Agent-based simulations have reported some important impacts of SAVs. In particular, studies have found that 1-10 personal vehicles could be replaced by a single SAV (Zhang and Pavone, 2016; Fagnant and Kockelman, 2014; Chen et al., 2016b; Levin et al., 2017; Masoud and Jayakrishnan, 2017; Fagnant and Kockelman, 2018; Lokhandwala and Cai, 2018; Moreno et al., 2018). The majority of studies suggest an increase in vehicle miles traveled in the range of 5% to 25% (Fagnant and Kockelman, 2014; Masoud and Jayakrishnan, 2017; Jäger et al., 2017), though some studies suggest decreases when ride-sharing is allowed (Bischoff et al., 2017; Vosooghi et al., 2019). Two other major areas of research are vehicle rebalancing and electrification. Vehicle rebalancing (repositioning empty vehicles to anticipate future demand) is simplified in agent-based simulation, and several studies have demonstrated that this can reduce waiting times while increasing vehicles miles traveled (Fagnant and Kockelman, 2018; Lokhandwala and Cai, 2018; Vosooghi et al., 2019; Cramer and Krueger, 2016; Komanduri et al., 2018; Hörl et al., 2019). Hörl et al. (2019) notes that intelligent operations or larger fleet sizes can reduce the need for rebalancing, but that rebalancing along with demand forecasts could be critical to making SAV fleets competitive with other transportation options. The routing and recharging behavior of EVs is also easier in an agent-based simulation, and several studies have included these constraints (Chen et al., 2016b; Chen and Kockelman, 2016; Jäger et al., 2017; Loeb and Kockelman, 2019; Zhang and Chen, 2020). Loeb and Kockelman (2019) found that an SAEV fleet is not yet financially viable compared to gasoline hybrid-electric vehicles (HEVs), but that long-range EVs with fast-charging capabilities provide the best service and are the most profitable of any EV fleet studied and will have substantial environmental benefits when compared with HEVs.

Though the benefits found in agent-based simulations make a strong case for the use of SAVs, the range of results suggests a need for an optimization framework that can better control vehicles across scenarios (Zhao and Malikopoulos, 2022). In addition, Hörl et al. (2019) suggest that the simplistic approaches used in many large-scale simulations are insufficient to estimate the true benefit of SAVs, and that many results reported in the past may underestimate those benefits. However, analytical frameworks used for optimization of the entire fleet can quickly become computationally expensive unless major assumptions are made (Levin, 2022). Hyland and Mahmassani (2018) demonstrated that several optimization-based methods outperformed simplistic first-come-first-serve assignment strategies that are often employed using agent-based simulations. These gains are largest when fleet sizes are small. Other authors have considered user equilibrium (Chen and Levin, 2019; Ge et al., 2021), and system optimal (Levin et al., 2019a; Salazar et al., 2019; Wollenstein-Betech et al., 2020) routing when congestion is included in the model. Other extensions such as ridesharing (Alonso-Mora et al., 2017; Tsao et al., 2019), rebalancing (Robbennolt and Levin, 2023) and EV charging (Iacobucci et al., 2019; Boewing et al., 2020) constraints have also been modeled. These constraints present challenges as they vastly increase the computational complexity of the problem. However, rebalancing can reduce passenger wait times, ridesharing can reduce wait times and vehicle miles traveled, and electrification can be beneficial for sustainability. For this reason, these areas are all in need of additional exploration from an analytical perspective.

Vehicle rebalancing has been studied either as a second step after dispatch decisions have been made (Pavone et al., 2012; Volkov et al., 2012; Zhang and Pavone, 2016; Sayarshad and Chow, 2017; Wen et al., 2017), or jointly alongside the passenger assignment problem

(Fagnant and Kockelman, 2014; Burghout et al., 2015; Zhang et al., 2016; Guériau and Dusparic, 2018). Many authors using analytic approaches examine the long-run behavior of their model (Pavone et al., 2012; Volkov et al., 2012; Kang and Levin, 2021). The next section will examine a specific subset of these based on max-pressure control algorithms. Zhang et al. (2016) tested their algorithm against several others from the literature and found that their model predictive control methodology outperformed the other models (though it scales poorly as network size increase). Iacobucci et al. (2019) extended the same framework to examine the tradeoffs between charging EVs and reducing passenger wait times. They found that they could reduce charging costs without impacting waiting times significantly, but that the variability of electricity prices impacted their results significantly. Boewing et al. (2020) also used an analytic routing approach that accounted for EV battery level and energy availability. Several other authors have examined network flow problems coupling the energy and transportation networks, though they typically do not focus on direct dispatch decisions and often assume passenger requests are known a priori (Rossi et al., 2020; Estandia et al., 2021; Tucker et al., 2019).

2.3 Maximum Stability Dispatch

Maximum stability dispatch is a type of optimal dispatch based on a queuing model. This strategy attempts to find a policy that can serve all passenger demand if any policy can serve all demand. This is a mathematically provable property under certain assumptions about how vehicles move in the network. For a stable policy, the arrival rate is equal to the service rate and the policy maximizes throughput. Maximum stability policies are not unique to SAV dispatch. Tassiulas and Ephremides (1992) first proposed a maximum stability policy called backpressure control to scheduling data transfers in multihop radio networks. This policy was later extended to traffic networks by Varaiya (2013) and Wongpiromsarn et al. (2012). These authors developed max-pressure control algorithms for traffic signal controllers and proved that they could serve all demand if any controller could serve all demand.

Since the introduction of max-pressure control to the traffic context, many authors have studied traffic signals to incorporate these provable properties (Xiao et al., 2014; Gregoire et al., 2015; Le et al., 2015; Wu et al., 2018; Sun and Yin, 2018; Mercader et al., 2020; Levin et al., 2020; Robbennolt et al., 2022). Extensions have also been made to ensure stability in other areas of the transportation systems including route choice (Taale et al., 2015; Zaidi et al., 2016; Chai et al., 2017), pedestrian access to autonomous intersections (Chen et al., 2020), and dynamic lane reversals (Levin et al., 2019b). All of these applications rely on the fundamental idea that when the control mechanism is insufficient, queue lengths grow with no bound. However, using a Markov decisions process, it is possible to prove that some controllers can stabilize queues if any controller can serve all demand.

The same idea can be applied to an SAV dispatch policy. In this case, a fixed fleet of SAVs is used to serve passenger demand and the goal is to stabilize the queue of passengers if possible. Most proofs have ensured that as time grows to infinity the number of passengers waiting for a vehicle will not also grow to infinity. Kang and Levin (2021), Xu et al. (2021), and Robbennolt and Levin (2023) all used a similar queuing model. The initial paper developed a stable dispatch policy using a planning horizon in their stability proof (Kang and Levin, 2021). The subsequent papers developed similar policies that did not rely on a planning horizon (Xu et al., 2021), and extended the policy to allow for vehicle rebalancing (Robbennolt and Levin, 2023). These three papers provide the basis for the queuing model that will be utilized in the dispatch policy developed below.

Several other papers developed stable dispatch policies around the same time. Li et al. (2021b) examined the stability of an electrified SAV fleet. Though they include electric vehicle charging constraints in their model, they do not include any vehicle rebalancing. They also did not consider any electric grid constraints. They modeled the vehicles and passengers as nodes in their network, utilizing a different queuing structure and stability proof. Finally, Levin (2022) developed a more general characterization of the dispatch problem that allowed electric SAVs, dynamic ridesharing, and integration with public transit. They also define stability slightly differently, defining the network to be stable if the head-of-line waiting times for passengers remain bounded. Though this changes the proof of stability, it leads to the same maximum throughput property of the other controllers. Finally, Xu et al. (2023)

developed a framework that allowed passengers to exit due to long waiting times. They redefined stability to ensure that the average cumulative number of unserved passengers in the long run equals zero.

2.4 Electric Grid Integration

EV routing studies are very similar to the traditional vehicle routing problem, but with the added constraints that EVs must find places to charge when low on energy (Felipe et al., 2014; Lin et al., 2016; Paz et al., 2018). This is a particular concern for today's vehicles, which have limited battery capacity and long charging times, but could be less problematic (for short trips) as capacities increase in the future. Though this is a well-studied topic (Pelletier et al., 2016; Juan et al., 2016; Dammak et al., 2019; Erdelić and Carić, 2019; Qin et al., 2021), Kucukoglu et al. (2021) suggests that more research needs to be done on the impact of realistic monetary objective functions combining the costs of travel time, charging, emissions, etc. Several notable constraints that can increase computational time are the need to keep track of the (potentially stochastic) state of charge, the potentially heterogeneous fleet of EVs, and the availability of charging stations (which could cause queue buildup) (Abid et al., 2022). We refer interested readers to Abid et al. (2022) and Schiffer et al. (2019) for comprehensive reviews on EVs routing and charging behavior. In addition, several of the studies mentioned above on SAVs have included EV constraints.

Many transportation studies have neglected the impact of EVs on the grid. Many assume that infinite power is available both spatially (Goeke and Schneider, 2015; Pourazarm et al., 2016) and temporally (Rotering and Ilic, 2011; Tushar et al., 2012). Subsequent studies assumed some interaction between grid operators and EV owners through pricing schemes (Hadley and Tsvetkova, 2009; Wang et al., 2010; Shimizu et al., 2010). Though SAEV routing poses some constraint on fleet operations, a large concern is the impact of charging behavior on the electric grid. This effect is often neglected in routing studies but has long been recognized as a potential drawback of EVs if not managed correctly. Putrus et al. (2009) found that incorrectly managed EV charging could lead to power quality problems, but that appropriate control could negate these concerns and lead to benefits such as peak shaving and voltage and frequency control. The impacts of EV charging have also been studied in the context of charging location (Deb et al., 2018; Galadima et al., 2019; Unterluggauer et al., 2022). Such studies find that EVs can cause major voltage instabilities, reduce reliability, and cause power losses in the distribution system if charging locations are not carefully selected and upgraded (Deb et al., 2018). Though the siting of charging stations is not considered in this study, these concerns can be alleviated from an operational perspective if vehicle charging is coordinated (Ahmad et al., 2022).

Though concerns still exist, it is clear that there are also many potential benefits to the electric grid. Tomić and Kempton (2007) found that a fleet equipped with vehicle to grid (V2G) charging technology was economical to operate and could also improve stability of the grid. Lund and Kempton (2008) demonstrated that integration of EVs and renewable has benefits to each in helping to align the electricity demand and supply curves. Peak shaving is of particular importance and V2G charging allows EVs to shift loads between peak and off-peak times. Moradijoz et al. (2013) found that optimal allocation of parking lots and charging/discharging scheduling can lead to economic benefits for EV users and grid operators due to peak shaving. Other studies have found similar benefits when considering coordinated control of EV charging (Liu et al., 2013; Shimizu et al., 2010; Zhong et al., 2014; Wu et al., 2022b). However, these studies often consider only charging station behavior or examine vehicles in driving or parked states only.

Unfortunately, studies examining the effects of EVs on the distribution and optimizing charging behavior generally assume predefined probability distributions of EV availability and use patterns which may not be realistic. Some recent behavioral research has attempted to fill this gap by using activity based modeling to predict when vehicles will be available at charging stations (Daina et al., 2017a,b; Chung et al., 2019; Latinopoulos et al., 2021). Latinopoulos et al. (2021) combined behavioral modeling with a pricing scheme to demonstrate revenue increases for parking operators along with stability benefits to the energy grid. Though this research direction has yielded promising results, the representation of charging behavior is still not sufficiently realistic (Daina et al., 2017b). In the short term, research into behavioral modeling of individual charging decisions is critical. However, the use of an SAEV fleet means the modeling of charging behavior can be neglected in favor of a optimal dispatch approach. There are few studies that have considered both the routing and charging impacts of and SAEV fleet together from an analytical perspective, particularly considering power flow in the distribution system (Boewing et al., 2020).

2.5 Resilience and Electric Grid Restoration

Though the day-to-day operation of SAEVs and the electric grid is of critical importance, disaster resilience is also an area of concern. Generally, one of the primary goals post-disaster is to ensure as many electric loads are served as possible (Wang et al., 2016). Much work has been done on using stationary distributed energy resources to help with grid restoration (Chanda and Srivastava, 2016; Panteli et al., 2017). This can be done by splitting the isolated distribution system into microgrids which aggregate loads for each generator (Gao et al., 2016; Xu et al., 2018; Chen et al., 2016a). Other approaches include using topology switching (Huang et al., 2017; Wang et al., 2017), mobile generators (Sedzro et al., 2018; Lei et al., 2018), load shedding (Kabir et al., 2020), and transportable energy storage systems (Yao et al., 2019).

Though little research has been done on SAEVs and grid reliability and restoration, there has been recent work on dispatch of other distributed energy resources (DERs) (also called transportable energy storage systems (TESSs) or mobile energy storage systems (MESSs)). Gao et al. (2017) and Xu et al. (2019) studied the role of electric bus dispatch in distribution system load restoration. However, neither paper considered the continued transit needs of those resources. Li et al. (2021a) developed a bus dispatch policy which continued transit operations but modified existing bus routes to allow some buses to be used for grid restoration. This framework allows routes to be assigned a priori, negating the need to make decisions as a function of time. Additional research indicates that mobile energy generators or storage systems can provide additional benefits if they are jointly optimized with grid reconfiguration (Sun et al., 2015; Kim and Dvorkin, 2018; Yao et al., 2019; Kim and Dvorkin, 2019; Yao et al., 2020; Lu et al., 2022). Kim and Dvorkin (2019) notes that these technologies can allow costly distribution systems to be deferred, and TESSs can be more environmentally friendly and portable than portable emergency generators.

Several previous studies have specifically examined EVs as mechanisms for grid resilience enhancements. Gouveia et al. (2013) performed extensive simulation demonstrating that leveraging the flexibility of EVs can have positive impacts on service restoration. In particular they demonstrated that they could reduce frequency deviations when connecting new active loads to the microgrid and that EVs provide improvements in voltage quality. Rahimi and Davoudi (2018) used EVs and hybrid electric vehicles (which could also generate electricity with gasoline engines) to provide residential power after a hurricane. However, they only considered a scenario of individual vehicles providing power to individual households rather than a coordinated fleet providing power to localized outages. Mohsen et al. (2014) utilized a fleet of EVs to provide power to islanded power grids but did not incorporate routing constraints. Though they also do not include routing constraints, Dong et al. (2023) developed a distributed control algorithm for EVs which provides many of the same benefits while reducing computational complexity and increasing privacy. Many subsequent studies have also shown benefits of using EVs as mobile energy resources during grid restoration (Sun et al., 2019; Hamidi et al., 2019; Ali et al., 2021).

Unfortunately, EVs controlled by individual drivers are unpredictable and some users might not allow these resources to be used if they are not directly benefited. This means that these approaches are forced to rely on predictions of stochastic availability of vehicles (which may not be accurate in disaster scenarios) (Sandels et al., 2010; Chukwu and Mahajan, 2011; Han et al., 2011). Though these are necessary approaches in the short term, future developments in pricing schemes or SAV technology could allow vehicle routing to be added to the decision-making process. Erenoğlu et al. (2022) defined a EV dispatch system for load restoration assuming a collaboration between a fleet operator and distribution system operator. However, they assume that EVs are always willing to assist in restoration when nearby regardless of transportation system requirements. Wu et al. (2022a) addresses some of these concerns by utilizing a clustering methodology for grid restoration and a incentive mechanism based on Nash Bargaining Theory. However, the need for EVs to serve passengers are still neglected. Amirioun et al. (2023) is the only paper to study an SAEV fleet under energy grid resilience objectives. Though they allow the fleet to serve passengers, they assume predictable outages and require vehicles to stop to discharge once that outage has occurred. In addition, though they demonstrate promising results, they rely on agent-based simulation and a dispatch heuristic which has no guarantee of optimality.

2.6 Contributions

Based on the literature surveyed above we note an important gap in the perspective of researchers examining integration of EVs with the electric grid. Transportation engineers tend to assume that energy is always available at charging stations and neglect the impacts that vehicles can have on the grid, which could lead to instabilities. In the context of an SAEV fleet, overlooking these constraints could cause underestimates of the charging time needed for vehicles to reach full power and result in estimates of fleet sizes and travel times that are too low. On the other hand, benefits such as peak shaving are often overlooked which could affect vehicle replacement rates if the value of this benefit is high enough to offset the cost of vehicles that are only used for transportation needs during peak hours. Electrical engineers, on the other hand, often consider only the charging behavior of vehicles with less consideration of their availability for transportation needs. This is particularly apparent in studies of EVs as a resilience tool after power outages where there is generally assumed to be no passenger demand. However, this assumption is unrealistic as many passengers may be reliant on SAEV services, including essential workers whose services may be needed in the aftermath of a natural disaster. Neglecting the continued demands on these vehicles to serve passengers can lead to overestimates of their abilities to serve electric demands across the network. In particular, as an SAEV fleet would generally have a higher utilization rate than individually owned vehicles, neglecting transportation demands could lead to overestimates of the benefits of peak shaving.

We propose a dispatch framework that would bridge this gap by incorporating constraints from both the electric grid and the transportation system. We develop a constraint set based on the LinDistFlow model of the electricity distribution system to characterize the interaction between EVs and the grid (see (Baran and Wu, 1989b,c; Turitsyn et al., 2010; Yeh et al., 2012; Yao et al., 2019)). We build the transportation side dispatch policy based on Markov queuing model and a constraint set that has been proven to maximize demand wherever possible in the absence of electric grid constraints (Kang and Levin, 2021). Though these models have been used before individually, their combination provides new insights into passenger throughput, fleet size, energy peak shaving, and resilience. We provide particular attention to the resilience of the electric grid after a disaster and demonstrate how the excess (mobile) battery capacity of a SAEV fleet can be harnessed to serve electric loads that would otherwise be cut off from the grid. Though this has been examined in the past, the goal of also serving passengers has always been neglected.

Combining these constraints to find an optimal dispatch policy is a multi-objective decision problem. In cases when all electric loads and passenger demands cannot be served, decisions need to be made about which to prioritize. Though we make no claims of an optimal pricing scheme, we demonstrate the impacts of different pricing schemes in a simulation. At the same time this simulation allows us to compare our dispatch strategy to strategies considering only passenger demand or electric demand in their optimization. We demonstrate that existing approaches examining only one system will overestimate either the transportation benefits or the electric grid benefits of the SAEV fleet slightly. However, we note that the combined policy can have significant benefits to both systems without significant decreases in performance to either system (particularly when fleet sizes are large relative to demands).

Chapter 3: Maximum Stability Dispatch

3.1 Introduction

The passenger queuing model used in this paper is based on maximum stability dispatch policies developed by Kang and Levin (2021), Xu et al. (2021), and Robbennolt and Levin (2023). These papers developed dispatch policies that were proven to serve all demand if any policy can serve all demand. The contributions of the modified policy presented in this section are that: (1) We include potential charge and *discharging* behaviors, extending the methodology of Levin (2022) but utilizing passenger queues instead of head-of-line waiting time in the stability analysis. (2) We develop a policy which can dispatch a heterogeneous fleet of vehicles to serve multi-commodity demand. (3) We characterize the minimum fleet size and minimum cost fleet needed to serve all demand given a set of known vehicle types.

In order to develop a dispatch policy that can incorporate vehicle charging into the stability proof we must make two assumptions (which will be relaxed in future sections). First, we assume that there is some subset of charging stations connected to the grid from which we can take arbitrarily high amounts of power. Other charging stations may potentially be disconnected from the grid due to disasters and will require SAEVs to discharge to satisfy those demands. This is a very common constraint for transportation routing studies and is realistic for vehicles with low charging rates and small batteries (Erdelić and Carić, 2019). Second, we assume that electric demands form a queuing model much like passenger demands. We assume electric demands do not need to be served immediately, but instead accumulate until served. This assumption is sufficient for some loads that can be put off until after the outage (such as personal EV charging), but many other continuous loads might be paused temporarily and restarted as normal after the outage. A queuing assumption is not as realistic for these loads. Equivalently, we can reformulate this by assuming an arbitrarily large battery located at each node which starts fully charged. The proof of stability will demonstrate that this battery will never become depleted given some finite starting charge.

Again, there are instances where this could be realistic (such as critical facilities like hospitals), but is not always appropriate for all loads. Note that if this assumption does not hold in reality the network will still be stable (since lost loads will decrease the queue length), but not all demand will be served in the long run. The proof of stability is still important from an equity perspective (all loads will be served if possible, regardless of how difficult they are to serve).

3.2 Queuing Model

We are given some network $\mathcal{G} = (\mathcal{N}, \mathcal{A})$ with nodes $\mathcal{N}$ and links $\mathcal{A}$ (see Table A1 for a list of notation). We also have a set of vehicles $\mathcal{V}$ and a set of commodities that need to be served (passengers, goods, other services) $\mathcal{M}$. Each vehicle has a state of charge e which is discretized between the bounds $\underline{e}$ and $\bar{e}$. $x_q^{v,e}(t) \in \{0, 1\}$ denotes whether vehicle v is parked at node q with charge e at time t. Using the travel times ${}_\alpha C_{qr}^{v,e}$ and energy changes ${}_\alpha B_{qr}^{v,e}$, we can track the evolution of parked vehicles. These travel times and energy consumption depend on the vehicle v, initial state of charge e, starting and ending nodes (r and s), and the decisions variable α which will be defined later. Generally, $x_q^{e,v}(t)$ will be zero unless a vehicle stays parked from the previous timestep. It will also become 1 if a vehicle arrives at node q having departed s ${}_\alpha C_{sq}^{v,(e - {}_\alpha B_{sq}^{v,e'})}$ timesteps ago with charge $e - {}_\alpha B_{sq}^{v,e'}$. If $x_q^{v,e}(t)$ was previously 1, it will become 0 if the vehicle is dispatched. We also note that travel times and charging behavior could vary by vehicle and energy level of the vehicle. These variables include any charging and discharging at the destination node which could increase the travel time and either increase or decrease the state of charge e.

$$x_q^{v,e}(t+1) = x_q^{v,e}(t) + \sum_{s \in \mathcal{N}} \sum_{e' \in [\underline{e}^v, \bar{e}^v]} y_{sq}^{v,e - {}_\alpha B_{sq}^{v,e'}}(t + 1 - {}_\alpha C_{sq}^{v,(e - {}_\alpha B_{sq}^{v,e'})}) - \sum_{r \in \mathcal{N}} y_{qr}^{v,e}(t)$$
$$\forall q \in \mathcal{N}, \forall e \in [\underline{e}^v, \bar{e}^v], \forall v \in \mathcal{V} \qquad (3.1)$$

The dispatch decision $y_{qr}^{v,e}(t)$ represents a vehicle dispatched to drive from q to r with starting energy value e. This can only to occur if there is a vehicle parked at q available for dispatch.

$$\sum_{r \in \mathcal{N}_R} y_{qr}^{v,e}(t) \leq x_q^{v,e}(t) \qquad \forall q \in \mathcal{N}, \forall e \in [\underline{e}^v, \bar{e}^v] \tag{3.2}$$

Finally, we must keep track of queues of each commodity m with ${}^m w_{qr}(t)$. These queues represent any use of the SAEV including serving passengers moving between q and r taking taking packages or food between those nodes, or discharging energy at node r. We also admit different types of passenger queues such as mobility-on-demand services today which allow passengers to request different vehicle types or services (large vehicles, luxury/economy options, options allowing pets, or vehicles which can accommodate other special needs). Each of these options would be stored in a separate queue. Ridesharing between the same origin and destination is allowed, but do not allow sharing between riders with different origins or destinations. Refer to Levin (2022) for how this behavior could also be incorporated.

$$\begin{aligned} {}^m w_{qr}(t+1) = {}^m w_{qr}(t) + {}^m d_{qr}(t+\tau) - \min\{{}^m w_{qr}(t), \sum_{v \in \mathcal{V}} \sum_{e \in [\underline{e}^v, \bar{e}^v]} {}^m \alpha_{qr}^{v,e}(t) \times y_{qr}^{v,e}(t)\} \\ \forall (q,r) \in \mathcal{N}_R^2, \forall m \in \mathcal{M} \end{aligned} \tag{3.3}$$

Here, the decision variable ${}^m \alpha_{qr}^{v,e}$ is the number of units each vehicle removes from the queue ${}^m w^{qr}$. These may differ across the network and across vehicles. Note that in general this admits some other constraints: a vehicle may not be able to carry two types of customers at once, so it is possible that ${}^1 \alpha_{qr}^{v,e}$ and ${}^2 \alpha_{qr}^{v,e}$ cannot be non-negative at the same time. An alternate rule could set a maximum number of passengers, so two queues could be served but their total would be constrained (${}^1 \alpha_{qr}^{v,e} + {}^2 \alpha_{qr}^{v,e} \leq c^v$ where c^v is the passenger capacity of vehicle v). On the other hand, since the state of charge and charging/discharging behavior does not affect the capacity of the vehicle (unlike serving passengers, picking up packages, etc.), ${}^{discharge} \alpha_{qr}^{v,e}$ can always be set to the discharge rate if there is a charging station at r and 0 otherwise.

Note that ${}_\alpha B_{rs}^{v,e}$ and ${}_\alpha C_{rs}^{v,e}$ are constant (including charging/discharging time) regardless of ${}^m \alpha_{qr}^{v,e}$ for all commodities m other than charging or discharging. However, they should include some time for the decision to charge/discharge. Then, we can write ${}_{\alpha}B_{rs}^{v,e} = B_{rs}^{v,e} + b \times {}^{charge}\alpha_{rs}^{v,e} + b \times {}^{discharge}\alpha_{rs}^{v,e}$. Here b is a charging rate to convert the alpha term to the appropriate units (a similar equation could be written with c to convert to the time needed for the charging or discharging ${}_{\alpha}C_{rs}^{v,e}$). This formulation also admits trips from q to the same node q which would never serve any passengers but would have potentially non-zero travel times if any charging or discharging behavior occurs. Any implementation of this multi-commodity dispatch problem would need to define these constraints to ensure that each vehicle is respecting capacity constraints based on each commodity individually and in all combinations. For this formulation to work we will include an infinite "queue" of available energy at any charging station connected to the grid to allow vehicle to take energy, and a queue of energy representing accumulated demand at any disconnected stations (with no available power). However, the commodity representing vehicle charging at stations connected to the grid will not be included in the objective function since this commodity is not a service and is rather only allowing vehicles to recharge.

The Markov decision process is represented by the network state: ${}^{m}w_{rs}(t)$, and $x_q^{v,e}(t)$ and the decision variables represented by the dispatch decision ${}^{m}\alpha_{qr}^{v,e}(t)$ and $y_{qr}^{v,e}(t)$. When the dispatch policy is known, this forms a Markov chain. The state of the system evolves based on equations (3.1), (3.2), and (3.3).

3.3 Maximum Stability Dispatch

In this section we present the maximum stability dispatch policy $\pi^{\star}$. For now we include only the pressure term in the objective function, but will later describe additional terms that can be added to achieve goals other than stability without impacting the stable region.

$y_{qr}^{v,e} \in \{0, 1\}$ continues to represent the dispatch decision for a vehicle v with state of charge e to travel from node q to r. We will also denote ${}^{m}Y_{qr}^{v,e} \geq 0$ to represent the reduction in queue length (number of passengers, packages, amount of energy, etc.) that vehicle v will achieve from queue m. This will be constrained by the availability of the vehicles and the queue length of that commodity. The program is run over the horizon $[t, t+T]$ (indexed by τ). The first set of decisions (when $\tau = 0$) is saved and the rest is discarded. The program can the be run again at the next timestep with updated information.

We state the full mixed integer-linear program as follows:

$$\max \quad \frac{1}{T}\sum_{\tau=1}^{T}\sum_{(q,r)\in\mathcal{N}^2}\sum_{m\in\mathcal{M}} {}^{m}w_{qr}(t)\times\left[\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^{m}Y_{qr}^{v,e}(t+\tau)\right] \tag{3.4a}$$

$$\text{s.t.} \quad x_q^{v,e}(t+\tau+1) = x_q^{v,e}(t+\tau) + \sum_{s\in\mathcal{N}_R}\sum_{e'\in[\underline{e}^v,\bar{e}^v]} y_{sq}^{v,e-{}_{\alpha}B_{sq}^{v,e'}}(t+\tau+1-{}_{\alpha}C_{sq}^{v,(e-{}_{\alpha}B_{sq}^{v,e'})})$$

$$-\sum_{r\in\mathcal{N}_R} y_{qr}^{v,e}(t+\tau) \qquad \forall q\in\mathcal{N}_R, \forall e\in[\underline{e}^v,\bar{e}^v], \forall v\in\mathcal{V}, \forall\tau\in[0,T] \tag{3.4b}$$

$$\sum_{r\in\mathcal{N}_R} y_{qr}^{v,e}(t+\tau) \le x_q^{v,e}(t+\tau) \qquad \forall q\in\mathcal{N}_R, \forall e\in[\underline{e}^v,\bar{e}^v], \forall v\in\mathcal{V}, \forall\tau\in[0,T] \tag{3.4c}$$

$$\sum_{m\in\mathcal{M}} {}^{m}Y_{qr}^{v,e}(t+\tau) \le M\times y_{qr}^{v,e}(t+\tau) \quad \forall (q,r)\in\mathcal{N}_R^2, \forall m\in\mathcal{M}, \forall e\in[\underline{e}^v,\bar{e}^v], \forall v\in\mathcal{V}, \forall\tau\in[0,T] \tag{3.4d}$$

$${}^{m}Y_{qr}^{v,e}(t+\tau) \le {}^{m}\alpha_{qr}^{v,e}(t+\tau) \qquad \forall (q,r)\in\mathcal{N}_R^2, \forall m\in\mathcal{M}, \forall e\in[\underline{e}^v,\bar{e}^v], \forall v\in\mathcal{V}, \forall\tau\in[0,T] \tag{3.4e}$$

$$\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^{m}Y_{qr}^{v,e}(t+\tau) \le {}^{m}w_{qr}(t+\tau) \qquad \forall (q,r)\in\mathcal{N}_R^2, \forall m\in\mathcal{M}, \forall\tau\in[0,T] \tag{3.4f}$$

$$y_{qr}^{v,e}(t+\tau)\in\{0,1\} \qquad \forall (q,r)\in\mathcal{N}_R^2, \forall e\in[\underline{e}^v,\bar{e}^v], \forall v\in\mathcal{V}, \forall\tau\in[0,T] \tag{3.4g}$$

$${}^{m}Y_{qr}^{v,e}(t+\tau)\ge 0 \qquad \forall (q,r)\in\mathcal{N}_R^2, \forall m\in\mathcal{M}, \forall e\in[\underline{e}^v,\bar{e}^v], \forall v\in\mathcal{V}, \forall\tau\in[0,T] \tag{3.4h}$$

$${}^{charge}Y_{qr}^{v,e}(t+\tau) = 0 \qquad \forall (q,r)\in\mathcal{N}_R^2, \forall e\in[\underline{e}^v,\bar{e}^v], \forall v\in\mathcal{V}, \forall\tau\in[0,T] \tag{3.4i}$$

$${}^{m}\alpha_{qr}^{v,e}(t+\tau)\ge 0 \qquad \forall (q,r)\in\mathcal{N}_R^2, \forall m\in\mathcal{M}, \forall e\in[\underline{e}^v,\bar{e}^v], \forall v\in\mathcal{V}, \forall\tau\in[0,T] \tag{3.4j}$$

$${}^{m}\alpha_{qr}^{v,e}(t+\tau)\le {}^{m}\zeta^{v} \qquad \forall (q,r)\in\mathcal{N}_R^2, \forall m\in\mathcal{M}, \forall e\in[\underline{e}^v,\bar{e}^v], \forall v\in\mathcal{V}, \forall\tau\in[0,T] \tag{3.4k}$$

Note that since constraints (3.4d) and (3.4e) are linearizations of the constraint $y_{qr}^{v,e}(t+\tau)\times {}^{m}\alpha_{qr}^{v,e}(t+\tau) \geq {}^{m}Y_{qr}^{v,e}(t+\tau)$ using big-M notation. These constraints along with constraint (3.4f) restrict the removal of units from each queue according to equation (3.3). Constraints (3.4b) and (3.4c) correspond to equations (3.1) and (3.2). The constraint on the charging decision, constraint (3.4i), continues to allow vehicles to charge but does not encourage them to do so by removing that term from the objective function (hence setting ${}^{charge}Y_{qr}^{v,e}(t+\tau) = 0$). Finally, since we did not define specific relationships between the ${}^{m}\alpha_{qr}^{v,e}$ variables, constraint (3.4j) restricts this decision to be non-negative and constraint (3.4k) stands in for other relationships between these based on the capacity of the vehicle. The remaining constraints ensure non-negativity and of queue removals and binary dispatch decisions.

This program determines optimal dispatch ${}^{m}\alpha_{qr}^{v,e}(t)$ and $y_{qr}^{v,e}(t)$ (where $\tau = 0$). The remainder of the solution is discarded and the problem will be solved again with updated queues at the next timestep.

3.4 Definition of Stability

We follow the logic of Varaiya (2013) and Kang and Levin (2021), and define the *stability* of the network as follows:

Definition 1. *The network is stable if the expected number of waiting passengers remains bounded over time. Thus, the network is stable if there exists a $\kappa < \infty$ such that*

$$\lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} \sum_{(r,s)\in\mathcal{N}_R^2} \sum_{m\in\mathcal{M}} \mathbb{E}\left[{}^{m}w_{qr}(t+\tau)\right] \leq \kappa \tag{3.5}$$

This definition is equivalent to Theorem 2 of Leonardi et al. (2001) where strong stability was defined as follows:

Lemma 1. *The system is stable if there exists a Lyapunov function $\nu(\boldsymbol{w}(t)) \geq 0$ and constants $\kappa < \infty$, $\epsilon > 0$ such that*

$$\mathbb{E}\left[\nu(\boldsymbol{w}(t+1)) - \nu(\boldsymbol{w}(t)) |\, \boldsymbol{w}(t)\right] \leq \kappa - \epsilon |\boldsymbol{w}(t)| \tag{3.6}$$

Proof. Following the proof of Theorem 2 by Varaiya (2013), we can take the expectation of both sides of equation (3.6) and then sum from $t = 1$ to $t = T$:

$$\mathbb{E}\left[\nu(\boldsymbol{w}(T+1)) - \nu(\boldsymbol{w}(1)) |\, \boldsymbol{w}(t)\right] \leq \kappa T - \epsilon \sum_{t=1}^{T} |\mathbb{E}\left[\boldsymbol{w}(t)\right]| \tag{3.7}$$

The absolute value in the final term can be dropped since the number of waiting passengers must always be non-negative. In addition, the expectation on the left can be broken into the two components. Finally, dividing equation (3.7) by T allows it to simplify:

$$\begin{aligned}
&\epsilon \frac{1}{T} \sum_{(t=1)}^{T} \mathbb{E}\left[\boldsymbol{w}(t)\right] \\
&\leq \kappa - \frac{1}{T} \mathbb{E}\left[\nu(\boldsymbol{w}(T+1))\right] + \frac{1}{T} \mathbb{E}\left[\nu(\boldsymbol{w}(1))\right] \\
&\leq \kappa + \frac{1}{T} \mathbb{E}\left[\nu(\boldsymbol{w}(1))\right]
\end{aligned} \tag{3.8}$$

Equation (3.8) is equivalent to the definition of stability in Definition 1. □

Based on this definition we will first provide an analytic formulation to determine the minimum fleet size to keep passenger queues bounded. This can also be used to show bounds on waiting times and analytically demonstrate the stable region. Next, we will demonstrate that there is a minimum planning horizon for the dispatch policy $\pi^\star$ which will achieve stability. Finally we will provide a formal proof of the stability of the developed dispatch policy $\pi^\star$. We note that if some dispatch policy is stable for every demand in $\mathcal{D}$ then it has the maximum stability property.

3.5 Minimum Fleet Size

Previous authors have needed to developed clever tricks to quantify the fleet size. Kang and Levin (2021) used a summation over all vehicle locations since they kept track of the vehicle at every location along their paths. Xu et al. (2021) and Robbennolt and Levin (2023) instead noted that the average dispatch rate multiplied by the travel time must also be less than the fleet size F. The queuing model developed in this paper keeps track of each vehicle separately, so the fleet size is known. However, we can define a large set of *potential* vehicles $\tilde{\mathcal{V}}$ which a program can choose from. To do this we will define the term $\rho^v \in \{0,1\}$ as a binary variable indicating whether vehicle v is in the fleet. Previous authors have minimized only the fleet size itself, though we note that simply multiplying the vehicles by their cost R^v can also determine the minimum cost fleet. This is valuable when considering a heterogeneous fleet of vehicles.

$$\min \quad \sum_{v\in\tilde{\mathcal{V}}} R^v \times \rho^v + \epsilon \tag{3.9a}$$

$$\text{s.t.} \quad \sum_{q\in\mathcal{N}_R} \sum_{e':e'+_{\bar{\alpha}}B^{e'}_{qr}=e} \bar{y}^{v,e'}_{qr} = \sum_{s\in\mathcal{N}_R} \bar{y}^{v,e}_{rs} \qquad \forall r\in\mathcal{N}_R, \forall v\in\tilde{\mathcal{V}}, \forall e\in[\underline{e},\bar{e}] \tag{3.9b}$$

$$\sum_{v\in\tilde{\mathcal{V}}} \sum_{e=\underline{e}}^{\bar{e}} \rho^v \times {}^m\bar{\alpha}^{v,e}_{qr} \times \bar{y}^{v,e}_{qr} \geq {}^m\bar{d}_{qr} + \epsilon \qquad \forall (q,r)\in\mathcal{N}_R^2, \forall m\in\mathcal{M} \tag{3.9c}$$

$$0 \leq \sum_{(q,r)\in\mathcal{N}_R^2} \sum_{e=\underline{e}}^{\bar{e}} {}_{\bar{\alpha}}\bar{C}^{v,e}_{qr}\bar{y}^{v,e}_{qr} \leq 1 \qquad \forall v\in\tilde{\mathcal{V}} \tag{3.9d}$$

$$0 \leq {}^m\bar{\alpha}^{v,e}_{qr} \leq {}^m\zeta^v \qquad \forall (q,r)\in\mathcal{N}_R^2, \forall m\in\mathcal{M}, \forall e\in[\underline{e}^v,\bar{e}^v], \forall v\in\tilde{\mathcal{V}} \tag{3.9e}$$

For any given fleet size, it is possible to find some demand vector $\bar{\boldsymbol{d}}$ for which no dispatch policy can stabilize the demand. However, given a demand vector and some potential fleet of vehicles which is arbitrarily large. It is possible to determine the minimum number of vehicles (or minimum cost of those vehicles) that can serve all demand. Program (3.9) determines what this minimum fleet size should be by multiplying the binary indicator variable ρ^v times the cost R^v of vehicle v. This minimization is subject to the conservation constraint (3.9b) which represents conservation of both energy and vehicles. We also must ensure that all demand is served in the long run (constraint (3.9c)). This constraint could be linearized like (3.4d) and (3.4e), but we leave it as is for clarity. The average utilization of the vehicle is represented by ${}_{\bar{\alpha}}\bar{C}^{v,e}_{qr}\bar{y}^{v,e}_{qr}$, which must be kept between 0 and 1 (constraint (3.9d)). Finally, the average reduction in queue length is again left as a general constrain to be filled in for the specific application (constraint (3.9e)).

The stable region $\mathcal{D}$ is the set of demands that can be satisfied by any dispatch policy with some fixed fleet size. We note that neglecting the η in the objective and constraint (3.9c) of program (3.9) would the fleet to serve demand on the boundary of $\mathcal{D}$, leading to a null recurrent Markov chain. Though technically demand will still be served, there is no bound on the service time. Thus, Lemma 1 defines stability only on the interior of $\mathcal{D}$ (denoted $\mathcal{D}^0$) where the above equations are strict inequalities.

Recall that $\pi^\star$ requires the use of a planning horizon. If this becomes arbitrarily large then ϵ can become arbitrarily small. However, shorter time horizons introduce more error and require the use of a larger value of ϵ. The appropriate selection of this term is based on the time horizon, and will be addressed later.

Recall that to get the minimum fleet size F, the cost R^v can be dropped from the objective. This can be used to get the maximum replacement ratio $\mathcal{R}$, which can be calculated analytically as:

$$\mathcal{R} = \frac{\sum\limits_{r,s \in \mathcal{N}_R^s} \bar{d}_{rs}}{F} \tag{3.10}$$

Kang and Levin (2021) also demonstrated that the maximum demand that a fleet size F can serve will increase proportionally with respect to and increase in F (Proposition 1). The same logic holds true here as long as vehicle availability is not a constraint (i.e. the set of *potential* vehicles is arbitrarily large for all vehicle types). Replacing ρ^v with $(\beta\rho^v)$ in the objective and constraint (3.9c) allows ${}^m\bar{d}_{rs}$ to increase by β for all $(r,s) \in \mathcal{N}_R^2$ and all

$m \in \mathcal{M}$. If the set of *potential* vehicles $\tilde{\mathcal{V}}$ is sufficiently large, then they should be chosen in the same proportions as they were in the original problem.

Finally, we demonstrate that if the demand is outside of the stable region then no dispatch policy can stabilize demand (including $\pi^\star$):

Proposition 1. *If $\bar{\boldsymbol{d}} \notin \mathcal{D}$ then no dispatch policy $\bar{\boldsymbol{y}}$, $\bar{\boldsymbol{\alpha}}$ can stabilize the system.*

Proof. If $\bar{\boldsymbol{d}} \notin \mathcal{D}$ then for every dispatch policy $\bar{\boldsymbol{y}}$, $\bar{\boldsymbol{\alpha}}$ there must be some η such that ${}^m\bar{d}_{qr} - \sum\limits_{v\in\mathcal{V}} \sum\limits_{e=\underline{e}}^{\bar{e}} {}^m\bar{\alpha}_{qr}^{v,e} \bar{y}_{qr}^{v,e} \geq \eta$ for some m, r, and s. Then,

$$\mathbb{E}\left[\boldsymbol{w}(\tau)\right] \geq \mathbb{E}\left[\boldsymbol{w}(0)\right] + \tau\eta \tag{3.11}$$

Taking the limit as $T \to \infty$ yields:

$$\lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}\left[\boldsymbol{w}(\tau)\right] \geq \lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} [\mathbb{E}\left[\boldsymbol{w}(0)\right] + \tau\eta] = \infty \tag{3.12}$$

It should be clear that the length of at least one queue increases by at least η each timestep on average. Then, equation (3.12) shows that as time grows, the queue also grows with no bound. This is a violation of Definition 1, so the network is not stable (regardless of the dispatch policy). □

3.6 Minimum Planning Horizon

The policies derived in Xu et al. (2021) and Robbennolt and Levin (2023) did not need planning horizons to prove stability. This simplified the analysis since a decision by the linear program corresponded directly to the dispatch behavior. In Kang and Levin (2021) and this work, the planning horizon means different decisions may be made later as more information is added. Thus, it is important to demonstrate that decisions will equate to steady state flows.

Proposition 2. *There exists a sequence of dispatch decisions $\boldsymbol{y}(t)$, $\boldsymbol{\alpha}(t)$ such that:*

$$\lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T}\boldsymbol{y}(t)=\bar{\boldsymbol{y}} \tag{3.13}$$

and

$$\lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T}\boldsymbol{\alpha}(t)=\bar{\boldsymbol{\alpha}} \tag{3.14}$$

regardless of initial vehicle location.

Proof. Note that it takes $2\max\{_{\alpha}C_{qr}^{v,e}\}+\max\{C^v\}=K_1$ time for all vehicles to move from their starting positions. We assume that vehicles have sufficient power to move to some charging station (which could be at the far side of the network). Then vehicles must charge (we denote C^v as the time to fully charge vehicle v), and then return to some other location.

Next, define rational numbers $f_{qr}^{v,e}$ and ${}^m g_{qr}^{v,e}$ such that $|\bar{y}_{qr}^{v,e}-f_{qr}^{v,e}|<\epsilon$ and $|{}^m\bar{\alpha}_{qr}^{v,e}-{}^m g_{qr}^{v,e}|<\epsilon$. These numbers can satisfy conservation (as defined in (3.9b)) since there is a rational number between any two real numbers. Set K_2 as the least common denominator of all these numbers then,

$$\sum_{t=0}^{K_2}\boldsymbol{y}(t)=\bar{\boldsymbol{f}}K_2 \tag{3.15}$$

and

$$\sum_{t=0}^{K_2}\boldsymbol{\alpha}(t)=\bar{\boldsymbol{g}}K_2 \tag{3.16}$$

Thus, after K_1+K_2 time there exists a $\boldsymbol{y}(t)$ and $\boldsymbol{\alpha}(t)$ that are less than ϵ from $\bar{\boldsymbol{y}}$ and $\bar{\boldsymbol{\alpha}}$. $\square$

Based on Proposition 2, we present a quadratic program to solve for the minimum time horizon T. Note that if not all vehicles are parked, then we must set $x_q^{v,e}(t)=0$ for all $v\in\mathcal{V}$, $e\in[\underline{e}^v,\bar{e}^v]$, and t less than the arrival time of the vehicle at its first node q. The remainder of the $x_q^{v,e}(t)$ terms can be determined within the program:

$$\min \sum_{(q,r)\in\mathcal{N}_R^2} \sum_{v\in\mathcal{V}} \sum_{e=\underline{e}}^{\bar{e}} \left(\bar{y}_{qr}^{v,e} - \frac{1}{T} \sum_{t=0}^{T} y_{qr}^{v,em} \right)^2 + \sum_{(q,r)\in\mathcal{N}_R^2} \sum_{m\in\mathcal{M}} \sum_{v\in\mathcal{V}} \sum_{e=\underline{e}}^{\bar{e}} \left({}^m\bar{\alpha}_{qr}^{v,e} - \frac{1}{T} \sum_{t=0}^{T} {}^m\alpha_{qr}^{v,e} \right)^2 \tag{3.17a}$$

$$\text{s.t.} \quad x_q^{v,e}(t+1) = x_q^{v,e}(t) + \sum_{s\in\mathcal{N}_R} y_{sq}^{v,e-{}_\alpha B_{sq}^v}(t+1-{}_\alpha C_{sq}^{v,(e-{}_\alpha B_{sq}^v)}) - \sum_{r\in\mathcal{N}_R} y_{qr}^{v,e}(t)$$

$$\forall q \in \mathcal{N}_R, \forall e \in [\underline{e}^v, \bar{e}^v], \forall v \in \mathcal{V}, \forall t \in [0,T] \tag{3.17b}$$

$$\sum_{r\in\mathcal{N}_R} y_{qr}^{v,e}(t+\tau) \le x_q^{v,e}(t+\tau) \qquad \forall q \in \mathcal{N}_R, \forall e \in [\underline{e}^v, \bar{e}^v], \forall v \in \mathcal{V}, \forall t \in [0,T] \tag{3.17c}$$

$$\sum_{q\in\mathcal{N}_R} \sum_{e':e'+{}_{\bar{\alpha}}B_{qr}^{e'}=e} \bar{y}_{qr}^{v,e'}(t) = \sum_{s\in\mathcal{N}_R} \bar{y}_{rs}^{e}(t) \quad \forall r \in \mathcal{N}_R, \forall v \in \mathcal{V}, \forall e \in [\underline{e}, \bar{e}], \forall t \in [0,T] \tag{3.17d}$$

$$\sum_{v\in\mathcal{V}} \sum_{e=\underline{e}}^{\bar{e}} {}^m\bar{\alpha}_{qr}^{v,e} \times \bar{y}_{qr}^{v,e} \ge {}^m\bar{d}_{qr} \qquad \forall (q,r) \in \mathcal{N}_R^2, \forall m \in \mathcal{M}, \forall t \in [0,T] \tag{3.17e}$$

$$0 \le \sum_{(q,r)\in\mathcal{N}_R^2} \sum_{e=\underline{e}}^{\bar{e}} {}_{\bar{\alpha}}\bar{C}_{qr}^{v,e} \bar{y}_{qr}^{v,e} \le 1 \qquad \forall v \in \mathcal{V}, \forall t \in [0,T] \tag{3.17f}$$

$$0 \le {}^m\bar{\alpha}_{qr}^{v,e}(t+\tau) \le {}^m\zeta^v \qquad \forall (q,r) \in \mathcal{N}_R^2, \forall m \in \mathcal{M}, \forall e \in [\underline{e}^v, \bar{e}^v], \forall v \in \mathcal{V}, \forall t \in [0,T] \tag{3.17g}$$

Note that constraints (3.17b) and (3.17c) are the same as the first two constraints in $\pi^\star$. The other constraints are the same as those in 3.9. Since $\bar{\boldsymbol{y}}$ and $\bar{\boldsymbol{\alpha}}$ are decision variables, this program is only quadratic for a fixed T. A binary search can be used to find the minimum value of T.

3.7 Proof of Stability

From here, the proof of stability follows vary closely to the set of lemmas developed in Kang and Levin (2021). The proofs differ slightly since we need to consider each individual vehicle and multi-commodity queuing behaviors. This means that slightly different bounds on some terms will be necessary, but the logic is the same. We will first prove that a dispatch policy using dispatch defined above is stable for $\bar{\boldsymbol{d}} \in \mathcal{D}^0$. Next, we will demonstrate that if the policy is stable at some t it will also be stable over any time horizon T regardless of the control vector. Finally, we will show that the max-pressure policy $\pi^\star$ is stable when $\bar{\boldsymbol{d}} \in \mathcal{D}^0$.

Lemma 2. *If $\bar{\boldsymbol{d}} \in \mathcal{D}^0$ and the average dispatch $\bar{\boldsymbol{y}}$ and $\bar{\boldsymbol{\alpha}}$ is used, there exists a Lyapunov function $\nu(\boldsymbol{w}(t)) > 0$ and constants $\kappa < \infty$ and $\eta > 0$ such that:*

$$\mathbb{E}\left[\nu(\boldsymbol{w}(t+1)) - \nu(\boldsymbol{w}(t)) \middle| \, \boldsymbol{w}(t)\right] \leq \kappa - \epsilon|\boldsymbol{w}(t)| \tag{3.18}$$

Proof. Consider the Lyapunov function $\nu(\boldsymbol{w}(t)) = \sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}}({}^m w_{qr}(t))^2$. Substituting into (3.18), we have:

$$\mathbb{E}\left[\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}}({}^m w_{qr}(t+1))^2 - ({}^m w_{qr}(t))^2 \middle| \boldsymbol{w}(t)\right] \leq \kappa - \epsilon|\boldsymbol{w}(t)| \tag{3.19}$$

We can also define an intermediate variable ${}^m\delta_{qr}(t)$:

$${}^m\delta_{qr}(t) = {}^m w_{qr}(t+1) - {}^m w_{qr}(t) = {}^m d_{qr}(t) - \min\{{}^m w_{qr}(t), \sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^m\bar{\alpha}_{qr}^{v,e}(t)\times\bar{y}_{qr}^{v,e}(t)\} \tag{3.20}$$

Plugging ${}^m w_{qr}(t+1) = {}^m\delta_{qr}(t) + {}^m w_{qr}(t)$ into equation (3.19) produces:

$$\mathbb{E}\left[\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}}({}^m\delta_{qr}(t))^2 + 2({}^m w_{qr}(t)\times{}^m\delta_{qr}(t)) \middle| \boldsymbol{w}(t)\right] \leq \kappa - \epsilon|\boldsymbol{w}(t)| \tag{3.21}$$

Call the maximum possible service rate for commodity m between nodes q and r ${}^m\tilde{w}_{qr}$, and the maximum demand ${}^m\tilde{d}_{qr}$. Then, ${}^m\delta_{qr}(t)$ is bounded by the larger of those. Further, if K is the largest value over all commodities and OD pairs then:

$$K = \max_{(q,r)\in\mathcal{N}_R^2}\{\max_{m\in\mathcal{M}}\{\max\{{}^m\tilde{w}_{qr}, {}^m\tilde{d}_{qr}\}\}\} \tag{3.22}$$

Based on this bound, we can bound the first term of equation (3.21):

$$\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}}({}^m\delta_{qr}(t))^2 \leq K^2\times|\mathcal{M}|\times|\mathcal{N}_R|^2 \tag{3.23}$$

Note that the expectation of a constant is still a constant, so the first term can be replaced by κ from the right side of equation (3.18). The second term remains and we will show that it is no greater than $\epsilon|\boldsymbol{w}(t)|$.

Again plugging in ${}^m\delta_{qr}(t)$, we get:

$$\begin{aligned}
&\mathbb{E}\left[\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}}2({}^m w_{qr}(t)\times{}^m\delta_{qr}(t))\middle|\boldsymbol{w}(t)\right]\\
&=\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}}{}^m w_{qr}(t)\left({}^m\bar{d}_{qr}-\min\{{}^m w_{qr}(t),\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]}{}^m\bar{\alpha}_{qr}^{v,e}(t)\times\bar{y}_{qr}^{v,e}(t)\}\right)
\end{aligned}\tag{3.24}$$

If the number of waiting passengers is less than the dispatch decision, all passengers will be served. Otherwise, the minimum term simplifies to $\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]}{}^m\bar{\alpha}_{qr}^{v,e}(t)\times\bar{y}_{qr}^{v,e}(t)$. However, the lemma assumes that $\bar{\boldsymbol{d}}\in\mathcal{D}^0$, so there must exist some ϵ such that ${}^m\bar{d}_{qr}-\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]}{}^m\bar{\alpha}_{qr}^{v,e}(t)\times\bar{y}_{qr}^{v,e}(t)\leq-\epsilon$.

$$\begin{aligned}
&\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}}{}^m w_{qr}(t)\left({}^m\bar{d}_{qr}-\min\{{}^m w_{qr}(t),\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]}{}^m\bar{\alpha}_{qr}^{v,e}(t)\times\bar{y}_{qr}^{v,e}(t)\}\right)\\
&=\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}}{}^m w_{qr}(t)\left({}^m\bar{d}_{qr}-\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]}{}^m\bar{\alpha}_{qr}^{v,e}(t)\times\bar{y}_{qr}^{v,e}(t)\right)\\
&\leq-\epsilon\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}}{}^m w_{qr}(t)\\
&\leq-\epsilon|\boldsymbol{w}(t)|
\end{aligned}\tag{3.25}$$

□

The dispatch policy $\pi^\star$ works by choosing dispatch strategies for timesteps $t+\tau$ for all $\tau < T$. Another intermediate result (Lemma 3) will be helpful in dealing with these τ moving forward.

Lemma 3. *For any control which stabilizes the network and any time horizon T, we can define $\epsilon > 0$, $\kappa_1, \kappa_2 < \infty$ such that equation (3.26) implies equation (3.27):*

$$\mathbb{E}\left[\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}}({}^m w_{qr}(t+1))^2 - ({}^m w_{qr}(t))^2 \middle| \boldsymbol{w}(t)\right] \leq \kappa_1 - \epsilon|\boldsymbol{w}(t)| \tag{3.26}$$

$$\frac{1}{T}\sum_{\tau=1}^{T}\mathbb{E}\left[\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}}({}^m w_{qr}(t+\tau+1))^2 - ({}^m w_{qr}(t+\tau))^2 \middle| \boldsymbol{w}(t+\tau)\right] \leq \kappa_2 - \epsilon|\boldsymbol{w}(t)| \tag{3.27}$$

Proof. First note that ${}^m w_{qr}(t+\tau) - {}^m w_{qr}(t) \geq -\tau K$, where K was defined in Lemma 2 to be the maximum of the maximum possible service rate and demand. This is not the lowest upper bound, but is sufficient for this proof. Then take the summation from $\tau = 1$ to T on both sides of equation (3.26):

$$\frac{1}{T}\sum_{\tau=1}^{T}\mathbb{E}\left[\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}}({}^m w_{qr}(t+\tau+1))^2 - ({}^m w_{qr}(t+\tau))^2 \middle| \boldsymbol{w}(t+\tau)\right] \leq \kappa_2 - \epsilon|\boldsymbol{w}(t)| \tag{3.28}$$

$$\leq \frac{1}{T}\sum_{\tau=1}^{T}\kappa_1 - \epsilon|\boldsymbol{w}(t+\tau)| \tag{3.29}$$

$$\leq \frac{1}{T}\sum_{\tau=1}^{T}\left(\kappa_1 - \epsilon\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}}({}^m w_{qr}(t) - \tau K)\right) \tag{3.30}$$

$$\leq \kappa_2 - \epsilon\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}}{}^m w_{qr}(t) \tag{3.31}$$

$$\leq \kappa_2 - \epsilon|\boldsymbol{w}(t)| \tag{3.32}$$

□

We now focus specifically on the dispatch policy $\pi^\star$.

Lemma 4. *When $\bar{\boldsymbol{d}} \in \mathcal{D}^0$ and the dispatch policy $\pi^\star$ is used, there exists some sufficiently large $M < \infty$ such that any time horizon T larger than M will satisfy:*

$$\mathbb{E}\left[\frac{1}{T}\sum_{\tau=1}^{T}\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}}({}^m w_{qr}(t+\tau+1))^2 - ({}^m w_{qr}(t+\tau))^2 \middle| \boldsymbol{w}(t)\right] \leq \kappa - \epsilon|\boldsymbol{w}(t)| \tag{3.33}$$

Proof. Based on Lemma 1 and Lemma 2, we know that some vector of average dispatch assignments $\bar{\boldsymbol{y}}$ and $\bar{\boldsymbol{\alpha}}$ leads to a stable policy. Proposition 2 also demonstrated that some sequence of assignments (which we will call $\hat{\boldsymbol{y}}$ and $\hat{\boldsymbol{\alpha}}$) can approximate the average flows for a sufficiently large time horizon T. If we show that $\pi^\star$ ($\boldsymbol{y}^\star$ and $\boldsymbol{\alpha}^\star$) outperforms any other feasible control, this will demonstrate that $\pi^\star$ outperforms both $\hat{\boldsymbol{y}}$, $\hat{\boldsymbol{\alpha}}$ and the control $\bar{\boldsymbol{y}}$, $\bar{\boldsymbol{\alpha}}$. This will imply that $\pi^\star$ is also stable.

We begin by plugging equation (3.20) into 3.33 as in Lemma 2, which produces:

$$\mathbb{E}\left[\frac{1}{T}\sum_{\tau=1}^{T}\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}}({}^m\delta_{qr}(t+\tau))^2 + 2({}^m w_{qr}(t+\tau)\times {}^m\delta_{qr}(t+\tau)) \middle| \boldsymbol{w}(t)\right] \leq \kappa - \epsilon|\boldsymbol{w}(t)| \tag{3.34}$$

As above, the first term is bounded by $K^2 \times |\mathcal{M}| \times |\mathcal{N}_R|^2$. The second term is slightly different than Lemma 2 due to the time horizon. We will still replace ${}^m\delta_{qr}(t)$ to get:

$$\mathbb{E}\Bigg[\frac{1}{T}\sum_{\tau=1}^{T}\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}} 2\,{}^m w_{qr}(t+\tau)\Bigg({}^m\bar{d}_{qr} - \min\{{}^m w_{qr}(t+\tau), \sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^m\alpha_{qr}^{v,e}(t+\tau)\times y_{qr}^{v,e}(t+\tau)\}\Bigg)\Bigg|\,\boldsymbol{w}(t)\Bigg] \tag{3.35}$$

Now, we must get rid of the ${}^m w_{qr}(t+\tau)$ by replacing it with: ${}^m w_{qr}(t+\tau) = {}^m w_{qr}(t) + \tau \times$

${}^m\bar{d}_{qr} - \sum_{\tau'=1}^{T} \min\{{}^m w_{qr}(t+\tau'), \sum_{v\in\mathcal{V}} \sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^m\alpha_{qr}^{v,e}(t+\tau') \times y_{qr}^{v,e}(t+\tau')\}$:

$$\begin{aligned}
&\frac{1}{T}\sum_{\tau=1}^{T} \sum_{(q,r)\in\mathcal{N}_R^2} \sum_{m\in\mathcal{M}} 2\left({}^m w_{qr}(t) + \tau \times {}^m\bar{d}_{qr}\right) \\
&\qquad \times \left({}^m\bar{d}_{qr} - \min\{{}^m w_{qr}(t+\tau), \sum_{v\in\mathcal{V}} \sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^m\alpha_{qr}^{v,e}(t+\tau) \times y_{qr}^{v,e}(t+\tau)\}\right) \\
&\qquad - \frac{1}{T}\sum_{\tau=1}^{T} \sum_{(q,r)\in\mathcal{N}_R^2} \sum_{m\in\mathcal{M}} \left(\sum_{\tau'=1}^{T} \min\{{}^m w_{qr}(t+\tau'), \sum_{v\in\mathcal{V}} \sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^m\alpha_{qr}^{v,e}(t+\tau') \times y_{qr}^{v,e}(t+\tau')\}\right) \\
&\qquad \times \left({}^m\bar{d}_{qr} - \min\{{}^m w_{qr}(t+\tau), \sum_{v\in\mathcal{V}} \sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^m\alpha_{qr}^{v,e}(t+\tau) \times y_{qr}^{v,e}(t+\tau)\}\right)
\end{aligned} \tag{3.36}$$

We can establish bounds on the second term. We will again use K as a bound which is a function of the maximum service rate (a function of F and bounds on ${}^m\alpha_{qr}^{v,e}$ based on vehicle capacities) and exogenous demand rate. Note that this term includes the dispatch control:

$$K \geq \left[\sum_{v\in\mathcal{V}} \sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^m Y_{qr}^{v,e}(t+\tau)\right] = \min\{{}^m w_{qr}(t+\tau), \sum_{v\in\mathcal{V}} \sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^m\alpha_{qr}^{v,e}(t+\tau) \times y_{qr}^{v,e}(t+\tau)\} \tag{3.37}$$

It also includes a term bounded by the average incoming demand:

$${}^m\bar{d}_{qr} \geq {}^m\bar{d}_{qr} - \min\{{}^m w_{qr}(t+\tau), \sum_{v\in\mathcal{V}} \sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^m\alpha_{qr}^{v,e}(t+\tau) \times y_{qr}^{v,e}(t+\tau)\} \tag{3.38}$$

This means that the second term in (3.36) can be bounded by $K \sum_{(q,r)\in\mathcal{N}_R^2} \sum_{m\in\mathcal{M}} {}^m d_{qr}^{v,e}$. We can use the bound in equation (3.38) to bound part of the first term of (3.36) as well:

$$\begin{aligned}
2\tau \sum_{(q,r)\in\mathcal{N}_R^2} \sum_{m\in\mathcal{M}} \left({}^m\bar{d}_{qr}\right)^2 \geq &\frac{1}{T}\sum_{\tau=1}^{T} \sum_{(q,r)\in\mathcal{N}_R^2} \sum_{m\in\mathcal{M}} 2\tau \times {}^m\bar{d}_{qr} \\
&\times \left({}^m\bar{d}_{qr} - \min\{{}^m w_{qr}(t+\tau), \sum_{v\in\mathcal{V}} \sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^m\alpha_{qr}^{v,e}(t+\tau) \times y_{qr}^{v,e}(t+\tau)\}\right)
\end{aligned} \tag{3.39}$$

The remaining term is:

$$\frac{1}{T}\sum_{\tau=1}^{T}\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}} 2\times {}^{m}w_{qr}(t)\left({}^{m}\bar{d}_{qr}-\min\{{}^{m}w_{qr}(t+\tau),\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^{m}\alpha_{qr}^{v,e}(t+\tau)\times y_{qr}^{v,e}(t+\tau)\}\right) \tag{3.40}$$

Using the logic developed in equation (3.37) we note that this term contains the objective function of the optimization problem $\pi^\star$: $(\frac{1}{T}\sum_{\tau=1}^{T}\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}} {}^{m}w_{qr}(t)\left[\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^{m}Y_{qr}^{v,e}(t+\tau)\right]$. The other term is constant with respect to the maximization. Based on these observations we can write:

$$\begin{aligned}&\frac{1}{T}\sum_{\tau=1}^{T}\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}} {}^{m}w_{qr}(t)\left(\min\{{}^{m}w_{qr}(t+\tau),\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^{m}\overset{\star}{\alpha}{}_{qr}^{v,e}(t+\tau)\times \overset{\star}{y}{}_{qr}^{v,e}(t+\tau)\}\right)+f^\star(\cdot)\\ &\geq \frac{1}{T}\sum_{\tau=1}^{T}\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}} {}^{m}w_{qr}(t)\left(\min\{{}^{m}w_{qr}(t+\tau),\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^{m}\hat{\alpha}_{qr}^{v,e}(t+\tau)\times \hat{y}_{qr}^{v,e}(t+\tau)\}\right)+\hat{f}(\cdot)\end{aligned} \tag{3.41}$$

This equation simply denotes the fact that $\pi^\star$ will choose a higher function value than any other feasible assignment. We also include the term $f(\cdot)$ to represent other terms that might appear in the objective function. Other authors have included penalty terms to ensure vehicles anticipate demand and reposition, and we will later explore how additional terms can be incorporated into the SAEV dispatch problem. However, we need the terms in this function to be bounded. If that is the case, we can write equation (3.40) as:

$$\begin{aligned}&\frac{1}{T}\sum_{\tau=1}^{T}\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}} {}^{m}w_{qr}(t)\left({}^{m}\bar{d}_{qr}-\min\{{}^{m}w_{qr}(t+\tau),\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^{m}\overset{\star}{\alpha}{}_{qr}^{v,e}(t+\tau)\times \overset{\star}{y}{}_{qr}^{v,e}(t+\tau)\}\right)\\ &\leq \frac{1}{T}\sum_{\tau=1}^{T}\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}} {}^{m}w_{qr}(t)\left({}^{m}\bar{d}_{qr}-\min\{{}^{m}w_{qr}(t+\tau),\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^{m}\hat{\alpha}_{qr}^{v,e}(t+\tau)\times \hat{y}_{qr}^{v,e}(t+\tau)\}\right)+C\end{aligned} \tag{3.42}$$

We drop the factor of 2. As above, we note that if the number of waiting passengers is less than the number of dispatched vehicles then all passengers will be served. Otherwise, it remains to ensure queues are bounded. Thus, we can transform (3.43) into:

$$\frac{1}{T}\sum_{\tau=1}^{T}\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}} {}^m w_{qr}(t)\left({}^m\bar{d}_{qr}-\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^m\overset{\star}{\alpha}{}_{qr}^{v,e}(t+\tau)\times \overset{\star}{y}{}_{qr}^{v,e}(t+\tau)\right)$$
$$\leq \frac{1}{T}\sum_{\tau=1}^{T}\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}} {}^m w_{qr}(t)\left({}^m\bar{d}_{qr}-\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^m\hat{\alpha}_{qr}^{v,e}(t+\tau)\times \hat{y}_{qr}^{v,e}(t+\tau)\right)+C \quad (3.43)$$

We know that the dispatch policy using the average flow vector is stable. According to Proposition 2 we know that for some η, there is an $M<\infty$ such that for all $T>M$, $\hat{y}_{qr}^{v,e}$ and $\hat{\alpha}_{qr}^{v,e}$ converge within η of their average.

$$\frac{1}{T}\sum_{\tau=1}^{T}\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}} {}^m w_{qr}(t)\left({}^m\bar{d}_{qr}-\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^m\overset{\star}{\alpha}{}_{qr}^{v,e}(t+\tau)\times \overset{\star}{y}{}_{qr}^{v,e}(t+\tau)\right)$$
$$\leq \frac{1}{T}\sum_{\tau=1}^{T}\sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}} {}^m w_{qr}(t)\left({}^m\bar{d}_{qr}-\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^m\hat{\alpha}_{qr}^{v,e}(t+\tau)\times \hat{y}_{qr}^{v,e}(t)\right)+C$$
$$\leq \sum_{(q,r)\in\mathcal{N}_R^2}\sum_{m\in\mathcal{M}} {}^m w_{qr}(t)\left({}^m\bar{d}_{qr}-\sum_{v\in\mathcal{V}}\sum_{e\in[\underline{e}^v,\bar{e}^v]} {}^m\bar{\alpha}_{qr}^{v,e}(t)\times \bar{y}_{qr}^{v,e}(t)\right)+C$$
$$\leq \kappa-\epsilon|\boldsymbol{w}(t)| \quad (3.44)$$

□

Finally, it is trivial to demonstrate that the policy $\pi^\star$ is stabilizing.

Proposition 3. *If $\bar{\boldsymbol{d}}\in\mathcal{D}^0$ the dispatch policy $\pi^\star$ is stabilizing.*

Proof. The proof follows directly from Definition 1, the equivalent statement in Lemma 1, and the statement of Lemma 4. See Kang and Levin (2021) (Proposition 4) for details. □

Corollary 1. *If $\bar{\boldsymbol{d}}\in\mathcal{D}^0$ the dispatch policy $\pi^\star$ ensures that the average waiting times are also bounded.*

Proof. Using Little's Law, if the average incoming demand is strictly positive and the queue lengths are bounded, then the wait times must also be bounded. □

3.8 Conclusions

In this section we developed a max-pressure SAEV dispatch policy. The proof of stability ensures that when demand is in the stable region, no queue will grow to infinity. This directly implies that throughput will be maximized in the stable region and the dispatch policy can serve all demand if any policy can serve all demand. The queuing model created individual queues for each commodity between every set of OD pairs. This allows us to incorporate more complicated demands on the SAEV fleet such as allowing them to serve passengers of different types (larger vehicle requirements, or other special accommodations), deliver food or packages, or even discharge to the electric grid. Discharging to the grid is particularly important from a resilience perspective. Recall that we can incorporate this behavior by assuming there exists a large battery at each node and the 'queue' is the amount of energy taken from that battery by consumers. The proof of stability ensures that a large battery of finite size will never be depleted. However, we note that demand is exogenous and queues may grow arbitrarily long before being served. On the other hand, since all demand will eventually be served, Little's Law implies that the wait times are also bounded.

Li et al. (2021b) examined EVs in their stable dispatch policy but did not characterize the stable region. Levin (2022) suggested a similar approach, to the one used here but used head of line waiting times in their proof of stability. Neither study examined the potential to discharge to the grid. Unfortunately, the inclusion of EVs makes the problem more complex. Even if every vehicle is not tracked independently as discussed here, we would still need to keep track of state of charge using discretized ranges of battery charge. This adds complexity to the problem and could make the policy difficult in real time. This is compounded by the fact that a time horizon is required which also increases the number of variables significantly.

On the other hand, the inclusion of the time horizon is convenient when predictions of future demand are possible. Since additional terms can be added to the objective function (as long as they are bounded) and the stability can be maintained, the planning horizon enables predictions of future demand to be incorporated into the planned movements of SAEVs. We will examine this potential in the policy developed in the next section. That policy will address two major concerns: (1) We assume that no commodity will leave the queue regardless of waiting time. This is not a perfect assumption for the transportation system, but is even worse for the electric grid. Generally we need to ensure that the supply is equal to the demand at all times (not just in the long run), so a queuing model is not a very good model of reality. (2) We assumed that vehicles could draw infinite power from the electric grid at charging stations. This is a standard assumption made by transportation engineers, but may not always be realistic. As battery capacities and charging rates grow it is likely that more optimization will need to occur at charging stations to ensure the electric grid operates efficiently. The next section of this paper will develop a modified dispatch policy which is not proven to be stable, but incorporates many of the same functional forms as the policy developed above. This new policy may be a more acceptable option in practice for operators balancing the costs of a multi-objective dispatch policy.

Chapter 4: Resilient SAEV Dispatch Policy

4.1 Introduction

In this section we develop a resilient SAEV dispatch policy ($\tilde{\pi}^{\star}$) which can serve passenger demand and transport power throughout the grid. As we will discuss, this policy can also help with peak shaving and to reduce total EV energy consumption if pricing schemes are chosen correctly. We begin with transportation side constraints based on the queuing model developed in Chapter 3. Since $\pi^{\star}$ was proven to serve all passengers if any policy can serve all passengers, an approximation of that behavior will be incorporated into the dispatch decision under certain cost structures. Next, we discuss additional constraints that arise when considering grid integration, building on work by Li et al. (2021a) and Yao et al. (2019). Finally, we present the resilient dispatch policy and discuss its properties under different pricing schemes and time windows.

Several key assumptions are present throughout this paper. (1) We assume all travel times and energy consumption on arcs at all times is known. These values could include congestion, but we assume that the SAEV fleet does not affect these values. (2) We have predictions of passenger demand and electricity demand for some future time horizon (though we will demonstrate that even basic predictions can be sufficient for some behaviors). (3) Fractional electric loads can be served at each node. (4) We assume infinite parking at nodes but potentially limited charging stations. (5) We assume that vehicles dispatched to move between nodes (either to rebalance or to serve passengers) cannot be reassigned until they reach their destination. (6) Finally, we assume that each SAEV can only serve a single passenger at a time (no ride-sharing).

4.2 Dispatch Policy

Before discussing the constraints we will first set up the basic network representation of both the roadway network and the electric grid. Much of the notation is reused from the previous section, though some variables are redefined slightly as the model is modified for more realistic implementation. See Table A2 for a list of notation. Consider a roadway network $\mathcal{G}_R = (\mathcal{N}_R, \mathcal{A}_R)$ with nodes $\mathcal{N}_R$ and links $\mathcal{A}_R$, and an electric network $\mathcal{G}_E = (\mathcal{N}_E, \mathcal{A}_E)$ with nodes $\mathcal{N}_E$ and links $\mathcal{A}_E$ (sometimes called buses and branches). We note that these networks are connected by charging stations located at nodes. We denote these connections using the binary variable $\delta_{qi} \in \{0, 1\}$, where $\delta_{qi} = 1$ if node $q \in \mathcal{N}_R$ is connected to node $i \in \mathcal{N}_E$ and 0 otherwise. We also define a fleet of vehicles $\mathcal{V}$ that can serve passengers on the roadway network as well as charging and discharging through charging stations to the electric grid. The fleet size F is defined as $F = |\mathcal{V}|$. We optimize vehicle dispatch through a model predictive control framework. At each timestep t, the optimization will run over the time horizon $[t, t + T]$.

In the previous section we assumed that travel times and energy consumption included the charging and discharging times. This is convenient to simplify the proof of stability, though it is cumbersome for practical applications. Instead, we will enable vehicles to stay parked and charge/discharge for a single timestep. Since we are assuming vehicles cannot change their decisions once dispatched, this also provides more flexibility in determining when to charge and for how long. Vehicles are controlled by the defined dispatch policy with decisions variables:

- $y^v_{qr}(t + \tau)$ – {0,1} whether vehicle v will drive between nodes q and r.
- $Y^v_{qr}(t + \tau)$ – {0,1} whether vehicle v pick up a passenger at q and take them to r.
- $\gamma^v_{q,ch}(t + \tau)$ – [0,1] charging rate if vehicle v will stay at node q and charge.
- $\gamma^v_{q,dch}(t + \tau)$ – [0,1] discharging rate if vehicle v will stay at node q and discharge.

As vehicles can only be dispatched when they have completed a trip, these quantities are only defined when a vehicle is parked at node q. We will later define $x^v_q(t + \tau) \in \{0, 1\}$ to denote whether a vehicle is parked at q at time $(t + \tau)$. Based on this setup, a simple constraint on this dispatch of each vehicle v is:

$$\sum_{r\in\mathcal{N}_R} y^v_{qr}(t+\tau) + \hat{\gamma}^v_{q,ch}(t+\tau) + \hat{\gamma}^v_{q,dch}(t+\tau) \leq x^v_q(t+\tau) \quad \forall q \in \mathcal{N}_R, \forall v \in \mathcal{V}, \forall \tau \in [0,T] \quad (4.1)$$

Each vehicle can only chose 1 action (drive, charge, or discharge) each timestep. $y^v_{qr}(t+\tau)$ and $Y^v_{qr}(t+\tau)$ are binary, but $\gamma^v_{q,ch}(t+\tau)$ and $\gamma^v_{q,dch}(t+\tau)$ can take any fractional value between 0 and 1. Thus, we define $\hat{\gamma}^v_{q,ch}(t+\tau) \in \{0,1\}$ and $\hat{\gamma}^v_{q,dch}(t+\tau) \in \{0,1\}$ to denote whether a vehicle is charging or discharging:

$$\gamma^v_{q,ch}(t+\tau) \leq \hat{\gamma}^v_{q,ch}(t+\tau) \qquad \forall q \in \mathcal{N}_R, \forall v \in \mathcal{V}, \forall \tau \in [0,T] \qquad (4.2)$$

$$\gamma^v_{q,dch}(t+\tau) \leq \hat{\gamma}^v_{q,dch}(t+\tau) \qquad \forall q \in \mathcal{N}_R, \forall v \in \mathcal{V}, \forall \tau \in [0,T] \qquad (4.3)$$

Based on these basic decision variables for vehicle dispatch we can begin to define the other constraints to develop Markov decision process for passenger queuing and vehicle charging.

4.2.1 Passenger Queuing Constraints

We define $x^v_q(t+\tau) \in \{0,1\}$ to be a binary variable denoting whether SAEV v is available at node q at time $(t+\tau)$. Based on this definition, we can constrain the dispatch of SAEVs traveling from q to r depending on whether vehicle v is actually parked at node q. $x^v_q(t+\tau)$ is set to 0 whenever a vehicle is driving or parked at any node other than q. To do this we define C_{qs} to be the travel time between nodes q and s. This travel time is assumed to be constant (not impacted by SAEV dispatch), but could include congestion. Since charging/discharging is a separate dispatch decision we will not consider travel times or battery consumption based on state of charge (though this could easily be included in practice if a complicated energy consumption model was considered). Then, vehicle state evolves as:

$$x_q^v(t+\tau+1) = x_q^v(t+\tau) + \sum_{s\in\mathcal{N}_R} y_{sq}^v(t+\tau+1-C_{sq}) - \sum_{r\in\mathcal{N}_R} y_{qr}^v(t+\tau) \quad \forall q \in \mathcal{N}_R, \forall v \in \mathcal{V}, \forall \tau \in [0,T] \tag{4.4}$$

Note that in general vehicles may have to travel from some node q to get to the pickup location r to finally take a passenger to s. Thus, the number of vehicles carrying passengers from r to s can be less than the total number of vehicles driving between these nodes:

$$Y_{qr}^v(t+\tau) \leq y_{qr}^v(t+\tau) \qquad \forall (q,r) \in \mathcal{N}_R^2, \forall v \in \mathcal{V}, \forall \tau \in [0,T] \tag{4.5}$$

We consider exogenous demand $d_{qr}(t+\tau)$ to enter the network at node r with destination s at time $(t+\tau)$. These passengers form a separate queue $w_{qr}(t+\tau)$ at each origin for each destination. The queuing model will evolve just as defined above when discussing stable dispatch. However, within the optimization problem we will assume that queues evolve based on predicted future demand $(\tilde{d}_{qr}(t+\tau))$. We still assume that passengers are willing to wait indefinitely to be served. Multiple commodities can be included as in Chapter 3, though we will define additional variables to take the place of the 'queue' of energy demand. For now we will continue with a single queue of passenger demand between each OD pair, though multiple commodities could be added easily by adding the index m and another decision variable α. Then, $w_{qr}(t+\tau)$ evolves as follows:

$$w_{qr}(t+1) = w_{qr}(t+\tau) + \tilde{d}_{qr}(t+\tau) - \sum_{v\in\mathcal{V}} Y_{qr}^v(t+\tau) \qquad \forall (q,r) \in \mathcal{N}_R^2, \forall \tau \in [0,T] \tag{4.6}$$

The passenger queuing model allows for the conservation constraint that the number of vehicles dispatched to serve passengers must be less than to total passenger demand:

$$\sum_{v\in\mathcal{V}} Y_{qr}^v(t+\tau) \leq w_{qr}(t+\tau) \qquad \forall (q,r) \in \mathcal{N}_R^2, \forall \tau \in [0,T] \tag{4.7}$$

All of the constraints listed in this section match those in program (3.4) except that we have so far neglected the state of charge of the vehicles. All rational behind these equations is built on the same queuing model as above except we have so far assumed a single commodity problem. The next section will address vehicle state of charge constraints with the added complication that in the electric distribution system both active and reactive power must be accounted for.

4.2.2 Vehicle Charging Constraints

Two concerns about vehicle charge need to be addressed in the constraint set. First, we need to ensure that any charging and discharging by vehicles at nodes in the roadway network is transferred to the electric grid. In addition, we need to constrain the dispatch of vehicles based on the amount of charge each vehicle has. This requires us to track the state of charge (SOC) of vehicles as they are dispatched. In program (3.4) we kept track of energy within fixed intervals. Here we keep track of a single value of state of charge for each vehicle which is convenient and realistic for practical applications. This is equivalent to discretizing the battery capacity into infinitely many sections in the proof of stability (though in that notation there would have been infinity many variables).

We define $EP_i(t+\tau)$ to be the amount of active power vehicles take (positive) or give (negative) to the grid at node $i \in N_E$ at time $(t+\tau)$. $EQ_i(t+\tau)$ is defined similarly for reactive power. Also, $ep_q^v(t+\tau)$ and $eq_q^v(t+\tau)$ denote the active and reactive power that any individual vehicle parked at node $q \in N_R$ takes from or gives to the grid. These flows evolve based on the maximum charging and discharging rates $\Gamma_{q,ch}^v$ and $\Gamma_{q,dch}^v$. We assume a potentially heterogeneous fleet of vehicles and charging stations. In simulation, we assume all chargers are compatible with all vehicles but with minimum charging rate between the two (i.e. each vehicle has charging rate Γ_{ch}^v and each charging station has rate $\Gamma_{q,ch}$. Then the real charging rate at station q for vehicle v is $\Gamma_{q,ch}^v = \min\{\Gamma_{q,ch}, \Gamma_{ch}^v\}$). The same is true for the discharging rate, real power constraint $(\bar{es}_q^v)$, and charging/discharging efficiencies $(\eta_{q,ch}^v/\eta_{q,dch}^v)$ defined below.

$$ep_q^v(t+\tau) = \gamma_{q,ch}^v(t+\tau)\Gamma_{q,ch}^v - \gamma_{q,dch}^v(t+\tau)\Gamma_{q,dch}^c \qquad \forall q \in \mathcal{N}_R, \forall v \in \mathcal{V} \forall \tau \in [0,T] \qquad (4.8)$$

As in Singh and Tiwari (2020), we assume that EVs are (potentially) equipped with bi-directional chargers that can inject/absorb reactive power without affecting the state of charge or battery life. Based on the active power taken from the grid, each vehicle is limited in the amount of reactive power that they can take (Kisacikoglu et al., 2015; Pirouzi et al., 2018; Kisacikoglu et al., 2010). We define $eq_q^v(t+\tau)$ as the amount of reactive power that vehicle v takes from the grid. We will later add a term to the objective function to account for costs due to battery degradation which will be based on only the active power, not reactive.

We can then constrain the reactive power flow based on a linear approximation of the real quadratic constraint $(ep_q^v(t+\tau)^2 + eq_q^v(t+\tau)^2 \leq ([\hat{\gamma}_{q,ch}^v(t+\tau) + \hat{\gamma}_{q,dch}^v(t+\tau)]\bar{es}_q^v)^2)$ where $\bar{es}_q^v$ is the maximum allowed real power flow. Recall that if $[\hat{\gamma}_{q,ch}^v(t+\tau) + \hat{\gamma}_{q,dch}^v(t+\tau)] = 0$ then no active or reactive power is allowed to be transferred through the charging station at q. The active power is already constrained by constraint (4.8), but this term constrains the reactive power as well. The linearization process depicted in Figure 4.1, is commonly used when constraining power flow though the distribution system (Yeh et al., 2012; Yao et al., 2019; Li et al., 2021a). In this figure, the circle represents the real constraint, and the red lines depict the linearization.

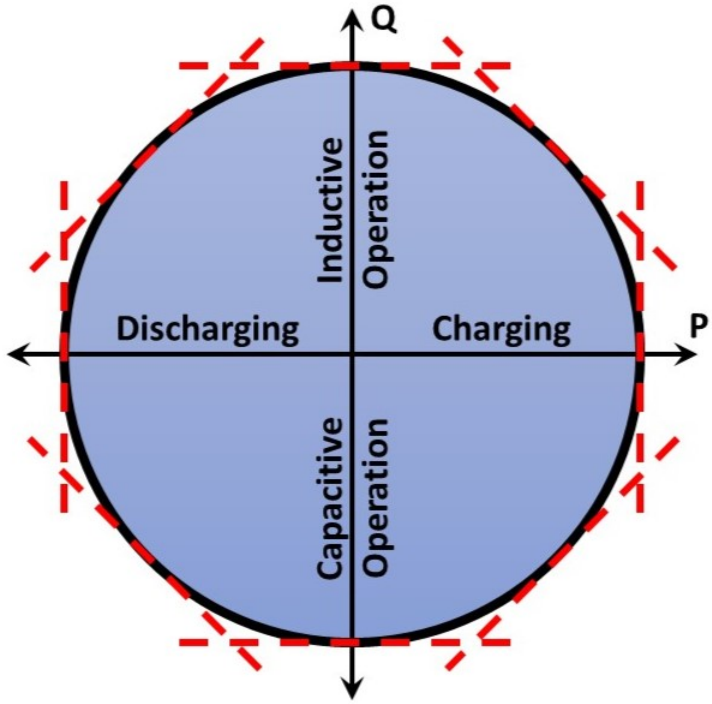

Figure 4.1: Trade-off between active and reactive power produced by a single EV with capacitive /inductive charging enabled.

$$-[\hat{\gamma}^v_{q,ch}(t+\tau)+\hat{\gamma}^v_{q,dch}(t+\tau)]\bar{es}^v_q \leq ep^v_q(t+\tau) \leq [\hat{\gamma}^v_{q,ch}(t+\tau)+\hat{\gamma}^v_{q,dch}(t+\tau)]\bar{es}^v_q \quad \forall q \in \mathcal{N}_R, \forall v \in \mathcal{V}, \forall \tau \in [0,T] \tag{4.9}$$

$$-[\hat{\gamma}^v_{q,ch}(t+\tau)+\hat{\gamma}^v_{q,dch}(t+\tau)]\bar{es}^v_q \leq eq^v_q(t+\tau) \leq [\hat{\gamma}^v_{q,ch}(t+\tau)+\hat{\gamma}^v_{q,dch}(t+\tau)]\bar{es}^v_q \quad \forall q \in \mathcal{N}_R, \forall v \in \mathcal{V}, \forall \tau \in [0,T] \tag{4.10}$$

$$-\sqrt{2}[\hat{\gamma}^v_{q,ch}(t+\tau)+\hat{\gamma}^v_{q,dch}(t+\tau)]\bar{es}^v_q \leq ep^v_q(t+\tau)+eq^v_q(t+\tau) \leq \sqrt{2}[\hat{\gamma}^v_{q,ch}(t+\tau)+\hat{\gamma}^v_{q,dch}(t+\tau)]\bar{es}^v_q \quad \forall q \in \mathcal{N}_R, \forall v \in \mathcal{V}, \forall \tau \in [0,T] \tag{4.11}$$

$$-\sqrt{2}[\hat{\gamma}^v_{q,ch}(t+\tau)+\hat{\gamma}^v_{q,dch}(t+\tau)]\bar{es}^v_q \leq ep^v_q(t+\tau)-eq^v_q(t+\tau) \leq \sqrt{2}[\hat{\gamma}^v_{q,ch}(t+\tau)+\hat{\gamma}^v_{q,dch}(t+\tau)]\bar{es}^v_q \quad \forall q \in \mathcal{N}_R, \forall v \in \mathcal{V}, \forall \tau \in [0,T] \tag{4.12}$$

Next, the values of power for individual vehicles need to be aggregated and converted to demands or supplies on the electric grid:

$$EP_i(t+\tau) = \sum_{q \in N_R} \sum_{v \in \mathcal{V}} \delta_{qi} ep^v_q(t+\tau) \qquad \forall i \in \mathcal{N}_E, \forall \tau \in [0,T] \tag{4.13}$$

$$EQ_i(t+\tau) = \sum_{q \in N_R} \sum_{v \in \mathcal{V}} \delta_{qi} eq^v_q(t+\tau) \qquad \forall i \in \mathcal{N}_E, \forall \tau \in [0,T] \tag{4.14}$$

We also need to ensure that vehicle are only allowed to charge and discharge if stations are available that their current node:

$$\sum_{v \in \mathcal{V}} \left[\hat{\gamma}^v_{q,ch}(t+\tau)+\hat{\gamma}^v_{q,dch}(t+\tau)\right] \leq N_q \qquad \forall q \in \mathcal{N}_R, \forall \tau \in [0,T] \tag{4.15}$$

Where N_q is the number of charging stations at q.

For the vehicle energy tracking, we calculate the energy impacts of the dispatch decision as soon as vehicles are dispatched (this is possible since energy consumption is known for all links and all time periods). If $e^v(t+\tau)$ is the charge of vehicle v at time $(t+\tau)$, this can be updated as:

$$e^v(t+\tau+1) = e^v(t+\tau) - \sum_{(q,r) \in \mathcal{N}_R^2} y^v_{qr}(t+\tau) B_{qr} \tag{4.16}$$

$$+ \sum_{q \in \mathcal{N}_R} \left[\gamma^v_{q,ch}(t+\tau)\Gamma^v_{q,ch}\eta^v_{q,ch} - \frac{\gamma^v_{q,dch}(t+\tau)\Gamma^v_{q,dch}}{\eta^v_{q,dch}}\right] \quad \forall v \in \mathcal{V}, \forall \tau \in [0,T] \tag{4.17}$$

Where B_{qs} is the energy needed to get from node q to node s.

Once each vehicle's state of charge is known, it is straightforward to constrain it between some upper ($\bar{e}^v$) and lower ($\underline{e}^v$) bound:

$$\underline{e}^v \leq e^v(t+\tau) \leq \bar{e}^v \qquad \forall v \in \mathcal{V}, \forall \tau \in [0, T] \tag{4.18}$$

Note that we could assume that $\underline{e}^v$ is a fixed bound or that it is based on the energy consumption needed to get to the nearest charging station. If so, this bound can be calculated at each timestep deterministically based on vehicle location and known travel times and energy consumption to get to each charging station in the network.

4.2.3 Grid Topology Constraints

The power flow model described in Section (4.2.4) is the LinDistFlow model (which will be more fully described in the next section) (Baran and Wu, 1989b,c; Turitsyn et al., 2010; Yeh et al., 2012; Yao et al., 2019). This model assumes a radial distribution system. In order to use this model, the distribution system needs to be reconfigured. Reconfiguration was done in a static context by Li et al. (2021a) and Yao et al. (2019), and examined dynamically by Xin et al. (2022).

In order to maintain radial grid topology, the grid can be split into several islands that are disconnected from the main grid. In some cases these islands may have no sources of power, in which case demand is not satisfied. Otherwise, each grid will be connected to an EV charging station or distributed generator. These power sources can provide energy to these microgrids that would otherwise not receive power.

We utilize directed spanning trees to define a set of microgrids which can be updated dynamically each timestep. To do this, we define a virtual network in which each node in the real network is assigned 1 unit of demand. Each source node is connected to a supersource (we will arbitrarily name node 0). Then, we can model the flow of virtual power through this updated network which will correspond connectivity in the real network. In this approach, each node is either a parent or a child, and each child node is assigned a parent (source) node. In contrast to some previous papers, we do not require that each charging station be a parent node. Instead we allow them to be parent nodes in isolated microgrids but do not require them to be islanded if connection to the grid is possible. This approach allows for aggregation of any discharged energy without the need to form additional microgrids.

Since we are considering line failures in the electric grid, we use the variable $u_{ij}(t+\tau) \in \{0,1\}$ to denote the line state (which is exogenous to the problem); $u_{ij}(t+\tau) = 0$ if a line has failed and is not repaired by time $(t+\tau)$, $u_{ij}(t+\tau) = 1$ otherwise. We also define $s_{ij}(t+\tau) \in \{0,1\}$ to indicate the line states; $s_{ij}(t+\tau) = 1$ if line (i,j) is closed (allowing power to flow). In addition we define the variables s^d_{ij} and s^r_{ji} in the same way for a directed line between (i,j) and (j,i) respectively. Since power may only flow in one direction on each line, the topology is constrained by:

$$s_{ij}(t+\tau) \leq u_{ij}(t+\tau) \qquad \forall (i,j) \in \mathcal{A}_E, \forall \tau \in [0,T] \tag{4.19}$$

$$s_{ij}(t+\tau) = s^d_{ij}(t+\tau) + s^r_{ji}(t+\tau) \qquad \forall (i,j) \in \mathcal{A}_E, \forall \tau \in [0,T] \tag{4.20}$$

$$s^r_{j0}(t+\tau) = 0 \qquad \forall j \in \mathcal{K}_G \cup \mathcal{K}_C, \forall \tau \in [0,T] \tag{4.21}$$

$$s^d_{0j}(t+\tau) = 1 \qquad \forall j \in \mathcal{K}_G, \forall \tau \in [0,T] \tag{4.22}$$

$$s^d_{0j}(t+\tau) \leq 1 \qquad \forall j \in \mathcal{K}_C, \forall \tau \in [0,T] \tag{4.23}$$

Where the set $\mathcal{K}_G$ is the set of source nodes connected to the grid. $\mathcal{K}_C$ is the set of EV charging stations that can act as source nodes if disconnected from the grid but need not otherwise (the subset of $\mathcal{N}_E$ that are attached to a charging station in $\mathcal{N}_R$). Here, constraint (4.19) enforces the limitation that power cannot flow on damaged lines. Constraint (4.20) ensures that power can only flow in one direction. Finally, constraints (4.21) and (4.22) require power flows from the virtual supersource while constraints (4.21) and (4.23) allow power flows from the virtual supersource.

We can also define the variable $z_i(t+\tau) \in \{0,1\}$ to represent the state of power supply of the distribution nodes; $z_i(t+\tau) = 1$ if node i is powered by some source (EV, distributed generator, or the main grid). These variables, along with virtual demands $f_i^L = 1$ for all nodes and virtual power flows f_{ij} allows us to construct the radial network:

$$\sum_{i \in \mathcal{N}_E:(i,k)\in \mathcal{A}_E} s^d_{ik}(t+\tau) + \sum_{j \in \mathcal{N}_E:(j,k)\in \mathcal{A}_E} s^r_{jk}(t+\tau) \le 1 \qquad \forall k \in N_E, \forall \tau \in [0,T] \tag{4.24}$$

$$\sum_{i \in \mathcal{N}_E:(i,k)\in \mathcal{A}_E} s^d_{ik}(t+\tau) + \sum_{j \in \mathcal{N}_E:(j,k)\in \mathcal{A}_E} s^r_{jk}(t+\tau) \ge z_k(t+\tau) \quad \forall k \in N_E, \forall \tau \in [0,T] \tag{4.25}$$

$$s_{ij}(t+\tau) - 1 \le z_i(t+\tau) - z_j(t+\tau) \le 1 - s_{ij}(t+\tau) \quad \forall (i,j) \in \mathcal{N}_E^2, \forall \tau \in [0,T] \tag{4.26}$$

$$z_i(t+\tau) = \sum_{j \in \mathcal{N}_E} f_{ji}(t+\tau) - \sum_{j \in \mathcal{N}_E} f_{ij}(t+\tau) \qquad \forall i \in \mathcal{N}_E, \forall \tau \in [0,T] \tag{4.27}$$

$$-s_{ij}(t+\tau) \times |\mathcal{N}_E| \le f_{ij}(t+\tau) \le s_{ij}(t+\tau) \times |\mathcal{N}_E| \qquad \forall (i,j) \in \mathcal{A}_E, \forall \tau \in [0,T] \tag{4.28}$$

Constraint (4.24) requires the in-degree of each node to be less than or equal to 1 to ensure the network is radial. Constraint (4.25) ensures that each child node (powered) is assigned a single parent node. Constraint (4.26) enforces consistency between the state of each line and the state of the node on either side (if node i is powered by a source and j is not then the line between them cannot allow power to flow). Constraints (4.27) and (4.28) constitute flow conservation on the virtual network where $|\mathcal{N}_E|$ is the number of distribution nodes.

4.2.4 Power Flow Constraints

To model the power flow we use the LinDistFlow model. This is a linearization of the DistFlow model developed in Baran and Wu (1989a,b,c). The DistFlow model has since been verified to be reliable, and the LinDistFlow model has been used extensively (Gilbert et al., 1998; Turitsyn et al., 2010, 2011; Yeh et al., 2012; Li et al., 2021a). The linear approximation is valid since the nonlinear terms have been shown to represent losses which are generally much smaller than the power terms. Yeh et al. (2012) provides a comprehensive description of the development of the LinDistFlow model and Turitsyn et al. (2010) demonstrates minimal differences between LinDistFlow and DistFlow.

For this problem, we need to decide whether to serve a load, and if we plan to serve the load how much we can serve. Unlike transportation passengers which are assumed to wait indefinitely for a ride, any electric demand not served immediately is assumed to be lost. Though some large loads may not be able to split into smaller loads, we assume that any fractional amount of load can be served. This is done using the variable $l_i(t+\tau)$. Based on network topology we can define:

$$0 \leq l_i(t+\tau) \leq 1 \qquad \forall i \in \mathcal{N}_E, \forall \tau \in [0,T] \tag{4.29}$$

$$l_i(t+\tau) \leq z_i(t+\tau) \qquad \forall i \in \mathcal{N}_E, \forall \tau \in [0,T] \tag{4.30}$$

We can then define active and reactive power constraints to ensure we serve all demand ($P_i^L(t+\tau)$ and $Q_i^L(t+\tau)$ respectively) that has been chosen for pickup.

$$\sum_{j \in \mathcal{N}_E : (i,j) \in \mathcal{A}_E} P_{ij}(t+\tau) = P_i^G(t+\tau) - l_i(t+\tau) P_i^L(t+\tau) - EP_i(t+\tau) \quad \forall i \in N_E, \forall \tau \in [0,T] \tag{4.31}$$

$$\sum_{j \in \mathcal{N}_E:(i,j)\in\mathcal{A}_E} Q_{ij}(t+\tau) = Q_i^G(t+\tau) - l_i(t+\tau)Q_i^L(t+\tau) - EQ_i(t+\tau) \quad \forall i \in N_E, \forall \tau \in [0,T] \tag{4.32}$$

The generated power $P_i^G(t+\tau)$ and $Q_i^G(t+\tau)$ is constrained within known limits:

$$\underline{P}_i^G \leq P_i^G(t+\tau) \leq \bar{P}_i^G \qquad \forall (i,j) \in \mathcal{A}_E, \forall \tau \in [0,T] \tag{4.33}$$

$$\underline{Q}_i^G \leq Q_i^G(t+\tau) \leq \bar{Q}_i^G \qquad \forall i \in \mathcal{N}_E, \forall \tau \in [0,T] \tag{4.34}$$

Next, the active and reactive power flows ($P_{ij}(t+\tau)$ and $Q_{ij}(t+\tau)$) must be bounded based on the real power constraint. This is done using a linear approximation of the real quadratic constraint ($P_{ij}(t+\tau)^2 + Q_{ij}(t+\tau)^2 \leq s_{ij}(t+\tau)\bar{S}_{ij}^2$) where $\bar{S}_{ij}$ is the maximum allowed real power. Recall that if $s_{ij}(t+\tau) = 0$ then no power is allowed to flow on line (i,j). This is the same approach used in approximating the real power constraint for vehicle reactive power management.

$$-s_{ij}(t+\tau)\bar{S}_{ij} \leq P_{ij}(t+\tau) \leq s_{ij}(t+\tau)\bar{S}_{ij} \qquad \forall (i,j) \in \mathcal{A}_E, \forall \tau \in [0,T] \tag{4.35}$$

$$-s_{ij}(t+\tau)\bar{S}_{ij} \leq Q_{ij}(t+\tau) \leq s_{ij}(t+\tau)\bar{S}_{ij} \qquad \forall (i,j) \in \mathcal{A}_E, \forall \tau \in [0,T] \tag{4.36}$$

$$-\sqrt{2}s_{ij}(t+\tau)\bar{S}_{ij} \leq P_{ij}(t+\tau) + Q_{ij}(t+\tau) \leq \sqrt{2}s_{ij}(t+\tau)\bar{S}_{ij} \quad \forall (i,j) \in \mathcal{A}_E, \forall \tau \in [0,T] \tag{4.37}$$

$$-\sqrt{2}s_{ij}(t+\tau)\bar{S}_{ij} \leq P_{ij}(t+\tau) - Q_{ij}(t+\tau) \leq \sqrt{2}s_{ij}(t+\tau)\bar{S}_{ij} \quad \forall (i,j) \in \mathcal{A}_E, \forall \tau \in [0,T] \tag{4.38}$$

Finally, the LinDistFlow model includes constraints on the voltage. We include these constraints using big M notation where M is some very large positive number. First, constraints (4.39) and (4.40) relate the voltage ($V_i(t+\tau)$) to the power flows using the resistance R_{ij} and reactance X_{ij} of the lines. Then, constraints (4.41) and (4.42) sets a constant voltage

V_0 for all nodes that supply power, and constrains the voltage between set bounds ($\underline{V}_i$ and $\bar{V}_i$) for all other nodes. Note that in general $V_0 = 1$.

$$V_i(t+\tau) - V_j(t+\tau) \leq M\left(1 - s_{ij}(t+\tau)\right) + \frac{R_{ij}P_{ij}(t+\tau) + X_{ij}Q_{ij}(t+\tau)}{V_0} \quad \forall (i,j) \in \mathcal{A}_E, \forall \tau \in [0,T] \tag{4.39}$$

$$V_i(t+\tau) - V_j(t+\tau) \geq M\left(s_{ij}(t+\tau) - 1\right) + \frac{R_{ij}P_{ij}(t+\tau) + X_{ij}Q_{ij}(t+\tau)}{V_0} \quad \forall (i,j) \in \mathcal{A}_E, \forall \tau \in [0,T] \tag{4.40}$$

$$V_i(t+\tau) = V_0 \qquad \forall i \in \mathcal{K}_G, \forall \tau \in [0,T] \tag{4.41}$$

$$z_i(t+\tau)\underline{V}_i \leq V_i(t+\tau) \leq z_i(t+\tau)\bar{V}_i \qquad \forall i \in \mathcal{N}_E \setminus \mathcal{K}_G, \forall \tau \in [0,T] \tag{4.42}$$

4.2.5 Objective Function

Once constraints on the passenger queuing model, vehicle charging, electric grid topology, and power flow through the electric grid have been established, an objective function can be defined. In an ideal scenario, the dispatch policy ($\tilde{\pi}^{\star}$) would serve all passenger and electricity demand at every timestep. In this case, the goal should be to minimize either the total electricity consumption or the cost of electricity. However, this is unlikely to be the case in a disrupted network where vehicles may have competing demands by passengers and electric loads. In such a scenario, it makes more sense to maximize the profit or social welfare (which will also minimize electricity consumption/cost where possible). To do this we add up revenues from serving passengers and electric loads and subtract the cost of generating electricity (either buying from the grid or using distributed generators). In addition, we can impose costs from delays for passengers and excessive charging and discharging of batteries which can reduce their lifetimes.

The objective function is as follows:

$$
\begin{aligned}
\frac{1}{T}\sum_{\tau=1}^{T}\Bigg[& \sum_{(r,s)\in\mathcal{N}_R^2} \mu_0(r,s,t) w_{rs}(t) \sum_{v\in\mathcal{V}} Y_{rs}^v(t+\tau) + \sum_{(r,s)\in\mathcal{N}_R^2} \mu_1(r,s,t+\tau) \sum_{v\in\mathcal{V}} Y_{rs}^v(t+\tau) \\
& + \sum_{i\in\mathcal{N}_E} \mu_2(i,t+\tau) l_i(t+\tau) P_i^L(t+\tau) - \sum_{i\in\mathcal{N}_E} \mu_3(i,t+\tau) P_i^G(t+\tau) \\
& - \sum_{(r,s)\in\mathcal{N}_R^2} \mu_4(r,s,t+\tau) w_{rs}(t+\tau) - \sum_{v\in\mathcal{V}} \mu_5(v) \sum_{(q)\in\mathcal{N}_R} \left(\gamma_{q,ch}^v(t+\tau)\Gamma_{ch} + \gamma_{q,dch}^v(t+\tau)\Gamma_{dch}\right) \\
& + \sum_{i\in\mathcal{N}_E} \mu_6(i,t+\tau) l_i(t+\tau) P_i^L(t+\tau) \frac{CP_i^L(t+\tau)}{CP^L(t+\tau)}\Bigg]
\end{aligned} \tag{4.43}
$$

In the objective function (equation (4.43)) the $\mu \geq 0$ functions are pricing terms that must be set by the operator. We note that these could be linear terms that are fixed in time, or more complicated functions. The setting of these terms can cause different behavior, so possible cost structures are discussed in the Section 4.3. For the remainder of the paper we refer to the terms associated with μ_0-μ_6 as Costs (0)-(6). Cost (0) is a demand responsive cost that should increase the payments by customers as demand in their queue increases. Cost (1) represents revenue from passengers once they are dropped at their destination based on distance or average travel times. We note that eventually the revenue from Cost (1) will always be the same regardless of dispatch policy as long as passenger queues do not grow to infinity since passengers will wait indefinitely for a ride. Cost (2) represents revenue generated by payments for energy supplied to customers. Under typical conditions this cost will also be fixed as the electric grid can serve these loads, though if links are damaged some loads may not always be served. Cost (3) is the price of generating energy. Cost (4) is a cost for additional waiting time for passengers, which will encourage vehicles to prioritize passengers over charging where possible and will promote rebalancing to anticipate future demand. Cost (5) is the cost of battery degradation from charging and discharging. This cost will prevent excessive discharge to the grid unless it is necessary to serve loads that are otherwise cut off or it is economically viable due to high energy costs during peak periods. Finally, Cost (6) is a term to ensure equity in energy discharge and will be discussed more in Section 4.3.3 ($CP_i^L(t+\tau)$ is the cumulative unserved energy at node i and $CP^L(t+\tau)$ is the sum of that quantity over all nodes).

Since $w_{rs}(t)$ is a constant with respect to $\tilde{\pi}^{\star}$, the final optimization problem is a mixed integer linear problem (assuming linear cost functions μ). It is stated in full as follows:

max	Objective Function (4.43)
s.t.	Dispatch Constraints: (4.1)–(4.3)
	Passenger Queuing Constraints: (4.4)–(4.7)
	Vehicle Charging Constraints: (4.8)–(4.18)
	Grid Topology Constraints: (4.19)–(4.28)
	Power Flow Constraints: (4.29)–(4.42)

4.3 Cost Structure

The optimization problem designed in this paper uses a multi-objective cost structure to optimize vehicle activities in a range of situations. In this section we compare the optimization problem to others found in the literature and demonstrate some special properties given different cost structures. We first demonstrate that this policy can reduce to policies developed to transport passengers alone or energy alone. We have discussed several previous dispatch policies throughout this Chapter, and this section describes their relationship in more detail. We then turn our attention to the relationship between stability and equity. This concept has not been well examined in the past and we provide a more explicit explanation of why stable dispatch is important from and equity perspective.

It is important to note that this paper generally assumes a cooperation between grid operators and EV dispatch companies. However, in general the grid operations can be viewed as a prediction by SAEV dispatchers which will be carried out similarly by grid operators if optimal. Under this framework the fleet operator would be buying and selling power at prices set by the grid operator. To further complicate these pricing terms there may be some constraints set by regulatory agencies to ensure equity or to achieve other goals. Future work should examine how these terms should be set by each party to maximize their own subset of these objectives. For now, we examine the dispatch policy with an exogenous set of pricing terms and study the behavior if different terms are included.

4.3.1 Stable Dispatch

As discussed in the literature review, there has been much interest in recent year in developing SAEV dispatch policies that have mathematically provable properties, rather than just relying on promising results in simulation. The passenger queuing model used in this paper is based on a maximum stability dispatch policy developed by Kang and Levin (2021), Xu et al. (2021), and Robbennolt and Levin (2023). These papers developed dispatch policies that were proven to serve all demand if any policy can serve all demand.

Recall that Definition 1 suggests that the network is stable if passenger queues are bounded. Based on Chapter 3, when Cost (0) is included, the network is stable with respect to passenger queues as long as the other terms in the objective function are bounded. Note that Cost (1) is bounded by μ_1 times the fleet size F. Cost (2) is bounded by μ_2 times the maximum possible energy demand (by customers) at any individual timestep. Cost (3) is bounded by μ_3 times the sum of electric customer demand and energy demand from EV charging (bounded by F times the maximum charging rate). Cost (4) cannot be bounded, and Cost (5) is bounded by μ_5 times the sum of the maximum charging and discharging rates times the fleet size. Finally, Cost (6) is bounded ny μ_6 times the maximum possible energy demand at any timestep. Thus, $\tilde{\pi}^\star$ is stable if $\mu_4 = 0$ we include this term because it could be a realistic pricing term when fleet sizes are very large or demand is small.

On the other hand, since $\tilde{\pi}^\star$ assumes that energy supply and demands must be equal at all times (rather than in the long-run), we cannot guarantee that all electric demands will be served. This is realistic in practice since during normal operations, when the grid is connected, all loads should be served by normal grid operations and Cost (2) should always be maximized. However, if there is a disruption and the fleet size is insufficient to serve both electric and passenger demands Cost (0) will eventually dominate and prioritize the transportation demand over the electric demand.

Under steady state conditions (when electric demands can all be served by the grid), this dispatch policy simplifies to a similar policy to the one developed by Kang and Levin (2021). They used aggregate vehicle counts in their formulation which is more efficient if the state of charge does not need to be tracked. They also add terms to minimize the movement of vehicles where possible (which we take care of by buying energy from the grid and introducing battery degradation). They also have a term discounting future trips (we do not discount since we add predictions of future demand). However, if $\mu_4 = 0$, the long run behavior should be similar (see the objective function of Kang and Levin (2021) rewritten in our notation below):

$$\frac{1}{T}\sum_{\tau=1}^{T}\Bigg[\sum_{(r,s)\in\mathcal{N}_R^2} w_{rs}(t)\sum_{v\in\mathcal{V}} Y_{rs}^{v}(t+\tau) - \lambda \sum_{(r,s)\in\mathcal{N}_R^2}\sum_{v\in\mathcal{V}} y_{rs}^{v}(t+\tau) + \frac{\lambda}{\tau}\sum_{(r,s)\in\mathcal{N}_R^2}\sum_{v\in\mathcal{V}} Y_{rs}^{v}(t+\tau)\Bigg] \tag{4.44}$$

Under these steady state conditions, we expect this dispatch policy to behave very similarly to the dispatch policy of Kang and Levin (2021). They performed a simulation on the Sioux Falls network (24 nodes and 76 links with a demand of 10,115 travelers per hour). Their numerical results demonstrate that when demand is in the stable region the policy is indeed able to stabilize demand (with tje number of waiting passengers fluctuating around some average queue length). Unfortunately, they also demonstrate that as the planning horizon grows, the running times increase dramatically (as much as 120 minutes for a simulation of 40,000 seconds with a planning horizon of 3000 seconds). This suggests that a faster heuristic may be needed (even for their simpler program) for real-time implementation on larger networks. Finally, they demonstrate the linear relationship between fleet size and demand described in Chapter 3.

During standard operation, it is likely that many of the above assumptions about discharging and separation from the electric grid are valid and that the simplified objective is a good approximation. However, clearly there are times when the expanded dispatch policy is necessary since any disruptions to the electric grid could shift priority from serving passengers onto moving electricity. It is also important to note a major drawback of the proof of maximum stability which says that queues will not grow infinitely assuming incoming passenger demand has some average rate of arrival $\bar{d}_{rs}$. In reality it is likely that vehicle fleets may not be stable during peak periods and queues may form which then dissipate at the end of peaks (even when there are no electric grid disruptions). For this reason numerical simulation is necessary along with the proof of stability to ensure that other properties such as passenger waiting times and travel times are optimized as well as the throughput.

4.3.2 Transportable Energy Storage

We also compare $\tilde{\pi}^{\star}$ to the dispatch policy for TESS in Yao et al. (2019). Their objective function is also very similar to $\tilde{\pi}^{\star}$, with terms for the penalty for unserved electricity demand (Cost (2)), the generation cost of electricity (Cost (3)), a general transportation cost (for moving the TESS between nodes), and the cost of battery degradation (Cost (5)).

Since Yao et al. (2019) does not include any passengers, they neglect the queuing model developed in this study. However, they also use the LinDistFlow model in their energy flow constraints. They focus on resilience in the aftermath of a disaster when TESS may be used to move energy across the network. If we assume that there will be no travelers queuing in the network after a disaster then our policy simplifies in to a similar form.

Yao et al. (2019) uses a modified 33-bus test feeder electricity distribution system and model several different types of load. They found that the TESS could help reduce the energy imbalance across microgrids when some produce excess power and other do not produce enough. They also found that if some loads are prioritized (such as hospitals or other critical infrastructure) the TESS can be particularly effective at serving those specific loads when capacity is limited. They also determined that in cases where there were large peaks in electricity demand, the TESS could remain stationary and act as a large battery for peak shaving purposes.

Though their results suggest important resilience benefits of TESS, such resources are expensive to own and maintain in large numbers Li et al. (2021a). However, large SAEV fleets will be necessary to serve passenger demand at peak hours, and that battery capacity can be leveraged in the same way. As noted previously, however, these vehicles cannot be committed completely to grid restoration. Instead, $\tilde{\pi}^\star$ will balance the needs of grid restoration with the continued goal of providing transportation for critical workers.

4.3.3 Equitable Vehicle Dispatch

The definition of stability ensures that all demand (of all commodities) will be served in the long run if any policy can serve all demand. By extension, this implies that passengers on more 'difficult' routes will also be served. Specifically, a queue of passengers with longer routes on the edge of the study area would still eventually be served even though this requires more driving time for the vehicles. Note that this does not imply that these passengers will have less waiting time, only that their waiting time will not grow to infinity. The same can be said for energy demands that require more driving between charging and discharging stations. This property also ensures that passengers of different types (possibly with different vehicle requirements) that are tracked in separate queues will all eventually be served. Further, we note that a constant multiplier times the queue length between any OD pair will not affect the stability region (since this will become insignificant as queues growing to infinity). This means that some OD pairs (or commodities) can be prioritized if there are vulnerable populations or critical workers that should be served sooner. This weighting can also help to reduce waiting times at nodes with less demand.

Note that the dispatch policy $\tilde{\pi}^\star$ maintains this equability in serving passengers when Cost 0 is included. The other two terms that encourage vehicles to serve passengers are Cost 1 and Cost 4. Complicated functions for these costs could be devised to ensure equity, but in the basic case we consider linear terms. Then these functions provide a fixed benefit for each served passenger and a fixed cost for any additional waiting time. Note that these do not distinguish where vehicles are in the network. This means that vehicles will see more benefits making short trips around the city center where they will spend less time driving empty and remove as many passengers as quickly as possible. While this seems like a positive behavior, it could lead to very long queues around the periphery.

This formulation including waiting times (Cost (4)) is also slightly problematic with very long time horizons and high levels of demand. Even a single unserved person in a queue can cause this term to grow arbitrarily large (as the time horizon grows large) if they are never served. On the other hand, at a single timestep Cost (0) is bounded by μ_0 times the current queue length and does not depend on the time horizon. In fact, no other term in the objective function is dependent on the time horizon, making the units more challenging to interpret (especially when demand is outside the stable region).

A similar pattern can be shown with the possible terms for prioritizing power flow through the network. When Cost 3 is used, costs could be set based on the difficulty of getting power across lines to ensure vehicles also serve the more difficult demands. However, in general there is no guarantee that equity will be maintained. Instead, Cost 6 is included to ensure that in the long run power will be distributed as evenly as possible. The term $\frac{CP_i^L(t+\tau)}{CP^L(t+\tau)}$ represents the portion of unserved energy that came from node i, and is bounded between 0 and 1. This term prioritizes serving areas that have historically had more underved energy demand, just as Cost 0 prioritizes nodes with longer queues. Including this terms should ensure more equitable service throughout the network than simply serving as much demand as possible.

4.4 Conclusion

Chapter 3 determined the minimum fleet size necessary to serve all demand. This included both passenger demand and potential electricity demands if the network was disconnected due to a disaster (but had large battery backups so energy did not have to remain temporally consistent). This chapter developed a more realistic policy which considered the flow of electricity through the grid. The dispatch policy develops a queuing model for passenger demand and keeps track of continuous state of charge for each vehicle individually. The vehicles can take and supply both active and reactive power to the electric grid. We incorporate real-time grid reconfiguration to maintain radial topology and utilize the LinDistFlow model to ensure that electricity demands are served where possible.

The final dispatch policy uses elements from Kang and Levin (2021) and Yao et al.

(2019) to model correct behavior at steady state and in the aftermath of a disaster. Based on the results of those studies we expect that good choices of the pricing terms μ will lead to a policy that is stable with respect to passenger queues and serves as much electricity demand as possible. We also expect to see some peak shaving behavior if the time horizon is sufficiently long. Finally, we discussed the impacts of the different possible pricing terms on equitable vehicle dispatch and demonstrated how some intuitive cost functions may lead to less equitable outcomes. The next chapter will explore this dispatch policy in simulation to see how it might perform in practice.

Chapter 5: Simulation

5.1 Introduction

One of the biggest drawbacks of optimized dispatch policies for SAVs is that there are a large number of variables, many of which are integers. This makes it difficult for commercial solvers to solve the problem sufficiently fast for real-time implementation. This is exacerbated for electric vehicles when state of charge must be tracked at each timestep. In addition, when attempting to simultaneously optimize vehicle dispatch and power flow there are more variables from both problems and the time horizon must be extended. This is because vehicle dispatch needs to be solved often (generally every 15 seconds to 1 minute), while fluctuations in power demand tend to occur over the space of hours or days. Accounting for these large variations is especially important if peak shaving is a goal of the dispatch policy.

We will leave future work to find heuristics to solve this problem faster for real-time implementation, and instead focus our attention on behavior and policy implications when tested on a small network (where more simulations can be run relatively quickly). Few test networks exist combining the electric distribution system and the roadway network, so we developed a new test network defined below. The roadway network has 4 nodes and 10 directed links, and the electric distribution system has 5 nodes and 5 bidirectional links. Though small, these networks are sufficient to examine behavior of vehicles that must move energy across a break in the distribution system. We examine a potential failure between nodes 2 and 4 in the distributions system. This causes about 30% of the active power to be unserved if vehicles are not used to move power.

The case study was designed so that the line limits, number of charging stations, and generation capacity are limiting power flow. Our focus is on the movement of vehicles across the broken line rather than on limitations on power flow within the existing system (though this would be an interesting area for future research). All values are fixed in time so that the long run behavior can be studied. We run the simulation for 43,200 seconds to ensure that steady state conditions are reached. Stochasticity is included by sampling passenger demands from a Poisson distribution and electric demands are perturbed around the mean using a uniform distribution (within 10%). Finally, since we assume costs are fixed in time there will be no peak shaving behavior. This means a time horizon of several hours is not necessary, though it still must be sufficiently long for charging and moving behavior to be planned in advance.

Table 5.1: Roadway Network

Start Node	End Node	Travel Time (min)
1	2	10
2	1	10
1	3	5
3	1	5
2	3	10
3	2	10
2	4	5
4	2	5
3	4	15
4	3	15

Table 5.2: Distribution Network

Start Node	End Node	Resistance (p.u.)	Reactance (p.u.)
1	2	0.000893	0.000620
2	3	0.001347	0.000926
3	1	0.001793	0.001231
2	4	0.000893	0.000611
4	5	0.003595	0.002462

Table 5.3: Electric Demands and Charging Stations

Node	Charging Station	P^L (MW)	Q^L (MVAr)
1	2	0.035	0.036
2	-	0.056	0.057
3	-	0.112	0.114
4	-	0.035	0.036
5	3	0.056	0.057

Table 5.4: Passenger Demand Matrix

	1	2	3	4
1	0.0	1.0	1.0	3.0
2	1.0	0.0	1.0	1.5
3	0.5	1.0	0.0	1.0
4	2.5	1.0	2.0	0.0

Table 5.5: Vehicle Fleet Parameters

Parameter	Value
Charging Power (MW)	0.2
Discharging Power (MW)	0.2
Max SOC (MWh)	0.1
Min SOC (MWh)	0.01
Charging Efficiency	0.9
Discharging Efficiency	0.9

Throughout this section we assume three possible modes of vehicle operation. Vehicles dispatched using policy $\tilde{\pi}^\star$ (resilient dispatch serving both passengers and the electric grid) are denoted *SAEVs*. We also define a modified policy for *SAVs*, which are still electric vehicles which must charge, but do not discharge to the grid. Finally, *TESSs* are vehicles which do not serve passengers but are allowed to charge and discharge to move power across the fault. Table 5.6 shows the chosen values of μ for each of these scenarios. These values are constant across all nodes, vehicles, and timesteps, except for μ_1 which is a function of travel time (constant between each OD pair).

Table 5.6: **Cost functions for SAEVs, SAVs, and TESSs**

Cost	SAEVs	TESSs	SAVs
μ_0 (\$/pass)	1	0	1
μ_1 (\$/hr)	20	0	20
μ_2 (\$/MWh)	2000	2000	0
μ_3 (\$/MWh)	500	500	500
μ_4 (\$/hr)	0	0	0
μ_5 (\$/MWh)	200	200	200
μ_6 (\$/MWh)	0	0	0

5.2 Comparing SAEVs, SAVs, and TESSs

Based on the network, it takes 1,800 seconds for a vehicle to travel between the two farthest nodes and back. For a dispatch problem with no constraints on charging and discharging, this time horizon should be sufficient to reach stability Kang and Levin (2021). For the first set of simulations the network was run with 100% demand and a time horizon of 1,800 seconds. Figures 5.1, 5.2, and 5.3 depict the percent of energy that is served each timestep, the cumulative amount of unserved energy, and the passenger queues.

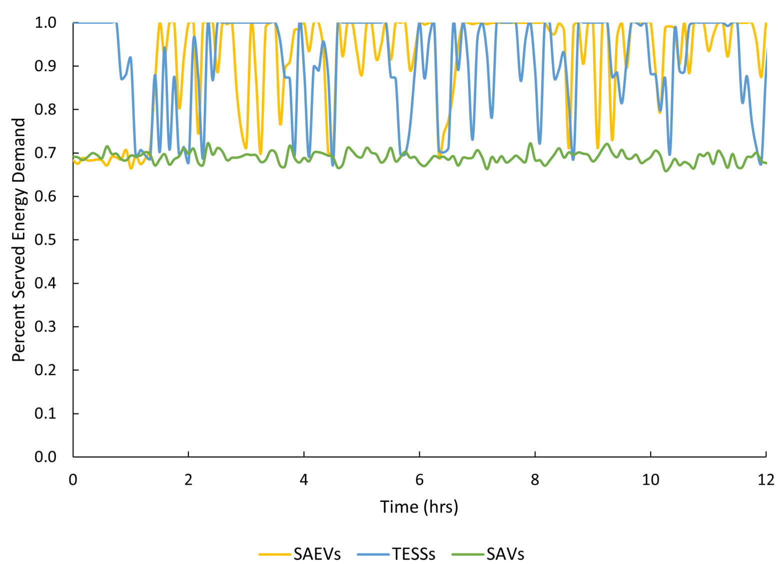

Figure 5.1: Percent of Served Energy (1800 second time horizon, 100% demand)

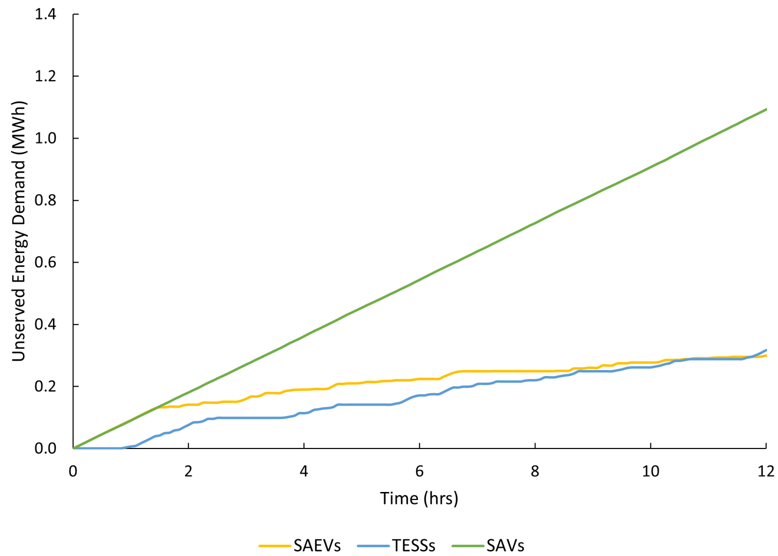

Figure 5.2: Cumulative Unserved Energy (MWh) (1800 second time horizon, 100% demand)

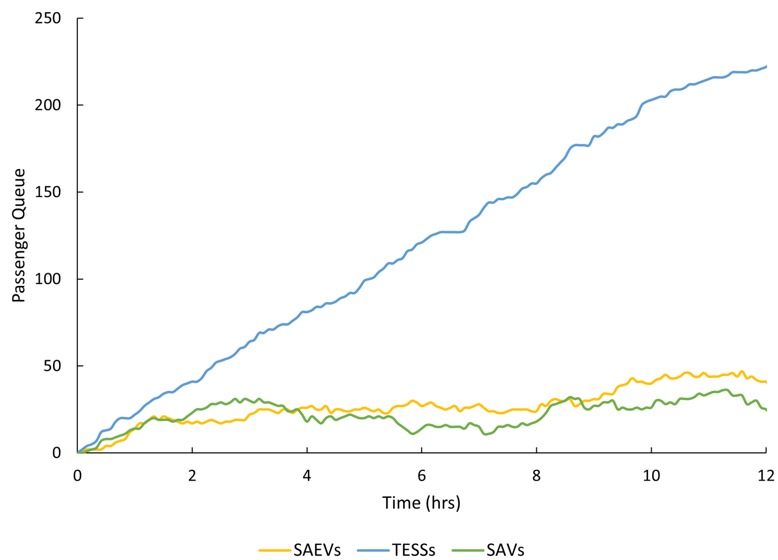

Figure 5.3: Queue of Passengers (1800 second time horizon, 100% demand)

Note that in Figure 5.2 the SAV line represents the 30% of the total electric demand that is on the far side of the disconnection in the grid (and is not served by any vehicles).

The other two lines are comparatively low with vehicles serving about 70-75% of the demand in that microgrid. Similarly, Figure 5.3 depicts all passengers waiting indefinitely if vehicles are operated as TESSs. More importantly, we see that in this scenario both the SAVs and SAEVs are able to stabilize the demand (queues of 20-50 passengers remain, but do not grow in the long run). This suggests that (at least when it is possible to stabilize the demand) vehicles can also engage in serving some other queues with excess capacity.

One surprise in the figures above is that the cumulative unserved demand for the SAEVs is slightly lower than for TESS at the end of the simulation. Though part of this can be explained by stochasticity in incoming demand (particularly with a fleet size of only 10 vehicles), another explanation is the short time horizon. The need for EVs to recharge means that a longer time horizon is needed for vehicles to move across the network, charge, move back, and discharge. Since the TESS are not moving to serve passengers, the time horizon is not sufficiently long for them to optimize their charging pattern. For this reason we extended the time horizon to examine the effect on unserved energy demand. Simulations with a time horizon of 3,600 seconds are shown in Figures 5.4, 5.5, and 5.6. These simulations show that the SAEVs are able to serve almost all of the passengers, while also serving all of the energy demand during all but 6 timesteps.

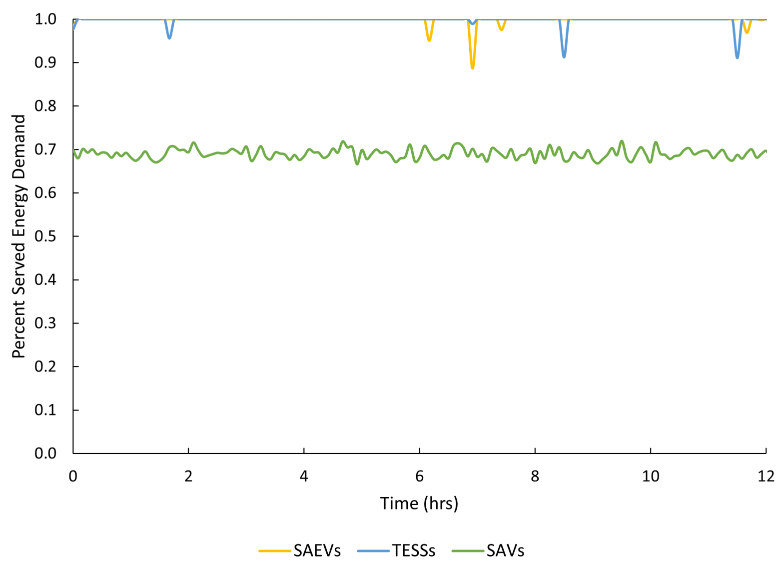

Figure 5.4: Percent of Served Energy (3600 second time horizon, 100% demand)

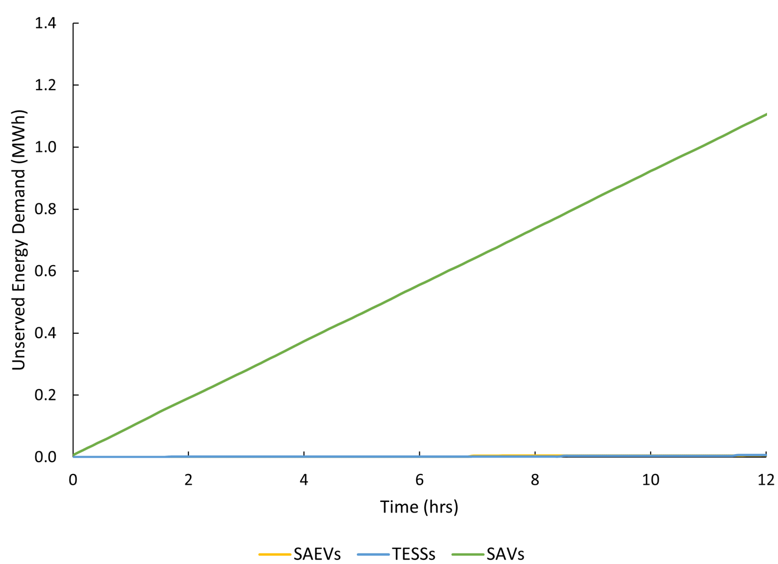

Figure 5.5: Cumulative Unserved Energy (MWh) (3600 second time horizon, 100% demand)

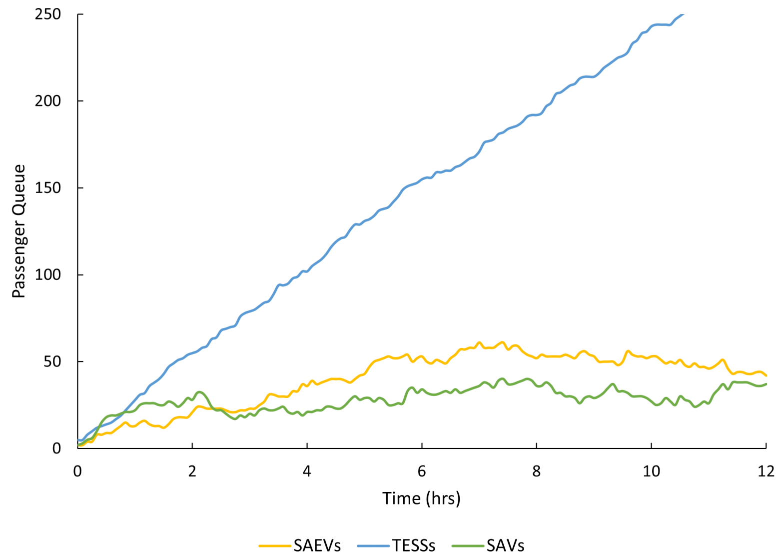

Figure 5.6: Queue of Passengers (3600 second time horizon, 100% demand)

In all of the simulations so far, the fleet size has been sufficient to serve all passenger demand (queues do not grow to infinity). In addition, with a sufficiently long time horizon the energy demand can also be served by discharging vehicles (except when there are a few unexpected spikes due to stochasticity). We now increase both the energy demand and passenger demand to demonstrate the tradeoff between serving passengers and serving demand. In this case (Figures 5.7, 5.8, and 5.9), we see that a significant amount of unserved energy accumulates by the end of the simulation when vehicles must serve passengers. Recall that the dispatch policy will eventually prioritize serving passengers as queues get long since Cost 0 grows to infinity and all of the other (included) cost terms are bounded. This means that, while queue lengths and waiting times grow for SAEVs relative to SAVs, they will all still be eventually served.

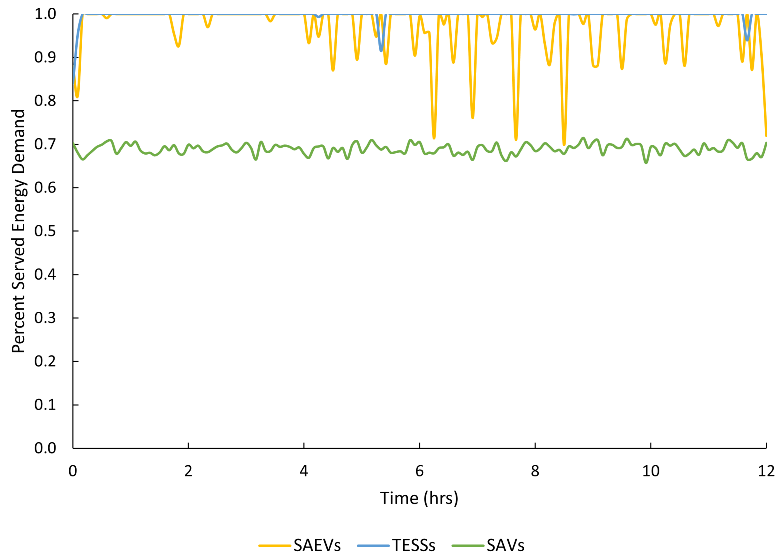

Figure 5.7: Percent of Served Energy (3600 second time horizon, 150% demand)

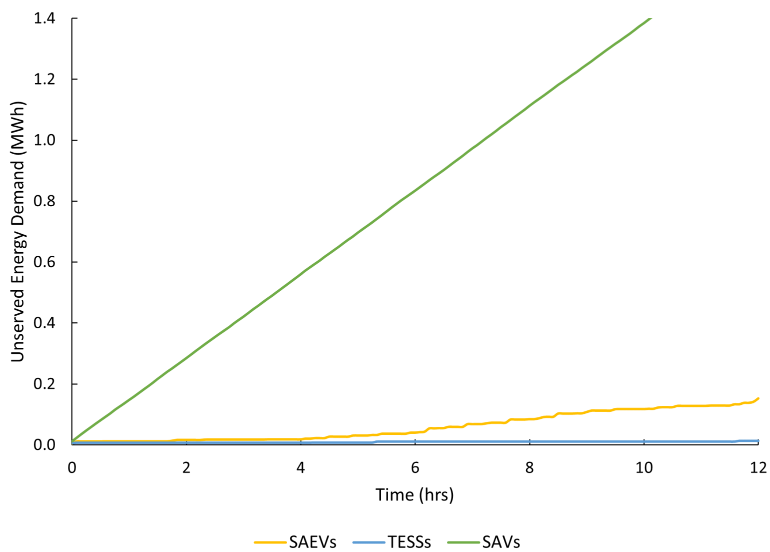

Figure 5.8: Cumulative Unserved Energy (MWh) (3600 second time horizon, 150% demand)

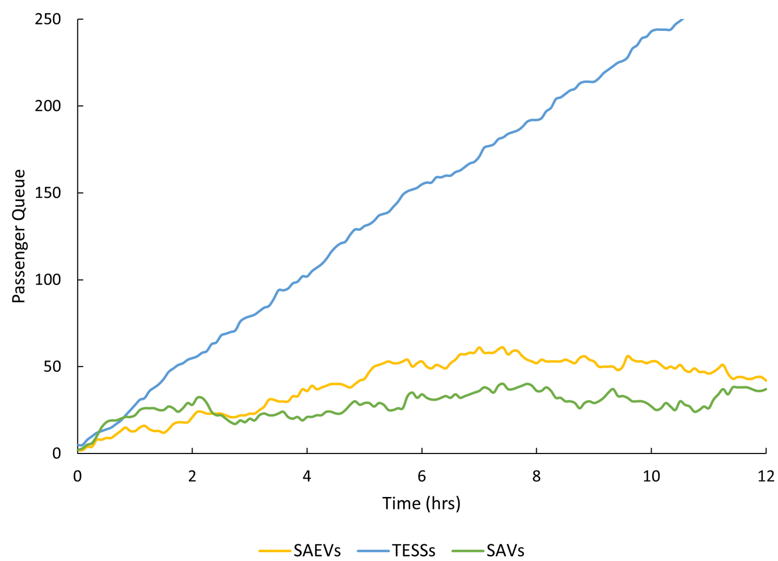

Figure 5.9: Queue of Passengers (3600 second time horizon, 150% demand)

Finally, it is interesting to compare the average amount of energy stored in the batteries across vehicle dispatch strategies and incoming demand scenarios. This is important if peak shaving is to be included in future studies. When SAEVs are used in the 100% demand scenario, they average 0.25 MWh of total energy stored in their batteries at steady state (the total battery capacity of all 10 vehicles is 1 MWh). Both TESS and SAVs store only 0.19 MWh. When demand is increased to 150%, average total state of charge at steady state increases to 0.31, 0.23, and 0.21 MWh respectively.

5.3 Pricing Implications

We have already discussed some of the issues when including a penalty for passenger waiting time, Cost (4), in the objective function. With this term stability is not ensured and dispatch may not be as equitable. However, the benefit of this term is that it prioritizes serving passengers as soon as possible. In Figures 5.10 and 5.11 we set $\mu_0 = 0$ and instead show three values of μ_4 (in \$/hr). When demand is low (100%), the passenger queues plotted in Figure 5.11 are stabilized and are much shorter than when Cost (0) (the pressure term) was used. Note that this is due to the units issue discussed in the previous chapter where serving a passenger early will reduce the waiting time significantly if the time horizon is long. Figure 5.11 demonstrates that this term tends to dominate the objective function and lead to large power losses as value of time increases. This occurs even with minimal reduction in queue length or waiting times.

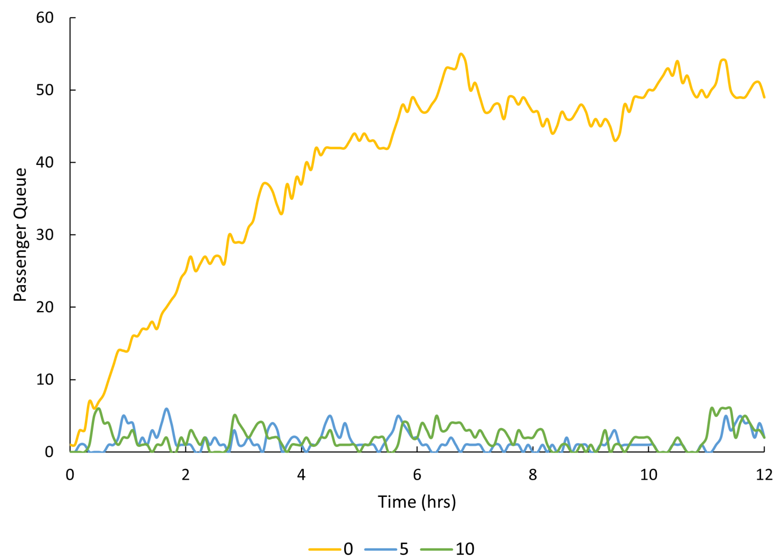

Figure 5.10: Queue of Passengers with Waiting Time Penalty (3600 second time horizon, 100% demand)

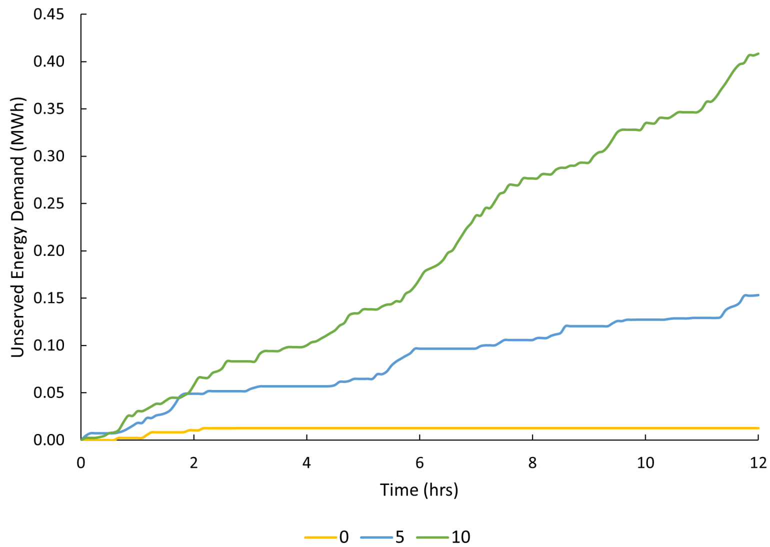

Figure 5.11: Cumulative Unserved Energy (MWh) with Waiting Time Penalty (3600 second time horizon, 100% demand)

Finally, we examine the issue of equity in the transportation network by increasing the demand so that it is outside the stable region. We run two scenarios, first including Cost (0) where $\mu_0 = \$1$ per passenger and second including Cost (4) where $\mu_4 = \$5$ per hour. In each scenario the other term is set to 0. We also increase the demand so that it is outside the stable region (300%). Figure 5.12 demonstrates the incoming demand proportions and the proportion of the total queue that is waiting between each pair of nodes (this matrix matches the passenger demand matrix in Table 5.4 (with nodes labeled in order 1 to 4). Note that when we include the pressure term derived through the stability analysis the queues grow roughly in proportion to the incoming demand. There are some areas with lower queue lengths such as the queues between nodes 1 and 3 or nodes 2 and 4. These are easier queues to serve, so they reduce more quickly. However, as the more difficult queues (such as the one between nodes 1 and 4) get longer they will eventually be prioritized.

When Cost (4) is used we see a different behavior. The dispatch policy empties the easiest queues first, leaving the more difficult ones with almost no service and very long queues. This is not an equitible system and leads to a very large disparity in waiting times for passengers traveling between OD pairs. While Cost (0) still has the longest waiting times for passengers trying to travel between nodes 1 and 4, the disparity is much lower than when Cost (4) is used. Note that the actual pattern of queue lengths is a function of both incoming demand and network structure. Figure 5.13 demonstrates that when demand changes the pattern of queue lengths changes for both cost functions, but the pressure term still maintains a more equitible distribution than the waiting time term.

Demand

0.000	0.061	0.061	0.182
0.061	0.000	0.061	0.091
0.030	0.061	0.000	0.061
0.152	0.061	0.121	0.000

Pressure - Cost (0)

0.000	0.046	0.039	0.200
0.074	0.000	0.084	0.035
0.025	0.053	0.000	0.046
0.196	0.056	0.147	0.000

Waiting - Cost (4)

0.000	0.013	0.082	0.327
0.000	0.000	0.000	0.006
0.000	0.000	0.000	0.101
0.270	0.000	0.201	0.000

Figure 5.12: Distribution of queue lengths with different cost functions.

Demand

0.000	0.061	0.182	0.030
0.091	0.000	0.061	0.091
0.152	0.061	0.000	0.061
0.030	0.152	0.030	0.000

Pressure - Cost (0)

0.000	0.016	0.143	0.104
0.060	0.000	0.077	0.033
0.121	0.027	0.000	0.071
0.077	0.077	0.192	0.000

Waiting - Cost (4)

0.000	0.007	0.273	0.093
0.000	0.000	0.000	0.007
0.187	0.040	0.000	0.127
0.053	0.000	0.213	0.000

Figure 5.13: Distribution of queue lengths with different cost functions for a second demand pattern.

5.4 Conclusion

This chapter developed a simulation to test the impacts of the resilient SAEV dispatch developed in Chapter 4. We demonstrate that this policy needs a longer time horizon than previous policies since it must be sufficiently long for vehicles to charge and discharge as well as moving across the network. This is a drawback since a longer time horizon can lead to significantly more computational effort. Future work should examine ways to reduce this effort for implementation on larger networks. We also demonstrated that when demand is low, vehicles can serve both passengers and energy demand using this optimized policy. This approach is shown to increase passenger waiting times slightly, but not affect the long term stability of the system.

Two major contributions of this thesis are to understand the implications of SAEV dispatch on resilience and equity. This section demonstrated that the policy $\tilde{\pi}^{\star}$ can have significant resilience benefits by providing power to isolated microgrids while still maintaining passenger throughput. We also demonstrate that when demand grows, care needs to be taken when choosing an objective function so that the dispatch is fair for all customers. Future research should examine how critical electric loads or higher priority passengers might affect the behavior of this policy. We also note that all tests were carried out under steady state conditions. Future work should examine the impact of spatiotemporal changes in costs and demands to examine how the vehicle fleet can respond.

Chapter 6: Conclusion

This Thesis examined the issue of shared autonomous electric vehicle (SAEV) dispatch. The literature review determined several different ways EVs are being studied by transportation and electrical engineers by planning routes around charging station availability and utilizing their battery capacity for peak shaving or resilience benefits. However, specific dispatch policies generally make large assumptions about power availability or vehicle availability which may not always be true in practice.

We consider the use of SAEVs for disaster resilience by allowing them to move power between charging stations when faults occur. Since the capacity of each vehicle's battery is separate from their passenger capacity, these vehicles can provide significant benefits to both systems without a significant increase in fleet size. On the other hand, when the fleet size is insufficient to serve all demand the dispatch policy must determine which system to prioritize.

In Chapter 3 we characterized the minimum fleet size (or minimum cost fleet if multiple vehicle types exist) needed to serve all demand. This included serving passengers and electricity demand (or demands of other commodities such as package deliveries or demands for specific vehicle types). We also provided a proof that the dispatch policy could serve demand if any policy could serve all demand. This proof required passengers and energy to form individual queues with no abandonment (if abandonment is included the network is always stable). Recall that this is realistic for passengers as long as waiting times are sufficiently short. For electricity this is equivalent to adding a large battery at each zone or charging station and proving that there is some finite capacity which is sufficient for demand in the long run. This may be realistic for some critical loads, but is not common today. In Chapter 4, we required electric loads to be served in real time (rather than forming a queuing model). This means that in the long run SAEVs will prioritize passenger queues over serving energy. This may be a realistic behavior in practice if the fleet owner and grid operator are separate entities and the fleet owner is simply buying and selling energy from the grid.

This thesis used queuing theory to develop dispatch policies which have analytically provable conditions in the long run. However, neither the transportation system nor the electric grid have stable average demand rates. Instead the fluctuate on daily cycles and have longer term trends over time. Vehicle fleets will likely not be sufficient to stabilize peak hour demand since demands drop off significantly during off-peak periods. This causes large queues to build and disperse throughout the day. Future research should examine the impact of these trends to determine the trade-offs between passenger waiting time and serving energy demands. The constraint that energy demands must be served in real time poses significant challenges and with high enough weight could lead to very long queues, even if the system is still stable in the long run.

Additional consideration should focus on the cost functions since these may not all be set by the dispatch company. It is likely that the company has some control over fares, but prices for energy might be set by the electric grid. In addition, if some pricing schemes are more equitable there could be policies in place encouraging certain behaviors. Future research should examine how each entity should set the terms that they control to maximize the terms in the objective that matter most to them. We demonstrated in simulation that there can be important equity impacts of different cost functions, and this should be considered for realistic implementation. Know distributions of vulnerable populations can help inform a weighted cost structure that prioritizes those who are more reliant on SAEVs while maintaining a high level of service throughout the system.

Finally, one of the biggest issues with optimized SAEV dispatch is the long computation times. The problem must be solved every 15 seconds to 1 minute, but needs to include many variables describing vehicle movements and power flow. In addition, longer time horizons are demonstrated to improve the solution but require significantly more computational effort. Future research should examine heuristics to solve the problem faster. The optimization could also be decomposed into smaller problems that could each be solved more quickly (and possibly at different time scales). This is a critical direction for future effort since it is necessary to test this policy on larger and more realistic networks and will eventually be critical for implementation.

Appendix: Notation

Table A1: List of Notation in Chapter 3.

Notation	Meaning
$\mathcal{A}$	Set of links in the roadway network, indexed by (q, r), (q, s), (r, s).
${}^{m}\alpha_{qr}^{v,e}(t)$	Amount of commodity m that vehicle v (with starting charge e) will take between nodes q and r at time t (if dispatched). Represented in vector form as $\boldsymbol{\alpha}(t)$.
${}^{m}\bar{\alpha}_{qr}^{v,e}$	Average amount of commodity m that vehicle v (with starting charge e) will take between nodes q and r. Represented in vector form as $\bar{\boldsymbol{\alpha}}$.
b	Unit conversion to calculate state of charge based on charging/discharging rate.
${}_{\alpha}B_{qr}^{v,e}$	Energy consumption for vehicle v (with starting charge e) to travel between nodes q and r given some dispatch decision α.
$B_{qr}^{v,e}$	Energy consumption for vehicle v (with starting charge e) to travel between nodes q and r (not including charging or discharging).
β	Some finite constant.
c	Unit conversion to calculate charging/discharging time based on charging/discharging rate.
c^{v}	Passenger capacity of vehicle v.
$C < \infty$	A Non-infinite constant.
${}_{\alpha}C_{qr}^{v,e}$	Travel time for vehicle v (with starting charge e) to travel between nodes q and r given some dispatch decision α.
${}_{\alpha}\bar{C}_{qr}^{v,e}$	Average travel time for vehicle v (with starting charge e) to travel between nodes q and r given some (average) dispatch decision $\bar{\alpha}$.
$C_{qr}^{v,e}$	Travel time for vehicle v (with starting charge e) to travel between nodes q and r (not including charging or discharging).
${}^{m}d_{qr}(t)$	Exogenous demand of commodity m between nodes q and r at time t. Represented in vector form as $\boldsymbol{d}(t)$.
${}^{m}\bar{d}_{qr}(t)$	Average incoming demand of commodity m between nodes q and r. Represented in vector form as $\bar{\boldsymbol{d}}$.

Continued on next page

Table A1: List of Notation in Chapter 3. (Continued)

Notation	Meaning
${}^m\tilde{d}_{qr}(t)$	Maximum possible incoming demand of commodity m between nodes q and r.
$\mathcal{D}$	Stable region of demand (the interior of $\mathcal{D}$ is denoted $\mathcal{D}^0$).
${}^m\delta_{qr}(t)$	The difference in queue between the current timestep and the next.
e	State of charge of some vehicle.
$\{\underline{e},\bar{e}\}$	Set of states of battery charge (between bounds $\underline{e}$ and $\bar{e}$), indexed by e or e'.
ϵ	An arbitrarily small positive constant.
$f(\cdot)$	Some additional objective function terms which must be bounded.
F	The total fleet size.
$\mathcal{G}$	Roadway network.
$K, K_1, K_2 < \infty$	Non-infinite constants.
$\kappa, \kappa_1, \kappa_2 < \infty$	Non-infinite constants.
M	Some arbitrarily large constant.
$\mathcal{M}$	Set of commodities, indexed by m.
$\mathcal{N}$	Set of nodes in the roadway network, indexed by q,r,s.
$\eta > 0$	A positive constant.
$\rho^v \in \{0, 1\}$	Whether vehicle $v \in \tilde{\mathcal{V}}$ is included in the fleet $\mathcal{V}$.
$\pi^\star$	Multi-commodity maximum stability dispatch policy for SAEVs.
R^v	The cost of vehicle v.
$\mathcal{R}$	The maximum replacement ratio.
t	Current time in the system.
T	Length of time horizon.
τ	Simulation timestep.
$\mathcal{V}$	Set of vehicles, indexed by v.
$\tilde{\mathcal{V}}$	Set of potential vehicles, indexed by v.
$\nu(\boldsymbol{w}(t))$	A Lyapunov function.
${}^m w_{qr}(t)$	Queue of commodity m between nodes q and r at time t. Represented in vector form as $\boldsymbol{w}(t)$.

Continued on next page

Table A1: List of Notation in Chapter 3. (Continued)

Notation	Meaning
${}^{m}\tilde{w}_{qr}$	Maximum possible service rate of commodity m between nodes q and r.
$x_q^{v,e}(t) \in \{0,1\}$	Whether vehicle v (with starting charge e) is parked at node q at time t.
$y_{qr}^{v,e}(t) \in \{0,1\}$	Whether vehicle v (with starting charge e) drives between at nodes q and r at time t. Represented in vector form as $\boldsymbol{y}(t)$.
$\bar{y}_{qr}^{v,e} \in [0,1]$	Average dispatch behavior of vehicle v (with starting charge e) between at nodes q and r. Represented in vector form as $\bar{\boldsymbol{y}}$.
${}^{m}Y_{qr}^{v,e}(t) \in \{0,1\}$	Reduction in queue length of commodity m due to vehicle v (with starting charge e) driving between at nodes q and r at time t.
${}^{m}\zeta^{v}$	Bound on the capacity of vehicle v for commodity m.

Table A2: List of Notation in Chapter 4.

Notation	Meaning
$\mathcal{A}_E$	Set of links in the electric grid, indexed by (i,j), (i,k), (j,k).
$\mathcal{A}_R$	Set of links in the roadway network, indexed by (q,r), (q,s), (r,s).
B_{qr}	Energy consumed when driving from node q to r.
C_{qr}	Travel time from node q to r.
$d_{qr}(t)$	Exogenous demand entering the network to travel from node q to r at time t.
$\bar{d}_{qr}$	Long term average arrival rate.
$\tilde{d}_{qr}(t+\tau)$	Prediction of vehicles entering the system at timestep $(t+\tau)$.
$\delta_{qi} \in \{0,1\}$	whether node $q \in \mathcal{N}_R$ is connected to node $i \in \mathcal{N}_E$ by a charging station.
$e^v(t)$	State of charge of vehicle v at time t.
$\underline{e}^v$, $\bar{e}^v$	Minimum and maximum levels of charge of each vehicle v.
$e\bar{s}_q^v(t)$	Bound on real power vehicle v takes from the grid at (roadway) node q at time t.

Continued on next page

Table A2: List of Notation in Chapter 4. (Continued)

Notation	Meaning
$ep_q^v(t)$, $eq_q^v(t)$	Amount of active and reactive power vehicle v takes from the grid at (roadway) node q at time t.
$EP_i(t)$, $EQ_i(t)$	Amount of active and reactive power all vehicles take from the grid at (grid) node i at time t.
$\eta_{q,ch}^v$, $\eta_{q,dch}^v$	Charging and discharging efficiencies of vehicle v at a charging station at node q.
$f_{ij}(t)$	Flow of virtual demand from node i to node j at time t.
$f_i^L = 1$	Virtual demand and node i.
F	Fleet size.
$\mathcal{G}_E$	Energy grid.
$\mathcal{G}_R$	Roadway network.
$\gamma_{q,ch}^v(t) \in [0,1]$	Charging rate if vehicle v will stay at q and charge at time t.
$\gamma_{q,dch}^v(t) \in [0,1]$	Discharging rate if vehicle v will stay at q and discharge at time t.
$\hat{\gamma}_{q,ch}^v(t) \in \{0,1\}$	Whether vehicle v will stay at q and charge at time t.
$\hat{\gamma}_{q,dch}^v(t) \in \{0,1\}$	Whether vehicle v will stay at q and discharge at time t.
$\Gamma_{q,ch}^v$, $\Gamma_{q,dch}^v$	Maximum charging and discharging rates of vehicle v at node q.
$\mathcal{K}_C \subset N_E$	Set of EV charging stations that can act as source nodes if disconnected from the grid but are not required to otherwise.
$\mathcal{K}_G \subset N_E$	Set of electric source nodes connected to the grid.
$l_i(t) \in [0,1]$	Fraction of load at node i to serve at time t.
$\mu_0(r,s,t)$	Demand responsive (pressure) cost.
$\mu_1(r,s,t)$	Payment for serving transportation passengers.
$\mu_2(i,t)$	Payment for serving electric loads.
$\mu_3(i,t)$	Cost of electricity generation.
$\mu_4(r,s,t)$	Cost of passenger waiting time.
$\mu_5(v)$	Cost battery charging/discharging.
$\mu_6(i,t)$	Added price to ensure equity in energy discharge.
N_q	Number of charging stations at node q.
$\mathcal{N}_E$	Set of nodes in the energy grid, indexed by i,j,k.

Continued on next page

Table A2: List of Notation in Chapter 4. (Continued)

Notation	Meaning
$\mathcal{N}_R$	Set of nodes in the roadway network, indexed by q, r, s.
$P_{ij}(t)$, $Q_{ij}(t)$	Active and reactive power flows from node i to node j at time t.
$P_i^G(t)$, $Q_i^G(t)$	Active and reactive power output (except EV discharge) at node i at time t.
$P_i^L(t)$, $Q_i^L(t)$	Active and reactive power demand (except EV charging demand) at node i at time t.
$\tilde{\pi}^\star$	Resilient SAEV dispatch policy.
R_{ij}	Resistance of line (i,j).
$s_{ij}(t) \in \{0,1\}$	Whether line (i,j) is closed (allowing power to flow) at time t.
$s_{ij}^d(t) \in \{0,1\}$	Whether the directed line from i to j is closed at time t.
$s_{ij}^r(t) \in \{0,1\}$	Whether the directed line from j to i is closed at time t.
$\bar{S}_{ij}$	Upper bound on apparent power in line (i,j).
t	Current time.
T	Length of the time horizon.
τ	Index of future timesteps within time horizon.
$u_{ij}(t) \in \{0,1\}$	Whether line (i,j) is operational at time t.
$V_0 = 1$	Voltage constraint for power supply nodes.
$V_i(t)$	Magnitude of the voltage at node i at time t.
$\underline{V}_i$, $\bar{V}_i$	Minimum and maximum voltage magnitude at node i.
$\mathcal{V}$	Set of vehicles, indexed by v.
$w_{qr}(t)$	Number of travelers waiting at node q to travel to r at time t.
$x_q^v(t) \in \{0,1\}$	Whether vehicle v is parked at node q at time t.
X_{ij}	Reactance of line (i,j)
$y_{qr}^v(t) \in \{0,1\}$	Whether vehicle v will drive between nodes q and r at time t.
$Y_{qr}^v(t) \in \{0,1\}$	Whether vehicle v pick up a passenger at q and take them to r at time t.
$z_i(t) \in \{0,1\}$	Whether node i is powered by a source at time t.

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