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The Role of Charging Infrastructure in Electric Vehicle Implementation within Smart Grids

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Abstract: In the integration of electric vehicle (EV) fleets into the smart grid context, charging infrastructure serves as the interlinkage between EV fleets and the power grid and, as such, affects the impacts of EV operation on the smart grid. In this study, the impacts of charging infrastructure on the effectiveness of different EV operational modes were simulated using a multi-component modelling approach, which accounts for both stochastic EV fleet charging behaviors as well as optimal energy vector dispatch operation. Moreover, a campus microgrid case study was presented to demonstrate the various design factors and impacts of charging infrastructure implementation affecting EV fleet adoption and operation. Based on results from the study, it was shown that charging infrastructure should be adopted in excess of the minimum required to satisfy EV charging for driving needs. In addressing uncontrolled charging behaviors, additional charging infrastructure improves EV owner convenience and reduces queuing duration. Meanwhile, controlled charging strategies benefit from increased resilience against uncertain charging behavior and operate more optimally in systems subject to time-of-use (TOU) electricity pricing. Lastly, it was demonstrated that successful vehicle-to-grid (V2G) implementation requires charging infrastructure to emulate the availability and fast response characteristics of stationary energy storage systems, which translates to excess charging port availability, long EV plug-in durations, and bi-directional power flow capabilities well beyond the level 2 charging standard.

Keywords: electric vehicle; smart grid; vehicle-to-grid; controlled charging; optimization

1. Introduction

Depleting natural fossil fuel resources and increased concern over the environmental impacts of high greenhouse gas (GHG) emissions have led to significant development of renewable and sustainable energy resources and technologies. Moreover, advancements in information and communication technology and increasing penetration of distributed energy resources (DERs) have sparked a shift from the traditional centralized power infrastructure toward a decentralized energy network configuration. Motivated by this transition, the smart grid concept has been proposed as a future energy distribution framework, which aims to leverage various DERs and communication technologies to yield advantages in overall grid efficiency, flexibility, and reliability [1]. In one aspect, a decentralized energy network has the potential to reduce active power losses through optimal planning of DER deployment [2,3]. In another, appropriate implementation of communication technologies will enable optimal operation of DERs within the smart grid context, accommodating increasing integration of renewable energy generation, energy storage systems (ESS), and future DER technologies [4]. Lastly, a system with sufficient local DER capacities enables operation under an islanded mode in order to ensure local energy security [5].

Concurrent to the transition towards a decentralized energy framework, mobility electrification in the transportation industry introduces electric vehicles (EV) as another potential DER, which can integrate into the smart grid to provide operational and planning benefits. While previous studies have addressed the various operational modes of EV integration and their corresponding advantages and disadvantages [6–11], there is a gap in the literature on quantifying the impact of charging infrastructure in serving as the interlinkage between EV fleets and the smart grid. This work addresses one of the common assumptions made in smart grid-related studies on EV integration, which is the adequate availability of charging infrastructure to facilitate EV fleet operation.

1.1. Literature Review of Smart Grid-Related Studies

In the literature, the characteristics of systems incorporating DERs are often studied in an energy hub or microgrid context [12,13]. In particular, both avenues of research emphasize the use of interconnected energy networks and communication technology to optimize the dispatch of energy vectors in response to intermittent power generation behavior, variable energy costs, and loss of connectivity to external energy networks. These studies generally consist of modelling and optimization of the flow of energy vectors within an (multi-)energy hub system, for which the foundational mathematical model and optimization approach is discussed in Geidl [14]. Extensions to this model have been proposed to account for energy storage losses and part-load efficiencies by Evins et al. [15], which improve the accuracy of the model by further accounting for realistic system behaviors and characteristics. Meanwhile, the energy hub model has been used in various studies to consider the applicability and characteristics of different DER technology configurations of energy hubs. For example, Vahid-Pakdel et al. [16] applied the model to study a complex multi-carrier energy hub system incorporating distributed wind-based power generation, a district heating network, demand response (DR) programs, and both thermal and electrical energy markets. In another study, Biglia et al. [17] developed the energy hub model to perform a dynamic simulation of an existing multi-energy system based on the Brotzu hospital system, in the context of Sardinia, Italy. The case study demonstrates modeling of realistic energy consumption behavior of the hospital complex, as well as simulation and analysis of potential combined heat and power (CHP) implementation within the system based on operational and economic criteria. With respect to the characteristics of energy hub systems, particular note has been made by Maroufmashat et al. [18] as to the high potential for optimized energy vector dispatch in systems containing a wide variety of load behaviors.

As to the applicability of different DERs within the smart grid context, several technologies have been considered in the literature. Among these, solar- and wind-based resources have been discussed as the most favorable candidates for integration into the existing power grid as distributed renewable generation capacities [19]. However, the intermittent generation behavior of such renewable resources was noted as one of the major challenges of incorporating them into the power grid [20]. Bukhsh et al. [21] have proposed matching flexible consumption loads to complement uncertain renewable generation behavior through DR programs as a solution. Similar approaches using DR programs have been considered by Nwulu et al. [22] and Richardson et al. [23] under different test systems and conditions. Such strategies, however, are contingent on the availability of sufficient flexible loads within the system. As an alternative to the DR approach, implementation of ESS to address the intermittency of renewable generation has been studied by Hill et al. [24] and Santos et al. [25]. In these studies, emphasis has been made on highlighting the role of ESS in compensating for the variability of renewable generation technologies, which has been discussed as a key requirement for significant adoption of renewable resources. Of course, while the optimal implementation of renewable generation will depend on unique system conditions, it is foreseeable that both flexible loads and energy storage capacities will play important roles in the implementation.

In addition to their roles for supporting intermittent renewable generation, energy storage systems have been considered as a DER for additional operational benefits. In one instance, the use of ESS for peak load shaving has been evaluated by Martins et al. [26], in which the economic advantages of peak load shaving are discussed in consideration of industrial load profiles, in the context of Germany. Other implementations of ESS for peak load shaving services have also been studied in hybrid systems. Wang et al. [27] study a hybrid solar photovoltaic-battery ESS system for peak shaving purposes in scenarios of high solar generation adoption, using a state-of-charge (SOC)-constrained Thevenin battery model and accounting for degradation effects. In another study, Zhao et al. [28] examine a hybrid wind-based generation ESS system for peak shaving, considering various ESS technologies and configurations. Meanwhile, the role of ESS technologies in the provision of ancillary services to the grid has been studied by Zou et al. [29], using a profit-maximizing model for ESS. The study discusses the competitiveness of fast-response ESS technologies within the ancillary services market, because of their ability to quickly ramp up and down demand to complement a high penetration of renewable resources. Whereas Tan et al. [30] present a technical control approach for a wind power-battery ESS system for frequency ancillary services, in which the ESS is used to coordinate the wind power system for frequency ancillary service purposes.

1.2. Integration of Electric Vehicles into the Smart Grid

The transition towards electric mobility in the transportation sector has introduced EVs as a novel DER technology with the potential to be incorporated into the smart grid framework. Specifically, EVs may be integrated via one of three operational modes:

1. Fixed loads (uncontrolled charging strategy)
2. Flexible loads (controlled or smart charging strategy)
3. Mobile energy storage systems (vehicle-to-grid)

Considering EVs as fixed loads, significant penetration of EVs into the automotive market will place additional consumption strain onto the power grid because of the aggregate charging behavior of EVs. EV charging will contribute to increasing both the overall electrical demand as well as the peak demand of the grid, which requires the installation of additional reserve generation capacities. Alternatively, EV fleet charging demands may be considered as flexible loads, which allows them to participate in DR programs and engage in controlled or smart charging behaviors. In contrast to uncontrolled charging, projections made by Verzijlbergh et al. [11] have shown that scheduled or smart charging strategies contribute to suppressing the peaking power demand of aggregate EV charging demand. Lastly, the energy storage capacities of EVs can serve as mobile energy storage elements within a smart grid context, alleviating the need for significant adoption of other ESS. Moreover, sufficient integration of electric mobility technologies may enable additional vehicle-to-grid (V2G) services, which provide improved flexibility and reliability for the power grid through bi-directional power flow between EVs and the grid. As discussed by Kempton et al. [7,8], V2G may be employed to provide baseload power, peak power, spinning reserve services, or power quality regulation services. However, with the consideration of the accelerated battery degradation effects of V2G battery cycling, the main avenue for economically feasible V2G implementation in the near-term is the provision of ancillary services.

From the results of previous studies considering the integration of EVs, the potential impacts of uncontrolled charging demand are generally well-understood. As an example, a study presented by Akhavan-Rezai et al. [6] discusses the potential impacts of various market penetration scenarios of EV fleets on the Canadian distribution grid. Meanwhile, current research efforts in EV integration into smart grids via controlled or smart charging strategies are largely concerned with the operational benefits of such strategies under different contexts. Weis et al. [9] explore the economic advantages of controlled charging strategies in comparison with uncontrolled charging in the context of New York, USA. Their study indicates that controlled charging strategies reduce the necessary plant construction for generation capacity expansion through peak demand reduction, and also have the potential to provide support for renewable generation integration. On this last point, EV fleet charging can be controlled to complement the intermittent nature of renewable generation resources by acting as flexible loads. This is further elaborated on by Mwasilu et al. [31], who review the literature on the interactions between EV fleet charging and renewable resources within a smart grid context. Additional benefits of controlled charging strategies include operational cost and emission reduction, achieved through charge scheduling to periods with lower electricity costs or to those employing a less emission-intensive mix of generation resources. These benefits are explored by Weis et al. [32] and Hoehne et al. [10]. In these studies, the role of EV fleets as mobile energy storage capacities has also been considered to further enhance the operational benefits of EVs through V2G capabilities. However, neither of the studies account for the effect of limited charging infrastructure on the feasibility of the proposed operational modes.

Further extending the operational flexibility offered by smart EV fleet charging strategies, the potential of bi-directional power flow between EV fleets and the power grid transforms EVs into active elements within smart grids. As proposed by Kempton et al. [7], the complementary characteristics of EV fleets and the power grid encourage the use of EVs as effective distributed energy storage capacities. This is motivated by the long parking periods expected of EVs, as well as their capacity to generate and store electricity. While this concept is not yet mature, several studies have been conducted to investigate the various potential applications of V2G technology. Tarroja et al. [33] discuss the key characteristics that differentiate EVs from stationary ESS considering V2G technology, noting the limitations imposed on V2G capabilities by the availability of charging infrastructure. Sarabi et al. [34] considered scenarios of V2G adoption with home and workplace cases, with the incorporation of uncertainties in EV availability. The study also recognizes that the availability of V2G infrastructure should be accounted for in considering feasible V2G implementation. Meanwhile, the potential for EV fleets to support the islanded operation of microgrid systems is discussed by Rodrigues et al. [35], who indicate that V2G could potentially be used to support islanded microgrid systems. A common assumption of these studies, however, is that there is sufficient charging infrastructure available to facilitate the scenarios considered. While this is reasonable for low EV market penetration scenarios, a significant market shift towards electric mobility in the future requires that the impacts and characteristics of limited charging infrastructure be taken into account when considering EVs in a smart grid context.

1.3. Contributions of this Work

In this paper, the role of charging infrastructure in serving as the interlinkage between EV fleets and a campus microgrid is investigated. In this effort, this work presents a multi-component simulation approach to forecast the optimal system operation considering varying levels of EV and charging infrastructure adoption. This work also develops upon the energy hub model in Geidl [14] to account for the role of EV fleets as energy storage components within the smart grid. The simulation approach is then applied to a case study of the Wilfrid Laurier University campus system in Waterloo, Ontario. From the results of the case study, a discussion is held on the applicability of different EV operational modes within smart grids, as well as on the potential impacts of limitations in charging infrastructure on these operational modes.

The contents of this paper are structured as follows: in Section 2, the modelling, simulation, and optimization approach employed in this work is detailed; the results of this work and relevant analysis are presented in Section 3; and concluding remarks are made in Section 4.

2. Methodology

In this work, a multi-component approach was used to model and optimize the technology configuration and operation of a campus microgrid system with diverse consumption load profiles, distributed generation technologies, energy storage capacities, and EV integration. A holistic representation of this approach is shown in Figure 1. In this approach, a building energy simulation was used in combination with metered energy consumption data and known building properties to determine the energy demand loads of buildings. Meanwhile, a stochastic EV fleet simulation model based on realistic EV parameters was used to determine the charging requirements of a projected EV fleet. These energy requirements were then fed into an energy hub model, which was used to simulate the optimal dispatch of energy vectors within the overall system to reflect the optimized system operation, under different energy technology configuration scenarios. Through this approach, this work develops the energy hub model discussed in Geidl [14] to incorporate EV fleets as an aggregate mobile electrical energy storage system (ESS), which is applied to evaluate the potential impact factors of EV integration into a smart grid context. These include the operating costs of the system configuration, its operational GHG emissions, the ability of the implemented system configuration to satisfy the charging needs of the EV fleet, as well as the impacts of EV implementation on the cycling experienced by local ESS capacities for cost optimization.

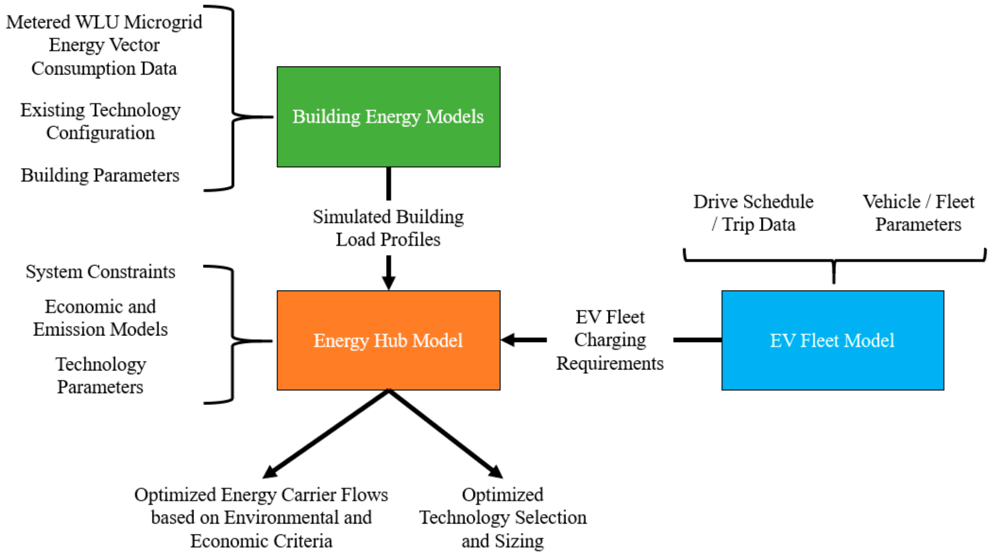

Figure 1. Holistic representation of multi-component simulation approach. EV—electric vehicles.

2.1. Energy Hub Model

The energy hub model used in this work can be understood as an energy balance expressed as shown in Equation (1). Specifically, the energy hub model employs a mathematical approach to consider energy vector coupling for a multi-energy vector system. Here, the various energy consumption requirements of a system are represented in relation to its energy conversion technology efficiencies, inflow of energy vectors from external sources, and energy storage capacities. A time-independent coupling matrix was considered to represent steady-state efficiencies, because it was assumed that transient behavior in energy conversion systems occurs in a much smaller timescale than the simulated one-hour timesteps, and does not significantly affect the expected behavior of the system. Moreover, capacity limitations for energy conversion technologies are represented by constraints on inflow rates of energy vectors, as expressed in Equation (2).

$$D_i(t) = C_{ij}F_j(t) \tag{1}$$

where $D_i(t)$ is the set of energy vector demands of size i of the energy hub for timestep t; C_{ij} is the coupling matrix for feed energy vector j to demand i; and $F_j(t)$ is the set of energy vector feeds of size j into the energy hub for timestep t.

$$F_{j,min} \leq F_j(t) \leq F_{j,max} \tag{2}$$

where $F_{j,min}$ is the minimum flow capacity for the feed energy vector j; and $F_{j,max}$ is the maximum flow capacity for the feed energy vector j.

Energy storage capacities within the system are modelled as shown in Equation (3) and are constrained by capacity and energy flow limitations as shown in Equations (4)–(7). The state-of-charge of each ESS is determined via a discrete backwards-difference method as shown in Equation (2), which accounts for charging and discharging efficiencies of the ESS, as well as standby losses.

$$Q_{k,stor}(t) = Q_{k,in}(t) \cdot \varepsilon_{k,in} - \frac{Q_{k,out}(t)}{\varepsilon_{k,out}} \tag{3}$$

where $Q_{k,stor}(t)$ is the net energy vector flow into energy storage system k for timestep t; $Q_{k,in}(t)$, $Q_{k,out}(t)$ are the inflow and outflow, respectively, of energy vector into the energy storage system k for timestep t; and $\varepsilon_{k,in}$, $\varepsilon_{k,out}$ are the energy vector inflow and outflow efficiencies, respectively, for energy storage system k.

$$Q_{k,in,min} \leq Q_{k,in}(t) \leq Q_{k,in,max} \tag{4}$$

where $Q_{k,in,min}$ is the minimum inflow rate of energy vectors into energy storage system k; and $Q_{k,in,max}$ is the maximum inflow rate of energy vectors into energy storage system k.

$$Q_{k,out,min} \leq Q_{k,out}(t) \leq Q_{k,out,max} \tag{5}$$

where $Q_{k,out,min}$ is the minimum outflow rate of energy vectors into energy storage system k $Q_{k,out,max}$ is the maximum outflow rate of energy vectors into energy storage system k.

$$SoC_{k,min} \leq SoC_k(t) \leq SoC_{k,max} \tag{6}$$

where $SoC_k(t)$ is the state-of-charge of storage system k at timestep t; $SoC_{k,min}$ is the minimum charge capacity of the storage system k; and $SoC_{k,max}$ is the maximum charge capacity of the storage system k

$$SoC_k(t) = \ SoC_k(t-1) + \frac{Q_{k,stor}(t)}{E_{max,k}} - SoC_{k,loss}(t) \tag{7}$$

where $SoC_k(t-1)$ is the state-of-charge of the storage system k at timestep $t-1$; $E_{max,k}$ is the maximum storage capacity of storage system k; and $SoC_{k,loss}(t)$ is the standby loss incurred by the storage system k at timestep t.

Meanwhile, EV acting as mobile energy storage components in the energy hub are modelled similar to ESS, but are subject to unique temporal constraints to reflect vehicle availability and charging infrastructural constraints. Specifically, additional time-variant power flow constraints to EVs have been imposed such that power flows are nonzero only during periods in which EVs are not driving and are connected to a charging station. These constraints are similar in form to Equations (4) and (5). EVs also experience capacity losses due to driving, as well as stochastic availability to the energy hub as storage capacities due to user behavior. As such, additional EV-unique constraints have been developed in the energy hub model for the EV fleet components to reflect these factors, which ensures that EVs adequately charge during charging sessions to satisfy driving requirements for subsequent trips. These are as expressed in (8).

$$Q_{PEV,stor}(t) = Q_{PEV,charge}(t) \cdot \varepsilon_{PEV,charge} - \frac{Q_{PEV,discharge}(t)}{\varepsilon_{PEV,discharge}} - \dot{E}_{PEV,loss}(t) \tag{8}$$

where $Q_{PEV,stor}(t)$ is the net flow of electricity into the EV fleet for timestep t; $Q_{PEV,charge}(t)$, $Q_{PEV,discharge}(t)$ are the power charged to and discharged from the EV fleet, respectively, for timestep t; $\varepsilon_{PEV,charge}$, $\varepsilon_{PEV,discharge}$ are the charge and discharge efficiencies for the EV fleet, respectively; and $E_{PEV,loss}(t)$ is the loss of stored electricity due to driving for the EV fleet for timestep t.

Finally, the overall model can be formulated as a mixed-integer problem (MIP) as expressed in (9), which is implemented via the GAMS platform. This model was then solved using the commercial CPLEX solver based on an economic objective function in order to reflect optimal operation of the energy hub configuration. The objective function is as expressed in (10). A visualization of the developed energy hub model is shown in Figure 2.

$$D_i(t) = C_{ij}F_j(t) + Q_{k,stor}(t) + Q_{PEV,stor}(t) \tag{9}$$

$$Z = Cost_{op} + Cost_{fuel} \tag{10}$$

where Z is the overall objective function; $Cost_{op}$ is the annual operating costs of the system; and $Cost_{fuel}$ is the annual fuel costs of the system.

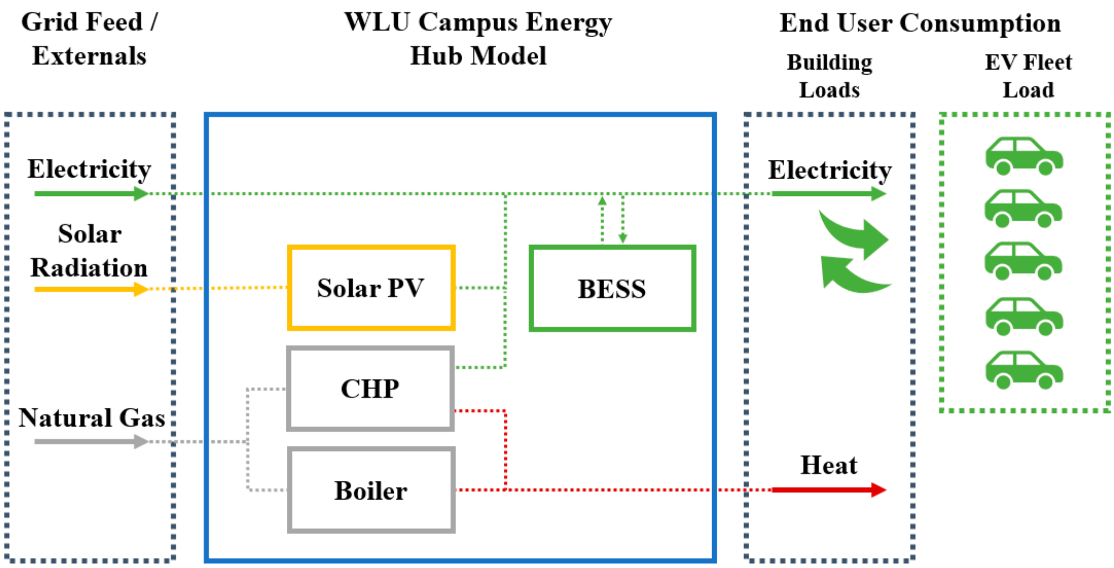

Figure 2. Holistic representation of energy hub model. CHP—combined heat and power.

2.2. Monte Carlo Simulation of Electric Vehicle Fleet Charging Demand

A Monte Carlo simulation was used to generate probabilistic scenarios of EV fleet charging demands considering distributions of EV vehicle battery capacities, trip arrival times, departure times, daily driving requirements, and minimum required state-of-charge (SOC) of the vehicle. In considering these factors, the simulation develops realistic EV fleet charging behavior that accounts for variations in vehicle characteristics and driver behavior. An illustration of this simulation approach is shown in Figure 3.

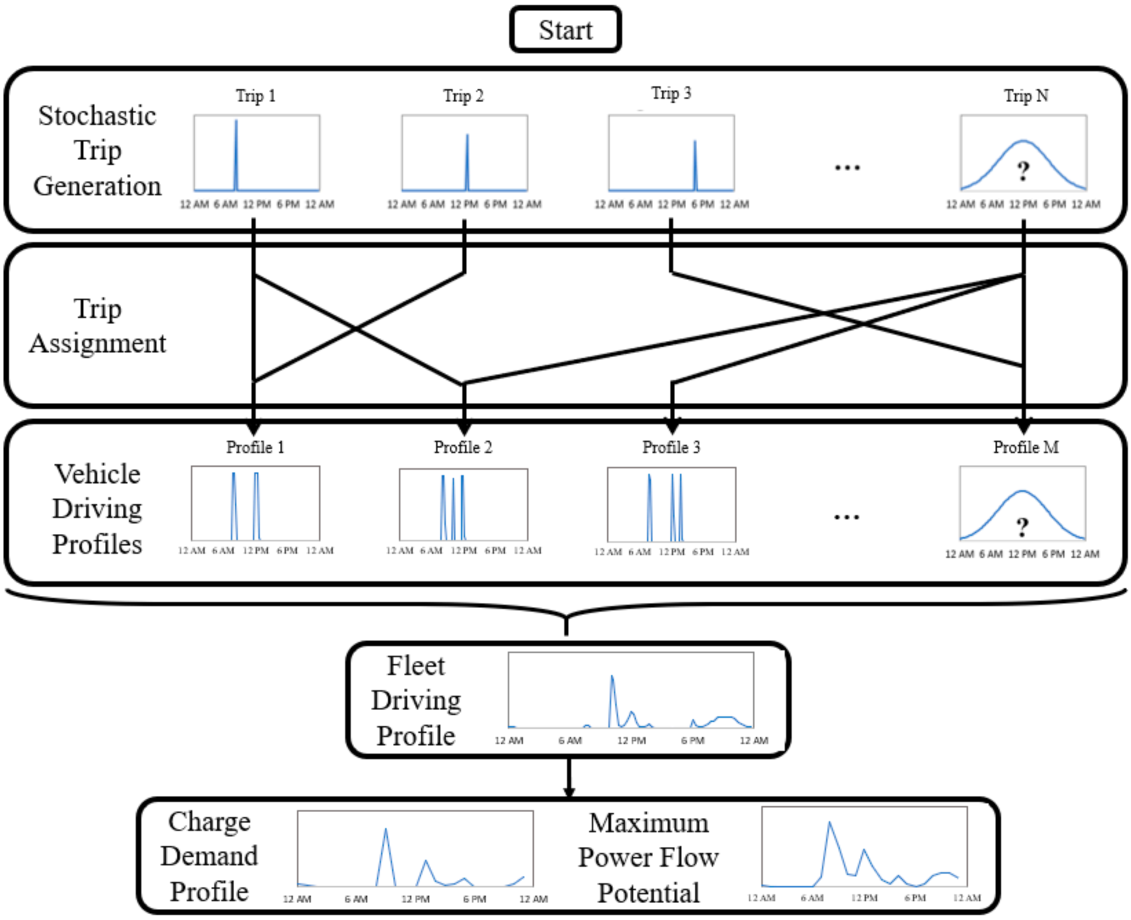

Figure 3. Flow chart of Monte Carlo simulation for EV fleet charging demand.

2.3. Case Study—Wilfrid Laurier University Campus Microgrid

The Wilfrid Laurier University campus in the Waterloo, Ontario region consists of over 35 buildings with a diverse mix of energy consumption behavior. The buildings consist of residential, commercial, research and academic, athletic, and administrative types and are used to service over 16,000 students. As a part of its Laurier Energy Efficiency Program, Laurier aims to incorporate DER within the campus with the objective of establishing a microgrid system. This includes the installation of rooftop solar arrays for ~500 kW of renewable generation, a 1994 kW(e) natural gas generator for distributed generation, and an on-site battery ESS for 6 MWh of energy storage capacity.

As the object of this study, eight buildings were selected that reflect the diverse mix of energy consumption behavior of the Laurier campus. The selected buildings are as indicated on the Laurier map as shown in Figure 4. The heating and electrical energy consumption data were metered and data collected over the 2016–2017 period were used to create representative energy models of the buildings via the TRNSYS software (TRNSYS Version 17.02.0005, Thermal Energy System Specialists, LLC, Madison, USA), considering the present HVAC and energy conversion technologies in each of the buildings. A summary of the building characteristics and simulated heating and electrical consumption loads can be found in Table 1.

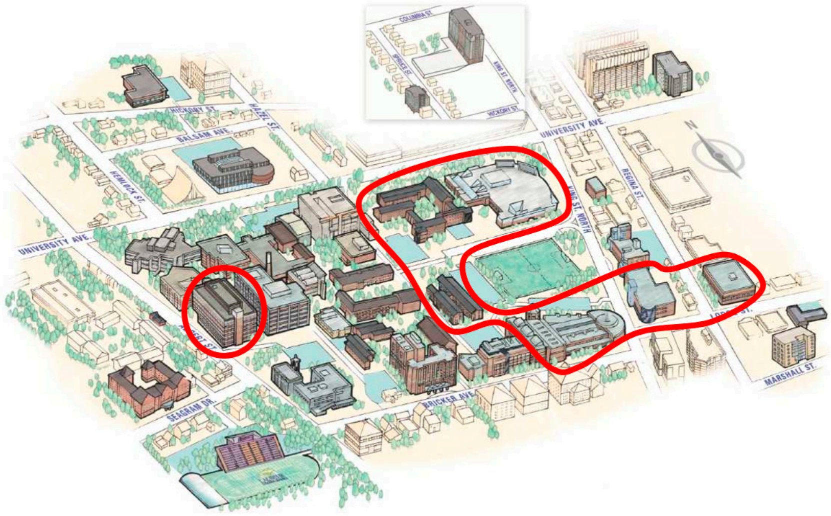

Figure 4. Map of Laurier campus. Only the highlighted buildings were considered in the case study [36].

Table 1. Summary of building characteristics and energy consumption loads of buildings considered in the case study.

Building (Type)	Total Conditioned Floor Area (m^2)	Total Conditioned Volume (m^3)	Heating Demand (MWh/yr)	Electricity Demand (MWh/yr)
Athletic (Athletic)	12,105	36,390	2470.24	1853.52
Clara Conrad (Residential)	7500	20,018	1481.60	313.10
Willison (Residential)	6132	16,693	1222.35	283.18
Library (Academic)	9700	30,443	4120.65	930.34
Science (Academic)	14,778	43,013	4061.60	2538.10
Science Research (Research)	3996	11,868	291.06	1085.01
202 Regina (Commercial)	7337	21,790	406.09	763.15
Career and Coop (Commercial)	2369	7041	294.63	254.88

As for the characteristics and behaviors of the EV fleet considered for the case study, the aforementioned Monte Carlo simulation approach was used to project a hypothetical fleet of 250 EVs that is reflective of light-duty vehicles used for workplace commutes, considering a market penetration of approximately 25%. Here, vehicles travel 50 km/day on average according to National Transportation Statistics [37] and participate in charging throughout the workday. The charging behavior for this fleet is reflective of workplace commuting, occasional lunchtime driving, and a small amount of sporadic driving throughout the workday. Furthermore, a small fleet of 50 EVs was simulated to reflect campus-owned vehicles, which are used to support campus operations during the day. This fleet was simulated to travel an average of 75 km/day and is expected to engage in night-time charging. It is noted that such behavior is similar to an above-average fleet of light-duty vehicles that participate solely in home-charging. A representative profile for the resulting uncontrolled charging behavior of the aggregate fleet is shown in Figure 5.

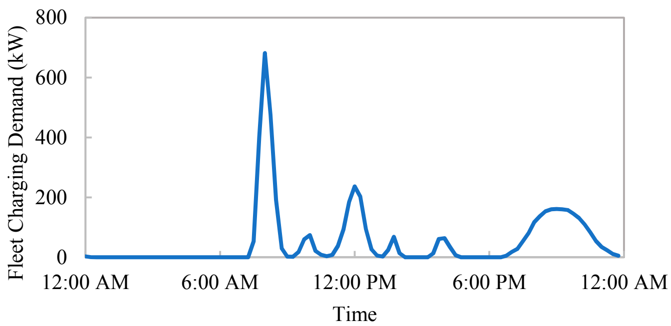

Figure 5. Representative uncontrolled charging demand for the EV fleet in the Laurier case study.

For the evaluation of fuel costs and emissions associated with system operation, Ontario conditions were used. Throughout the annual simulation, the time-of-use (TOU) electricity pricing scheme shown in Figure 6 was used to evaluate electricity costs, whereas a constant rate of 0.0308 $CDN/kWh was used for natural gas costs [38,39]. Meanwhile, a daily emission factor schedule was used to evaluate emissions associated with grid electricity consumption, based on an average daily schedule of Ontario generation resource mixes, while natural gas consumption incurred a constant emission factor of 525 g GHG/kWh [40,41].

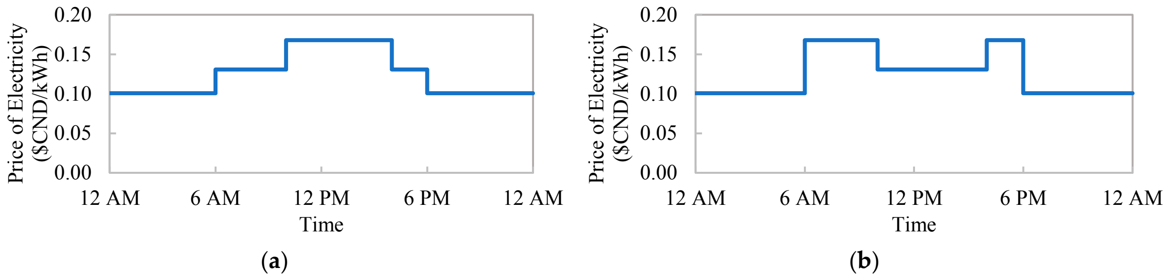

Figure 6. Time-of-use pricing scheme for electricity costs in Ontario, Canada for the following: (**a**) summer weekdays (1 May–31 October) and (**b**) winter weekdays (1 November–30 April).

2.4. Simulation Scenarios

In this study, the Laurier microgrid system is simulated under various EV operational modes, charging infrastructure availability implementations, and expected plug-in duration scenarios. In terms of the availability of charging infrastructure, both level 2 and DC fast charging rates were considered, as well as varying degrees of charging port sizing. Various levels of expected EV plug-in durations were also considered to anticipate different levels of charging urgency. Lastly, three operational modes for EV integration were considered, including uncontrolled charging behavior, controlled charging strategies, and V2G technology. A summary of simulation parameters considered is shown in Table 2.

Table 2. Summary of simulation parameters and range of values considered in the case study. V2G—vehicle-to-grid.

Parameter	Ranges Considered
Operational Mode	• Uncontrolled Charging • Controlled Charging • V2G
Charging Rate (kW)	• Level 2, Charging (6.6) • DC Fast Charging (66)
Infrastructure Availability (# of Charging Ports)	0–300
Plug-in duration (Hours)	0–4

3. Results and Analysis

3.1. Effect of Charging Infrastructure Limitations on EV Adoption and Feasibility of EV Operational Modes

Limited availability of charging infrastructure reduces the maximum possible power flow to and from the EV fleet. As a result, the potential of the implemented EV fleet operational mode may not be fully realized. In the worst case, EVs may not receive adequate charging to maintain their primary transportation function, which acts as a disincentive against EV adoption. Such consequences mainly manifest from the implementation of charging infrastructure, such as in the sizing of charging ports or in the selection of the charging rate. To demonstrate, results from the Laurier case study considering scenarios of insufficient charging infrastructure availability are shown in Figure 7.

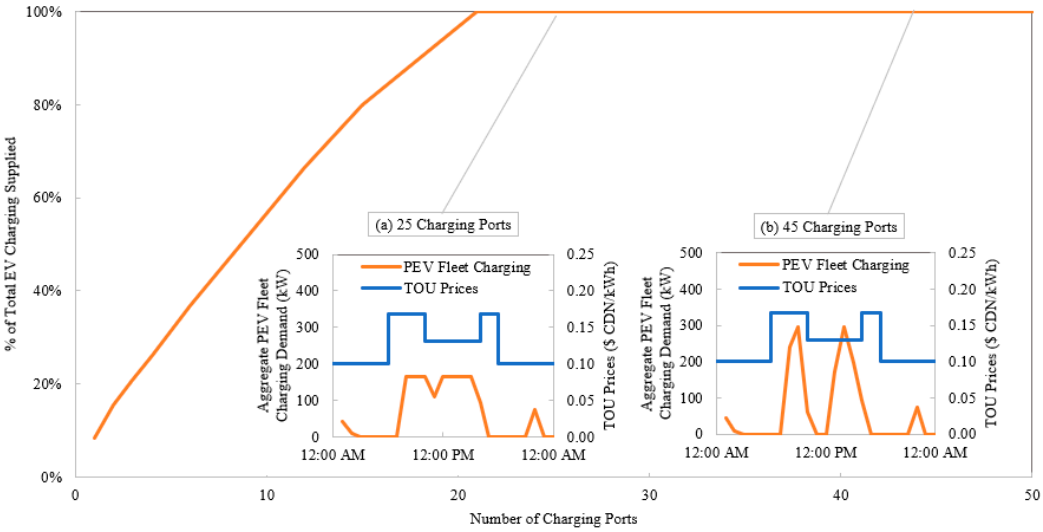

Figure 7. Charging delivered to EV fleet with increasing availability of charging infrastructure. EV fleet charging profiles are shown for (**a**) 25 charging ports and (**b**) 45 charging ports. TOU—time-of-use.

As observed from Figure 7, when considering charging infrastructure implementations that are inadequate for EV adoption, the amount of charging that can be provided to the EV fleet is insufficient to meet EV driving needs. The amount of required EV charging that is met increases with respect to increasing charging infrastructure. In the figure, this is represented by increasing the number of charging ports available to the EV fleet. The initial behavior is indicative of insufficient charging infrastructure and continues until a critical number of charging ports are available, which represents the minimum degree of charging infrastructure implementation required to accommodate the adoption of a certain fleet size of EVs. This minimum degree of charging infrastructure is a critical point under which the charging needs of the EV fleet will not be fully met, and it is dependent on various parameters of the projected EV fleet such as fleet size, expected plug-in duration, driving behavior, and coincidence with other vehicles' charging schedules. Beyond this critical point, any additional installation of charging ports only serves to increase the maximum power flow to and from the EV fleet, thereby increasing the resiliency of the implementation against charging demand uncertainties, as well as increasing its ability to address peak charging demands. These effects are considered by increasing the number of charging ports beyond the minimum required amount to satisfy EV charging. A comparison of the difference in peak charging behavior is shown in Figure 7 for simulated scenarios considering 25 and 45 charging ports, which are representative of peak-reduced charging behavior due to power flow limitations and a less limited scenario. As shown, the 25 charging port scenario constrains maximum EV charging at approximately 200 kW, whereas the 45 charging port scenario does not significantly constrain peak charging, resulting in charging peaks of as high as 300 kW.

In consideration of different EV operational modes, charging infrastructure implementations that are insufficient to serve the primary charging needs of the EV fleet will be similarly inadequate for any additional functionality required for advanced operational modes. In particular, charge-delaying control and bi-directional power flows for controlled charging strategies and V2G, respectively, will not be feasible in such conditions. This is because these services should be considered as secondary in comparison with the primary transportation function of EVs. As such, EV charging behavior will be indifferent to the presence of such capabilities because of the need to satisfy its base charging needs.

3.2. Effect of Charging Infrastructure on Uncontrolled Charging Behavior

The primary objective of EV fleets that engage in uncontrolled charging behavior is to meet the immediate charging needs of the fleet. As such, limitations in charging infrastructure impact two properties of this operational mode:

1. Peak charging behavior of the aggregate EV fleet.
2. Queuing and service durations experienced by EVs

It should be noted that these two impacts are not mutually exclusive. Rather, these are effects that manifest concurrently at different degrees of charging infrastructure availability. In the first and more obvious effect, the inadequate sizing of charging infrastructure hinders the ability of the system to meet peak EV charging demands, as a result of its inability to supply the high power flows required. In the second effect, the lack of charging infrastructure to support peak charging demands will result in peak-reduced and prolonged charging, which manifests as charging port queuing. Depending on the characteristics of charging peaks, long queuing durations may inhibit the ability of the EV to perform subsequent driving.

First, the peak-reduced and prolonged charging behavior increases the system's resiliency against variable electricity pricing and acts to indirectly suppress peaking power demand on the grid. This is because levelized demands are less intermittent and are thus less prone to incurring high charging costs because of incidence with on-peak periods. Reduced peaking behavior is also more manageable by the microgrid system or by the external power grid, requiring less ramping up and down of reserve resources to meet the peaking consumption demand. Again, this is owing to the consistency of levelized charging demand. To demonstrate this point, a comparison of uncontrolled EV charging demand between limited and unlimited charging infrastructure scenarios from the case study is shown in Figure 8. From this graph, it is observed that, in a system subject to TOU electricity pricing, higher costs can be incurred in the unlimited charging infrastructure case as a result of aggregate charging demand occurring during on-peak periods. Meanwhile, limitations in charging infrastructure mitigate and prolong these peak demands such that some of the charging demand is satisfied during periods of lower cost. Of course, the opposite could also occur, where peak EV demands occurring during off-peak periods may be prolonged into on-peak periods. The takeaway here, however, is that such behavior should be accounted for when considering uncontrolled charging conditions, in order to optimally design charging infrastructure to complement the operational costs of EV fleet charging.

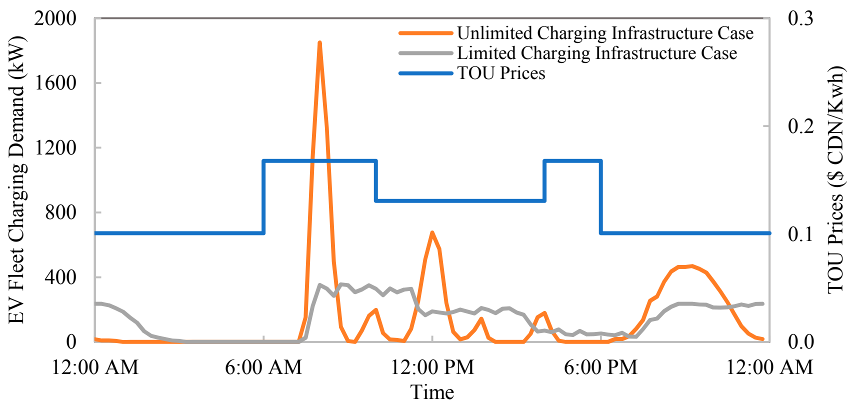

Figure 8. Comparison of uncontrolled EV fleet charging demand profiles between limited and unlimited charging infrastructure scenarios.

As for the second impact, long queuing durations for EV charging resulting from prolonged charging act as a disincentive against EV adoption. Practically, this can delay EV availability for subsequent trips. Manifestation of charging port queuing will also require the development and implementation of effective queuing strategies, as well as the infrastructure to coordinate queuing. To demonstrate, the prolonged charging duration effect can be inferred from Figure 9. On the basis of results from the case study, the additional waiting duration required for EVs in charging port queuing to satisfy the same amount of overall EV charging demand increases as the degree of charging infrastructure implementation decreases. This implies that vehicles must be remain in queuing for longer durations in order to meet their charging requirements. This is because, owing to the lack of available charging ports, EVs are required to queue for longer durations in order to meet their charging needs. Such effects on queuing duration should be considered when designing charging infrastructure implementations in order to optimize the utility of charging infrastructure to serve user convenience.

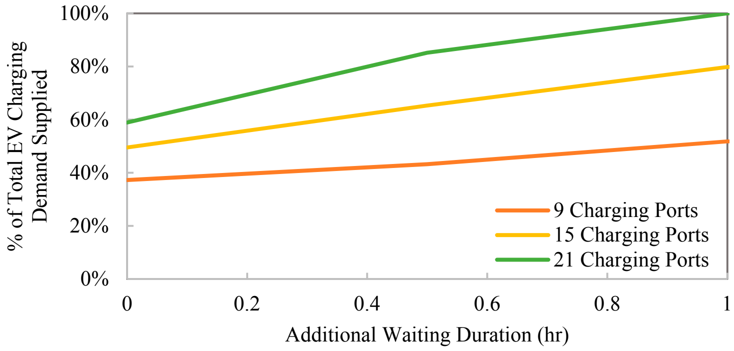

Figure 9. Comparison of delivered charging to EV fleet considering different sizing of charging ports.

3.3. *Effect of Charging Infrastructure on Controlled Charging Behavior*

Building on the benefits discussed in the previous section, controlled or smart charging is an operational mode that aims to derive operational benefits from EV charging via control of EVs as flexible loads. In this regard, the impact of limited charging infrastructure on controlled or smart charging strategies affects the following three properties:

1. Resiliency of controlled charging strategies against charging demand uncertainties.
2. Charge delaying potential.
3. Degree of interaction with stationary ESS.

Following from the discussion on the feasibility of controlled charging strategies under limited charging infrastructure implementation, inadequate availability of charging infrastructure invalidates the operational feasibility of controlled charging strategies. The potential for controlled charging strategies becomes apparent, however, once excess charging infrastructure is installed and the immediacy for EV charging becomes less urgent. Once these conditions are met, increasing the availability of charging infrastructure will provide increasing flexibility and resiliency for controlled EV charging to achieve operational benefits, without impeding the EVs' primary function. Additionally, adoption of controlled charging strategies within a smart grid context creates a beneficial interaction between EV fleets and stationary ESS capacities. In comparison with uncontrolled charging behavior, controlled charging strategies alleviate cycling experienced by stationary ESS for operational cost optimization. This is because stationary ESS are required in a lesser capacity for load balancing purposes, as controlled EV charging can be leveraged to achieve similar results.

In order to contextualize these impacts, results from the case study are used to illustrate the effect of limited charging infrastructure on the controlled charging operational mode. As shown in Figure 10, the controlled charging behaviors for both limited and unlimited charging infrastructure cases are compared, considering charging cost optimization based on TOU electricity prices. As shown, limitations in charging infrastructure reduce the ability of the EV fleet to function as a flexible load. In one effect, charging is incurred during on-peak periods because charge-delaying would result in significant queuing. In another, limitations on maximum charging rates result in some charging demand being delayed beyond optimum charging periods. Both effects reduce the potential of controlled charging strategies for cost-optimized charging. Consequently, limitations on charging infrastructure also reduce the resiliency of controlled charging strategies against unanticipated charging demands, as inflexible charging behavior is less adaptable to unanticipated demands.

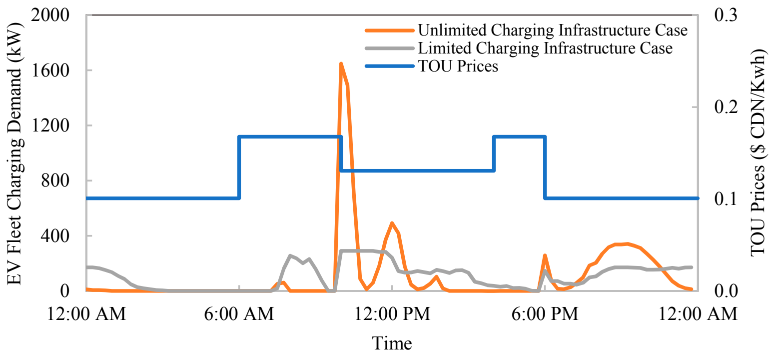

Figure 10. Comparison of controlled EV fleet charging demand profiles between limited and unlimited charging infrastructure scenarios.

Also demonstrated in the case study, the cycling demand experienced by the stationary ESS was shown to decrease with respect to increasing charging infrastructure and increasing allowable queuing duration. This is illustrated in Figure 11a. One conclusion to be drawn from this is that appropriate implementation of controlled charging strategies mitigates the cycling demand experienced by stationary ESS capacities, reducing cycling degradation and the required sizing of such capacities. However, this is accommodated only by sufficient charging infrastructure and EV charging behaviors, as the charging needs of the EV fleet would not be fully met otherwise. As shown in Figure 11a, increasing both degrees of charging infrastructure availability and allowable queuing durations, beyond those required to meet the charging needs of the fleet, reduces cycling of stationary ESS for charging cost optimization. This is because much of the load-balancing operation is substituted by controlled charging. It should be noted, however, that short plug-in durations for EVs do not significantly alleviate load-balancing cycling experienced by the stationary ESS, despite increasing charging infrastructure availability. This is because of the behavior of aggregate EV charging and its interaction with the TOU electricity pricing scheme considered in the case study. As the plug-in duration of the EV charging behavior is short and is coincident with on-peak periods, the EV fleet is not able to access low TOU electricity rates, thus becoming reliant on stationary ESS support for optimizing charging costs. As a general takeaway, this suggests that controlled charging strategies for TOU cost optimization should account for the expected plug-in behavior of the target EV fleet, because it can impact both the optimal charging infrastructure implementation and the operation of supporting ESS. Similarly, it is also demonstrated that controlled charging strategies are more operationally economical in systems without any ESS capacities. This is largely because of the derived benefits of charging cost optimization from charge-delaying control of EV fleet charging. An illustration of this effect from the case study results is shown in Figure 11b, for scenarios varying in charging port sizing and allowable queuing durations at charging ports.

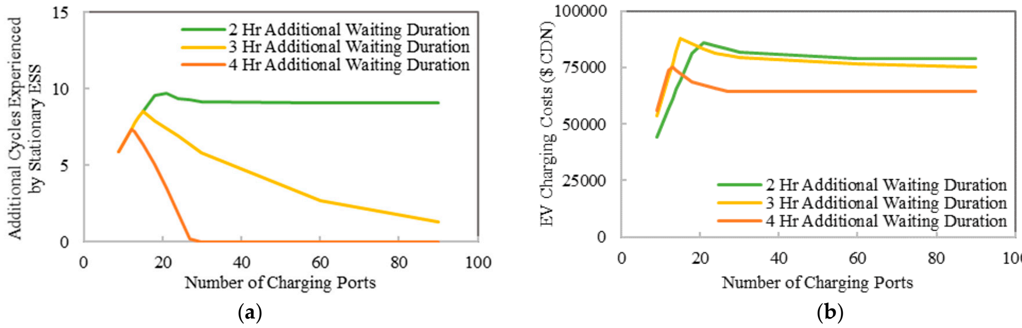

Figure 11. Comparison of (**a**) additional cycling imposed on stationary energy storage systems (ESS) and (**b**) additional operating costs imposed on the microgrid system by the EV fleet between different scenarios of allowable queuing duration.

3.4. Effect of Charging Infrastructure on V2G

The V2G operational mode utilizes bi-directional power flow capabilities in order to transform EVs into mobile energy storage capacities, which can potentially displace the need for stationary ESS installation. Considering their role in enabling bi-directional power flow, limitations in charging infrastructure impact the following three properties of the V2G operational mode:

1. Resiliency of V2G operation against charging demand uncertainties.
2. Potential of V2G for fast response.
3. Displacement of cycling experienced by stationary battery ESS.

Similar to the feasibility of controlled charging strategies, the success of V2G is dependent on the availability of charging infrastructure. In one extreme, unlimited power flows in charging ports allow full accessibility of EV energy storage capacities for V2G purposes. In the other, constrained power flows to and from EV fleets limit the amount of charging and discharging possible, thus mitigating the potential benefits of V2G implementation. Between these two extreme conditions, several factors emerge that affect the success of V2G implementation. Considering the first impact listed above, limitations in power flow and availability of charging infrastructure for EV fleets reduce the resiliency of V2G implementation against uncertainties in EV demands. Extending from the discussion on controlled charging, low power flow rates and low availability of charging ports constrain the degree to which V2G may be employed, thereby reducing the flexibility of V2G services. Moreover, this effect is magnified for V2G services because V2G participation depletes EV capacities, which directly compete against the primary transportation function of EVs. Consequently, the resiliency of V2G against uncertain EV fleet demands is also reduced, as inflexible V2G operation is less adaptable to uncertain EV behavior, especially considering the competitive interactions between V2G and EV driving. Reasonably, this impact will manifest as an SOC constraint, in which V2G services cannot be performed by EVs with SOCs under a certain threshold, in order to mitigate the potential for V2G participation to affect EV driving as a result of uncertainty. Of course, this threshold decreases the accessible ESS capacity for V2G, thus indirectly reducing the overall functionality of EV fleets as mobile ESS capacities.

Limitations in charging infrastructure also have a more direct impact on the success of V2G, which is as described by the second impact. In this effect, limitations in charging infrastructure effectively reduce the available ESS capacity and the power flow potential for V2G. Specifically, the sizing of charging infrastructure limits the portion of total EV fleet capacity that is accessible for V2G, while charging rate constraints limit the power flow potential of the EV fleet for the provision of fast response services. Finally, the last impact concerns the interaction between V2G technology and stationary ESS. As discussed, sufficient integration of EVs within the smart grid as mobile ESS elements can potentially reduce or eliminate the need for stationary ESS. However, because the effective capacity and maximal power flow to and from the EV fleet is defined by the characteristics of charging infrastructure, the potential of the EV fleet to displace stationary ESS capacities is dependent on the implementation of charging infrastructure.

On the basis of the results of the case study, the impact of charging infrastructure limitations on the feasibility of V2G implementation can be inferred from Figure 12. The figures show that, considering increasing implementation of charging infrastructure, the cycling experienced by stationary ESS for load-balancing decreases. Within the case study, this is explored considering varying charging port sizing and different durations of plug-in periods for EVs, as well as two levels of charging rates. When considering a level 2 charging rate scenario, Figure 12a indicates clear limitations for V2G operation due to the power flow constraints imposed by the charging rate. With respect to the number of charging ports, it is shown that low sizes of charging infrastructure implementation impose additional cycling on stationary ESS capacities to provide support for cost-optimal operation; these are indicated by a negative amount of cycling alleviated from stationary ESS, which corresponds to additional cycling. Despite reasonable implementation of excess charging ports, it is still observed that V2G fails to alleviate cycling from stationary ESS for short plug-in durations. This is because, while charging port availability may not limit V2G participation, the potential of V2G is constrained by two additional factors.

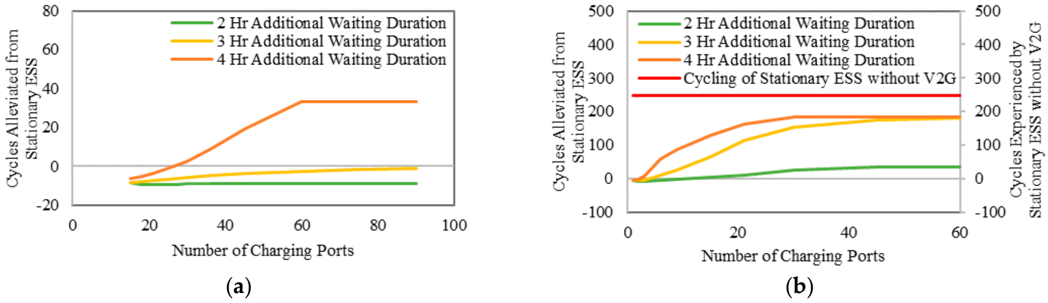

Figure 12. Cycling for load-balancing alleviated from stationary ESS by vehicle-to-grid (V2G) operation considering (**a**) level 2 and (**b**) DC fast charging rate limitation.

First, limited connectivity of EVs to the grid reduces their potential to provide V2G services. In comparison with stationary ESS, EVs are only connected to the grid via charging infrastructure, which is subject to competition for vehicle charging needs. Moreover, EVs must remain connected to the grid for a sufficient duration in order to perform load balancing services, in addition to the plug-in duration required to meet its own charging needs. Secondly, low power flow capabilities for charging infrastructure limit the rate at which EVs may inject power into the grid. This further hinders the operational potential of V2G by limiting the maximum amount of charge cycling that is possible. The effects of such limitations are demonstrated in the level 2 charging rate case, in which V2G is only able to successfully offset stationary ESS capacity cycling considering long EV plug-in durations and significant excess charging port sizing. In contrast, scenarios considering implementation of DC fast charging for V2G operation were able to displace significant cycling from stationary ESS. As shown in Figure 12b, the high power flow rates considered in the DC fast charging scenarios improve the potential of V2G operation for fast response, displacing cycling experienced by the stationary ESS by up to 74%. Simultaneously, higher power flows lower the expected durations of connectivity for EVs for V2G participation and a lower number of charging ports is necessary.

From these results, it has been shown that the feasibility of V2G operation is highly dependent on the rate of power injection from EVs, as well as the connectivity of EVs to the grid. Specifically, the case study shows that charging infrastructure with level 2 charging rates is insufficient to support V2G operation considering reasonable durations of grid connectivity for participating EVs. More generally, however, the results indicate that, in order to effectively displace stationary ESS capacities, charging infrastructure implementation for V2G operation must emulate the availability and fast response capabilities of existing stationary ESS technologies.

4. Conclusions

The implementation of charging infrastructure is a multi-faceted design problem that requires accurate forecasting of the degree of EV market penetration, prediction of driver behavior, and consideration of unique system conditions and constraints. Moreover, the appropriate planning and implementation of charging infrastructure plays a key role in determining the feasibility of operational modes under which EVs can operate within the smart grid context. This work develops a multi-component simulation approach to account for the role of charging infrastructure in serving as the interlinkage between EV fleets and the power grid. This approach improves upon previous simulation approaches by accounting for the impact of charging infrastructure availability on EV charging behavior, which may be incorporated into future research endeavors to simulate more realistic conditions for EV integration into the smart grid. Within this study, the impact of charging infrastructural limitations imposed onto EV fleets are examined in three operational modes: uncontrolled charging behavior, controlled or smart charging strategies, and V2G technology. Furthermore, a campus microgrid case study was considered to demonstrate the role of charging infrastructure under realistic conditions.

In the planning of charging infrastructure for EV fleets operating under an uncontrolled charging strategy, several considerations have been discussed on charging infrastructure design for EV fleet integration. First, limitations on charging infrastructure availability have been discussed with respect to its effect on supporting the driving requirements of the EV fleet, which directly constrain the degree of EV adoption. Secondly, the effect of additional charging infrastructure installations on improving user convenience have been discussed, in which additional infrastructural installations reduce the queuing and service durations required for meeting peak charging needs. However, high charging peaks enabled by excess charging infrastructure may impose additional stress onto generation reserves, which should be considered in charging infrastructure designs. Meanwhile, in considering the incorporation of aggregate EV fleet charging as a flexible load, several conclusions have been drawn from this study. First of all, limited charging infrastructure and short EV plug-in durations reduce the functionality of EVs as flexible loads under controlled charging strategies, which reduces the resiliency of controlled charging against uncertainties in EV charging behavior. Secondly, increasing charging infrastructure and longer EV plug-in durations allow controlled charging strategies to more optimally meet the charging needs of the EV fleet, while minimizing cycling demand on supporting ESS capacities for charging cost optimization. It was also shown that similar operating cost reductions are achievable in systems without supporting ESS. As for the implementation of EV fleets as mobile ESS under V2G operation, the effects of charging rate, charging port sizing, and EV plug-in duration on V2G applicability have been discussed. From the results of the Laurier case study, it was demonstrated that the success of V2G for displacing stationary ESS capacities is dependent on its ability to emulate the availability and fast response capabilities of stationary ESS.

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Nomenclature

The following abbreviations and symbols are used in this manuscript:

BESS	Battery energy storage system
DER	Distributed energy resource
DC	Direct current
DR	Demand response
ESS	Energy storage system
EV	Electric vehicle
GHG	Greenhouse gas
HVAC	Heating, ventilation, and air conditioning
MIP	Mixed-integer problem
PV	Photovoltaic
SOC	State-of-charge
TOU	Time-of-use
V2G	Vehicle-to-grid
WLU	Wilfrid Laurier University

Variables

i	Index for inflow energy vector set
j	Index for energy demand load set
k	Index for energy storage technologies
t	Index for time
C_{ij}	Coupling matrix
$Cost_{op}$	Annual operating costs of the system
$Cost_{fuel}$	Annual fuel costs of the system
$D_i(t)$	Energy vector demands of the energy hub
$\varepsilon_{k,in}$	Energy vector inflow efficiency for energy storage system
$\varepsilon_{k,out}$	Energy vector outflow efficiency for energy storage system
$\varepsilon_{PEV,charge}$	Charge efficiency for the EV fleet
$\varepsilon_{PEV,\ discharge}$	Discharge efficiency for the EV fleet
$E_{max,k}$	Maximum storage capacity of storage system
$E_{PEV,loss}(t)$	Loss of stored electricity due to driving for the EV fleet
$F_j(t)$	Energy vector feeds into the energy hub
$F_{j,max}$	Maximum flow capacity for the feed energy vector
$F_{j,min}$	Minimum flow capacity for the feed energy vector
$Q_{k,in}(t)$	Inflow of energy vector into the energy storage system
$Q_{k,in,max}$	Maximum inflow rate of energy vectors into energy storage system
$Q_{k,in,min}$	Minimum inflow rate of energy vectors into energy storage system
$Q_{k,out}(t)$	Outflow of energy vector into the energy storage system
$Q_{k,out,max}$	Maximum outflow rate of energy vectors into energy storage system
$Q_{k,out,min}$	Minimum outflow rate of energy vectors into energy storage system
$Q_{k,stor}(t)$	Net energy vector flow into energy storage system
$Q_{PEV,charge}(t)$	Power charged to the EV fleet
$Q_{PEV,discharge}(t)$	Power discharged from the EV fleet
$Q_{PEV,stor}(t)$	Net flow of electricity into the EV fleet
$SoC_k(t)$	State-of-charge of storage system
$SoC_{k,max}$	Maximum charge capacity of the storage system
$SoC_{k,min}$	Minimum charge capacity of the storage system
Z	Overall objective function

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