World Electric Vehicle Journal

MDPI

Article

Observational Evaluation of the Maximum Practical Utilization of Electric Vehicle DCFC Infrastructure

Nathaniel S. Pearre * and Lukas G. Swan

Renewable Energy Storage Laboratory, Dalhousie University, 5217 Morris Street, 4th Floor, P.O. Box 15000, Halifax, NS B3H 4R2, Canada
* Correspondence: nathaniel.pearre@dal.ca

Abstract: Central to the design of a direct current fast charging (DCFC) network is the question of how much energy a DCFC of a given power can supply to vehicles without users being forced to queue to charge. We define 'utilization factor' as the ratio of the energy delivered by a DCFC in a multi-day period to the maximum amount of energy it could deliver in period. Three and a half years of data from 12 DCFCs are examined, characterizing each charging event by both the utilization factor and the time lag since the termination of the previous charging event. Short lags between events are inferred to indicate queuing. To keep the fraction of would-be users who have to queue below 10%, the overall utilization of the DCFC must likewise be limited to 10% (or 7–17% in exceptionally heterogeneous or exceptionally homogeneous traffic patterns, respectively). E.g., a 100 kW DCFC should not be expected to deliver more than 240 kWh per day (100 kW $\times$ 24 h $\times$ 10%).

Keywords: electric vehicle; charging; utilization; infrastructure; capacity; network

Citation: Pearre, N.S.; Swan, L.G. Observational Evaluation of the Maximum Practical Utilization of Electric Vehicle DCFC Infrastructure. *World Electr. Veh. J.* **2022**, *13*, 190. https://doi.org/10.3390/wevj13100190

Academic Editors: Grzegorz Sierpiński, Roberta Di Pace and Angelo Coppola

Received: 30 August 2022
Accepted: 12 October 2022
Published: 16 October 2022

1. Introduction

Sales of electric vehicles (EVs) are expanding rapidly everywhere in the world, yet in many locations the infrastructure for en-route direct fast charging (DCFC) is not. While there is much interest in how to plan and design DCFC infrastructure, there is little guidance from the literature on how to optimally size individual charging hubs to support future fleets of EVs. What there is tends to rely either on speculative and complex modeled driver behavior based on existing (internal combustion engine) trip data, or on highly granular traffic flow data, which may only be available in select locations and for select routes. We circumvent these shortcomings with a top-down observational approach, relying only on more common daily traffic data, combined with observations of historical DCFC utilization. The result is an indicator for charging hub sizing (DCFCs per hub) that is accessible and implementable to policymakers and infrastructure planners. While this scope seems restricted, it investigates a metric that is both important to the design of EV charging infrastructure, and not well covered in the literature.

This research introduces a focus on the amount of energy DCFC infrastructure can supply through time, relating that to the amount of energy a fleet of EVs will need from each charging hub. We present a multi-day 'utilization factor', the average power that can be delivered by a DCFC relative to its rated output. This is a crucial input to infrastructure planning for future vehicle fleets with high penetrations of EVs. We use a top-down approach to describe the fraction of EVs seeking charge that arrive to find the DCFC occupied vs. the utilization of the DCFC across a multi-day window.

This work provides a crucial parameter of the operation of DCFC infrastructure. For entities attempting to provide such infrastructure for the rapidly expanding population of EVs, understanding this parameter and how it impacts charging hub design is crucial to providing suitable infrastructure that will be able to provide enough energy to power future vehicle fleets.

1.1. Structure of Report

This research examines one specific factor that impacts the number of DCFCs of a given power required at each charging hub: the average 'utilization factor' (*UF*) that can be achieved by a DCFC before an excessive fraction of would-be users arrive to find it occupied. In Section 1.2, the relevant cultural and academic context are presented as a literature review. In Section 1.3, the definition and application of *UF* is described via a comprehensive and fully generalizable equation. In Section 2, the data used in the investigation are described, including source, extents, quality control, and the determination of *UF* from the data. The final subsection of Section 2 presents the definition, justification of the assumptions, and the calculation of queuing probability (*QP*) from the data. In Section 3 the results are presented as *QP* vs. *UF* curves, in a series of sensitivity analyses to the underlying assumptions. In Section 4 there is discussion of factors that should be considered in interpreting or extrapolating the results to other cases. In Section 5 the main conclusions of the research are presented, along with policy implications.

1.2. Literature Review

One of the attractions of EVs for users is that a majority of charging can be done while the vehicle is parked at home or work, eliminating the inconvenience of detouring to a gas station and pumping fuels. This quantity has been evaluated by numerous studies. Infrastructure and energy modelling for both the USA [1] and Austria [2] found that 88% of EV charging (by energy) takes place at home, while a charging infrastructure model for Western Australia found that 90% of charging takes place at home or work [3]. Despite this, when regional trips outside the EV range occur, the availability, reliability, speed, and convenience of DCFCs is critical to providing equivalent transportation service to gasoline or diesel vehicles.

Many indicators suggest that enroute DCFC is a key enabler of EV uptake. In 2008, the electric utility in Toyko, Japan deployed a fleet of Mitsubishi iMiEV EVs, but found they were not used extensively. Several months later, a 50 kW DCFC was installed about 10 km from the vehicle depot. Average monthly driving distance then increased by a factor of seven and the EV was returned to the depot with lower states of charge [4]. More recently, a timeseries analysis by municipalities in Norway found that public charging infrastructure led to EV uptake [5]. Similarly, counties in the US state of Washington exhibit a clear correlation between the availability of DCFCs and the EV adoption rate, a fact which is used as an input for siting recommendations for new DCFCs [6].

It is worth noting that vehicle shoppers may not initially consider the availability of DCFC infrastructure in purchase decisions. A survey of Canadian car buyers found that in general, DCFC availability was described as being of little importance relative to purchase cost and technological familiarity [7]. This, along with challenging economic realities for operators of DCFC infrastructure in an immature market, may correspond to differences between the rate of adoption of EVs and the deployment of DCFC infrastructure. In some jurisdictions however, charging infrastructure deployment has been vigorous. In the USA, 2022 saw a roughly 20% increase in the number of public DCFCs [8].

According to a survey of Canadian drivers, there is decreasing concern over the technical abilities of EVs and a corresponding increase in concern of the convenience, availability, and reliability of charging infrastructure [9]. The design of networks, however, is regarded as "one of the most pressing challenges" for governmental entities concerned with the electrification of transportation, while the design and sizing of such a network is poorly understood [10]. Regardless of motivations or decision criteria for EV purchase, EVs need to be able to travel public highways with nearly the same ease as gas- and diesel-powered vehicles. Only the availability of electricity at key locations and at high power rate via a DCFC permits such travel.

The market is evolving towards larger EVs including trucks, larger battery packs for longer driving range, and better thermal management. All of these factors contribute to increased ability of EVs to accept high power charging and for longer periods. While just a decade ago 50 kW charging power was the state of the art, that is no longer the case. At the time of writing, the highest power charger on the market can deliver 360 kW [11], and this value is widely expected to increase in the future.

The advantages of higher speed charging are widely recognized. The US Department of Transportation proposed a design rule whereby charging hubs seeking federal funding need a power rating of 150 kW or higher [12]. Some researchers argue that where there is an adequately robust electrical grid, 350 kW DCFCs should be used in all locations, and when potential grid impacts make that problematic, 150 kW charging power should be regarded as a functional minimum [3]. Similarly, a survey of German car buyers indicated that they may be less swayed by the number of charging hubs than by the promise of very high power rates [13].

Ideally, chargers should be located within 'hubs', with multiple high power DCFCs at the same location. Grouping DCFCs together offers several benefits to various stakeholders relative to sporadic single units, even if the same broad area density of DCFCs is achieved.

For users:

- There is one destination to drive to, where if one DCFC is occupied, another is nearby
- If all DCFCs are occupied, the risk of a long wait time is reduced, assuming a single queue for whichever DCFC becomes available next.
- Multiple co-located DCFCs offer greater reliability through redundancy. A recent study in California's Bay Area found that roughly 1 in 4 DCFC were unable to charge a test vehicle [14].

For builders/operators:

- A charging hub may develop greater and more consistent traffic, so related business opportunities (convenience stores, fast food, etc.) have more potential market. This potentially presents both an improved experience for users and a local business opportunity.
- Having multiple DCFCs of the same make and model increase the efficiency of keeping spare parts, and technician knowledge can be more specialized, reducing maintenance costs and improving uptime.
- There are significant economies of scale in land acquisition, site preparation and permitting, as well as in burying electrical conduit, buying and placing transformers, etc. A large proportion of the cost of a DCFC charging hub in North America are 'soft costs', such as process costs and permitting [15].

These benefits, along with the advantage of providing a charging ecosystem as a means to sell cars, are understood by industry. This has led both Tesla [16] and Audi [17] to invest in charging hubs with multiple DCFCs at each, and increasingly an array of consumer amenities. Likewise, the proposed US-DOT rules for charging hub design specify four or more DCFCs at each [12].

To avoid duplicated effort and to leverage economies of scale, central planning would seem to be necessary for efficient investment. A USA national study [1] models EV adoption scenarios and describe the total number of charging hubs and DCFCs needed in 'cities', 'towns', and 'rural' areas, but do not provide specific guidance on placement [1]. Many authors develop algorithmic DCFC hub location strategies, some of these within highly constrained spaces such as along specific highway routes [18,19]. This leaves open the question of how a network of hubs should be designed to provide universal substitutability of EVs.

Various network design strategies have been proposed, but there is no consensus on what characteristics to prioritize. An agent-based model was used to support charging hub recommendations based on simulated charging choices during trips within the USA state of Washington [20]. Other researchers focus on locations with consumer amenities [21,22]. A modified flow-refueling location model is used to design a charging hub network to cover the continental USA in [19], but restricted it to long distance highway travel between major destinations, leaving much of the land mass inaccessible.

A key parameter in hub network design is the target driving distance between hubs. This parameter must be related to the range of EVs [23], but there is much disagreement as to the nature of this relationship. A Canadian model uses a value of 65 km for Highway 401 in southern Ontario [18]; A 2022 proposal from the US White House specified a target hub spacing of 80 km [12]; A 2017 report by the US Department of Energy uses a target hub spacing of 112 km [1]; Tesla Motors, known for offering EVs with higher range than many competitors, install hubs with a maximum spacing of ~175 km, [16]; Finally, [3] use a target hub spacing of 200 km for an infrastructure model in Western Australia. EV driving ranges are generally trending up, so greater spacing may be defensible [1], though support for older, lower range vehicles is also a consideration.

EV range not only affects hub spacing, it also impacts the amount of energy that the network as a whole must deliver, i.e., the number of DCFCs at a hub and the power of each unit. A trip modelling study of USA driving patterns suggests that the number of DCFC charging sessions and energy sourced from enroute DCFCs drops dramatically as vehicle ranges increase [24]. I.e., the more range an EV has, the less frequently it will need to charge anywhere other than at home or work. In aggregate, this will decrease the systemwide number of DCFCs needed, an effect reflected in at least some charging infrastructure models. This effect is responsible for a roughly six-fold variability in the necessary quantity of DCFC charging based on vehicle fleet assumptions in [1].

1.3. Context of This Analysis

This investigation is intended to inform a larger question related to designing a network of charging hubs to support EV adoption. The larger question is 'how many DCFCs are needed at this charging hub?' to supply the energy needed by EVs seeking charging. That question itself is contingent on having established a charging hub network design. Note that charging hubs may be loosely differentiated into two categories; One set primarily in urban locations to serve the charging needs of EV drivers who lack a dedicated parking/charging location; Another set strategically located to serve long distance driving, to enable travel by EV throughout a region. This analysis targets the later segment of infrastructure, and as such is strictly subject to the exogenous nature of highway traffic volumes. The number of DCFCs to place at a hub in a network may be answered with Equation (1), which is relatively simple in construction and is designed to use broadly available daily traffic data, but requires careful evaluation of assumptions.

$$\text{DCFCs per hub} = \frac{\sum\left(N \times \frac{D}{2}\right) \times \frac{1\ \text{day}}{24\ \text{h}} \times \overline{C} \times F_{DC}}{P \times \Psi \times UF} \tag{1}$$

In Equation (1) the sum in the numerator $\sum(\ldots)$ seeks the total quantity of vehicle-kilometers per day on a set of non-duplicative routes within this hub's catchment. "Non-duplicative" in this context means a driver is unlikely to transit more than two such routes (one arriving and one departing the catchment) on a given one-way trip. The "catchment" of the hub is the geographic area within which this is the closest hub, and for which this hub can be thought of as being responsible for providing energy. We refer to these routes as 'spokes' around the hub.

The first term within the sum, N, with units of "vehicles/day", is vehicle count on the 'worst day' traffic along a given spoke. Traffic throughput is an exogenous input relying on standardized traffic volume data, which is most widely and reliably available as daily vehicle counts. This term refers only to EVs, and must be scaled to projected future EV fleet fractions, and according to projected overall population growth.

The second term within the sum, D, with units "km/hub", is the distance along this spoke across which this hub needs to supply energy. In idealized terms, D is the hub spacing, though spoke specific values should be applied in practice where geometrically regular hub spacing is impossible. Note that the target spacing D is divided by two, because half of the distance along each route (and by inference half of the energy) is provided by the hub at the other end.

The third variable in the numerator, numerator $\overline{C}$ is the weighted averaged worst case energy consumption of EVs, in units of "kWh/km". This value must likely be based on winter conditions unless a non-winter driving season dominates seasonal variability.

The final term in the numerator of Equation 1, F_{DC}, is unitless "$\text{kWh}_{\text{DCFC}}/\text{kWh}_{\text{Total}}$". It is the fraction of vehicle charging done at DCFCs by energy delivered. F_{DC} is an exogenous input, estimates for which are informed by historical observations about EV use, and may be tailored to this specific hub if suitable data are available. Within the literature, F_{DC} is subject to a range of values from 1.5% in an Austrian modelling study [2] to 5% in a USA modelling study [25], to 10% in a Canadian observational study [26]. It will be strongly influenced by vehicle range [24].

In the denominator, P, in "kW", is the power rating of each cordsets. The number of cordsets, Ψ, has units "Vehicles / DCFC" and a default value of one (1). Ψ may take on values other than one (1) if the DCFC equipment can supply multiple vehicles at once. E.g., Tesla's 2nd generation superchargers supplied 150 kW to two heads [27], and ABB's Terra 360 supplies 360 kW to four heads [11]. In such a power sharing arrangement P must be the total power of the DCFC divided by Ψ.

The final variable term in the denominator, UF, is unitless "$\text{kWh}_{\text{MaxUse}}/\text{kWh}_{\text{Potential}}$", the design maximum utilization factor of a DCFC. This is a design decision, and the focus of this research, which attempts to answer the question 'how much service can a DCFC deliver before would-be users frequently have to wait for other EVs to finish charging'.

It should be noted that the accuracy of this equation's output will depend on the quality of data available. For example, traffic patterns may vary with day of the week or with the season (e.g., summer driving vacation season or school season). Where such data are available, a seasonally varying value of N and $\overline{C}$ may be appropriate. Similarly, $\overline{C}$ and F_{DC} may vary from one hub location to another according to the local mix of vehicles and driving patterns. In such cases, the final result must be based on the worst (highest demand) case.

2. Materials and Methods

This research is a data driven analysis of the relationship between DCFC utilization and the frequency with which users must wait for another vehicle to finish charging before they can access a DCFC. The sole data requirements is historical charging event data from DCFCs.

2.1. Data

The electricity utility of the province of Nova Scotia, Canada owns and operates a network of 12 hubs, with each hub having one 50 kW DCFC, in a network with approximately 80 km hub spacing. These hubs are along the major highways, and as of writing, account for roughly half of the DCFC hubs in operation in the province. Recorded individual charge event data from these DCFCs were provided for this study. The unit of analysis of these data is the charging event, consisting of an activation and deactivation of a DCFC. In addition to start and end times, each record includes a unique user number, the quantity of energy delivered (kWh), the reason for session termination (user action, vehicle action, fault, etc.) and several other parameters.

Quality control and pre-processing steps undertaken before the subsequent analysis consist of:

(1) Locating and deleting duplicated events (same location, start time & kWh delivered).
(2) Aggregating multiple charging events by the same user, at the same location, if 20 min or less –and no other user events– separate the end of one from the start of the next. It was assumed that such iterated charging events reflect unexpected charging session termination before the driver intended. In such cases, other EVs would likely not

have had the opportunity to charge, so the utility of the charging infrastructure was legitimately reduced.

(3) Disregarding any charging events remaining after (2) that transfer less than 1 kWh of energy (a sensitivity analysis on this value showed no obvious cut-off points). Such events were inferred to be EV drivers testing the system to verify vehicle compatibility, so will likely become less frequent as EV ownership experience grows.

(4) Disregarding charging events that took place prior to the official launch of the network. Such events were assumed to be technicians verifying the functionality of the equipment.

After these quality control and pre-processing steps, just under 13,000 charge events remained, covering about 4.2 years starting at the public activation of the network in June 2018, and ending with the delivery of the data set in early September 2022.

Figure 1 plots individual charging events at each of the 12 hubs for five days (Thursday, 18 August, through Monday, 22 August, 2022) as colored bars. The period shown is one of the busiest in the dataset. Each event (i.e., each unique user) is given a contrasting color to preceding and following charging events. Yellow triangles indicate where a charging event started within 10 min of the termination of the previous charging event.

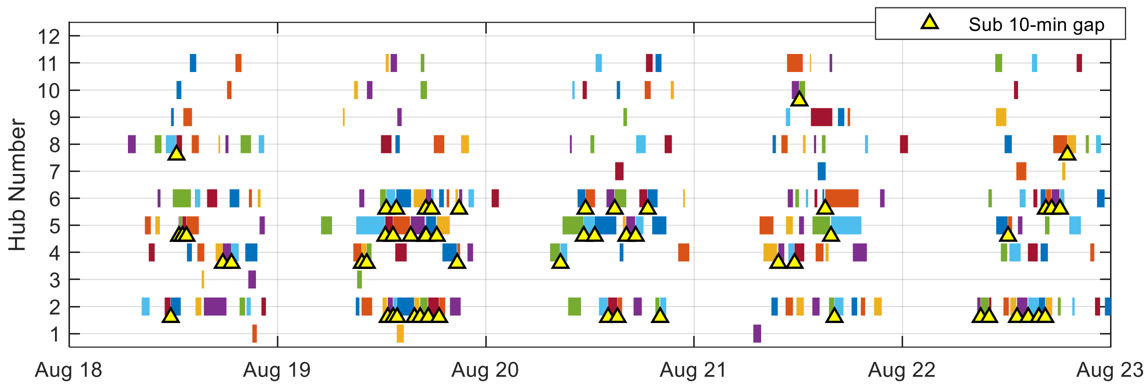

Figure 1. Individual charge events (individual colors) after quality control, at the 12 DCFCs for which data are available, during five days in August 2022. Yellow triangles indicate short time lags between charging events. Note: "Each event (i.e., each unique user) is given a contrasting color to preceding and following charging events."

Figure 1 shows several important features related to travel patterns. First, there are enormous differences between the number of charge events at different hubs (note that hub #12 is believed to have been nonfunctional during this period). Second, the distribution of charging events throughout the day is highly variable, with large clusters of events during the middle of the day and evening, and very few charge events overnight and in the early morning. This indicates that the maximum practical *UF* of these DCFCs will never reach 100% because it is a function of inter-hourly traffic patterns, as noted by other researchers [18]. Figure 1 also shows many back-to-back charging events with little or no time separating them (yellow triangles). These events are important for this analysis, as we seek to inform DCFC hub design which requires very little queuing.

2.2. Queuing for an Occupied DCFC

At points marked by yellow triangles, Figure 1 show little to no time lag between successive charging events. It may be inferred that an EV driver was queuing for another vehicle to finish charging and leave. Of interest to this research is the threshold time lag that indicates queuing. The distribution of time lags between the termination of one charging event and the start of the next for the full 4.2 years of data is shown in Figure 2. The x-axis has been limited to 0–120 min for readability and relevancy.

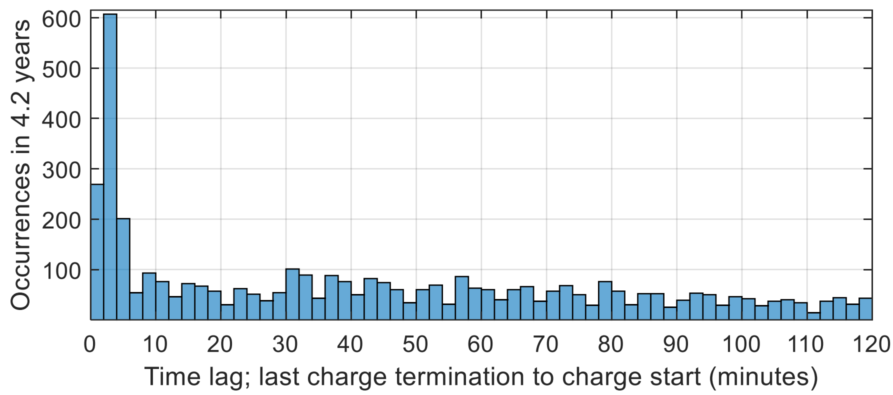

Figure 2. Distribution of time lags (in 2-min bins) between the termination of one charging event and the start of the next event at the same DCFC.

In Figure 2 there is a distinct reduction in the frequency of event lags between 6 min and about 10 min. From this distribution, values less than ~10 min seem plausible as indicating that a 2nd car was waiting for another vehicle to finish charging. No higher values of time lag seem to indicate any behavioral or operational threshold relevant to the analysis.

A threshold of 6–10 min makes some intuitive sense. Even for users familiar with their vehicles and the DCFC equipment and network, it could plausibly take tens of seconds for each of (i) unplugging the connector and arranging the cord on the hanger (ii) driving the vehicle out of the charging spot, (iii) driving the second vehicle into the charging spot, (iv) gathering the cord and attaching the connector to the second vehicle, and (v) establishing communication, authorizing payment, and initiating charging. For those unfamiliar with the equipment or the network, or simply not rushing, any of those steps could take correspondingly longer.

Figure 2 also makes clear that a vehicle can arrive at any time after a previous charging event terminates. Specifically, a total of 1229 events start within 10-min of another charging event's end. This value must be compared to an average of 262 charging events which start in each 10-min window between 10 and 120 min. Thus, only a fraction of $(1229 - 262)/1229$ ~78% of those events starting in the first 10 min can be attributed to queuing. This correction reduces the sensitivity to the lag length used to define queuing.

2.3. DCFC Utilization Factor

Each charging event in the data set was characterized in two ways. (1) the time lag by which it followed the termination of the previous charging event at that hub, and (2) the unitless parameter 'utilization factor' (*UF*), defined in Equation (2) for a single cordset DCFC.

$$UF = \frac{\sum_{C=1}^{M} E_C}{P \times \Delta t} \tag{2}$$

The sum in the numerator $\sum(\ldots)$ refers to the total quantity of energy dispensed by the DCFC within the time window Δt. It is the sum of energy E, in kWh, of each charging event C, among M events that occur in Δt. We defined Δt symmetrically around the start of each charge event, such that each charging event has an associated *UF* that describes how much service that charger is providing at around that time. For example, a 2-day window around a charging event starting a 07:00 on Tuesday would span from 07:00 on Monday to 07:00 on Wednesday.

The term in the denominator of Equation (2) represents the maximum amount of energy that could be dispensed, i.e., P, the nameplate capacity of the DCFC (50 kW in this data set) multiplied by the width of the window Δt (in hours).

For this analysis it is stipulated that in an *adequate* network of DCFCs, it should be *rare* that an EV driver arrives at a hub and find all the DCFCs occupied. The terms '*adequate*' and '*rare*' are italicized because of their highly subjective nature and definition. However, avoiding a queue at a DCFC is important for EV drivers in making long distance trips [28].

2.4. Computing the Probability of Queuing

To calculate the 'queue probability' (*QP*) as a function of *UF*

1. The set of all ~13,000 charging events was segregated into bins by *UF*. Bin sizes were selected such that 20 bins would span the range of data for each Δt evaluation.
2. For each *UF* bin, the charging events that started within a fixed time lag (10 min by default) of the previous event's termination (at that DCFC) were identified and counted as events where there was a queue.
3. This count of queuing events was divided by the total number of charging events within that *UF* bin. This quotient is described as the 'queue probability' (*QP*) for this *UF*.
4. The *QP* was multiplied by a factor of 78% to account for the vehicles that would have arrived within that 10-min window irrespective of the presence of the previous vehicle (refer to Section 2.2).
5. To improve model robustness, bins containing fewer than 6 data points were excluded from subsequent analysis.

3. Results

The results of this analysis are presented as graphs of *QP* vs. *UF*. Each graph presents a sensitivity analysis to one of the modelling input parameters or characteristics of the data.

3.1. Sensitivity to Time Window Δt Width

Figure 3 shows the *QP* as a function of *UF* and of the time window Δt used to calculate *UF*. For this analysis, sequential charging events less than 10 min apart are used to define queuing. The number of events in each UF bin are plotted on the right hand *y*-axis for context in assessing significance.

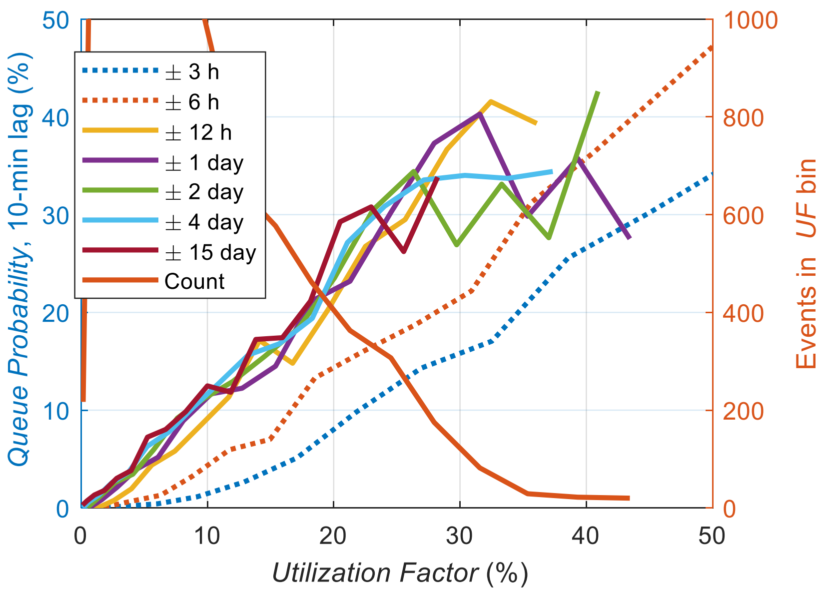

Figure 3. The impact of Δt window width on the relationship between *QP* and *UF* using a 10-min lag criterion for *QP*.

In Figure 3, *QP* vs. *UF* curves for values of Δt between 6 h ($\pm$3 h, blue dots) and 30 days ($\pm$15 days, dark red line) were evaluated. Note that Δts of less than one day (dotted lines) begin to account only for vehicle switching and connecting time and overlook daily traffic patterns, and also fail to correspond to the widely available daily traffic data referred to in Equation 1. Such short evaluations will also vary dramatically throughout the day, so make interpretation of the results far more complex, since infrastructure cannot vary throughout the day.

Longer duration Δt are of interest as they dilute rare or unrepresentative traffic events, such as a surge after a sporting event, during which some charging inconvenience may be tolerable in the real world. A 30-day Δt (dark red line) is of interest as it closely emulates the span of time (usually 1 month) over which electricity tariff demand charges are evaluated by the utility and are likely billed to the charging hub operator.

The results from Δt of 24 h and greater in Figure 3 (solid lines) follow similar trends and have reasonably similar values. All indicate that *QP* increase with *UF* but follow slightly different paths. Figure 3 indicates that queuing is always possible but will happen about 10% of the time when DCFCs see 10% utilization, and slightly more than 20% of the time at 20% utilization.

Counterintuitively, there seems to be some flattening of *QP* vs. *UF* curves at high *UF*. This effect occurs only where event counts per bin fall below ~200 per bin, but should not be discounted. We do not know why this is, but conject that EV drivers may be redistributing themselves when arriving at a DCFC with a queue. This behavior could in theory increase the *UF* of nearby DCFCs without increasing the *QP* at any of them. It relies on EV drivers having knowledge of the network and ideally on real-time network utilization. Such information is not formalized in the network providing data, though crowd-sourced information may be available (e.g., [29]).

3.2. Sensitivity to Time Lag in QP Definition

An investigation of the time lags between charging sessions indicated no obvious threshold value greater than ~6 min (refer to Figure 2). The distribution of lag lengths in Figure 2 requires that the choice of lag length used to identify queuing will impact the QP curve. This is evaluated in Figure 4 for time lags between 1 and 20 min using a 2-day window Δt.

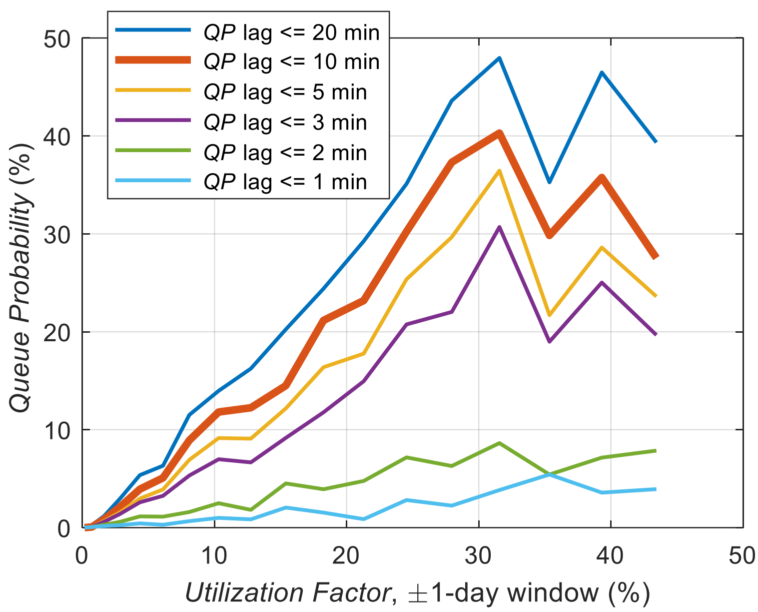

Figure 4. Impact of the choice of lag to identify queuing on the *QP* vs. *UF* curve.

As the distribution of lag duration in Figure 2 would suggest, the impact of different lag length to indicate a queuing are small above ~5 min, but consistent. As the definitional lag length is reduced, the allowable *UF* for a target *QP* increases. Figure 4 shows high sensitivity when the definition of queuing is defined as lags of less than 5 min. This indicates that it typically takes a minimum of about 3 min for the transaction of finishing one charge session and starting another for a queuing EV. There is considerably less sensitivity from 3 min up to 20 min, suggesting that while there is no "correct" number of lag minutes to define queuing, the results from this range are appropriate for planning purposes.

3.3. Sensitivity to Seasonal Driving Patterns

Nova Scotia, where the DCFC data originate, experiences an influx of tourist traffic in the late summer [30]. The charging event data show a strong peak likely corresponding to tourism. Corresponding seasonal peaks in DCFC network averaged utilization (total energy delivered divided by total network power times window width) are shown in Figure 5.

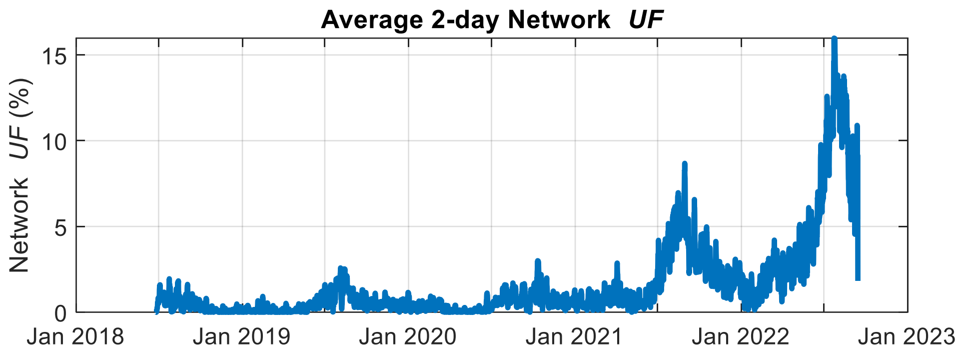

Figure 5. Average *UF* of the DCFC network throughout the data set.

Note that in the summer of 2020 tourist travel, and much intra-provincial travel by Nova Scotians, was inhibited by a set of restrictions intended to prevent the spread of the COVID-19 virus. 2020 exhibits a distinctly lower late summer DCFC network utilization peak than it otherwise might. Furthermore, note that systemwide utilization is far lower (peaking at ~16%) than the higher values observed at the more heavily trafficked DCFC sites (peaking at ~43%, purple line in Figure 3), this is due to intra-regional differences in traffic volume and in the availability of DCFCs not included in these data.

The magnitudes of the late summer peaks are striking. Tourists (or long distance drivers in general) are likely to be more reliant on public charging than local residents, who primarily charge at home. Given this, it seems plausible that the *QP* vs. *UF* curve is impacted by tourist traffic, which may be presumed to have different intra-day and intra-week driving patterns than aggregate driving data. To investigate this, charging events taking place in 'tourist season' (July–September inclusive) were isolated and evaluated separately from those taking place the rest of the year. The results are shown in Figure 6.

Figure 6 shows that the tourist season (July through September, blue line) *QP* vs. *UF* curve is neither consistently higher nor consistently lower than the 'rest of the year' curve (orange line). Corroboration of the hypothesis that tourist season driving is more clustered during the day is weak, suggesting that the preceding curves, and the conclusions of this analysis in general, are relevant to all driving seasons. From Figure 6 it is also evident that the *UF* in October through June (orange line) peaks at a far lower number, yet even these less busy times see as much as 20% of users queuing, suggesting that the existing network may already have been inadequate for the number of EVs on Nova Scotia's roads as of the fall of 2022, at least along more heavily used corridors.

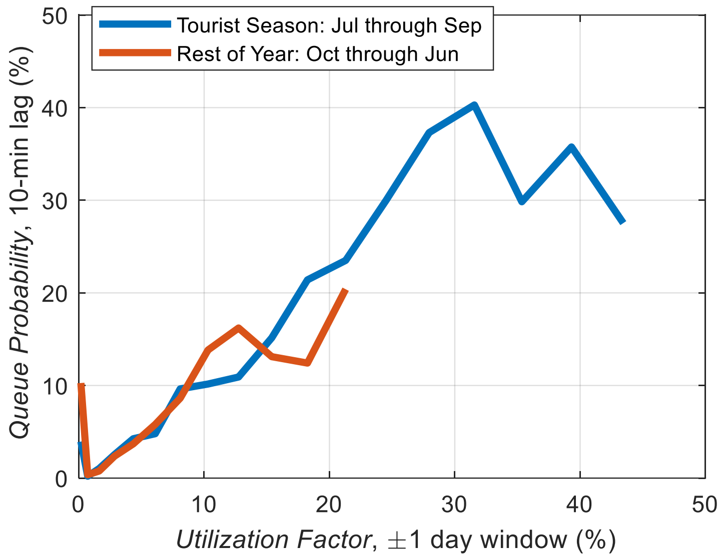

Figure 6. Impact of 'tourist season' (July through September, blue) driving pattern on *QP* vs. *UF* curve compared to the rest of the calendar year (orange).

3.4. Sensitivity to Sub-Regional Driving Patterns

A range of different driving environments are represented in the data, including near an international airport, corridors between urban population centers where commuter traffic is significant, rural fishing villages, and routes to popular tourist and recreation destinations. The differences of inter-hour traffic patterns at such sites may be expected to have a significant impact on the *QP* vs. *UF* curve; Where traffic is more consistent across time one might expect lower *QP* values for a given *UF*, while at sites where traffic is more concentrated in certain hours of the day, higher *QP* would result.

Separate *QP* vs. *UF* curves were constructed for each of the 12 sites, and the diversity of these curves was characterized by a minimum, maximum, mean, and standard deviation of *QP* values for each *UF*. This is presented in Figure 7. Note in interpreting Figure 7 that different DCFC sites have different maximum *UF* values, so representation of traffic pattern diversity is lost as higher *UF* values are considered, particularly above about 20% where only half of the sites contribute.

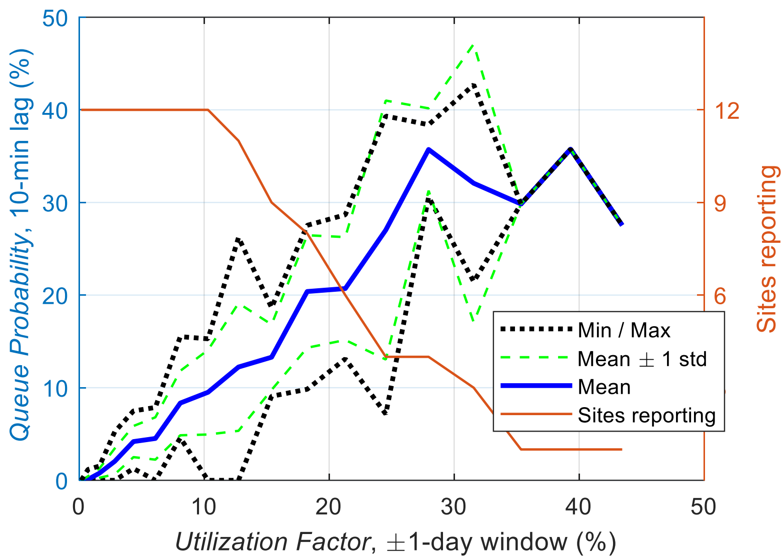

Figure 7. Impact of site specific driving pattern on *QP* vs. *UF* curves of the 12 different DCFC sites.

Figure 7 shows that there is indeed a range of *QP* vs. *UF* curves. It suggests that within the scope of traffic pattern variability exhibited in these data, a 10% *QP* could result from *UF*s ranging from roughly 7% to roughly 17%. This is a significantly higher sensitivity than is exhibited to the other model parameters, and points to the importance of evaluating the homogeneity of traffic volumes throughout the day at sites of interest.

4. Discussion

Due to the intuitive and reported [28] desire of EV drivers to not have to wait to access DCFCs on trips, we propose designing charging networks such that that occurs less than 10% of the time. I.e., EV drivers would arrive at a fast charging hub to find all DCFCs occupied fewer than once in 10 times. From this analysis, that design choice requires a maximum *UF* of DCFCs (UF $kWh_{MaxUse}/kWh_{Potential}$, in Equation (1)) be restricted to 10% in designing such a network. This result is reasonably stable with respect to variables used in the construction of the analysis, including time window used to define *UF*, the lag between charging events used to infer if a user was queuing, or the driving patterns of tourist season. Notably, this recommended UF is comparatively sensitive to traffic patterns, which may enable *UF*s to range between about 7–17% to realize the same *QP*. In addition, we have identified four factors impacting these conclusions that may benefit from further examination.

4.1. DCFC Rated Power

The DCFC units providing data to this analysis are 'first generation' 50 kW units. In practice that means that most of the EVs charging at them can make full use of the rated power over a wide range of battery states of charge. As the state of the art technology pushes the nominal power capability of DCFCs higher, it may be the case that fewer of the vehicles they service will make as good use of their nominal rating.

UF as defined is normalized by the rated power of the DCFC. A future network of 350 + KW DCFCs may rarely supply their rated power (or specifically, rarely supply as close to their rated power as these 50 kW units). This would result in lower *UF* values for a given *QP*, i.e., it would compress the curves shown in Figure 3, etc. to the left, reducing the target maximum *UF* to achieve a desirable *QP*.

4.2. Vehicles Choosing Not to Queue

If a vehicle arrives at the DCFC and finds it occupied, rather than joining a queue it could depart for some other charger or activity. This will not be captured in the data used to construct these curves because the data offers no record of their arrival. This represents a systematic underestimation of the fraction of vehicles 'inconvenienced' by the degree of utilization of the charger, i.e., *QP* underrepresent inconveniencing EV drivers. A curve of 'inconvenienced drivers' would be somewhat higher (greater value for a given *UF*) than that observed. Estimating the magnitude of this effect is difficult, but it may be presumed to increase rapidly with overall *UF*. This effect would suggest that a lower design *UF* would be appropriate to achieve a target level of driver inconvenience.

4.3. Power Sharing

New designs of DCFC include power sharing among multiple cordsets. In such cases Equation (2) must be modified to account for average shared power available through a cordset. The data used in this analysis were not able to evaluate this scenario. The number of people who have to queue will inevitably decrease, but the *UF* would remain the same. In such cases the allowable design *UF* could be increased without exceeding a target *QP*.

Driving Patterns

While an effort was made to explore different driving patterns by tourist vs. non-tourist driving (Section 3.3) and by driving patterns in different regions of the province (Section 3.4), it is possible that substantially different driving patterns in other jurisdictions may produce different results. In particular, in a location where there is minimal variation in traffic volumes throughout the day, a higher *UF* for a given *QP* may be realized.

5. Conclusions

Charging event from a network of 12 charging hubs were characterized by the utilization factor of that charger around that event and by the time lag since the conclusion of the preceding charging event. Short time lags were inferred to indicate that the second event was delayed by the first, i.e., an EV was in a queue, waiting to access the DCFC. By comparing the frequency with which DCFC users had to queue with the *UF* of the DCFC, recommendations of the practical maximum *UF* of a DCFC, beyond which an excessively large fraction of EVs would have to queue to charge, could be constructed. This parameter then defines how much energy a DCFC of a given power rating can deliver over a day, which indicates how much EV travel it can support. The design of a network of DCFC hubs to supply a future population of EVs requires this parameter to avoid under or over investment.

5.1. Key Results

A design maximum DCFC utilization factor of 10% is recommended to keep the probability of queuing below 10%. Note that queuing will still occur, and that this probability is not (necessarily) constant throughout the day, but applies to all vehicles using the DCFC. This conclusion exhibits low sensitivity to changes in the parameters of the analysis (*UF* analysis time window, event lag threshold to define queuing, and seasonal driving patterns), so is considered robust. However, sensitivity to driving patterns was shown to be relatively high, accounting for variations on the order of ±50% (i.e., result in *UF* values from 7–17% to obtain a 10% *QP*). The need to queue to access a DCFC increases as utilization factors increase. A utilization factor above 30% may not be possible without persistent and prolonged queuing.

5.2. Policy Implications

Fast charging infrastructure for EVs must supply electricity to those travelling beyond the singe charge range of their vehicles. In a model of centralized planning to enable the transition to EVs, this requires planners be able to translate known traffic patterns into infrastructure needs. Knowing the impact of *UF* to the user experience of EV drivers is key to the design of adequate charging networks. This value of 10% DCFC *UF* to limit *QP* to 10% is crucial to such planning.

Similarly, charging hub operators must design revenue models and set prices that yield a profit in the context of upstream electricity costs that likely include both energy (per kWh) and demand (per peak kW for the month) charge. Such revenue models must balance between the limitations of client frustration at insufficient infrastructure and untenable demand charges to the electric utility. Absent specially designed electricity tariffs, this predicament may in some cases push hub operators to creative solutions like throttling charging during peak hours [31].

Author Contributions: Conceptualization, N.S.P.; methodology, N.S.P.; software, N.S.P.; validation, N.S.P. and L.G.S.; formal analysis, N.S.P.; investigation, N.S.P. and L.G.S.; resources, L.G.S.; data curation, L.G.S.; writing—original draft preparation, N.S.P.; writing—review and editing, N.S.P. and L.G.S.; visualization, N.S.P.; supervision, L.G.S.; project administration, L.G.S.; funding acquisition, L.G.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was conducted as part of a larger project in collaboration with Clean Foundation Nova Scotia (CNS), with funding support from the Nova Scotia Department of Natural Resources and Renewables. We appreciate Nova Scotia Power Inc. for sharing the DCFC charging data.

Data Availability Statement: The data used in this analysis were supplied by the provincial electric utility Nova Scotia Power Inc. to the authors under the terms of a non-disclosure agereement, and therefore cannot be shared.

Conflicts of Interest: There is no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

1. Wood, E.; Rames, C.; Muratori, M.; Raghavan, S.; Melaina, M. *National Plug-In Electric Vehicle Infrastructure Analysis*; US Department of Energy: Washington, DC, USA, 2017.
2. Baresch, M.; Moser, S. Allocation of e-car charging: Assessing the utilization of charging infrastructures by location. *Transp. Res. Part A Policy Pract.* **2019**, *124*, 388–395. [CrossRef]
3. Bräunl, T.; Harries, D.; McHenry, M.; Wager, G. Determining the optimal electric vehicle DC-charging infra-structure for Western Australia. *Transp. Res. D Transp. Environ.* **2020**, *84*, 102250. [CrossRef]
4. Anegawa, T. Characteristics of CHAdeMO Quick Charging System. *World Electr. Veh. J.* **2010**, *4*, 818–822. [CrossRef]
5. Schulz, F.; Rode, J. Public charging infrastructure and electric vehicles in Norway. *Energy Policy* **2022**, *160*, 112660. [CrossRef]
6. MacKenzie, D.; Jabbari, P.; Khaloei, M. *Locating Fast Charging Stations for Safe and Reliable Intercity Electric Vehicle Travel in Washington*; PacTrans: Tacoma WA, USA, 2018.
7. Miele, A.; Axsen, J.; Wolinetz, M.; Maine, E.; Long, Z. The role of charging and refuelling infrastructure in sup-porting zero-emission vehicle sales. *Transp. Res. D Transp. Environ.* **2020**, *81*, 102275. [CrossRef]
8. Brown, A.; Schayowitz, A.; White, E. *Electric Vehicle Charging Infrastructure Trends from the Alternative Fueling Station Locator: Fourth Quarter 2021*; NREL: Golden, CO, USA, 2022.
9. ChargeHub, MogileTech; Marcoux, B.; Ouellette, S. *Identification of Current and Future Infrastructure Deployment Gaps*; Mogile Technologies Inc.: Pointe-Claire, QC, Canada, 2021.
10. Chakraborty, D.; Bunch, D.S.; Lee, J.H.; Tal, G. Demand drivers for charging infrastructure-charging behavior of plug-in electric vehicle commuters. *Transp. Res. D Transp. Environ.* **2019**, *76*, 255–272. [CrossRef]
11. Terra 360 ABB. ABB Inc. 2022. Available online: https://new.abb.com/ev-charging/terra-360 (accessed on 17 May 2022).
12. Federal Highway Administration. *Biden-Harris Administration Takes Key Step Forward in Building a National Network of User-Friendly, Reliable, and Accessible Electric Vehicle Chargers*; US Department of Transportation: Washington, DC, USA, 2022.
13. Illmann, U.; Kluge, J. Public charging infrastructure and the market diffusion of electric vehicles. *Transp. Res. D Transp. Environ.* **2020**, *86*, 102413. [CrossRef]
14. Rempel, D.; Cullen, C.; Matteson Bryan, M.; Vianna Cezar, G. Reliability of Open Public Electric Vehicle Direct Current Fast Chargers. *arXiv* 2022, *Submitted for Publication*. [CrossRef]
15. Nelder, C.; Rogers, E. *Reducing EV Charging Infrastructure Costs*; Rocky Mountain Institute: Basalt, CO, USA, 2020. [CrossRef]
16. Tesla. Find Us | Tesla n.d. Available online: https://www.tesla.com/en_ca/findus? (accessed on 12 June 2022).
17. Mihalascu, D. *First Audi Charging Hub A Success, Three More Coming This Year*; InsideEVs: Miami, FL, USA, 2022. Available online: https://insideevs.com/news/591069/audi-charging-hub-success-three-more-coming-this-year/ (accessed on 8 June 2022).
18. Wu, Y.; Ribberink, H. Methodology to Estimate the Need for Direct-Current Fast-Charging Stations along Highways in Canada. *J. Transp. Eng. A Syst.* **2020**, *146*, 04020108. [CrossRef]
19. He, Y.; Kockelman, K.M.; Perrine, K.A. Optimal locations of U.S. fast charging stations for long-distance trip completion by battery electric vehicles. *J. Clean. Prod.* **2019**, *214*, 452–461. [CrossRef]
20. Pathak, C. *Electric Vehicle Infrastructure Decision Support System*; University of Washington: Tacoma WA, USA, 2021.
21. Khan, H.O.A.; Saeed, F.; Owais, H.; Khan, A.; Saeed, F.; Arshad, N. Propelling the Penetration of Electric Vehicles in Pakistan by Optimal Placement of Charging Stations. *Eng. Proc.* **2021**, *11*, 34. [CrossRef]
22. Csonka, B.; Csiszár, C. Determination of charging infrastructure location for electric vehicles. *Transp. Res. Procedia* **2017**, *27*, 768–775. [CrossRef]
23. Kavianipour, M.; Fakhrmoosavi, F.; Shojaei, M.H.; Zockaie, A.; Ghamami, M.; Wang, J.; Jackson, R. Impacts of technology advancements on electric vehicle charging infrastructure configuration: A Michigan case study. *Int. J. Sustain. Transp.* **2022**, *16*, 597–609. [CrossRef]
24. Bryden, T.S.; Hilton, G.; Cruden, A.; Holton, T. Electric vehicle fast charging station usage and power require-ments. *Energy* **2018**, *152*, 322–332. [CrossRef]
25. Borlaug, B.; Salisbury, S.; Gerdes, M.; Muratori, M. Levelized Cost of Charging Electric Vehicles in the United States. *Joule* **2020**, *4*, 1470–1485. [CrossRef]
26. Goody, M.; Lepold, S.; Koke, H.; Smallacombe, K. Charge the North: Findings from the complete data set of the world's largest electric vehicle study. In Proceedings of the 33rd Electric Vehicle Symposium (EVS33), Portland, OR, USA, 14–17 June 2020. [CrossRef]
27. Field, K. *A Quick Guide to Tesla's New V3 Supercharging*; CleanTechnica, Posted 16 August 2019. Available online: https://cleantechnica.com/2019/08/16/a-quick-guide-to-teslas-new-v3-supercharging/ (accessed on 20 June 2022).
28. KPMG Canada. 2022 Auto Poll. KPMG 2022. Available online: https://home.kpmg/ca/en/home/insights/2022/01/kpmg-2022-auto-poll.html (accessed on 23 May 2022).
29. PlugShare. 2022. Available online: https://www.plugshare.com/ (accessed on 14 October 2022).

30. Statcan. *National Travel Survey, Fourth Quarter 2018 and Annual 2018*; The Daily; Statistics Canada: Ottawa, ON, Canada, 2019.
31. Fitzgerald, G.; Nelder, C. *EVgo Fleet and Tariff Analysis Phase 1: California*; Rocky Mountain Institute: Basalt, CO, USA, 2017.