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Modelling electric vehicle charging network capacity and performance during short-notice evacuations

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ABSTRACT

Electric vehicles (EVs) may add new challenges during mass evacuations. Understanding the magnitude of the impacts EVs may have during the pre-departure stage of mass evacuations is an essential first step when planning for mass evacuations in a future where EVs are more common. In this paper, a generalized framework based on a G/G/c/N queueing model (general arrival process, general service process, c charging stations, and N EVs) was developed to estimate the number of vehicles that can be charged in the pre-departure evacuation stage and thus assess the pre-departure impacts. The model outputs are the number of vehicles that have or have not been served during the evacuation period, as well as average queue times and maximum queue lengths. This model is tested using the current electric vehicle fleet and charging infrastructure of Prince George, British Columbia, as a case study with a hypothetical short notice forest fire scenario. It was found that for the present-day case of Prince George, there is not enough charging network capacity to service all vehicles before departure. Increasing the number of charging stations, providing earlier evacuation notices, and ensuring a balanced makeup of level 3 fast-charging of different types were all found to be effective in increasing the number of EVs that received adequate charging before departure.

1. Introduction

Mass evacuations are difficult situations to manage. There are many uncertainties and potential problems that might arise during evacuations. Electric vehicles (EVs) may add new challenges to an already difficult situation, both for evacuees and for emergency managers. While, in the present, EVs make up a small proportion of the total vehicles on the road, their numbers continue to grow. As EVs continue to increase in popularity [1], it will be prudent to identify what problems might arise from their introduction to mass evacuation situations, model their impacts, and to explore potential solutions before being forced to deal with them in retrospect. (FIg. 1)

While EVs may promise reductions in emissions and potentially reduction in fuel costs for their users, in their current form, they bring some significant trade-offs. EVs often have longer charging times than conventional vehicles' fueling times, leading to concerns about charging network capacity in emergency situations. They also often have shorter ranges than conventional vehicles, leading to concerns about vehicles running out of charge en route to their destination. Although these range and fueling times differ significantly among EV makes and models, overall many EVs still perform worse in these metrics than conventional vehicles in the present. While these are manageable hurdles in business-as-usual situations, they may magnify existing challenges during evacuations, especially under short-notice scenarios.

Very little research has explored the topic of EVs and during mass evacuations. One of the leading efforts in this direction is the research by Adderly et al. [4]. To our best knowledge, with the exception of this work, no other work has modelled charging or refueling of vehicles before an evacuation. One potential problem that EVs will magnify is vehicle refueling before evacuations. Reports of long lineups at gas stations during evacuations are quite common [5–13]. Increased charging times and shorter ranges would increase the time spent refueling and the number of stops during evacuations. Any vehicle that has insufficient charge to evacuate will likely be temporarily abandoned, which will at best only impede the evacuation of the passengers of that vehicle if they abandon their vehicle far to the side of the road, and at worst could prompt a partial lane closure were an out-of-fuel vehicle to fully or partially block a lane of traffic. Even stalled vehicles on the shoulder can reduce the capacity of roadways as other motorists reduce their speed when passing. In an evacuation situation, stalled vehicles on

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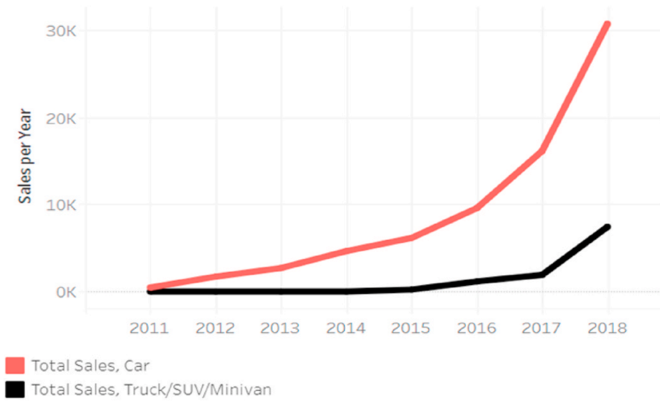

Fig. 1. Electric vehicle sales in Canada over time. Reprinted from "Market Snapshot: EVs in Canada" by Canadian Energy Regulator [2].

the shoulder can also block emergency vehicles and supplies.

To further complicate the issue, in the present, EV charging stations come in a variety of types and with different vehicle adapters. In contrast with gas stations, which are very common and are compatible with the vast majority of conventional passenger vehicles, today's limited availability of EV charging stations and the diversity in the types of charging station and related compatibility with the specific EV models further limits the number of options evacuees have. Thus, not every EV model may be equipped to charge at a certain station. Some vehicles can not make use of DC fast charging stations at all.

On top of pre-evacuation charging concerns, EV range concerns become apparent when considering the kind of disasters that frequently cause mass evacuations. The distance that evacuees need to travel varies heavily between different disasters. In the 1979 Mississauga train derailment, 200,000 evacuees travelled an average of only 10 km outside the mandatory evacuation area [14]. In contrast, when Hurricane Floyd approached Florida, Georgia, and the Carolinas in 1999, 2 million evacuees travelled 242–402 km on average [15]. During the 2016 Fort McMurray wildfire, the nearest major city, Edmonton, was as far as 435 km away. A hypothetical evacuee from Key West, Florida may have to travel over 640 km to reach Orlando. This would likely require multiple stops to refuel vehicles. Hurricanes and wildfires are the two most likely candidates to prompt long distance evacuations as they affect large areas and can pose a significant risk to human life.

While EVs are popular in urban areas in the present, introduction of battery-electric pickup trucks may encourage some rural residents to switch from conventional fuel vehicles. Ford has recently announced a battery-electric version of the F-150, the most popular vehicle series in North America [16]. EVs evacuating from wildfires in Northern Alberta or British Columbia may not be as much of a stretch of the imagination as it presently seems.

To better understand the magnitude of the impacts EVs may cause pre-departure during mass evacuations, this paper develops a framework based on a G/G/c/N queuing model to estimate the charging network capacity in an area before the departure during a short-notice evacuation. Throughout this work, Kendall's notation will be followed when describing queuing models. The queuing models discussed in this work have an arrival process following a certain distribution which governs arrivals to stations (general – G, or a Markovian Poisson process – M), a service time process following a certain distribution which governs the time it takes for charging to be completed (general – G, or a Markovian Poisson process – M), a defined number of charging stations (a whole number of value c), and a defined number of arriving EVs (a whole number of value N).

Modelling the problem as a queueing problem with a wide range of input parameters provides a generalized framework capable of realistically estimating EV charging network capacity. This work is novel in that it is the first to model charging or refueling of vehicles before an evacuation and does so by being the first to incorporate different EV makes and models, as well as different levels of charging stations in a model of EV charging network capacity. Furthermore, rather than using a Poisson arrival process, this research presents the first work that incorporates a realistic arrival process that reflects historically observed evacuation patterns. Having a more realistic arrival process and service processes is important because traditional queueing assumptions, like Poisson arrival and service processes do not apply in evacuation scenarios.

The outputs of the developed model are performance indicators in the form of number and percentage of vehicles that have or have not been fully charged during the evacuation period, average queue times and maximum queue lengths. While the work in this study focusses on evacuations, the methods used to incorporate different vehicle models and charging station types could be used to estimate charging capacity under business-as-usual scenarios as well. Thus, this newly developed model can be used as a decision support tool for: 1) informing decision-makers to assist in evaluating the capacity of their EV charging network, and 2) allowing emergency managers to better assess whether their communities, especially those that do not have a large number of fast-charging stations, can handle the demand for charging generated by a mass evacuation. While this research uses Prince George as a case study, the framework is general enough and thus transferable to other communities by changing the input parameters (e.g. type and number of charging stations) to incorporate EVs into their evacuation planning. Furthermore, the trends in charging network capacity and traffic models should be similar in any remote location at risk of wildfire.

2. Review of the literature

The majority of the literature on EV charging networks focusses on optimal placement locations [17–22]; or the impacts on the electrical grid [23–27]. Feng et al. [23] in particular is worth noting as it deals directly with EV evacuations. While it does not address capacity issues relating to demand for EV charging during pre-evacuation queuing, it suggests that there may be electrical grid capacity issues from a surge in power demand due to increased charging in the pre-evacuation period.

While no work focusses on the maximum throughput of EVs under emergency circumstances, work that models charging network capacity under business-as-usual circumstances can be drawn on. Adderly et al. [4] are the only authors to date to examine the challenges that EVs may give rise to in mass evacuations. Their work focusses on potential policy implications and provides simple estimates of EV charging network capacity and recommended distances between charging stations. This study did not model the impacts of EVs after departure.

Aveklouris et al. [28] examine both charging station and parking capacity as M/M/c queues with abandonment, but do not examine different vehicle or charger classes. Said et al. [29] and Akbari & Fernando [30] model the problem as a M/M/c queue and M/M/1 queue respectively, but again do not take different vehicle models or charging station types into consideration. Zhang & Grijalva [31] model residential vehicle charging station impacts on the grid as an M/G/∞/N model where charging time is based on an empirical distribution informed by smart meters at homes with level 2 charging stations. Liu & Bie [32] incorporates multiple types of different charging stations with the goal of determining the optimal allocation of charging stations under business-as-usual conditions. As discussed in more detail in Sections 3.3-3.5, pre-evacuation charging may not resemble business-as-usual charging, leading to different assumptions about the structure of the queueing problem than those used in the studies above. While this work builds a solid foundation, there is room to explore models that incorporate different arrival processes, different vehicle makes and models, and different types of charging stations.

Evacuations may have relatively long or relatively short notice times. In the case of Hurricane Katrina, a voluntary and then mandatory evacuation notice went out 47 h and 42 h respectively before the storm made landfall [33]. In the case of the 2011 Earthquake in Japan, an evacuation notice was sent out 3 min after the earthquake struck, leaving only 27–37 min before the tsunami made landfall [34]. Other events, like the 2016 Fort McMurray wildfire fall somewhere in between. At 2:00PM, May 3rd, mandatory evacuation orders were given for southern communities. This expanded to a full mandatory evacuation for all of Fort McMurray at 6:20PM the same day. During this time period, over 45% of the population leaving the city by vehicle had evacuated. By 12:00AM that night, almost 90% of those leaving by vehicles had evacuated. Over this 10 h period, nearly 35,000 people (17, 500 vehicles) evacuated the city.

Many authors have explored the distinction between voluntary and mandatory evacuation notices and their accompanying impacts on when individuals choose to evacuate [35–39]. Voluntary and mandatory evacuation notices play a significant role in predicting when evacuees choose to depart, particularly in short-notice or no-notice evacuations [40–45]. Auld et al. [41] notes that during no-notice respondents who received a government order to evacuate and see others evacuating rate their likelihood of evacuating as well at a 4.5 on a scale of 1-to-5. Beverly & Bothwell [46] found that in a 27 year study of 547 wildfire evacuations in Canada, 90% of evacuees left due to an evacuation order by the government.

There have been numerous efforts to model evacuation time based on evacuee behaviour during hurricanes [47]; Dixit et al., 2012; [37,48], as noted by Golshani et al. [49] no studies have focused on no-notice or short-notice behaviour-based evacuation time models. Absent further behaviour-based models of short-notice or no-notice evacuation departure times, reconstructed empirical departure curves will be relied on to estimate departure curves for this work.

Based on past events, the US National Oceanic and Atmospheric Administration's National Hurricane Center issues hurricane watches 48h and hurricane warnings at 36h before an area experiences tropical storm force winds [50]. Similar time frames were seen in practice during Hurricane Irene [51] and Hurricane Floyd in South Carolina [15]. A partial evacuation order for the town of Paradise, California was issued 1 min after wildfires were reported in town, and the full evacuation order was not given for another 1 h and 17 min [52]. In the 2016 Fort McMurray wildfire, mandatory evacuation of the western communities like Abasand began at 2:34PM, with fires reported in the community at 4:09PM, giving the time between warning and event at 95 min.

Many authors have also tried to create empirical departure curves and fit those curves to theoretical distributions. Most notably, Lewis [53] proposed using sigmoid curves, Radwan et al. [54] proposed using logistic distributions, Tweedie et al. [55] proposed using Rayleigh distributions, Cova & Johnson [56] proposed using Poisson distributions, and [57] proposed a sequential logit model. These studies primarily focused on hurricane evacuations, while Cova & Johnson focused on wildfire evacuations. These theoretical models are often difficult to validate given the changing circumstances and characteristics of each disaster. Thankfully, some excellent studies have been carried out to determine empirical evacuee departure curves. Li et al. [51] constructed an evacuation curve based on traffic data during Hurricane Irene. They determined that Rayleigh and logit distributions best fit the empirical departure curves [58]. constructed an empirical evacuation curve for vehicles leaving Fort McMurray but did not fit it to any specific distribution.

3. Methodology

3.1. Simulation methodology & parameterization

In this paper, the problem of modelling EV behaviour during short notice evacuation will be based on a G/G/c/N queueing problem (general arrival process, general service process, c charging stations, and N EVs). The justification for this choice will be discussed further below as the details of emergency evacuation scenarios and EV characteristics are explored in more depth.). Only battery EVs (from here on referred to as just "EVs") will be examined for this study as plug-in hybrid electric vehicles operate similarly to conventional vehicles with their batteries often supplying only a moderate portion of total range.

The problem is approached using Monte Carlo methods and is simulated in the R programming language [59].

The model is a discrete-event simulation with randomized inputs. Vehicles arrive with randomized vehicle makes and models, charge levels, and arrival times. The number of vehicles, the number and type of charging stations, and the time window in which vehicles are able to charge are fixed based on the scenario explored. The service times for each charging station vary depending on initial charge levels, vehicle make and model, and charging station level. The outputs of the model are the number of vehicles served, the maximum queue lengths, and the average time spent in queue (Fig. 2).

To compensate for the relatively low number of input vehicles and the large amount of potential variability due to the differences in charging time and server availability between makes and models, the simulation was run 1000 times for each scenario and all outputs were averaged over this number of samples.

Two options present themselves for how to model multiple charging stations. The first is to model each charging station as its own queue. The second is to model multiple stations as a single queueing problem with as many servers as there are charging ports. The first option would be more accurate if arrival curves differed at the different charging stations. A model that takes into account travel time to charging stations would benefit from this setup. As this model does not take travel times into account and assumes the same arrival curve for each charging station, it is a useful simplifying assumption to model each charging station as belonging to the same queue. The problem will be simulated in the R programming language [59]. It is also assumed that all drivers are familiar with their surroundings and have perfect information about which charging stations their vehicles are compatible with and would not queue for a charging station they would not be able to use. This assumption is justified in part by the rise of mapping technology like Google Maps or ChargeHub that allows EV owners to locate EV charging stations with adapters they can make use of. This assumption may not hold in all cases, such as a scenario where communication infrastructure is not available. However, an assumption of imperfect information would not significantly change the results of this simulation as additional delays from EV owners who discover they are mistaken and requeue at a different charging station are only incurred if travel time to and from stations is taken into account.

While a closed-form solution could be created, it would be a complex and inefficient undertaking. The different classes of servers and customers would make any closed-form equations unwieldy. Approximations that might simplify this effort, such as Little's Law, would not hold as the system is not stationary.

3.2. Overview of the case study

In 2017, wildfires in British Columbia displaced over 45,000 people and caused over 10,000 people to evacuate to Prince George [60]. The next year similar circumstances prompted the evacuation of nearly 3000 people from the surrounding region to Prince George [61]. While fires in these seasons did not directly affect Prince George, Prince George has been identified as being at high risk for wildfires [62,63].

Currently, Prince George has nine EV charging stations at five different locations. There is one level 3 fast-charging station, and eight level 2 charging stations. Prince George has a population of 86,622 as of 2016 [64]. The province of British Columbia had a population of 4.648 million in 2016. The latest estimate for total number of EVs registered in British Columbia is 31,000 as of Q3 2019 [65], with approximately 51% being battery EVs [66]. There is no data available comparing sales in larger and smaller municipalities. It is assumed that EVs are not evenly

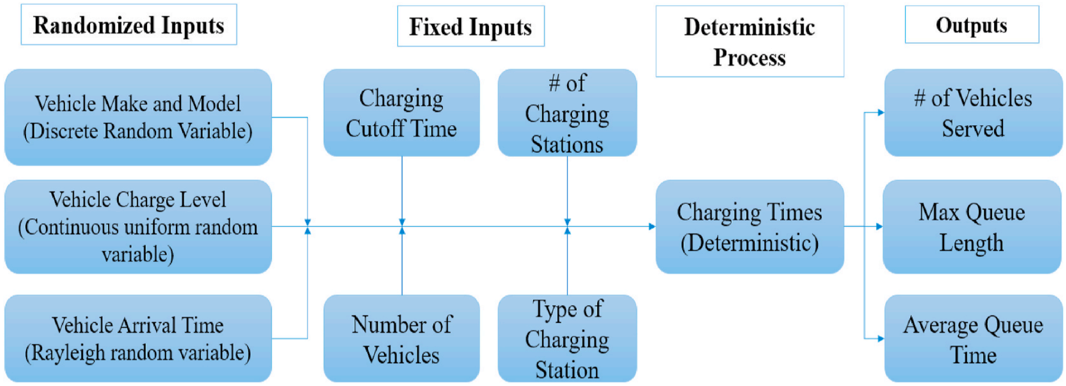

Fig. 2. Inputs and outputs of the queueing model.

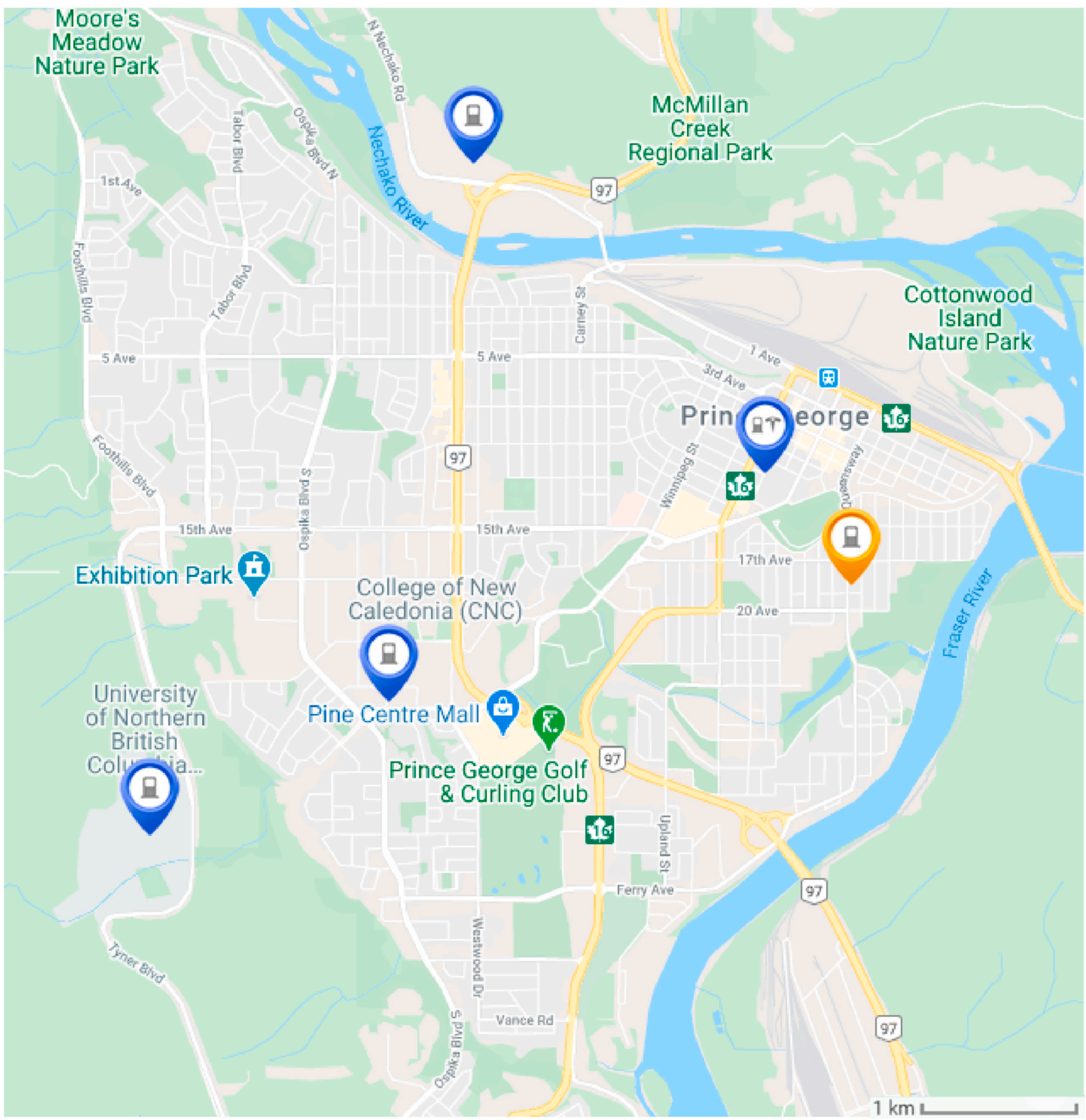

Fig. 3. Locations of charging stations in Prince George. Yellow markers are level 3 charging stations, and blue markers are level 2 charging stations. Some markers have multiple charging stations at that location [3]. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

distributed throughout the population, and that a mid-sized and geographically isolated municipality like Prince George would be expected to have a smaller proportion of EV ownership than a larger municipality like Vancouver. EV sales in the Cariboo region which includes Prince George are only 7% of the EV sales percentage of Vancouver and Victoria (CTV News, 2019). As Prince George is the largest municipality in the Cariboo region, their EV sales percentage is likely to be higher than in other neighboring small rural municipalities and is likely to bring this ratio up slightly. A conservative assumption will be made that EVs will be found at 20% the rate of the background population in BC. This leads to an estimated $n_{TotalEVs}$ of 59 (Fig. 3).

Prince George has EVs and EV associations, as well as EV charging stations and dealerships that sell EVs [67]. This location strikes a balance between having a manageable level of complexity given the relatively small number of EVs and charging stations, while still being large enough and at high enough risk to be investigated for a mass evacuation scenario.

Prince George shares similarities to Fort McMurray, Alberta, Canada, in terms of population and wildfire risk. Both are relatively far distances from other major population centers and have a limited choice of evacuation routes. In summer 2017, Fort McMurray was subject to a wildfire warranting a mandatory evacuation notice. With this similarity between the two cities, the departure curves for Prince George can be inferred from past empirical work by Woo et al. [58].

For this case study we will consider a hypothetical wildfire with a relatively short notice time. Four hours and 20 min will pass between voluntary evacuation and mandatory evacuation, with fires reaching the city by 8 h. The cutoff time T_{evac} at which fires enter the city and charging is no longer possible will be the 8-h mark.

3.3. Arrival process

To estimate an arrival rate for vehicles at EV charging stations, one must determine what type of distribution the arrival to stations follows, how many vehicles may need to be serviced in a location, how much time is available for charging in an emergency scenario, and the period of time in which charging can occur. Any fueling of vehicles would have to be done either in preparation for evacuation (during evacuation alerts or during voluntary evacuation notices, if there are any), or in the evacuation time period.

Departure curves for the city can be inferred from past empirical work, as discussed in Section 2. The departure curve created by Woo et al. [58] is the closest analogue to the case study examined in this paper. During the Fort McMurray wildfire, a mandatory evacuation notice was given 4 h and 20 min after evacuation began, and the time at which 90% of vehicles had evacuated was approximately 11 h after evacuation began. The left tail of each curve is much shorter than the right tail indicating rapid mobilization prior to mandatory evacuation notices, followed by long delays for the last 10% of evacuees.

Caution should always be taken when trying to generalize theoretical departure curves from the limited data available for two very different types of emergency. With this in mind, a Rayleigh distribution will be chosen due to the existing evidence in its favor in both hurricane evacuations and the Fort McMurray evacuation.

From these departure curves, we can theorize an arrival curve for charging stations. In short warning notice situations like wildfires, it will be assumed that refueling will likely be the last action before departing, taking place during or after the process of gathering family members, belongings and supplies, and making other arrangements [42,68–70]. This means it can be assumed that for all vehicles that need to charge before departure, the cumulative arrival curve at charging stations will take the same shape as the evacuee departure curve. This simplifies matters greatly, however, it is important to note that significant delays due to charging could slow down the rate of departures from the charging stations, and these new delays due to charging would not be represented in the departure curves of the empirical studies in Section 2.

A theoretical Rayleigh departure curve with a scale parameter σ controlling the slope of the curve can be inferred from the cumulative departure of vehicles over time in the case studies that share similarities with the scenario being modelled. The cumulative distribution function for the Rayleigh distribution is given in Equation (1):

$$F(x;\sigma) = 1 - e^{\frac{-x^2}{(2\sigma^2)}} \tag{1}$$

Without access to the datasets used in the studies discussed, σ can only be estimated from the reported cumulative percentage at the mandatory evacuation time. Fitting the Rayleigh distribution to a cumulative probability of 45% at the mandatory evacuation time (260 min) gives a σ of 237.78. This scale parameter models the right tail reasonably well; giving an 87% cumulative percentage of departures at 8 h into the evacuation, compared with roughly 85% cumulative percentage of departures at the same time in the Fort McMurray departure curve (Fig. 4).

Using inverse transform sampling, a set of independent and identically distributed Rayleigh random variates, X, can be generated from Equation (2):

$$X = \sigma\sqrt{-2 \ln U} \tag{2}$$

Where X is a Rayleigh random variate, and U is a uniform random variate. These variates are then sorted from least to greatest and the differences of these sorted random variates are the inter-arrival times of vehicles to the system. An example of these cumulative arrival and interarrival time curves for a single sample are given in Fig. 5.

It should be noted that in comparison to an exponential distribution, a Rayleigh distribution has less dispersion (coefficients of variation of 1 and 0.523 for exponential and Rayleigh distributions respectively).

The scale parameter will need to be fit for each evacuation window considered. T_{evac} will be considered the period of time between a voluntary evacuation notice being issued, and the interruption of charging services (e.g. fires entering the affected community forcing immediate departure or losing power at a charging station). It will be assumed that this is the period of time between the voluntary evacuation notice and a cutoff time when cumulative evacuation percentage passes roughly 85%. It can be reasonably assumed that stations at this time will no longer be able to operate for the reasons listed above.

3.4. Service time distribution

Each EV model has its own battery size, charging profile, and type of charger it is compatible with. Service times will vary between models and chargers. As such, it is appropriate to use a class-based system to model service times. Each vehicle is assigned a class that represents its model and the type of charging station(s) it is compatible with. The number of EVs of each model can be estimated from the ratio of sales of a specific model to the total number of EVs sold. Each vehicle entering the system is not likely to have the same initial charge. It will be assumed that vehicles will have some preexisting charge between 20% and 100%. EV owners are unlikely to let their vehicles drain completely to prevent battery capacity reductions from deep discharges. Lithium-ion batteries under 20% and above 80% battery charge have severe diminishing returns on charging per unit time [71]. It will be assumed that vehicles above 80% battery charge leave the system immediately (having chosen to evacuate without spending further time charging). The number of EVs requiring charging after removing the EVs already above 80% battery charge, n_{rEVs}, is 44 (rounded to the nearest whole). It can be assumed that preexisting charge is uniformly distributed absent any prior evidence to the contrary. No abandonment of queues will be assumed (Fig. 6).

Given the many different factors that go into charging time, charge times for EVs using level 2 and level 3 chargers are estimated from manufacturer information. Detailed charging profiles are not supplied by manufacturers. Service times are assumed to be linear given that

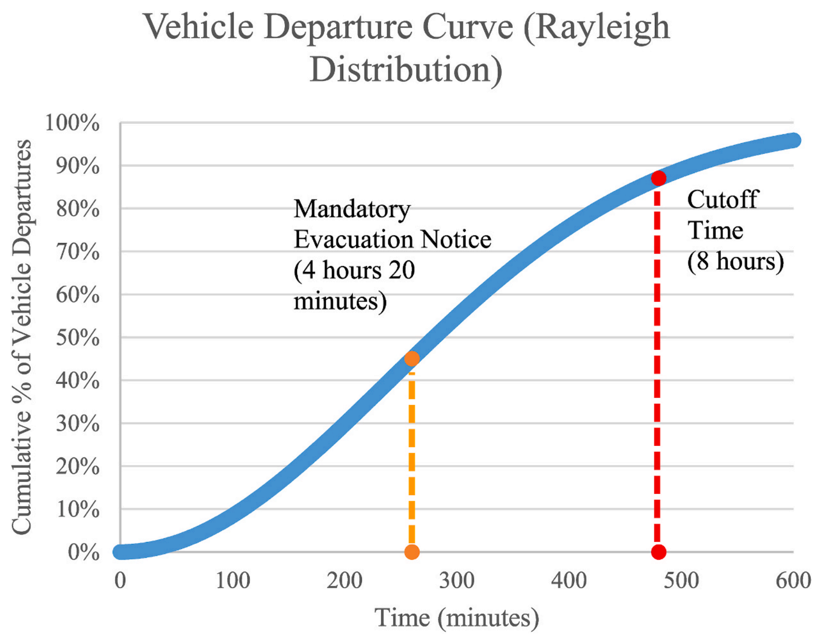

Fig. 4. Departure curve for σ = 237.78.

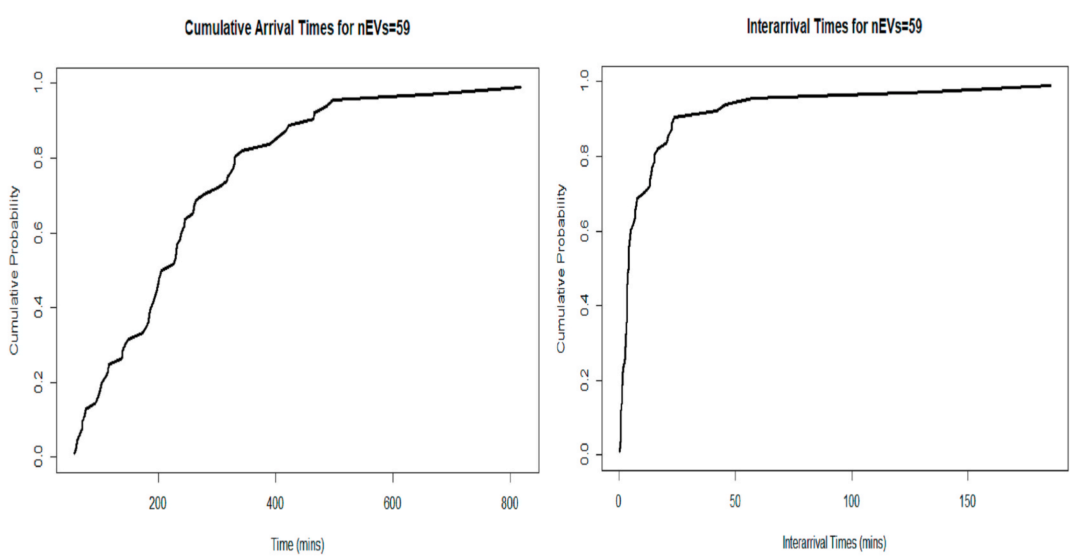

Fig. 5. Single sample cumulative arrival and interarrival curves for σ = 237.78 and $n_{TotalEVs} = 59$.

charging speed is roughly constant between 20% and 80% charge level. The service times are given by Equation (3):

$$S_{ijk} = x^* C_{ijk} \quad (3)$$

Where S_{ijk} is the service time for an EV model i with a charge-to-80% time C_{ijk} for a charging class j on a charging station of level k. x is a uniformly distributed variable between 0.2 and 0.8 that represents the preexisting charge level of the vehicle.

For this scenario, it will be assumed that EVs will charge fully until reaching 80% charge level. Although there are no destination-surveys for Prince George, evacuation route choice is constrained, and evacuees would need to travel along one of the four evacuation routes out of town 228 km westward to Burns Lake, 403 km to northward to Dawson Creek, 209 km eastward to McBride, or 121 km southward to Quesnel. In comparison, a mid-size EV such as a Nissan Leaf has a maximum range of 243 km in older models and 364 km in newer models. There are no Research by Akbarzadeh and Wilmot [72] suggests that evacuees do take into account the actual and perceived levels of service (defined as the number of gas stations and hotels that actually exist and are the number believed to exist along the route respectively) when selecting evacuation routes during hurricanes, and the importance of these factors increases as the hurricane approaches. However, accessibility, distance, and road type are significantly more important factors for route choice than level of service. It is important to distinguish that these factors help determine *route* choice, but further research is needed to determine how, or if, evacuees take fuel or charge levels of their vehicles into account when determining *destination* choice. Range anxiety, which is a concern for even urban EV owners may combine with imperfect information about charging station availability along their chosen evacuation route (the perceived level of service), as well as the EV owner's uncertainty about the additional mileage gained per minute of charging, and these factors could further encourage charging to full. As such, for this scenario it will be assumed that EV owners charge without cutoff until the 80% point of steep diminishing returns. Empirical studies of charging

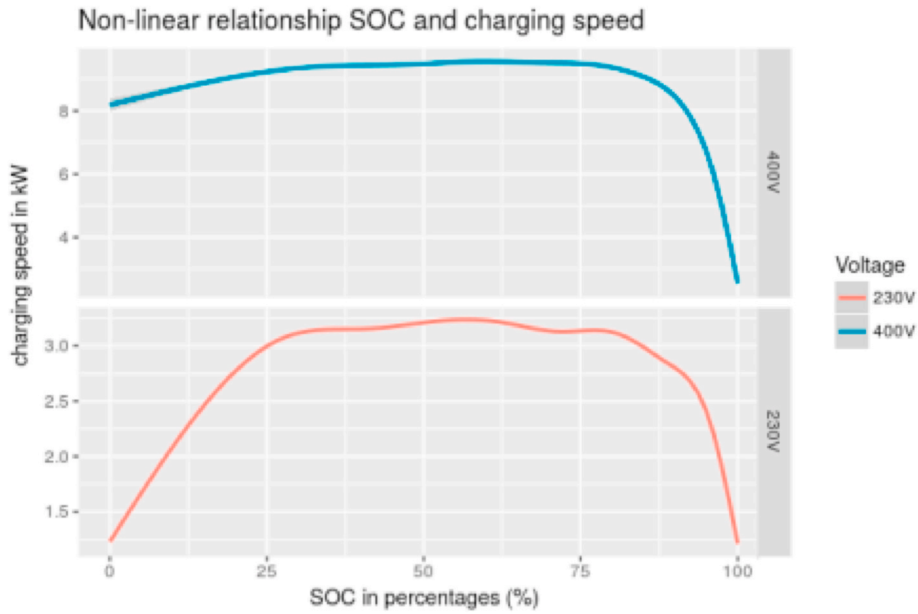

Fig. 6. Relation of battery capacity (State-Of-Charge) and charging speed. Reprinted from "Estimating the charging profile of individual charge sessions of electric vehicles in the Netherlands" by Mies, J. J., Helmus, J. R., & Van den Hoed, R, 2018, World Electric Vehicle Journal, 9(2), 17. CC BY-NC-ND [71].

behaviour will be needed to generalize this assumption to locations with charging stations located along evacuation routes.

Vehicles may only charge at charging stations of compatible charging classes and compatible charging station levels. Charging is first-come, first-served to charging stations that are able to serve vehicles of that particular class. A rank r is assigned to each vehicle based on its position in the queue with the oldest arrivals having the lowest rank. As charging stations of class j become available, the vehicle of the minimum rank with class j may leave the queue and begin service. If multiple stations are available, evacuees will choose to charge at the charging station with the highest level k compatible with their vehicle class. It is assumed that evacuees will use the first charging station available of their vehicle class j rather than waiting in the queue in hopes that a charging station with a higher level k will open up. Choosing realistic values for C_{ijk} will involve exploring the characteristics of EVs and EV charging stations in more depth (Fig. 7).

EVs charge at different speeds in different situations. Current level of charge, battery age, and external temperature can all affect the time it takes for an EV battery to charge. Charging speed also depends on the type of charging station used. Level 1 charging stations are 120V connections such as a standard household wall outlet. Level 2 charging stations are 240V connections and can be installed in homes or parking lots for an additional cost. Level 3 fast-charging stations have connections of 480V or more. The difference in charging times between levels is quite substantial. A Nissan Leaf can charge to 80% of its capacity in 40 min with a level 3 charger. The charge time increases to 6.5–11 h for a level 2 charger, and 18.5 h for a level 1 charger [73].

While recent studies such as Lee et al. [74] examining business-as-usual EV charging behaviour in California indicate that a majority of users make use of home-charging in the present, there are reasons to believe that in an evacuation public charging stations may play a larger role when evacuees may value their time differently. A Nissan Leaf using a public level 3 fast-charging station takes only 6% of the time to charge an equivalent amount at a home level 2 charging station. During a short-notice evacuation like the wildfire in this scenario, a hypothetical evacuee faces a decision about whether to charge

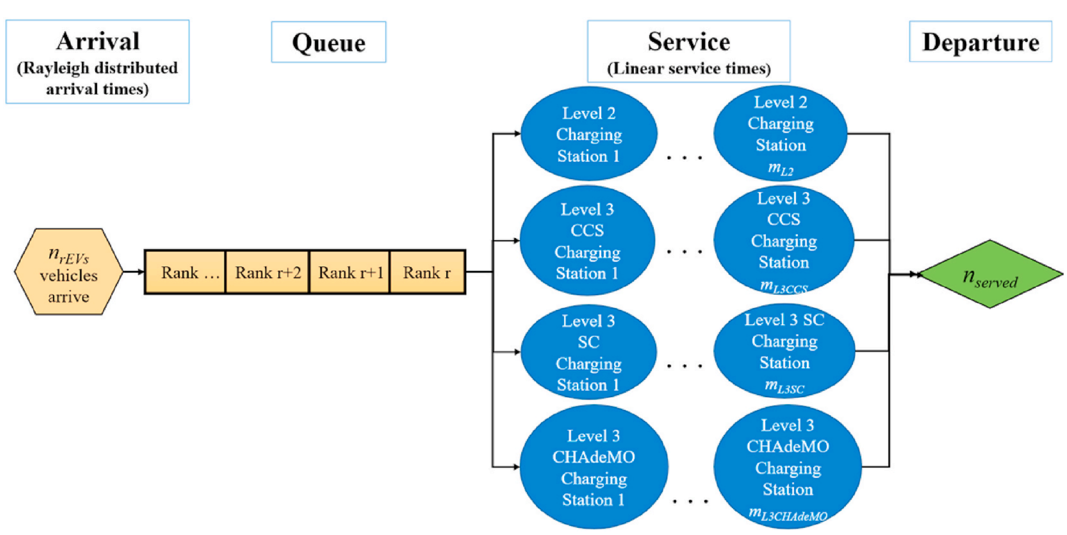

Fig. 7. Basic structure of the G/G/c/N queueing model used.

at home for a period of multiple hours or seek out a level 3 fast-charging station and charge in 20–40 min (the evacuee must also take into account the length of time they believe they would spend waiting in the queue when making this decision). Further research is needed to determine whether evacuees in an emergency situation are likely to choose to charge faster and depart earlier, potentially avoiding traffic and possible danger, or prioritize a shorter charging time so they could use their EV to gather family and supplies or make other trips.

While home charging is the most frequent mode of charging for EV owners in the present day, it is uncertain that it will continue to play such a primary role in the future. Early EV adopters are more likely to have higher incomes and have the resources to install home-charging stations, as well as own homes which are suitable for installing level 2 chargers. Lee et al. [74] note that >80% of respondents in their survey had incomes above the California median income, and >80% of respondents owned detached single-family homes. As EVs continue to decrease in price and the demographics of EV owners shift, it is likely that there will be more reliance on public charging facilities for people that can not afford to install home charging stations, or do not have the ability to install their own home chargers (renters, people living in areas with only on-street parking, people living in multi-family residences where access to charging stations is limited or shared among multiple residences). Engels et al. [75] predict that the demand for public charging infrastructure will continue to increase over time as middle and low-income households without home charging options begin to purchase more EVs. As EV ownership becomes more widespread, it is likely that during an evacuation these demographics without access to home charging will compete with time-sensitive evacuees that have home charging for public level 3 DC fast-charging charging stations.

Level 3 fast-charging stations are commonly found with three different specialized connectors: Combined Charging System (CCS), CHAdeMO, and Tesla Superchargers. Each have the same basic functionality, but different EV models are compatible with one or more of these connectors with adapters (see Appendix A for further discussion on charger types). Some models are only capable of making use of level 1 and level 2 chargers. Not every level 3 station provides the same charge rate, however, the EV models that have been selected tend to have an upper ceiling by design on how quickly they are able to charge. Future EV models and future level 3 charging stations are likely to provide faster charging rates [76]. Not every EV has the same charging profile.

To determine which EV charging classes will be used, total EV sales by model up to the year 2017 in Canada are used to determine which EVs are most common. For Canada, the total vehicle sales by model are available for the country as a whole and by province. Charge times and ranges for models with shares of greater than 1% of total battery-EV sales were examined. As a simplifying assumption, charge times and ranges are given for the latest make and model of each vehicle. This will increase the average ranges and likely increase charge times for the models chosen. This will provide a less accurate assessment of current scenarios which have vehicles of older makes on the road, but is in line with the trend of battery improvements to EVs when predicting the impacts of scenarios that take place in the future.

3.5. *Number and type of charging stations*

The number of public chargers c_{jk} of class j and level k is known with some confidence. Resources like ChargeHub [3] offer maps of public charging stations in a location. Other local resources may be used as well to determine the number, location, and type of charging ports available. It is up to the judgement on the modeler whether level 2 charging stations should be included as their long service times may only allow 2–4 vehicles to be serviced from 20% to 80% in a 24-h period. It may also be difficult to account for the number of private level 2 chargers installed in homes. Data on how many level 2 charging stations have been installed in homes could potentially be estimated from the number of rebates given for installing said chargers, if the location in question has rebates of this kind and tracks this data. Level 1 charging stations can be discounted in short-warning scenarios as they have prohibitively long charge times during a short-notice scenario and are theoretically ‘available’ at any location with a wall outlet.

3.6. *Performance measures*

The most important outputs of this simulation are number of EVs requiring charging that were served (n_{served}), the total number of EVs served ($n_{totalCharged}$ which includes the number of EVs that already had above 80% charge before entering the system), percentage of total EVs served, maximum global queue lengths ($N_{maxqueue}$), and average queue times ($T_{avgqueue}$). Taken on its own, the number of vehicles served is an indication of whether EV charging networks can handle the sudden influx of demand posed by a mass evacuation. The number of EVs unserved will also give an indication of how many vehicles will likely run out of charge en route to their destination. Maximum and average queue lengths may be a useful indicator of congestion from blocked intersections due to charging; however, these statistics are more useful in predicting area-specific congestion when queues for individual stations are modelled.

4. Results

The simulation was run 1,000 times for each scenario examined and all outputs are averages over this number of samples. While there is no empirical data to validate the model, the outputs were verified. No runs experienced errors with unexpectedly high or low service times, or with very high or very low numbers of EVs served. Queue times and lengths were reported correctly at very high and very low numbers of charging stations and over long and short cutoff times.

The parameters used for the baseline case are given in Table 1:

The results for the Prince George baseline case are given in Table 2:

In the baseline case, the charging networks in the city were shown to be not enough to accommodate demand during a mass evacuation under the present-day conditions described above. While this insight alone may be useful for Prince George as it currently is, what generalizations can be extracted for other communities facing similar challenges?

The number of EVs ($n_{TotalEVs}$) and the number of EVs requiring charging (n_{rEVs}), the cutoff time period (T_{evac}), and the number and type of charging stations can be changed to explore potential trends. Sensitivity analysis is conducted to examine the impact of important parameters on the network charging capacity. The parameters examined are given in Table 3:

For each scenario, for n_{served}, $N_{maxqueue}$, and T_{evac} the results were not normally distributed (Shapiro-Wilk test for normality, p«0.05). Given that the results are not normally distributed, a non-parametric Kruskal-Wallis H-test (one-way ANOVA on ranks) was used. All trials resulted in statistically significant differences between results (p«0.05).

The results of the trial in which the number of EVs is changed are given in Table 4:

As expected, when the number of EVs increases, the percentage of EVs in the system that are charged to completion decreases (a difference

Table 1
Parameters for the Prince George baseline scenario.

Parameter	Value
$n_{TotalEVs}$	59
n_{rEVs}	44
T_{evac} (hours)	8
Scale Parameter σ	237.78
Level 2 Chargers	8
Level 3 SC	0
Level 3 CCS	1
Level 3 CHAdeMO	0

Table 2
Results from the Prince George baseline case study.

Output	Mean	SD
n_{served} (# vehicles)	16	3.58
$\frac{n_{served}}{n_{rEVs}}$	0.36	
$N_{maxqueue}$ (# vehicles)	17	3.62
$T_{avgqueue}$ (mins)	91.7	21.33

Table 3
Parameters for different scenarios.

	Independent Variable Ratio	Parameters	
Ratio of # of EVs Compared to Baseline		$n_{TotalEVs}$	n_{rEVs}
	0.25	15	11
	0.5	30	23
	0.75	44	33
	1	59	44
	1.25	74	56
	1.5	88	66
	1.75	103	77
	2	118	89
Ratio of Cutoff Time Compared to Baseline		T_{evac} (hours)	**Scale Parameter σ**
	0.5	4	118.89
	1	8	237.78
	1.5	12	356.67
	2	16	475.56
	2.5	20	594.45
Ratio of number of Charging Stations Compared to Baseline		**# Level 2 Chargers**	**# Level 3 Chargers**
	0.5	4	0
	0.5	4	1 (1 CCS)
	1	8	1 (1 CCS)
	2	16	2 (2 CCS)
	3	24	3 (3 CCS)
	3	24	3 (1 CCS, 1 CHAdeMO, 1 SC)

of 10.6% when the number of EVs double), while the maximum queues and average queue times increase (182% increase and 55% increase respectively when the number of EVs doubles). One thing to note is that as the number of EVs increases, the number of EVs served increases as well. Shorter interarrival times as a result of more EVs needing to charge within the same time period lead to fewer unused charging stations towards the beginning of the time period examined. However, the demand quickly outstrips the number of charging stations available and the queue becomes saturated.

Even in cases where the number of EVs was reduced to 25% of the baseline level, 46% of EVs that required charging still did not charge to completion before evacuating. This is due to the arrival time curves to the stations not changing. Some vehicles may still choose to arrive only an hour before the potential cutoff time, leaving them unable to receive a full charge. Future research will be needed to determine how actual or perceived queues at EV charging stations impact the timing at which EV owners decide to charge their vehicles (Figs. 8–10).

The results of the trial in which the evacuation cutoff time is changed are given in Table 5:

As expected, when the cutoff time increases, the percentage of EVs in the system requiring charging that charge to completion increases (a difference of 25% when cutoff time doubles) while maximum queue length decreases (a 53% decrease when cutoff time doubles). Of interest is that as the cutoff time increases, average queue times increase before decreasing. These non-monotonic results are due to EVs having a longer time period in which they can wait in the queue before the simulation cutoff time forces them to leave the system. As the cutoff time continues to increase, interarrival times become further apart. This means that EVs are more likely to show up to an available charging station, as a result decreasing average queue time of the system (Figs. 11–13).

The results of the trial in which the number of EV charging stations is

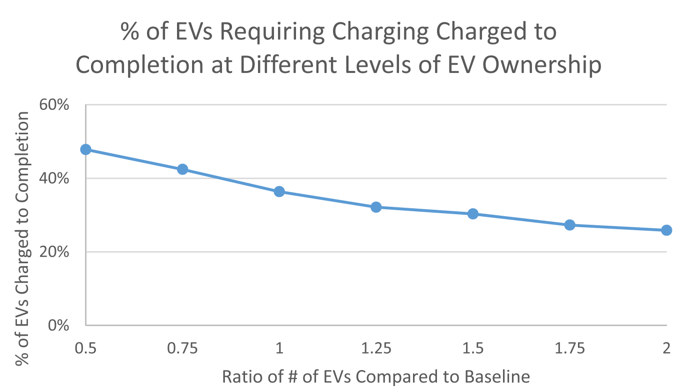

Fig. 8. Percentage of EVs requiring charging charged to completion at different ratios of number of EVs.

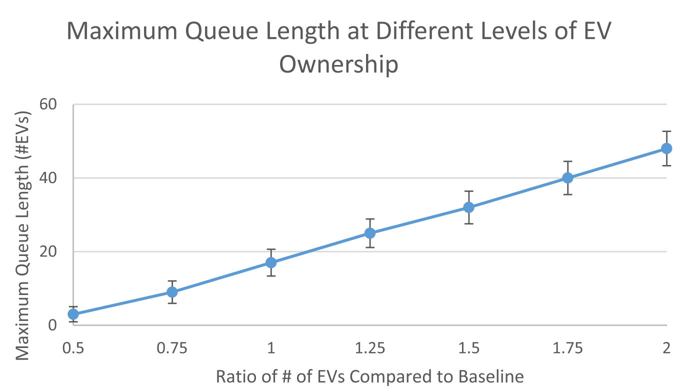

Fig. 9. Maximum queue length at different ratios of number of EVs.

Table 4
Results when ratio of n_{rEVs} to baseline is changed.

Ratio of n_{rEVs} to baseline	n_{rEVs}	n_{served} (# EVs)	σ_{served}	$\frac{n_{served}}{n_{rEVs}}$ x 100	$N_{maxqueue}$ (# EVs)	$\sigma_{maxqueue}$	$T_{avgqueue}$ (mins)	$\sigma_{avgqueue}$
0.25	15	6	1.92	54.5%	1	0.133	4.79	6.49
0.5	30	11	2.62	47.8%	3	2.06	26.97	19.67
0.75	44	14	3.23	42.4%	9	3.05	66.27	23.67
1	59	16	3.58	36.4%	17	3.63	91.7	21.33
1.25	74	18	3.57	32.1%	25	3.87	112.05	20.40
1.5	88	20	3.93	30.3%	32	4.43	123.83	18.19
1.75	103	21	3.91	27.3%	40	4.52	134.44	18.41
2	118	23	3.96	25.8%	48	4.68	141.88	17.00

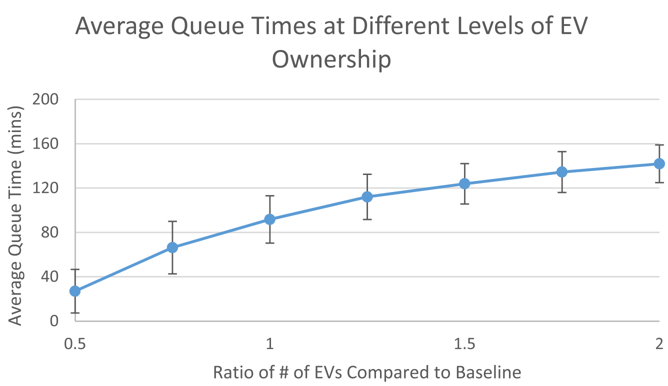

Fig. 10. Average queue time at different ratios of number of EVs.

changed are given in Table 6:

As expected, when the number of charging stations increases, the maximum queue length and average queue time decreases (a 76.5% decrease and 75% decrease respectively when number of charging stations doubles, and a 94.1% decrease and 92.8% decrease when the number of charging stations triples). Of interest is that as number of charging stations increases, the number and percentage of EVs in the system requiring charging that charge to completion increases before decreasing (from 27.3% of EVs charged at baseline to 45.5% at twice the number of charging stations, before falling to 40.9% at triple the number of charging stations). This is a side effect of the queueing behaviour implemented. EVs will always take the first available charger of the highest level available to them. Instead of waiting for a level 3 charger to be available, an EV will always take an unoccupied level 2 charger. This has the effect of slotting more EVs that could potentially make use of a level 3 charger into a level 2 charger instead. Queueing reduces the likelihood of this happening, as an EV that could make use a Level 3 charger might become placed in queue behind vehicles that can only make use of level 2 chargers. When a level 3 charger opens up, the EV that could make use of it "jumps the queue" ahead of the vehicles that could only make use of level 2 chargers. In effect some amount of queueing increases the likelihood that a vehicle that can make use of a level 3 chargers uses it instead of a level 2 charger. This behaviour represents a very risk averse evacuee who would rather take a guaranteed slot at a level 2 charger rather than gamble additional time spent in a queue to try and get a slot at a level 3 charger. In reality, some people would be likely to take this gamble (Figs. 14–16).

Two final trials were conducted to determine the impact of the types of charging stations in the system. Both trials were compared with each other and were found to have statistically significant differences between results ($p < 0.05$). The results of the trial without and with a level 3 charging station are given in Table 7:

As expected, when the one level 3 charging station is replaced with a level 2 charging station, there is a significant decrease in charging network capacity, in this case a 33.3% decrease in the number of EVs requiring charging served. The percentage of EVs in the system that are charged to completion decreases (a difference of 9.1%), while the maximum queues and average queue times increase (a 12.0% increase and a 13.8% increase respectively) (Fig. 17).

The results of the trial in which the level 3 charging stations are balanced evenly by type (see Appendix A for discussion of level 3 charger types) are given in Table 8:

When the three level 3 CCS charging stations are replaced with a

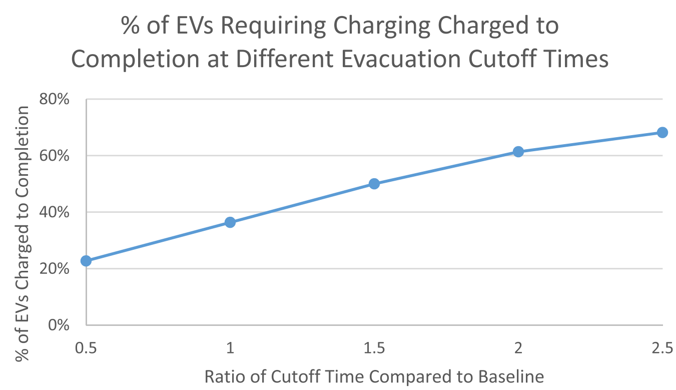

Fig. 11. Percentage of EVs requiring charging charged to completion at different ratios of cutoff time.

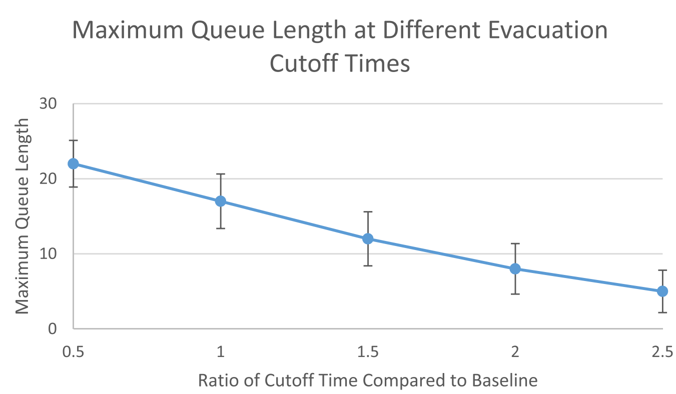

Fig. 12. Maximum queue length at different ratios of cutoff time.

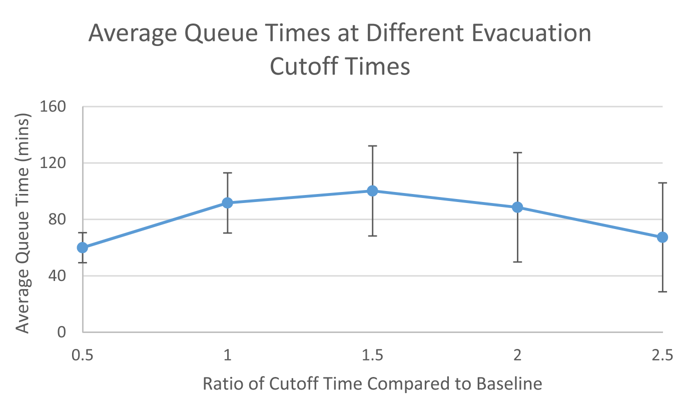

Fig. 13. Average queue time at different ratios of cutoff time.

Table 5
Results when ratio of T_{evac} to baseline is changed.

Ratio of T_{evac} to baseline	T_{evac} (h)	n_{served} (# EVs)	σ_{served}	$\frac{n_{served}}{n_{rEVs}}$ x 100	$N_{maxqueue}$ (# EVs)	$\sigma_{maxqueue}$	$T_{avgqueue}$ (mins)	$\sigma_{avgqueue}$
0.5	4	10	2.79	22.7%	22	3.11	59.99	10.64
1	8	16	3.58	36.4%	17	3.63	91.70	21.33
1.5	12	22	3.79	50.0%	12	3.60	100.20	31.91
2	16	27	3.87	61.4%	8	3.36	88.59	38.78
2.5	20	30	4.01	68.2%	5	2.83	67.31	38.64

Table 6
Results when ratio of number of charging stations to baseline is changed.

Ratio of # of Charging Stations to baseline	# of Level 2 Chargers	# of Level 3 Chargers	n_{served} (# EVs)	σ_{served}	$\frac{n_{served}}{n_{rEVs}}$ x 100	$N_{maxqueue}$ (# EVs)	$\sigma_{maxqueue}$	$T_{avgqueue}$ (mins)	$\sigma_{avgqueue}$
0.5	4	1 (1 CCS)	12	3.00	27.3%	25	3.17	146.25	24.53
1	8	1 (1 CCS)	16	3.58	36.4%	17	3.63	91.70	21.33
2	16	2 (2 CCS)	20	3.53	45.5%	4	3.01	22.71	13.37
3	24	3 (3 CCS)	18	3.12	40.9%	1	0.213	6.56	4.59

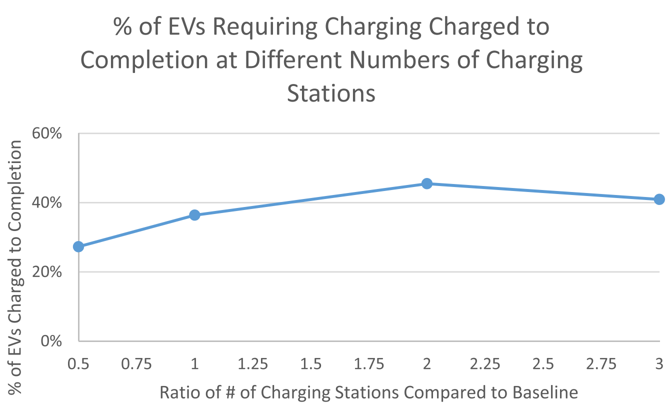

Fig. 14. Percentage of EVs requiring charging charged to completion at different ratios of number of charging stations.

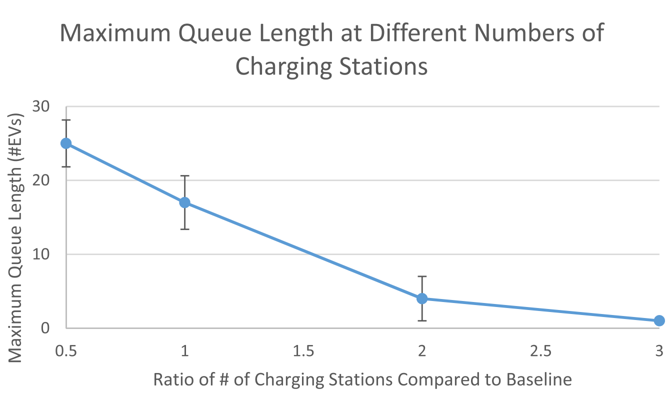

Fig. 15. Maximum queue length at different ratios of number of charging stations.

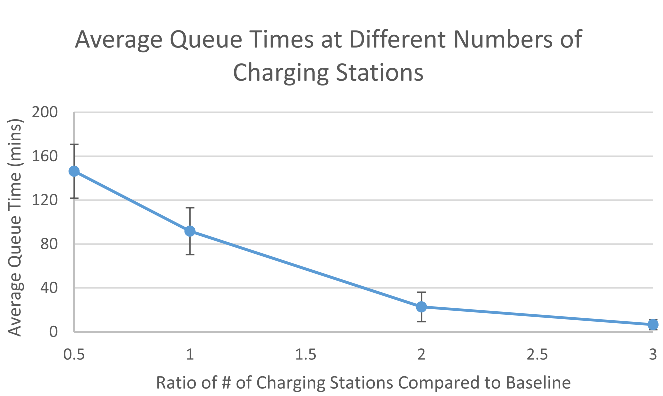

Fig. 16. Average queue time at different ratios of number of charging stations.

CCS, CHAdeMO, and SC station, there is a significant increase in charging network capacity, in this case a 61.1% increase in the number of vehicles served. The percentage of EVs requiring charging in the system that are charged to completion increases (a difference of 25%), while the maximum queues and average queue times decrease (a difference of 9.0%). While this may not have as large an effect in the future when charging stations with different adapters become more prevalent, or charging adapters become standardized, in the present systems with an unbalanced makeup of level 3 charging stations are at a disadvantage when compared with systems where the makeup of level 3 charging stations is more evenly balanced (Fig. 18).

It was found that with respect to maximum queue lengths, the model is most sensitive to decreasing the number of EVs, followed by increasing the number of chargers, followed by increasing T_{evac}. With respect to the number of vehicles served, the model is most sensitive to increasing the window of time between the voluntary evacuation notice and the interruption of charging, T_{evac}, followed by decreasing the number of vehicles, followed by increasing the number of chargers available. With respect to average queue times, the model is most sensitive to increasing the number of chargers, followed by decreasing the number of vehicles, followed by increasing T_{evac}. Ensuring a balanced makeup of level 3 chargers will increase the number of vehicles that can be charged in a mass evacuation.

5. Discussion

The results of the case studies modelled indicate that EVs will likely pose problems in a mass evacuation scenario in the present. Whether these problems will persist into the future will depend on a number of factors, particularly how fast EV ownership grows, how many EV charging stations are installed and when they are installed, and trends in battery capacities and charging speeds.

The results from the queueing model indicated that Prince George does not have enough charging network capacity to accommodate all EVs in a mass evacuation. Only 36% of vehicles requiring charging were charged to completion before being forced to depart. In addition to this, queue times were found to be very long at 92 min. There is a significant opportunity cost for evacuees waiting in queues, as they could spend this time gathering family members and supplies or making other preparations for the evacuation. Max queue lengths were found to be 17 vehicles long. Maximum queue lengths will be of more interest when they are location-specific. Unlike gas stations, many charging stations are today located in parking lots. It will depend on the layout of these charging stations whether queues may spillover into nearby streets, or whether there will be enough parking spots to accommodate maximum queues. As the number of EVs increase, potential traffic disruptions from long queues will become a more pressing consideration. The trends found during this case study should hold for most locations.

It would be wise to keep in mind what factors policymakers have control over. The number of EVs and the models of those vehicles will largely be out of policymaker's hands and to some extent, so too will the period of time in which the evacuation takes place (T_{evac}). T_{evac} will depend on the type of emergency being planned for, and emergency

Table 7
Results without and with a level 3 charging station.

Ratio of # of Charging Stations to baseline	# of Level 2 Chargers	# of Level 3 Chargers	n_{served} (# EVs)	σ_{served}	$\frac{n_{served}}{n_{rEVs}}$ x 100	$N_{maxqueue}$ (# EVs)	$\sigma_{maxqueue}$	$T_{avgqueue}$ (mins)	$\sigma_{avgqueue}$
0.5	5	0	8	2.29	18.2%	28	2.87	160	23.52
0.5	4	1 (1 CCS)	12	3.00	27.3%	25	3.17	146.25	24.53

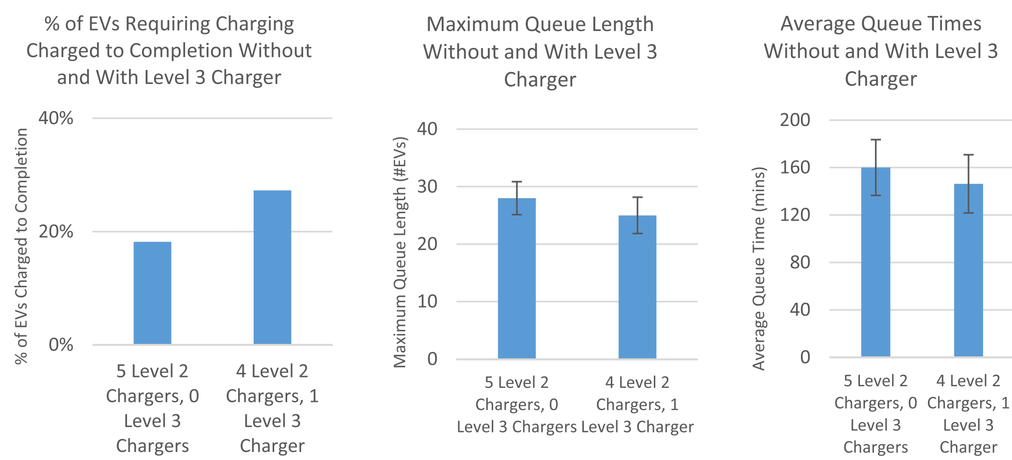

Fig. 17. Percentage of EVs requiring charging charged to completion without and with level 3 chargers, maximum queue length without and with level 3 chargers, and average queue time without and with level 3 chargers.

Table 8
Results with unbalanced and balanced level 3 charging station types.

Ratio of # of Charging Stations to baseline	# of Level 2 Chargers	# of Level 3 Chargers	n_{served} (# EVs)	σ_{served}	$\frac{n_{served}}{n_{rEVs}}$ x 100	$N_{maxqueue}$ (# EVs)	$\sigma_{maxqueue}$	$T_{avgqueue}$ (mins)	$\sigma_{avgqueue}$
3	24	3 (3 CCS)	18	3.12	40.9%	1	0.213	6.56	4.59
3	24	3 (1 CCS, 1 CHAdeMO, 1 SC)	29	3.60	65.9%	0	0	5.97	4.45

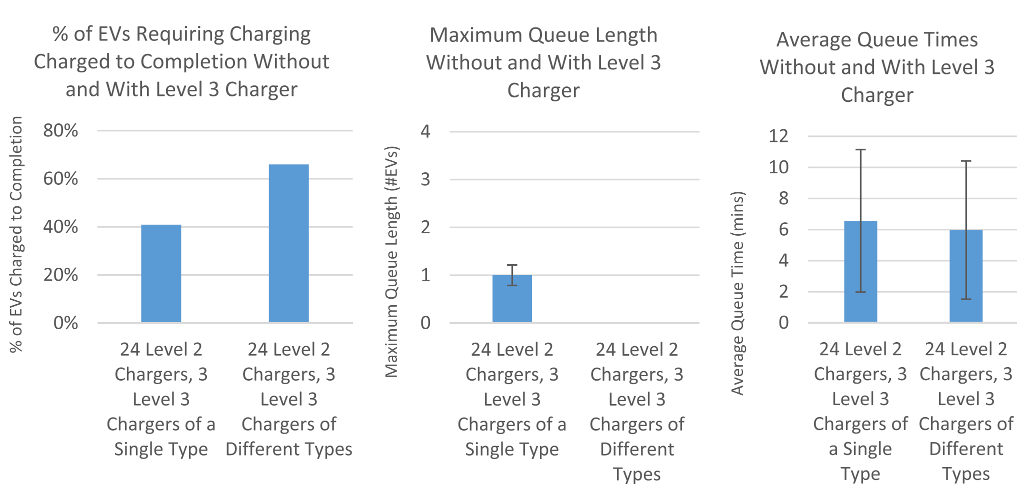

Fig. 18. Percentage of EVs requiring charging charged to completion without and with a balanced makeup of level 3 charging station types, maximum queue length without and with a balanced makeup of level 3 charging station types (no queue for the balanced makeup scenario), and average queue time without and with a balanced makeup of level 3 charging station types.

managers can be aware that a shorter T_{evac} by moving up mandatory evacuation notices will increase problems associated with EV charging and as a result on the number of EVs stalled en route to their destination post-departure. Charging and fueling will have to be weighed against other considerations when determining when to give a mandatory evacuation notice, as discussed in Chapter 5 of Lindell et al. [39]. Emergency managers may be able to reduce the time between voluntary and mandatory evacuations and as a result shift departure curves for the evacuation to encourage vehicles to charge and fuel earlier before loss of services at charging and fueling stations. Even if earlier notices can be given, there are further trade-offs to be considered when issuing voluntary and mandatory evacuation notices. Vehicle charging needs to be weighed against the cost of issuing earlier warnings which may not end up requiring mandatory evacuations. This imposes significant opportunity costs on evacuees who choose to evacuate unnecessarily [77].

Policymakers may have some element of control over how many EV charging stations there are, and the type of charging stations available. Subsidies to build EV chargers of certain classes that have adapters that are not currently available would help ensure all vehicles have some access to a level 3 charging station (if they can make use of level 3 chargers). Policymakers can also subsidize the construction or operation of new level 3 public charging stations, or level 2 home charging stations, if there is a risk of their location needing to undergo a mass evacuation. Of course, the cost of these subsidies needs to be weighed against the likelihood of a mass evacuation occurring and the costs associated with the total delays imposed by stalled EVs as a result of inadequate charging capacity.

To reduce demand on charging networks in the pre-departure stages, another potential policy intervention is to reduce the distance between charging stations along evacuation routes to reduce the amount of time EVs would need to charge before departing. Some work to determine optimal interurban placement of fueling and charging stations has already been done by Gao et al. [78] and Colmenar-Santos et al. [18] respectively. While it is likely that there will be a greater number of interurban charging stations in the future, subsidies to accelerate the rate at which they are built could be justified in part on the grounds of increased performance during evacuations.

It is possible that as the number of charging stations along evacuation routes increases, EV charging networks will perform better than conventional fuel networks. While conventional fueling stations may have fuel shortages during periods of high demand, EV charging stations can continue to operate as long as they have access to a power supply. If charging stations have grid access or are able to make use of off-grid solar, they may be able to service more vehicles than a fueling station that runs out of fuel during an evacuation. Legislation exists in Florida and New York that requires gas stations along evacuation routes to have back-up power generators at gas stations [79,80]. No similar requirement exists for EV charging stations along evacuation routes. This legislation would not guarantee that charging stations could be used during evacuations due to the inadequacy of back-up generator power output to meet EV charging needs, as well intermittency issues with off-grid solar photovoltaic charging systems [81]. Evacuations with compounding factors, like large amounts of smoke from wildfires or heavy cloud cover during hurricanes, could interrupt service at off-grid systems.

Emergency preparedness may be just one reason among many to subsidize EV charging infrastructure.

6. Conclusion and future research

In summary, EVs bring a number of benefits to society, however, mass evacuations may be one area where at the present time they may be more of a liability than an asset. The problem of EV charging during evacuations will magnify over time as EVs continue to grow in popularity. The model developed has the flexibility to incorporate different EV makes and models, as well as different levels of charging stations. Thus, while the analysis in this paper focusses on evacuations, with some extensions the model can estimate the charging capacity under business-as-usual or other planning scenarios.

A computer simulation model was developed and tested using Prince George, British Columbia, as a case study. The model agrees with trends intuitively expected and provides quantitative estimates that can be adjusted to fit a variety of communities and situations, particularly those involving remote communities at risk from wildfires. Sensitivity analysis was conducted to examine the impact of a larger number EV ownership rate, the number and type of charging stations and duration of evacuation window on the charging capacity of the examined network. The results of the queueing model indicated that, in the present, Prince George's EV charging network does not have the capacity to handle a short-notice mass evacuation. The results of the sensitivity analysis indicate that as the number of EVs increased and the number of charging stations decreased, the percentage of EVs that could be served significantly decreased, as expected. Providing a longer window for evacuation by giving earlier voluntary and mandatory evacuation notices increases the number of vehicles that can be served. Emergency managers may consider issuing earlier notices to EVs to charge and fuel earlier. However, there are some related risks to be considered when issuing earlier warnings that may not end up requiring a mandatory evacuation. Another important finding that policymakers potentially have a degree of control over is that of increasing the capacity of charging station network especially in jurisdictions where it is deemed insufficient for evacuations. For instance, for the examined case study, while maintaining the same number of charging stations having a balanced makeup of level 3 fast chargers of different types substantially increases the capacity of charging networks.

Future work could examine how charging network capacity changes as charging station adapters become standardized and as EV battery sizes increase over time. Future work could also further explore the behavioural dynamics of charging or refueling before evacuations to better understand arrival times to stations and queueing behaviour. More complex models aimed at fully understanding a certain location's evacuation dynamics could also incorporate travel time from residences to charging stations and consider the effects of evacuation traffic on those travel times, as well as the potential impacts of EV charging on evacuation traffic patterns, such as queues of EVs backing up onto streets and impeding traffic. Incorporating imperfect information about charging station locations, charger adapters and compatibility, and unknown queue lengths is another level of complexity which could be explored. Incorporating charging cutoff times if evacuees are knowledgeable of EV charging stations could add a further level of precision to future work, however, there are unsettled behavioural questions about charging behaviour during an evacuation that would need to be explored first. These considerations would aid both evacuation planning in the present day and planning for the location of future charging stations.

Research is needed to explore charging and refueling behaviour, and whether pre-evacuation charging behaviour for EVs is significantly different than refueling behaviour for internal combustion-engine vehicles. More specifically, research is needed to determine how actual or perceived queues at EV charging stations impact the timing at which EV owners decide to charge their vehicles. Determining whether there is a maximum amount of time EV owners are willing to wait in a queue to charge vehicles could inform whether it is reasonable to assume there is no abandonment in the queueing model. Research is also needed to determine whether EV owners, particularly those with level 2 charging stations at home, would risk leaving their home to queue for a level 3 charging station.

More research could be done to determine the likelihood that evacuees will take an EV if they own an ICEV as well. Some households might choose to leave an EV behind and only take a single ICEV if they are concerned about charging times or vehicle range during an evacuation. Understanding these changes in behaviour would be valuable to inform future models.

Incorporating EV charging into emergency evacuation planning, in the same way conventional vehicle refueling is incorporated into current evacuation planning, will go a long way towards mitigating this problem, or at the very least preventing unexpected surprises during a mass evacuation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Electric Vehicle Charging Stations

A table of electric vehicle charging stations is provided for reference. Note that charging times given below may vary based on environmental conditions, like temperature or the age and lifetime use of the battery.

Table 9
Overview of Charging Stations

Charging Station Type	Voltage	Charging Time for an Average-Sized EV (2020 Nissan Leaf)	Notes
Level 1	120V	18.5 h	Portable chargers compatible with 120V wall sockets are the most common Level 1 charger.
Level 2	240V	11.5 h	Level 2 wall charging stations require a 240V outlet. Most home Level 2 charging stations need to be purchased by the EV owner and installed by electricians.
Level 3 DC Fast Charger	~480V–500V	40 min	Voltage can vary by charging station and maximum voltage may be capped on certain EV models. The most common DC Fast Charging station adapter types are CCS, CHAdeMO, and Tesla Supercharger. While each has the same basic functionality, CCS is predominately used in American and European models, while Asian models predominately use CHAdeMO. Tesla models make use of Supercharger and CCS chargers.

Examples photos of the different charging stations are given below:

Fig. 19. An example of a Level 1 portable charger. "The 110/120V charging 'nozzle'" by Major Nelson is licensed under CC BY 2.0.

Fig. 20. Examples of an outdoor (left) and indoor wall mounted (right) Level 2 charging stations. "BMW i3 electric car" by Janitors is licensed under CC BY 2.0. "Skoda EV charger" by Ivan Radic is licensed under CC BY 2.0.

Fig. 21. An example of a Level 3 DC Fast Charging station with CHAdeMO (top right) and CCS (bottom right) adapters. "umn-chademo-and-ccs-charger" by Mulad is licensed under CC BY 2.0.

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