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Charging infrastructure for electric vehicles in New Zealand ☆

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ABSTRACT

The uptake of electric vehicles (EV) is closely interlinked with the availability of charging infrastructure. Fast charging stations (FCS) can facilitate the uptake of EV, but their installation requires significant investments affecting their profitability. An optimal determination of charging locations and capacities based on associated costs can help to provide infrastructure efficiently. As initial FCS affect installations and costs in later years, a strategic infrastructure development plan over multiple years is required to expand the infrastructure to satisfy the charging demand of a growing EV fleet, while pursuing the goal of minimal costs. Based on former work, a model for the investment-optimal allocation and sizing of FCS over multiple years (including costs for grid connection) is developed. For the first time, a multi-periodic capacitated Arc-Cover Path-Cover formulation with an investment-optimal objective is proposed and applied to New Zealand. The results are analysed with respect to the locations and sizes of FCS, the impact on the coverage of traffic flows, and the related trends over time. They indicate that FCS are to be located along highly trafficked corridors in densely populated regions for being applied profitably. The chosen station locations have below-average installation costs and are capable of covering high shares of EV traffic on inter-regional and highly frequented routes.

1. Introduction

Transportation is one of the major sources accounting for 15% of worldwide greenhouse gas emissions in 2019 (Intergovernmental on Climate Change, 2022). This emphasizes the need to shift transportation to a more environmentally friendly alternative and has motivated countries around the world to electrify their transportation sector. However, one core hurdle of a large-scale adoption of electric vehicles (EV) is seen in the lack of charging facilities (Coffman et al., 2016; Melaina and Bremson, 2008; Tsang et al., 2012). Accordingly, the development of a widespread infrastructure of charging stations can contribute to an increased uptake of EV (Sierzchula et al., 2014). Especially for long-distant journeys, the allocation of fast charging stations (FCS) at easily accessible and efficient locations along highly trafficked corridors that promote the use of EV as primary transport mode is required to reduce range anxiety. As significant investments are required by infrastructure providers for each FCS, the establishment of a widespread system of FCS is expensive and its profitability is still uncertain (Schroeder and Traber, 2012; Jochem et al., 2016, 2019). A strategic infrastructure deployment plan dedicated to promoting the use of EV along major traffic corridors while obtaining the goal of minimal investments required for the installation of FCS from a provider perspective can contribute to solving this issue. As the adoption level of EV, their charging demand and travel behaviour in future years remains subject to variations and infrastructure providers seek to install FCS compatible to the actual charging demand, the need to strategically plan and install FCS over a time horizon of multiple years arises.

From a provider's perspective, the key factor determining whether to invest in infrastructure is long-term profitability. The amount of investments spent plays a major role in profitability (Hecht et al., 2022). Keeping investments as low as possible while providing sufficient charging options for EV users to promote EV adoption represents a beneficial strategy for providers. There exist several options of location combinations suitable to serve the charging demand of EV sufficiently. In case location costs vary, the shift from high- to low-cost station locations can reduce infrastructure costs while still enabling EV trips equivalently. Thus, an investment-minimal infrastructure plan that provides a certain coverage level of charging demand of EV should be pursued from a provider perspective.

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The aim of this work is to develop a strategic charging infrastructure deployment plan that yields minimum investments by considering local grid connection costs. For this purpose, an investment-optimal model based on the Capacitated Arc Cover-Path Cover (CACPC) model by Hosseini and MirHassani (2017) is developed that places and sizes charging facilities according to EV users' charging needs over a time horizon of multiple years. Required input data and parameters are identified and processed based on several reliable sources. This makes the model easily applicable to other locations. Finally, optimal FCS locations for the highway network of New Zealand's North Island and their related size as well as the development of the charging infrastructure network over time are identified. The influence of several data inputs is analysed to verify the reliability of the results.

In particular, the following contributions are made:

(1) developing a model for strategic planning of FCS over multiple years obtaining minimal investments considering traffic flows as well as location-specific investment costs,

(2) illustrating a comprehensive approach of data processing for simplifying an application in other networks,

(3) determining the optimal charging infrastructure plan for New Zealand's North Island and its development over time as well as

(4) investigating the influence of selected input parameters and data sets on the model results.

The remainder of this work is structured as follows: Section 2 provides background information on the applied model and an overview over existing literature and research fields related to the allocation and sizing of charging facilities is given. Based on selected model formulations reviewed and their related assumptions, Section 3 includes the development of the investment-optimal and multi-periodic model formulation for the allocation and sizing of FCS. In Section 4 the required data is generated and acquired for the application of the proposed model to New Zealand's North Island. This includes the identification of potential facility locations and origin and destination paths as well as the traffic flow volumes travelling along them. In addition, required investments for FCS installations are identified. Section 5 presents our results in detail. Moreover, the influence of several input data sets and parameters on the results is investigated in a sensitivity analysis. Section 6 concludes the work and gives implications for further research.

2. Related work

There are several approaches for estimating an appropriate allocation of FCS to facilitate electric long-distance driving (Anjos et al., 2020). While the overall definition of charging location is hard to estimate, due to uncertainties in the availability of home-charging, most models focus on FCS in combination with long-distance trips (i.e. trips exceeding the range of the EV). Thus, the charging demand can be derived from travel patterns of EV users. The type how these travel patterns are transferred to electricity demand patterns can be used to classify corresponding optimization models.

Node-based models assume demand to be stationary and pooled at nodes. Charging facilities are to be located in such a way that the demand at nodes is satisfied (MirHassani and Ebrazi, 2013). These models neglect information on the flows running along the network routes which is essential when modelling transport networks (Hodgson, 1990). Additionally, complex travel patterns cannot be represented appropriately with node-based approaches (Deb et al., 2018) as demand is assumed to be covered if a single facility is available for service, but in fact, in reality more than one facility might be required to meet the demand (Green, 1984).

As an extension, Flow Capturing Location Model (FCLM) developed by Hodgson (1990) and Berman et al. (1992) consider traffic flows as demand along paths and place facilities to maximize the demand covered. In the FCLM, a path is assumed to be captured if at least one facility is available along the route. Nevertheless, in the case of EV charging stations, placing only one charging facility along each path might not fulfil the requirements of EV with a limited range which might need to be charged more than once to complete a trip considerably exceeding its range (Kuby and Lim, 2005). Thus, Kuby and Lim (2005) introduced the Flow Refueling Location Model (FRLM) as an extension of the FCLM, by incorporating that a path can only be covered if an EV does not run out of electricity between any successive FCS given the range of the EV as well as the origin and destination for each trip (Kuby and Lim, 2005).

Upchurch et al. (2009) extended the FRLM to the Capacitated Flow Refueling Location Model (CFRLM) in which each charging station is only capable to serve a limited number of EV. Here, multiple facilities might be assigned to a single location to ensure that the traffic flow volume can be captured (Upchurch et al., 2009). Zhang et al. (2018) established a CFRLM that aims to minimize investment costs for charging stations and charging points as well as costs that occur due to penalties for unsatisfied charging demand. Based on that, the authors additionally incorporate constraints of the electricity grid in their model formulation.

Chung and Kwon (2015) introduced a multi-periodic version of the FRLM for strategic planning of charging station deployment over time and apply it to the Korean expressway network. Besides, the authors propose two myopic methods that solve single-period problems one after another to approximate the multi-periodic view, but solve the problem computationally more efficient. Li et al. (2016) incorporated the possibility for drivers to take multiple paths between any origin and destination (OD) pair. Driving demand has to be satisfied for all trips, but does not necessarily run along the shortest path between origin and destination, but some possible deviation path within a given tolerance relative to the shortest path. The objective of the proposed method is to minimize installation and relocation costs of charging stations over multiple time periods.

Especially for real-world problems of large-scale network size, solvability is a prerequisite for benefiting from modelling the allocation problem for decision making purposes. Therefore, Lim and Kuby (2010) introduced heuristic solution methods to solve complex applications of the FRLM more efficiently. Likewise, Capar and Kuby (2012) addressed the issue of efficient solvability and propose to reformulate the problem as a Mixed Binary Integer Program that does not require to determine for each path beforehand which combinations of facilities are suitable to enable the path and is thus solvable for large-scale problems. More recently, Capar et al. (2013) proposed a new formulation of the FRLM that allows to generate the model without pre-generation of all possible facility combinations for each OD-path. In this so-called Arc Cover-Path Cover (ACPC) approach, a certain trip is seen to be covered, only if all directed arcs belonging to the path of the trip are covered by an opened refuelling station. Each trip is assumed to be a round trip to ensure that it can be taken recurrently without running out of fuel. Based on this new formulation, Hosseini and MirHassani (2017) further enriched the ACPC-FRLM by incorporating the idea of capacitated stations. This Capacitated Arc Cover-Path Cover (CACPC) model can be formulated as a set-covering or maximum-covering problem. Zhang et al. (2015) and Zhang et al. (2017) introduced a multi-periodic point of view in the ACPC formulation. They established a capacitated and multi-periodic version of the ACPC-FRLM that is suitable to determine the locations of charging stations as well as the number of charging points per station over time. Additionally, in their approach, Zhang et al. (2017) view charging demand to be dynamic and dependent on changing charging options and natural demand growth.

Finally, tour-based modelling approaches consider tours as trip-chains compounded from single short trips that would not require recharging individually, but in the aggregate (Hong and Kuby, 2016). Andrews et al. (2013) and Kang and Recker (2015) used this approach to find optimal charging station locations based on driving tours. He et al. (2015) additionally included driver behaviour and spontaneous trip adjustments or recharging decisions when locating charging infrastructure based on tours. On the one hand, tour-based approaches are capable to represent driving behaviour in a realistic manner, but, on the other hand, it requires complex data inputs such as daily travel data from individual households which are expensive to collect (Deb et al., 2018; Hong and Kuby, 2016).

In the literature, only few publications exist that consider economic aspects as the major objective when allocating charging infrastructure. Wang (2011) proposed a model for an economic deployment of charging infrastructure that serves the needs of tourists travelling long distances. MirHassani and Ebrazi (2013) formulate the FRLM as a Mixed Integer Linear Program (MILP) which can be solved for a cost optimization objective as well as maximum-cover objective. Huang et al. (2015) further extend the model as a Multipath Refueling Location Model (MPRLM) by incorporating deviation paths that allow drivers to complete a trip not only on the shortest path, but on any path between origin and destination not exceeding a maximum deviation. Furthermore, Wang and Lin (2009) proposed a FRLM that follows the objective of minimizing the total costs of installing the charging stations. A FRLM is used by Cruz-Zambrano et al. (2013) seeking to minimize total station installation costs in a real-world application for the city of Barcelona. In their approach, Li et al. (2016) included the costs required for each newly built charging station as well as the fixed and variable costs for relocating stations in the objective function. Xiang et al. (2016) sited and sized charging stations based on a coupled consideration of the transportation and the electricity distribution system. First, the traffic flow data is assigned to individual roads to capacitate the charging station locations. Secondly, the derived charging demand is used as input into a cost-minimizing model that takes into account investments for charging stations, costs of operation of substations as well as power-loss costs. Moreover, Baik et al. (2018) proposed a formulation that seeks to determine the number of charging stations and the equipment capacities that are optimal to maximize the profit of a single infrastructure operator. Zhang et al. (2018) use a CFRLM on a combined transportation and electricity distribution network that minimizes the fixed costs that arise for building charging stations, the size-dependent costs for each additional charging point as well as a penalty for unsatisfied demand. Lastly, Hosseini and MirHassani (2015) seek to minimize the construction costs of charging stations, the costs of recharging and time-dependent costs of travelling to the charging station.

Concluding, there is no model which considers an investment-optimal objective over a multi-periodic planning horizon using the efficient CACPC approach. Furthermore, only few models exist that are applied to a case study with empirical data considering site-specific grid-connection costs. In the following, we develop such a model and apply it to New Zealand's North Island. Our approach can additionally be used as a framework for an application to other real-world cases.

3. Optimal multi-periodic allocation of capacitated charging infrastructure

The ACPC formulation of the FRLM by Capar et al. (2013) serves as a basis for the applied extended model of this work. Due to the fact that no pre-processing of feasible facility combinations for each OD-path is required as it is in earlier types of the FRLM cf. Kuby and Lim, 2005, the ACPC-FRLM provides a computationally efficient formulation, which is introduced in the following.

Based on all arcs of all paths of a network, the detailed outline of the applied algorithm that determines the directional Candidate Set (CS) of each arc for each path is an extension of Jochem et al. (2019) and can be found in Appendix A.

3.1. Underlying assumptions of the IO-MP-C-AC-PC-FRLM formulation

Following Capar et al. (2013) and Upchurch et al. (2009) 11 assumptions are made: (1) The traffic flow of each OD-pair uses strictly the shortest path. (2) Complete knowledge of the traffic volume between each OD-pair is available. (3) All drivers have complete knowledge about available charging station locations and recharge sufficiently if needed. (4) FCS can only be installed at predefined nodes of the network. (5) All EV are assumed to be identical, especially with regard to their driving range. (6) EV electricity consumption is directly proportional to the travelled distance. So far all assumptions come from Capar et al. (2013). (7) Charging units are discrete and are capable of serving a discrete number of EV per day. (8) All traffic flows are continuous and infinitely divisible. This enables the possibility to be able to cover any possible fraction of a flow $z_q \in [0,1]$ with charging infrastructure. (9) The traffic volume is assumed to be uniformly distributed over time. (10) The capacity of chargers and charging demand is measured in arrived EV per unit of time, which is clearly a strong assumption, but when focused on peak-traffic, the resulting FCS-network can still cope with all traffic volumes. For FCS, the time a vehicle occupies a charging unit is the most limiting factor. As we assume that most drivers may also do other things during charging (such as drinking coffee) the plug-in time depends on many factors and, hence, the number of vehicles per unit of time is a reasonable choice to measure capacity of chargers. (11) EV drivers are sticking to the charging strategy (i.e. charging at dedicated FCS) presumed.

3.2. Investment-Optimal Multi-Periodic Capacitated AC-PC Model

An investment-optimal charging infrastructure development plan over multiple periods that provides sufficient charging capacities to serve a desired proportion of the EV traffic flow volume can be derived from the model developed in the following. The model uses the recharging logic of the CACPC model according to Hosseini and MirHassani (2017) and is partially oriented on the ideas of Zhang et al. (2017) in the multi-periodic view as well as in the definition of decision variables, parameters and constraints. The Investment-Optimal Multi-Periodic Capacitated Arc Cover-Path Cover (IO-MP-C-AC-PC) Model can be formulated as follows:

$$\min \sum_{i\in N}\sum_{t\in T} \delta_t \cdot [(z_i^t - z_i^{t-1}) \cdot C_{i,fix} + (x_i^t - x_i^{t-1}) \cdot C_{i,var}] \tag{1}$$

$$\text{s.t.} \sum_{i\in N_{jk}^{1q}} v_{iq}^{1t} + \sum_{i\in N_{jk}^{2q}} v_{iq}^{2t} \geq y_q^t \quad \forall q \in Q, a_{jk} \in A^q, t \in T \tag{2}$$

$$\sum_{q\in Q}\sum_{d\in D} f_q^t \cdot v_{iq}^{dt} \leq c \cdot x_i^t \quad \forall i \in N, t \in T \tag{3}$$

$$v_{iq}^{dt} \leq z_i^t \quad \forall q \in Q, i \in N, t \in T, d \in D \tag{4}$$

$$x_i^t \leq M \cdot z_i^t \quad \forall i \in N, t \in T \tag{5}$$

$$z_i^t \leq z_i^{t+1} \quad \forall i \in N, t \in T \tag{6}$$

$$x_i^t \leq x_i^{t+1} \quad \forall i \in N, t \in T \tag{7}$$

$$\sum_{q\in Q} f_q^t \cdot y_q^t \geq S \cdot \sum_{q\in Q} f_q^t \quad \forall t \in T \tag{8}$$

$$x_i^t \leq x^{max} \quad \forall i \in N, t \in T \tag{9}$$

$$0 \leq y_q^t \leq 1 \quad \forall q \in Q, t \in T \tag{10}$$

$$0 \leq v_{iq}^{dt} \leq 1 \quad \forall q \in Q, i \in N, t \in T, d \in D \tag{11}$$

$$z_i^t \in \{0,1\} \quad \forall i \in N, t \in T \tag{12}$$

$$x_i^t \in \{0\} \cup \mathbb{Z}^+ \quad \forall i \in N \tag{13}$$

Notation			
Sets and Parameters			
T	Set of all time periods t, t = 1, 2, …, T_{Max}	T_{Max}	Last considered time period
N	Set of all network nodes i	Q	Set of all OD-paths q
D	Set of all directions $d \in D$; $D = \{1, 2\}$	A^q	Set of all arcs on path q
N_{jk}^{dq}	Candidate set for the arc from node j to k on path q in direction d	f_q^t	Traffic flow volume on path q in period t
c	Capacity of each charging unit	M	Large constant number
$C_{i,fix}$	Costs of opening a charging station at node i	$C_{i,var}$	Costs of building one charging unit at node i
δ_t	Discount factor for period t	S	Minimum fraction of covered flows
x^{max}	Maximum number of charging units at one station	z_i^0	States whether a charging station exists at node i prior to the first period, $z_i^0 \in \{0, 1\}$
x_i^0	Number of charging units installed at node i prior to the first period, $x_i^0 \in \{0\} \cup \mathbb{Z}^+$		
Decision Variables			
y_q^t	Fraction of flow covered on path q in period t	z_i^t	Binary; 1 if a charging station is opened at node i in period t, 0 otherwise
x_i^t	Number of charging units built at node i in period t	v_{iq}^{dt}	Fraction of flow on path q that charges at node i in period t in direction d

The objective function (1) seeks to minimize the total discounted investment expenses for the installed FCS over all periods. For each period, it aggregates the fixed station installation costs for every newly installed FCS (i.e. fixed costs, $C_{i,fix}$) and the variable costs for each newly added charging unit (i.e. variable costs, $C_{i,var}$). Fixed station costs include all investments required to open a charging station at a specific location, such as expenses for newly built electricity lines to connect the stations to the grid, transformer stations, land costs and personnel and material costs for placing concrete, underground cabling, signage, etc. In addition, variable costs include the equipment for each charging unit itself as well as expenses for its installation. All these cost components are location-dependent.

In order to ensure that trips can be completed entirely, Constraint (2) represents the ACPC concept. In order to enable drivers to choose where to charge their EV in both directions independently, two separate CS, one for each direction of the round trip, are built to differentiate in which direction an EV stops to recharge at a specific FCS. This approach opens up the possibility for EV users to charge at different locations in the forward and backward direction of their trip such that drivers are not forced to recharge in the same locations in both directions.

Each charging unit has only some limited capacity c of serving EV per day which may not be violated (cf. Constraint (3)). In each period, the total number of EV recharging at a node i in either of the directions may not exceed the charging service of node i.

Furthermore, Constraint (4) restricts charging to locations that have an opened charging station available in the considered time period. In the same vein, Constraint (5) ensures that charging units can only be added to opened stations. Moreover, in Constraint (6) it is assumed that a charging station once opened will remain opened in future time periods. In real-world environments, it seems politically and socially undesirable to uninstall stations previously opened and thus to enable users to charge at certain locations at first and hinder them to charge at the same location in later years.

The same holds true for individual charging units (cf. Constraint (7)). The aim to provide charging infrastructure to some minimum fraction of EV users travelling along the paths of the entire road network is modelled in Constraint (8). At least a share $S \in [0, 1]$ of the total flow volume of EV travelling in the network must be sufficiently covered.

In this model formulation, special consideration is given to the maximum number of charging units to be installed at a single charging station location. At every FCS location, the number of charging units present in any period t may not exceed a specified maximum number of charging units x^{max} (cf. Constraint (9)) in order to keep grid impacts (cf. Slednev et al. (2021)) to a manageable level. Indeed, limiting the number of charging units to a maximum is a simple and myopic approach, but it fulfils the requirements at this point sufficiently and is manageable in terms of complexity. Lastly, Constraints (10), (11), (12), and (13) define the domains of the decision variables.

In summary, the IO-MP-C-AC-PC model combines the logic of the CACPC approach with an investment-optimal objective and a multi-periodic viewpoint. To the best of our knowledge, until now, no approach exists that combines these three characteristics.

Indeed, there exist multi-periodic CACPC formulations such as the approaches of Zhang et al. (2015) and Zhang et al. (2017). But, both of these show limitations and inflexibility when applied to real-world problems. EV drivers are forced to charge at an opened station they pass irrelevant of whether it is necessary for them to charge or not. This might limit traffic flows by the capacity of a station even if there is no need to charge. In addition, this model formulation imposes inflexibility on EV drivers as they are not allowed to charge at different locations on the way back than on the forward run. The model formulation developed here addresses these issues by incorporating the concepts by Hosseini and MirHassani (2017) of differentiating between directions and by introducing a decision variable v_{iq}^{dt} that determines the fraction of a flow f_q^t on q that recharges in a node i.

Moreover, an investment-optimal and multi-periodic approach was presented by Li et al. (2016) that does not make use of the idea of the ACPC-concept. The model was found to be difficult to solve for large-scale networks. For real-world applications, the assumption of capacitated stations and solvability even for large networks are a prerequisite for model development.

3.3. Solution method

Applying the developed IO-MP-C-AC-PC Model to a real-world problem results in a Mixed Integer Program (MIP) of considerable size and complexity. In order to allow for solvability even for large scale input data, we propose to follow a comprehensive solution procedure to decrease the problem size while persevering the multi-periodic nature. The problem is simplified to multiple subproblems that are each solved individually. The incorporation of the multi-periodic perspective introduces time as an additional dimension into the FRLM. This dimension is temporarily removed in each subproblem to reduce the model size. The resulting Single-Period Investment-Optimal CACPC Model is solved for every time period individually and the results of installed FCS and charging units of each period are transferred to the next period as a given input requirement. This is iteratively repeated until the end of the planning horizon is reached. In each iteration, all time-dependent input values such as the EV traffic flow volume are chosen accordingly. After all single-period subproblems have been solved, the obtained objective function values are summed to determine the total costs over the planning horizon. This approach is equivalent to solution procedures proposed in existing literature cf. Zhang et al., 2015, 2017; Chung and Kwon, 2015. In this research approach, it is assumed that no FCS and consequently no charging units are installed prior to the considered time horizon. Depending on the individual application case, already existing charging infrastructure might be included here, as well.

4. Case study: North Island of New Zealand

The IO-MP-C-AC-PC Model is applied to the North Island of New Zealand. The goal is to make well-founded suggestions for an investment-optimal allocation and sizing strategy for fast charging infrastructure over time for New Zealand. Hereby, insights into the real-world applicability of the model itself are provided. In order to gain insightful and realistic results, several data inputs are required to model the empirical situation.

For generating a weighted graph $G = (N, A)$ (where N denotes the set of nodes and A the set of distance-weighted arcs) to model the main highway corridors of New Zealand North Island, publicly available data has been used OpenStreetMap (OSM) cf. OpenStreetMap, 2020. In total 55,932 paths are considered in our model. The process is shown in Appendix B.

4.1. Traffic flows

For a realistic application of flow-based models on road networks, traffic flows from all origins to all destinations (OD-flows) need to be known for the siting and sizing of charging infrastructure. Therefore, a well-founded database of OD-flows and their trend over all time periods under consideration is mandatory to gain reliable and meaningful results. As stated earlier, OD-flow data is difficult and costly to collect. Thus, various theories have been developed in order to determine, describe and predict patterns of interaction between aggregated spatial regions from available alternative data sources. In this work, the Gravity Model (Erlander and Stewart, 1990) was used to determine the traffic flow volumes between all origins and destinations.

4.1.1. OD-traffic flow calculation using the gravity model

For the calculation of OD-flows of passenger vehicles on the northern island of New Zealand, the Gravity Model was applied to the extended network graph derived in Appendix B. In particular, the Gravity Model was implemented to calculate the total flow volume on every OD-path. As intra-regional traffic flows that travel from a node back to the identical node were neglected, in total 55,932 (237 × 236) OD-paths are considered.

Each of the 237 OD-nodes represents a region on the North Island, which was aggregated based on smaller administratively defined geographical areas as explained in Appendix B. For every of these Statistical Area 1 (SA1) entities, the New Zealand Census (Stats N.Z., 2020) provides a well-founded data basis to describe the OD-regions. Every OD-region is described by several characteristics (cf. Eq. (14)). All information of those SA1 entities that were aggregated to one OD-region was also aggregated, in order to obtain a single value that describes a specific characteristic of an entire OD-region.

In particular, for every SA1 entity, the total number of usual residents and the number of households were obtained from 2013 Census (Stats N.Z. Geographic Data Service, 2017). These values of all SA1 entities that are part of an OD-region were summed to represent the corresponding characteristic of the origin and destination zone. Since these two characteristics seem to show a strong correlation, the average number of people per household and the number of households were chosen as characteristics of each SA1 entity. Additionally, the median income was used as further attribute. The spatial separation of the two regions under consideration is modelled as the total driving distance from origin to destination as calculated in Appendix B.

Since the region-specific characteristics and the distance have different units of measurement on different scales (e.g. income measured in \$, distance measured in km), all input values were normalized in order to adapt them to a common scale while preserving the differences. The chosen region characteristics imply that the more people live in a region and the higher their income is, the more traffic flow is starting from this region and the more traffic this region attracts. The further one has to drive between the two regions, the less traffic will be observed between them. The actual influence of these characteristics on the flow volume between two regions represented by their calibration parameters is to be determined in the following.

The corresponding Gravity Model for the flow volume from origin i to destination j can be formulated as follows:

$$T_q = T_{(i,j)} = k \cdot \frac{V_1^{\alpha} \cdot V_2^{\beta} \cdot V_3^{\gamma} \cdot W_1^{\delta} \cdot W_2^{\epsilon} \cdot W_3^{\eta}}{C_{i,j}^{\theta}} \tag{14}$$

Where

V_1	Number of households of the origin region i
V_2	Average number of people per household of the origin region i
V_3	Median income of the origin region i
W_1	Number of households of the destination region j
W_2	Average number of people per household of the destination region j
W_3	Median income of the destination region j
$C_{i,j}$	Distance between the two regions i and j

For a reasonable determination of the calibration parameters α, β, γ, δ, ϵ, η and θ, as well as the scaling constant k, traffic count data serves as a data basis. It is important to notice that the actual values of the weights and the interpretation of the effect of their corresponding region characteristics are not particularly relevant for the application made here. In contrast to research on spatial interactions, not the impact of single region characteristics on interactions are analysed here, but the total flow generated between regions.

In New Zealand, highway traffic volume data is collected by the state highway data collection system which comprises approximately 1500 monitoring sites (New Zealand Transport Agency, 2019b). Thus, for a significantly high number of positions on the highway network, exact values of the average daily traffic are known. In addition, for each counting site, exact knowledge on the share of light passenger vehicles is available.

This high and accurate availability of counting data and the fact that travelled paths are assumed to be known in advance opens up the possibility to implement a new perspective on the determination of the calibration parameters. Since there is a lack of known interaction data at this point, existing methods based on a known interaction matrix are not applicable for calibrating the model. Furthermore, the interest is not in the influence of individual characteristics on the flow volume, but in the amount of the volume in general. Consequently, instead of estimating and validating the calibration parameters with the help of a known interaction matrix, here, the calibration parameters were calculated in a way that the obtained total traffic flows on each road segment are as close as possible to the corresponding traffic counts.

This equals an unconstrained optimization of the following objective:

$$\min \sum_{(h,k)\in A} \left| \sum_{q\in Q} T_q \cdot a^q_{(h,k)} - T \cdot C_{(h,k)} \right| \tag{15}$$

Where

A	Set of arcs with available traffic count, $(h,k) \in A$
Q	Set of paths, $q \in Q$
T_q	Calculated flow volume on path q
$TC_{(h,k)}$	Traffic count on arc (h,k)
N	Set of network nodes with $(h,k) \in N$
$a^q_{(h,k)}$	1 if arc (h,k) is used on path q, 0 otherwise

In other words, for every OD-path $q \in Q$ it is determined which arcs on the highway network graph are used. For all arcs, all OD-flow volumes that travel over this arc are summed and the total error to the actually counted traffic on all arcs or road segments is to be minimized. This results in a matrix that resembles OD-flows which are suitable to produce the observed traffic counts.

Only traffic counting sites along highway roads that are unambiguously represented by one and only one arc of the highway network graph are considered in the calculation of the calibration parameters.

If a road segment is represented by more than one arc in the highway network graph or there exists a redundant (or partly redundant) arc on the extended graph, the corresponding counting site is excluded from the determination of the calibration parameters. In total, 196 directed (i.e. 98 undirected) arcs could be identified that fulfil the requirement and possess a counting site. Since most traffic counting sites consider both directions, it is assumed that in this case half of the counted traffic runs in each direction. Furthermore, the share of heavy vehicles was excluded from each count. In fact, latest traffic count data is from the year 2018. To display traffic data for the year 2020 and for later time periods, an individual simple linear regression was used for every counting site to predict traffic counts based on the trend of the past years. This process is further explained in more detail in the next Section 4.1.2. The obtained expected counting data was assigned to the corresponding arcs of the highway network graph.

The optimization of the problem at hand was implemented in Matlab with the help of 'GlobalSearch' that can be used to find the global optimum of the underlying function. 'GlobalSearch' runs local solvers several times and determines the best solution out of a set of local optima. Thus, it does not guarantee to find the actual global optimum, but at least a good local optimum. In order to increase the probability to find a solution which is close to the optimal solution, the algorithm was run five times and the best out of these results was chosen to determine the calibration parameters.

The values obtained for the required calibration parameters were inserted in the calculation of $T_{i,j}$ in Eq. (15) to determine the flow volumes between any pair of OD-nodes with origin i and destination j. The most relevant and influential factor is the distance between origin and destination region (θ). The larger the distance the less traffic will take place between regions. Besides the distance, especially a high number of households in the destination region (weighted with δ) seems to have a positive influence on the flow volume obtained. The number of people per household (weighted with β and ϵ) is of minor importance for the generation and attraction of traffic volume. Thus, it follows that high traffic volumes will occur majorly between regions that lie close to each other and have a highly populated destination region. A comparison to two simpler approaches to calculate the OD traffic flow volumes in relation to the traffic count data is conducted in Appendix C.

Indeed, short paths often consist of only a few arcs in the network. Therefore, they are often not included in the calculation of the calibration parameters when they do not use any arc for which a traffic count value is available. Thus, very short distant paths are underrepresented in relation to longer paths in the determination of the calibration parameters. This underrepresentation of short paths could lead to the calculated parameters being unsuitable for determining traffic volumes on short paths. When applying the parameters to calculate flow volumes on very short paths, it seems that the obtained flow volumes are systematically overestimated. A further consideration of this matter or comparisons with flow data from other sources are suggested to make a more reliable statement on the relation between distance and traffic volume on very short paths. Indeed, only long travel paths that exceed the EV range are of interest in this application. Thus, an overestimation of traffic volumes on short paths can be disregarded, since these paths did not intervene in the calculation of the parameters and are not considered in the optimization model.

4.1.2. Future trends of traffic flows

Latest statistics on traffic counts date back to 2018 cf. New Zealand Transport Agency, 2019b. In order to be able to draw conclusions about today's infrastructure requirements, it is important to use up-to-date values. Especially for the consideration of future periods, well-founded forecasts for the development of traffic volumes must be established. To provide such data, previous developments of past years are projected to subsequent years.

As a data basis, traffic count data for the relevant 98 counting sites from the years 2014 to 2018 was used. For every of the 98 traffic monitoring site, an individual linear regression model was established based on the site's traffic counts of the past five years (2014–2018). With a linear regression a coefficient of determination of $R^2 = 0.80$ is yielded on average. With the help of the regression function, for every monitoring site the expected traffic counts for the years 2020, 2025, and 2030 were forecasted. The remaining input data for the region characteristics are assumed to stay relatively constant and thus all normalized data inputs remain unchanged.

Equivalently to the process explained in the previous section, the optimization procedure was applied two more times to the expected count data of 2025 and 2030. Thus, the calibration parameters of the Gravity Models for the years 2025 and 2030 were optimized with the help of 'GlobalSearch' based on the calculated expected traffic counts.

Afterwards, the expected OD-flows $T_{i,j}$ of every OD-pair i, j in all three time periods were calculated with the calibration parameters obtained in each case. Finally, as a result, expected OD-flow volumes of the years 2020, 2025, and 2030 were obtained for each OD-pair.

All in all, an average increase of the traffic volume on all OD-paths of 35.53% from 2020 to 2025 can be observed. For 96.20% of all OD-flows, the volume increases while only 3.80% of flows show decreasing traffic. On average, the total traffic volume further increases by 24.12% from 2025 to 2030. Here, 81.86% of OD-flows rise.

An illustration of the yearly total aggregated traffic volume of paths that exceed 100 km distance and originate from the same region is given in Appendix C. Additionally, Fig. 6 also depicts the sum of traffic volumes of all paths longer than 100 km that terminate in the same region for every OD-region in each year under consideration. Most traffic flows longer than 100 km start in regions that are highly populated and are located in close to medium proximity to other even higher populated regions. This relation is already evident in the values of the calculated calibration parameters stated in Section 4.1.1. The population density in the destination region has a larger effect on traffic generation than the population in the origin region (cf. α and δ in Section 4.1.1). Therefore, the most densely populated areas such as Auckland, Tauranga, Hamilton, Napier, and Wellington are those regions where most traffic terminates. Indeed, since only flow volumes on paths longer than 100 km are investigated, intra-city trips within the largest cities such as Auckland are not depicted. Especially in more densely populated areas where highways are already highly trafficked today, traffic volumes will further increase in later years, as the linear regression of traffic counts suggests.

4.2. Electric vehicle flow volume and OD-path reduction

The calculated flow volumes represent the traffic of all light vehicles on the considered OD-paths, irrelevant whether conventional or EV are travelling. The development of EV traffic volume for future years on New Zealand's highways is taken from the upper-case scenario of future EV uptakes as proposed by the New Zealand Centre of Advanced Engineering (CAENZ, 2010). The upper-case scenario assumes a rapid increase in the number of EV in the market, especially in the early phase of EV introduction. The absolute number of light passenger vehicles registered in New Zealand is assumed to linearly increase from 2.584 million in 2008 to 3.2 million in 2040. This leads to a total number of light passenger vehicles of 2,815,000 in 2020, of 2,911,250 in 2025 and of 3,007,500 in 2030. Following the upper-case scenario, a total number of 300,000 EV in the fleet are assumed for 2020, while for 2025 this number is expected to increase to 700,000 and for 2030 to 1,200,000 cf. CAENZ, 2010, p.31 ff.. It is further supposed that EV are used in the same manner as conventional vehicles. All in all, this leads to a fraction of 11% of the flow volume on the OD-paths to be EV in 2020, to a fraction of 24% in 2025, and 40% in 2030.

In order to reduce the absolute number of relevant paths, the following assumptions are made. First, every OD-path shorter than

100 km is ignored since the vehicle range is assumed to amount to 200 km and roundtrips of a path that measures up to 100 km one-way is possible without charging and can therefore be neglected in the allocation of charging stations. All in all, 91% of the total number of paths exceed 100 km distance. Furthermore, only paths that have a total flow volume of at least 300 EV per year in at least one of the assumed time periods are considered. This reduces the total number of relevant OD-paths to 5860. These account for only 11.5% of the number of paths that exceed 100 km distance, but cover 75.9% of their total EV-flow volume in 2020, 74.2% of the volume in 2025 and still 73.6% of the total EV traffic volume estimated for 2030.

4.3. Generation of directional candidate sets

For the application of the IO-MP-C-AC-PC FRLM on New Zealand North Island with the data inputs generated in the previous sections, a major input data set is generated. Namely, for every of the remaining 5860 OD-pairs under consideration, sets of candidate nodes for FCS have to be calculated. For every path q, for every arc on the path q, complete knowledge of the set of nodes suitable to refuel the arc is required as input for the ACPC model.

Since the location of an FCS is dependent on and only valid for a specific vehicle range, the assumed vehicle range must be defined in advance. We assume a range of 200 km for the following calculation, which is below current ranges of many new EV, but is already higher than assumptions of others e.g. Jochem et al., 2019. In addition, this conservative assumption results in a dense distribution of charging infrastructure and may help to compensate for range anxiety issues (Knutsen and Willen, 2013). Range anxiety is still an issue in New Zealand and a dense distribution of charging infrastructure that allows for the use of EV with shorter driving ranges is expected to increase the level of acceptance and actual use (Broadbent et al., 2021). In New Zealand, people tend to buy used cars and usually drive them for many years (Hasan et al., 2021), which means that we have to assume shorter driving ranges in average. In addition, many households own two (or more cars) and are more likely to buy one cheaper EV with a lower driving range, keeping the fuel car for long distance trips (Magnusson, 2021).

4.4. Capacity of individual fast charging station units

Current FCS or Level 3 charging facilities provide charging power between 50 and 300 kW at direct current (DC) (Nicholas and Hall, 2018; Hall and Lutsey, 2017). The concrete charging power depends on several circumstances and is often limited by the battery or the car. In the following a constant charging rate of 100 kW is assumed. Each charging unit can serve one EV at a time, while every charging station can contain several charging units.

The analysis of the power consumption of the EV fleet that is (as of January 2020) registered in New Zealand (New Zealand Transport Agency, 2019a) and is further investigated in Section 4.3, yields a volume-weighted average consumption of 0.169 kWh/km. This is in line with values that can be found in literature cf. Schroeder and Traber, 2012; Madina et al., 2016; Markkula et al., 2013. The identified EV efficiency for New Zealand is based on manufacturer's information which is usually kept optimistic and relies on ideal circumstances. In reality, energy consumption of vehicles depends on multiple factors such as road condition, driving behaviour, temperature or the use of heating or air-conditioning (De Cauwer et al., 2015). In addition, highway travelling as considered here has been found to be less efficient than intra-city trips (Madina et al., 2016). Therefore, a standard efficiency of 0.2 kWh/km is assumed to best describe the vehicle fleet and travelling conditions on New Zealand's highways. Consequently, each FCS can provide an overall mileage of 500 km per hour, or serve 2.5 EV per hour if each charges 200 km range at the maximum. In reality, this will hardly be the case, but serves as a reasonable lower bound for the capacity of each charging unit in terms of the number of EV that can be served in a given time frame. Furthermore, a service time of 14 h (e.g. from 6 a.m. to 8 p.m.) is supposed as an estimation to determine the daily capacity for each charging station unit. This resembles imputed driver preferences where drivers are unlikely to travel during the night. Instead, they have a need for recharging their vehicle especially in morning or evening hours in most cases. Thus, each charging station unit is assumed to be capable to serve up to 35 EV per day. In the remainder of this work, this is referred to as the capacity of the charging station unit.

4.5. Installation costs of charging infrastructure

In order to operate a system of charging stations economically profitable, stations have to be allocated in a way that high utilization rates are achieved. Additionally, the economics of FCS are largely determined by the initial installation investment. The installation costs for individual locations are highly affected by local conditions and subject to significant uncertainties. To provide sufficient charging infrastructure along highway corridors, charging stations might have to be installed in rural areas where existing electrical infrastructure is sparse and requires reinforcements, or in urban environments where space is limited and construction work is expensive. The distance to the grid that has to be covered by newly installed electricity lines as well as the type of the line and its corridor primarily determine grid connection costs. Even though these costs might fluctuate we try to estimate the total investments for each potential FCS location by identifying all relevant cost factors. We paid high attention to the site-specific investments required for the grid connection and additional electrical services per location. Although there is some uncertainty in these estimates, the relative difference between these locations could remain fairly stable as installation costs change. Consequently, most suitable location remain most attractive (but at higher costs).

We assume that each FCS is capable to include up to 25 charging units (which requires a 2.5 MW substation for guaranteeing at least 100 kW for each charging unit in parallel). Besides the grid connection, each charging station requires additional on-site equipment and work. In this research approach, all station components besides the number of charging units are assumed to be identically sized for all FCS irrelevant of the number of charging units built at this location.

For our analysis, we considered a comprehensive approach of evaluating grid connection costs of FCS in New Zealand. The full approach is explained in the Appendix D. In short, the potential locations for FCS vary substantially in their proximity to the electrical grid and in the population density of the environment that needs to be crossed by newly installed electricity lines. This proximity of a site to existing electrical infrastructure has been found in former installation projects to be the largest differentiating factor between locations (The E.V. Project, 2015). Additionally, the type of the electricity line that has to be installed significantly impacts the connection costs. Therefore, we propose to choose for each potential FCS the most cost efficient grid connection among a set of strongly simplified alternatives. Electricity lines are assumed to be installed in linear distance. In case an urban region is traversed, we assume that more cost intensive underground cables have to be installed, while in case a rural region is crossed, overhead lines are built. Among all realistic grid connection options, the most cost efficient connection option is chosen for each potential FCS location.

All in all, the following main cost components are decisive for New Zealand (cf. Table 1). All cost data provided in this paper are given in $\$US_{2020}$ if not stated differently. A basic distinction is made between location-dependent costs for opening the station (i.e. fixed costs) and size-dependent costs incurred for each additional charging unit on existing FCS (i.e. variable costs).

Investments are compared based on their net present value. For our calculations, we took an interest rate of $i = 4.5\%$, which is an average of

Table 1
Fixed and variable costs of components for FCS installation.

	Component	Costs
Location-dependent costs per station		
	Underground cable (11 kV)	141,700 $/km[a 1]
	Overhead line (11 kV)	35,970 $/km[a 1]
	Transformer (11 kV to 400 V)	25,070 $ (for 2.5 MW capacity)[a 1]
	Additional equipment and work	70,000 $[b]
Size-dependent costs per charging unit		
	Charging unit hardware (for a 100 kW unit)	65,800 $[b]
	Additional equipment and work	17,000 $[b]

[a] Estimate based on CONSENTEC (2006).
[b] Estimate based on Francfort et al. (2017), p.17.
[1] Exchange Rate: 1 € = 1.09 $.

values given in Ltd. (2019), W.E.L. Group Ltd. (2019), Unison (2019), Powerco Ltd. (2018) and assumed a desired service level of $S = 0.8$ i.e. 80% of the EV traffic volume on the OD-paths under consideration must be made travelable in each period by placing FCS. Discounting is applied because interest payments make it more valuable to incur expenditures at that time when they are necessary.

5. Results

The problem instance was solved with the help of IBM ILOG CPLEX Optimization Studio (CPLEX) following the solution procedure described in Section 3.3. For every iteration, the solver was terminated as soon as a feasible solution with a relative optimality gap of 0.5% was found.

In this section, the obtained results of the application of the IO-MP-C-AC-PC Model on northern New Zealand are described and analysed. First, the obtained locations and sizes of the FCS to be installed are investigated. Furthermore, details of the resulting necessary investments are presented. Afterwards, a closer look is taken on the coverage of traffic flow as well as on the locations of well-covered highway segments across the island.

5.1. Location and size of fast charging stations

Firstly, the optimal choice of nodes for the placement of FCS and the number of charging units to be installed at each location over the three considered time periods are investigated. The optimization results are depicted in Fig. 1. Nodes coloured in blue represent locations where a charging station needs to be installed. The size of the bubble is proportional to the number of charging units to be built per site. Light-blue coloured nodes represent charging units that are to be installed at the beginning of the time horizon in 2020. Medium-blue nodes indicate units required in 2025 while dark-blue nodes depict charging units that will be necessary in 2030. Several partly overlapping bubbles of different size at a single location mean that a charging station with a set of charging units is installed in a preceding period and further charging units are added in later periods.

All in all, in 2020, 18 FCS with 114 charging units are installed. In 2025, additional seven stations and 165 charging units are added. Finally, in 2030, eleven new FCS and 229 new charging units are installed. The charging stations are placed in and near the biggest cities (Auckland, Hamilton, Tauranga City, Napier City, Palmerston North City, and Wellington including its surrounding regions) as well as other populated areas and smaller cities in the central north and south of the island. It is clearly evident that the areas where stations are built are congruent with the regions where most traffic starts and ends. The first FCS installed in 2020 are majorly placed in or near the most densely populated areas. In later years, existing stations are enlarged and additional stations are opened in the more distant surroundings of large cities. In 2030, new stations are added in the Midwest, Mideast, and central regions of the island for example, where no FCS were available beforehand. Moreover, FCS are located along those highway corridors with the highest traffic flow volumes. In addition, especially at those highway segments that are highly trafficked the station size is large. In conclusion, the locations and sizes of FCS are consistent with the locations where most people live and population density is high as well as where most traffic takes place.

5.2. Necessary investments for installing the minimum number of fast charging stations

In order to start operating a charging station at a certain node, it is necessary to connect this location to the electricity grid. For each potential FCS, the necessary expenses to construct the grid connection had been identified in advance (cf. Section 4 and Appendix D). While FCS specific grid connection costs of the potential sites vary from approximately 9575 $ to approximately 2.68 million $ with an average value of approx. 695,000 $, the maximum connection cost value of the chosen sites amounts to 487,000 $ only. On average these connection costs amount to 169,000 $ per FCS.

A further analysis of the relationship between region and connection costs shows that grid connection costs are lower in areas where population density is high. This is especially the case in and near the largest cities Auckland, Hamilton, Tauranga, Wellington, Palmerston, and Napier City. The underlying reason is the higher density of (i.e. shorter distances to) substations in (close to) densely populated areas. Simultaneously, traffic volumes are higher in those areas.

The costs of the grid connection are inevitably linked to the length of the power lines to be laid. The majority of electricity lines required to open up all 36 FCS in 2030 is relatively short. They range from only 68 m to 11.5 km length with an average value of 2.7 km only. Compared to the line lengths of all potential FCS-nodes, short connections were chosen disproportionately often. In total, 96.82 km of newly established electricity lines are required out of which 74.6% are installed as underground cables in urban environments. This amounts to costs of approximately 10.2 million $ for the installation of all required underground cables and 884,584 $ for the remaining overhead lines to be built.

All in all, the application of the IO-MP-C-AC-PC model yields investments of 13,788,810 $ in the year 2020. For the following years 15,440,262 $ (which equals a net present value (NPV) of 12,390,810 $) and 22,337,288 $ (which equals a NPV of 14,382,980 $) are to be spend additionally in the years 2025 and 2030, respectively. This sums up to a current NPV of total investments of 40,562,600 $ to realize the proposed allocation and sizing of charging infrastructure (i.e. about 0.001% of current GDP).

In 2020, fixed opening costs accounted for 31.5% of the total expenses while this share decreases to 11.5% in 2025 and slightly increases to 15.1% in 2030. The relationship between the number of FCS and charging units and the required investments shows that the

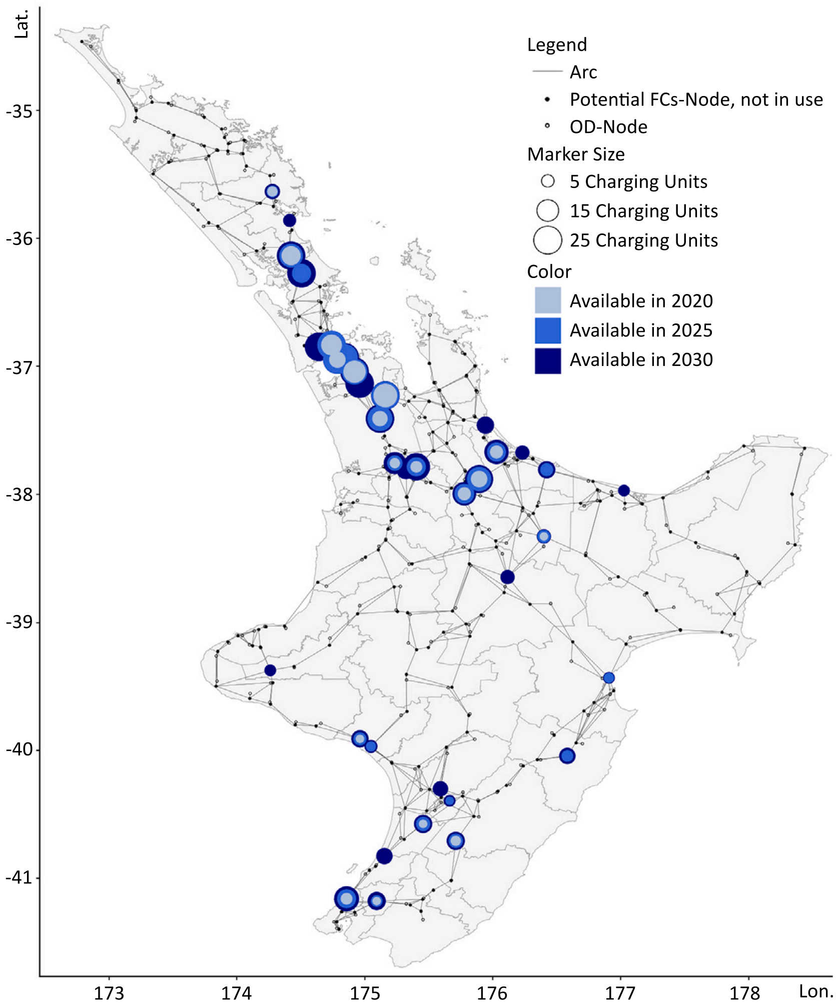

Fig. 1. Geospatial location and sizes of installed FCS over time. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

variable costs increase proportionally with an increasing number of newly installed charging units over time. In 2020, a large proportion of total expenses is made for installing and opening FCS, while in later years the amount spent on adding additional charging units increases. This is reasonable in terms of cost minimization. Since fixed costs of each location are high relative to the costs for an individual charging unit, adding further charging units to already opened stations (if this is possible from a traffic coverage perspective) is more cost-efficient than opening a new FCS.

5.3. Economic aspects

Compared to expected revenues these costs seem to be manageable — even in a conservative scenario: Assuming at least 10 customers a day per charging unit, the necessary payments for covering these fixed costs becomes 2.7 $ per customer (i.e. total investments of 40,562,600 $ divided by 508 charging units and number of operating days during the expected operating lifetime of the charging units of 8 years). A visualization of the costs for the grid connection of all potential FCS, the relationship between fixed and variable costs and the number of FCS as well as number of charging units over the course of the planning horizon can be found in Appendix E. This additional cost of 2.7 $ for the end-customer per charging (which amounts in average to 30 kWh) is reasonable as she or he may expect similar costs compared to her or his current car, which amounts to about 16 $ per 150 km[1] or 5.7 $ per 150 km what she or he is paying at home for charging.[2] Most FCS operators might have lower electricity tariffs than residentials and might charge higher additional costs than 2.7 $ per charge. This makes these FCS rather profitable – especially at locations of few alternatives (cf. profitability calculations for German FCS by Hecht et al. (2022)).

5.4. Covered electric vehicle traffic flow volume

As a condition for the deployment of charging stations, the optimization model incorporates that at least 80% of the total EV flow volume on the considered routes have to be adequately covered by charging infrastructure in every time period. However, this is a condition for the island as a whole, and local differences can be significant. In order to provide insights into the total number of EV that are present on each highway segment of New Zealand North Island, further analysis

[1] 150 km at current fuel prices of 1.76 $ per liter (https://www.globalpetrolprices.com/New-Zealand/gasoline_prices/) by a car using 6 liters per 100 km.

[2] 150 km at current electricity price for residentials of about 0.2 $ per kWh (https://www.canstarblue.co.nz/energy/electricity-providers/average-electricity-costs-per-kwh/) by an EV using 20 kWh per 100 km.

is conducted on this topic. Moreover, it is further investigated how many of those EV that want to travel an arc are actually able to pass it successfully. For this issue, the Share of Electric Vehicle-Coverage (SoEVC) is defined for each arc as the number of EV that are covered and can travel the arc successfully relative to the total number of EV that actually want to travel the arc. In other words, for the SoEVC for arc $a_{j,k}$ it holds:

$$SoEVC_{j,k} = \frac{\sum_{q\in Q} y_q^t \cdot f_q^t \cdot m_{(j,k)q}}{\sum_{q\in Q} f_q^t \cdot m_{(j,k)q}} \quad \forall t \in T \tag{16}$$

$$where \;\; m_{(j,k)q} = \begin{cases} 1 & \text{if } a_{j,k} \in q \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

The absolute total number of EV on each arc of the highway network can be seen in Fig. 2(a), i.e. on the purple-coloured left-hand side of the illustration, for the year 2020, 2025, and 2030 respectively. Furthermore, Fig. 2(b) (on the green-coloured right-hand side) presents the results for the SoEVC. All highway legs are illustrated as undirected arcs. The reader should note that the total number of EV presented in Fig. 2(a) (1) - (3) on each arc corresponds to the number of EV travelling in only one direction; the corresponding other direction is travelled by an identical number of EV.

It can be deducted from Fig. 2(a) that the regions where most EV drive correspond to the regions where most FCS are installed. In 2020, a major EV corridor emerges that runs from southern Northland, via Auckland in the direction of Hamilton and Tauranga. Although five FCS are opened in the southern part of the island, only few EV are present here. The addition of Fig. 2(b) (1) indicates that although the absolute total number of EV that use the roads in the southern part of the island is low, the majority of the highway legs are actually well covered and most of those EV seeking to travel along these arcs can do so. The same is true for rural regions in close proximity to the geographical triangle spanned by Auckland, Hamilton, and Tauranga. Indeed, only a small fraction (and a low absolute number) of EV is enabled to pass through the central region of the island, which spans from the Midwest to the Middle East. This indicates that very long tours running from the northern to the southern part (or vice versa) of New Zealand North Island can hardly be travelled with an EV with the proposed distribution of charging infrastructure.

In later periods, the number of EV on the highways significantly increases in the highly populated regions in the north as well as in the south of the island. Still, only few EV are travelling along those arcs which pass through the central region of the island. Nevertheless, the SoEVC increases in this region for a selected set of highway arcs.

Furthermore, the distribution of the SoEVC on the different highway segments shown in Fig. 2(b) (1)–(3) is equivalent to the distribution of the share of EV on the roads for long paths of 100 km and more even though projected to a different scale. Here, it is assumed that any trip of an EV that is not sufficiently covered by charging infrastructure, instead will be carried out by a conventional car. As it was found earlier, for any OD-path, the total number of EV that seek to complete the OD-trip is a fraction of the total traffic volume on this path. Therefore, the proportion of EV that can drive in relation to those that want to drive is identically distributed to the proportion of EV that can drive in relation to all cars on a road. The only difference between both measures is the scale.

Considering the obtained value of y_q^t, which is the fraction of covered flow volume from total EV-flow volume of every relevant path q in a specified time period t, significant differences can be identified between paths of different length. Y_{It}^{-} is defined as the average y-value obtained for the distance interval I for time period t, i.e. as $Y_{It}^{-} = \frac{\Sigma_{q\in I} y_q^t f_q^t}{\Sigma_{q\in I} f_q^t}$ for each $t \in T$ and length interval I. Short paths of up to 200 km distance are well covered in all three periods. For longer paths, the share of covered flow volume significantly decreases, especially in 2025 and 2030, and reaches nearly zero coverage for paths of 450 km and more. This result is straightforward when taking into account the absolute total EV-flow volume of relevant paths in each distance interval. Since more paths are under consideration for short distances and these have significantly higher EV traffic flow volumes compared to longer paths, covering short and highly trafficked paths first, will lead to a higher service level than covering less frequently used paths. As a consequence, the proposed allocation of FCS on the one hand covers EV traffic on short and medium distant paths (as they appear in the northern part of the island between Auckland, Hamilton, and Tauranga or in the southern region around Wellington and Palmerston North City for example) well on average. But on the other hand, it does not facilitate very long trips (which run from north to south for example).

In addition to considering the length of the paths that can be travelled by EV for individual users, it also makes sense from a global perspective to consider how many vehicle kilometres in total can be covered by EV by the proposed infrastructure placement. In 2020, 8.2% of all kilometres travelled are driven by an EV. This share significantly increases to 17.1% in 2025 and even further to 28.0% in 2030. Although long distances are often not or only marginally covered, a considerable part of all driven kilometres are covered by EV. This is caused by the circumstance that short distant paths are mostly often frequented than long paths and at the same time well covered by FCS. In addition, paths with a distance of less than 100 km have been neglected in the determination of charging infrastructure since under the assumption of an EV range of 200 km they can be travelled without intermediate recharging anyway. Therefore, the share of kilometres driven by an EV relative to all kilometres driven can be assumed to be significantly higher.

5.5. *Sensitivity to input factors*

In this section, we examine to which extent the results of the optimization model react to a change in values for a number of influencing factors. First, the influence of the choice of the pursued service level S is taken into account. Furthermore, a more detailed analysis is conducted on the effect of an improvement in the vehicle range on the required number and size of FCS. The influence of the limit of the FCS size x^{Max} is taken into consideration and lastly, lower EV uptake scenarios are investigated.

5.5.1. *Influence of the service level S*

Until now, a required coverage of 80% of the EV flow volume travelling across New Zealand North Island in every period under consideration is assumed. Enabling an higher share of EV users to complete their trips successfully can be desirable to further enhance EV's uptake. Fig. 3 shows the total number of FCS and charging units to be installed over the time horizon until 2030 in order to meet service levels of 85%, 90%, 95% and 100%. All in all, to fully enable all EV-traffic flows, 61 FCS are to be installed in 2020 (compared to 18 for 80% service level) with a totality of 167 charging units (compared to 114 units for $S = 80\%$). Over the course of the years, the number of FCS increases to 71 (compared to 36 for $S = 80\%$) with 771 units in total (compared to 508 units for $S = 80\%$). While the number of charging units required in the same period increases approximately linearly with S, the number of FCS locations to be opened increases exponentially with an increase in the service level (cf. Fig. 3). The last 5% of flow volume to provide full coverage (from 95% to 100% coverage) require 97% more FCS in 2020, 66% in 2025 and 48% in 2030 compared to a level of 95% covered flows. Especially in 2020, the high number of 61 FCS to be initially installed in this year result in high investments. Total expenditures for FCS in 2020 for 100% flow coverage amount to 51.15 million $, which is approximately 2.4 times the expenditures for 95% coverage is pursued. Starting from any other service level and in any other period, a 5% improvement in the service level increases total expenses by a share of 2.5%–19.9%, approximately linear with S.

For a 100% coverage of flows, 10 of the FCS installed in 2020 are opened with only one charging unit each and will not further be

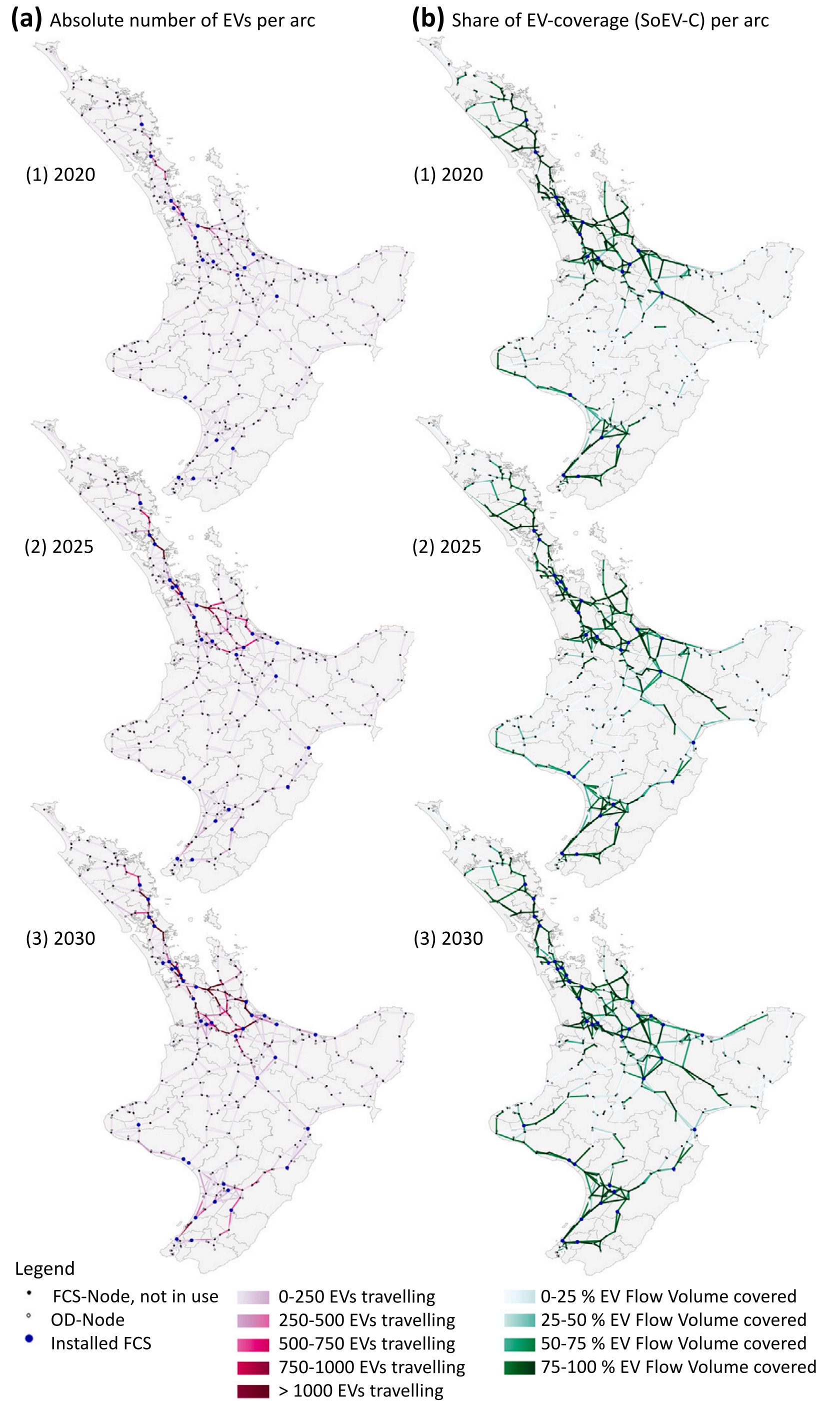

Fig. 2. Illustration of the total number of EV travelling along the arcs (a) and the share of EV covered per arc (b). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

enlarged in any subsequent period. These stations are necessary to capture traffic flows originating from (or ending in) remote regions or very long journeys crossing the island from north to south (or vice versa). Since only few EV users travel these paths, a minimal quantity of charging units is sufficient to capture their charging demand. The circumstance that there is the need to open these locations regardless of their size leads to substantial expenditures of fixed costs. Moreover, a 100% service level requires a much denser distribution of FCS across the island, especially in central regions from the middle west to the middle to north east. The average station size in each period stays relatively constant for service levels between 80% and 95%, with an approximate average number of five to six charging units in 2020, ten to eleven units in 2025 and 14 units in 2030. For a service level of 100%, FCS are on average significantly smaller with only 2.7 units in 2020, 6.6 units in 2025 and 10.9 units in 2030.

In summary, an increase of the service level of up to 95% leads to an approximately linear increase in the number of FCS and charging units to be offered to users in each period. The same applies to the costs for their installation. In total, a service level of 80% requires investments of 40,562,600 $ while a service level of 85% (90%, 95%) results in total investments of 44,921,030 $ (50,407,040 $, 57,696,210 $). For a service level of 100% investments of 89,287,040 $ are required. Indeed, significant additional financial efforts and a high number of additional FCS are needed to ensure that even particularly remote regions and

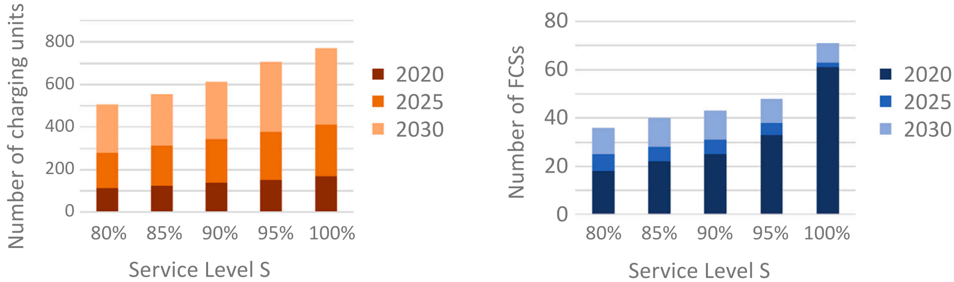

Fig. 3. Number of charging units and FCS to be installed for different service levels S.

low-traffic routes are fully supplied with infrastructure to enable a 100% service level.

5.5.2. Influence of the electric vehicle range

Furthermore, the distance an EV can travel without recharging significantly affects the number of FCS and charging units required to meet the service level under consideration. On the one hand, a higher vehicle range leads to less frequent charging. On the other hand, an EV with increased range requires a longer charging duration to add the full range to its battery. Thus, less EV can be served by a single charging unit per day. For an EV range of 200 km, each charging unit is assumed to be capable to serve up to 35 EV per day. Electricity consumption of the EV and supply of the charging unit as well as the relevant number of hours per day are assumed to remain unchanged. An increase of the range to 250 km thus leads to a reduction of the capacity of each charging unit to 28 EV per day and a further increase to 300 km range reduces the capacity to 23 EV per day.

As a result of an increased vehicle range, a decrease in the number of required FCS and charging units can be observed. The number of units to be installed diminishes to a smaller extent than the number of station locations to be opened. A plus of 25% (50%) additional range leads to a reduction of the total number of station locations by approximately 40% (65%) in each time period, but only a decrease of the total number of charging units by approximately 30% (53%). This is due to the fact that a single charging unit can serve less EV the higher their range is and thus, the average number of charging units per station increases with an increasing range. While a station offers on average 6.3 units in 2020 (11.16 in 2025, 14.11 in 2030) for an assumed range of 200 km, 8.8 charging units are placed per station on average in 2020 for a range of 300 km (16.2 in 2025, 19.1 in 2030). The total NPV over all three years diminishes by only 24.5% (46.1%) when the range increases by 25% (50%). This is a consequence of the FCS locations chosen in each case. For an increased EV range, station locations relatively inexpensive to install are not required any more to serve the demand and thus, the total costs decrease under-proportionally to the number of charging stations.

5.5.3. Influence of the number of charging stations per FCS x^{Max}

In order to limit the effects of the additional electricity load on the grid, all FCS have been restricted to a maximum size of 25 charging units. The influence of this maximum number of units x^{Max} was tested for values ranging from 10 to 50 in steps of 5 units.

The analysis of the effects of the station size limit reveals that the total NPV of the investments until 2030 is relatively insensitive to x^{Max} for station sizes of 15 units and more. Only in case of a maximum size of 10 units costs rise tangibly. While the total number of charging units to be built in each period only changes marginally, the charging units need to be spread over a higher number of FCS if the allowed FCS size is small. In 2020, the required number of FCS only decreases by at most one station when x^{Max} is increased, because the EV-traffic volume requires fewer charging units than the defined maximum in most location cases. Thus, a simple addition of units is possible. The size limit becomes particularly relevant in later years when EV uptake proceeds and the question arises whether it is possible to add further charging units to an opened station or whether it is not and a new FCS has to be installed to serve the charging demand. For a limit of 35 units and more, the maximum station size is reached only at a few locations and thus excess units at a specific location can be distributed to alternative existing FCS without the need to open new stations while still serving the demand sufficiently. Therefore, the total number of FCS only changes marginally for all $x^{Max} \geq 35$. For an infrastructure provider, this means that it is possible to flexibly distribute charging units to other existing stations that currently provide only a small number of units in case the grid is insufficient to handle a desired large FCS at a specific location.

5.5.4. Influence of the level of uptake of electric vehicles

For the model application made above, an EV uptake scenario as identified by The New Zealand Centre of Advanced Engineering (CAENZ) was taken as basis for the deployment of charging facilities. The most optimistic EV uptake case was selected to resemble EV traffic flow volumes. However, the adoption of EV in New Zealand is rather slow until now and there is reason to suppose that lower EV numbers than targeted could be realized in the upcoming years. Therefore, a medium 60% EV uptake 2040,cf. CAENZ, 2010, p.34 and the lower-case scenario of EV in the passenger vehicle fleet as suggested by CAENZ (2010) were investigated to analyse the effects of a lower adoption level on the charging infrastructure to be installed. In analogy to the process for the upper case presented in Section 4.2, for the medium and lower-case scenarios the shares of EV in the fleet in the three time periods were determined. For the lower-case scenario, 5% EV are obtained for 2020, 12% for 2025 and 20% for 2030 while for the medium case scenario, only 3% of the vehicle fleet are assumed to be EV in 2020, 6% in 2025 and 10% in 2030.

Although the total number of EV in 2020 is significantly lower in the lower-case uptake scenario than in the initially assumed upper case, only slight differences can be observed in the number and choice of locations were FCS need to be installed. While the upper-case scenario requires 18 FCS to be initially installed in 2020, the medium and lower-case uptakes necessitate 16 and 15 FCS. Apart from only few exceptions, the chosen locations are equivalent for the three scenarios. Thus, nearly independently from the actual market uptake of EV in New Zealand, infrastructure providers will be in charge of installing almost the same number of charging facilities at the same locations in 2020. Only in later periods, the actual uptake of EV in New Zealand has an effect on the number of additionally installed FCS. The higher the uptake of EV will be in 2025 and 2030, the more charging locations have to be opened to serve the demand.

When considering the required total number of charging units, there is a dependence on the EV uptake level. In each period, the total number of charging units required changes equivalently to the number of EV in the fleet according to the three scenarios. For example, doubling the share of EV from 6% in the lower case to 12% in the medium case for 2025 approximately doubles the number of charging units to be installed. Thus, the number of charging units to be added to the FCS highly depends on the number of EV to be served. The same holds true for the NPV of total expenses in each period. As the number of units increases with an increasing uptake, also costs for the addition of charging facilities depend on the uptake level.

To sum this up, these findings indicate that the initial locations of FCS should be chosen almost equally regardless of how many EV are adopted by the population in New Zealand. Over the years, the uptake will need to be closely monitored in order to complement charging infrastructure locations adequately according to EV's charging demand. Contrary, the number of charging units at the opened stations is highly sensitive to the EV uptake level. The more EV are present on the roads, the more charging units will have to be added to the FCS to serve the demand.

5.6. Policy recommendations

While the research stream of optimized charging infrastructure roll-out is broad (cf. Section 2), policymakers are still searching for easy accessible computation tools for concrete roll-out plans. However, it seems advisable that public authorities should rather accompany the installation of charging infrastructure (e.g. by giving corresponding incentives) and let operators and investors decide upon the concrete location (as the influences on the profitability of different locations are so manifold) (LaMonaca and Ryan, 2022; Powell et al., 2022).

Nevertheless, for getting a first indication of how many charging stations are required, such computation tools may build a basis for further policies. Therefore, our tool might be used by policymakers of other countries and, consequently, the source code of the model might be requested by the authors. However, for applying our approach to other regions the following data is required:

- **Highway network:** A simplified representation of the highway network should be provided in a table including all nodes (highway exits, entries and intersections) as well as potential locations for FCS (e.g. rest areas or resting facilities) as well as all distances between those locations and nodes. Finally, all consequential paths have to be defined (cf. Appendix B).
- **Flow data:** Besides the network also all traffic flows for each path is required. This data might also be modelled based on count data (cf. Appendix C).
- **Electricity grid data:** For considering the grid connection costs, the distance to the closest grid infrastructure has to be defined. Appendix D gives a simplified consideration based on open data.
- **Socio-techno-economic data such as cost parameters, charging rates, charging preferences, etc.:** As indicated in Appendix D, there are many additional parameters which influence the results. Hence, a critical review of each is highly recommended.

6. Conclusions and future research

In this work, the planning of capacitated FCS for EV over a time horizon of multiple years is studied. The ACPC FRLM is extended to a multi-periodic capacitated formulation for FCS deployment. Based on the idea that the widespread installation of charging infrastructure is costly, the proposed model formulation pursues the goal to minimize investments necessary to provide sufficient charging options for EV users based on their travel patterns. Our considerations comprehend a sophisticated consideration of location-specific investment costs depending mainly on grid connection costs. From a FCS provider perspective, a cost-efficient allocation and sizing of charging facilities can influence long-term profitability of the infrastructure system. Furthermore, a wider distribution of FCS can contribute to the goal of a faster market uptake of EV in the future. In order to restrict electricity grid impacts to a manageable level, the size of each installed FCS is constrained to a maximum number of individual charging units.

The proposed model is applied to New Zealand's North Island with a focus on long distant trips travelling along the state highway network. In addition, the access distances from the origin and to the destination (and vice versa) are incorporated for the representation of user journeys. In order to represent real-world recharging needs adequately, OD-regions and the EV traffic flow volume between them are modelled based on sound data sources. Further, the costs to install a FCS are identified individually for each potential location with special consideration of the required connection to existing electricity grid resources. Here, a distinction is made between urban and rural environments to be crossed by newly installed electricity lines in order to accurately take account of the influence of spatial circumstances on required installation investments. Taking the identified input data as a basis, the IO-MP-C-AC-PC Model is solved for New Zealand North Island following the dedicated solution procedure to reduce the model complexity. The applied data processing approaches can be transferred to other networks.

Besides other findings, the results indicate that FCS should preferably be located in regions where population density is highest and most long-distant traffic starts and ends. Placing several charging units at a single FCS can contribute to reduced total investments. Additionally, a provider can keep initial investments for opening FCS low by selecting locations that can be connected to the grid at low costs. The focus of trip coverage lies on highly trafficked and comparably short to medium-distant trips. Especially in early adoption phases, primary traffic corridors are well captured. Particularly long journeys that are sparsely driven can only be covered by sufficient charging infrastructure under significant additional installation costs. Furthermore, it was found that the limitation of the station size only has an effect on the number of FCS to be installed as well as the investments to be made for small station size limits. For any station larger than 35 charging units, excess units can be located at alternative opened stations without additional expenses. Moreover, the uptake of EV in New Zealand will only slightly influence the number and location of FCS to be opened in 2020. Contrary, in later years, the level of uptake significantly affects the number of additional FCS required. Indeed, the number of charging units required to serve the demand in any year highly depends on the number of EV present in the market. Besides initial opening of FCS, infrastructure providers will need to closely monitor the uptake of EV to complement the charging facilities in adequate size and at meaningful further locations in order to serve the charging demand without building excess facilities.

Until now, the proposed model and its application take into account only the connection of FCS to the medium-voltage distribution grid. However, further research could be carried out focusing on the connection of charging facilities to multiple electricity grid levels, limiting the size of each station based on the capabilities of the grid level it is connected to. This point of view could result in significantly lower costs for infrastructure provision. Furthermore, more detailed knowledge on the distribution of traffic flow volumes over the course of the day are necessary to investigate user preferences on charging at FCS. The actual daily traffic might be concentrated to only a few hours. This might result in waiting times at the charging facilities due to demands that exceed the station capacities. Future scientific efforts could address this issue by incorporating stochastic charging times and queuing models in order to be able to estimate the extent of waiting times in a realistic traffic distribution over the course of a day. Moreover, a maximum waiting time might be considered to serve as a constraint to be mandatorily fulfilled in the optimization procedure. This could contribute to a more widespread acceptance and use of EV in New Zealand and elsewhere.

CRediT authorship contribution statement

Regina Rabl: Data curation, Formal analysis, Methodology, Visualization, Writing – original draft. **Melanie Reuter-Oppermann:**

Conceptualization, Methodology, Project administration, Supervision, Validation, Writing – review & editing. **Patrick E.P. Jochem:** Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Patrick Jochem reports financial support, administrative support, and article publishing charges were provided by German Aerospace Center. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Detailed outline of the algorithm to determine directional CS

The detailed outline of the applied algorithm that determines the directional CS of each arc for each path can be found in the following pseudo code:

Algorithm 1: Generation of directional candidate sets

```
Initialize: rowindex i = 1, Drivendistance = 0,
 CurrentPath = 'O_1 − D_1'
while i ≤ Tablelength do
    if Path_i = CurrentPath then
        Drivendistance = Drivendistance + Distance_i
        if Drivendistance ≤ EV − Range then
            Pass
        else
            reverse counter = i
            helpdistance = Distance_i
            while helpdistance ≤ EV − Range do
                if Direction_i = 1 then
                    Add Arcstart_reversecounter to CSDirection1_i
                    reverse counter - 1
                    helpdistance = helpdistance + Distance_reversecounter
                else
                    if Direction_reversecounter = 2 then
                        Add Arcstart_reversecounter to CSDirection2_i
                        reverse counter - 1
                        helpdistance = helpdistance +
                          Distance_reversecounter
                    else
                        Add Arcstart_reversecounter to CSDirection1_i
                        reverse counter - 1
                        helpdistance = helpdistance +
                          Distance_reversecounter
        i + 1
    else
        Update CurrentPath; Drivendistance = 0
```

Appendix B. How the New Zealand's highway road network is generated

All potential locations for FCS within the considered highway network are selected in a way such that they are available as a charging option to EV users along their journeys. Considering the network of highways and additional large roads that connect smaller towns and villages to highways was chosen to represent the road network of New Zealand North Island. Road intersections, highway driveways and exits (in the following referred to as junctions) are chosen as potential FCS sites to provide a high level of availability. Any journey that uses the highway network for at least one leg will enter and exit the network at such junctions. The driving distance between some pairs of neighbouring junctions appears to be considerably large. Therefore, selected existing filling stations that lie in close proximity to the highway network as well as junctions with smaller roads were added to the set of potential charging sites in a way that enhances the network reasonably. Identified locations that lie less than 5 km distant to another location were removed. It is assumed that any of these potential FCS locations can be accessed from both directions of a road. The proximity of potential charging station sites is greater in urban regions than in rural areas. This is due to the denser road network and the higher number of relevant junctions that might serve as a charging station.

In this process, all data used was taken from publicly available OSM cf. OpenStreetMap, 2020. Every node is specified by the corresponding identification number from OSM and its geographical coordinates. This results in a set of 238 nodes which represent potential charging station sites. All identified potential FCS nodes and their distribution on New Zealand North island are shown in Fig. 4.

A weighted graph $G = (N, A)$ where N denotes the set of nodes and A the set of distance-weighted arcs was constructed to model the transportation network. The identified potential FCS locations serve as nodes of the graph while the highway roads serve as arcs. Each connection between two adjacent nodes is represented by two directed arcs, one for each direction. A version of the graph with undirected arcs is depicted in Fig. 4 by the blue nodes and solid lines.

To determine the demand for charging at given locations in the road network, the driving patterns were mapped in an aggregated, but representative form. For the representation of traffic flow volumes on the highway network graph, additional OD-nodes were added to the graph. Every OD-node represents a region where EV users start and end their journeys. For their trips between origins and destinations, EV users are assumed to use the highway network. Thus, OD-nodes act as sources and sinks of traffic flows in the graph, but do not serve as potential FCS themselves.

In this application to New Zealand Northern Island, the most recent data available and consistent with each other were used. Each OD-node represents a geographic area that lies in close proximity around the OD-node. As a basis, the geographical boundaries of SA1 as released on January 1st 2018 by Stats NZ cf. Stats N.Z. Geographic Data Service, 2018a are used. Each SA1 boundary defines a small spatial unit in New Zealand for which the geographical coordinates of the centroid are used as a representation. In addition, the number of usual residents as counted in the 2013 Census cf. Stats N.Z. Geographic Data Service, 2017 is available for every SA1 entity. The individual SA1 areas were aggregated to larger units to determine origin and destination representatives. This aggregation of SA1-areas to larger units is illustrated in Fig. 5. Each region with black borders represents an individual OD-region and is made up of the smaller SA1-areas depicted with light-grey boundaries that lie within the OD-region. The centre of gravity of all related SA1 centroids was calculated for each OD-region. To take mobility demand into account, the resident population count numbers of the corresponding SA1 areas serve as weights. Depending on the distribution of the population, this locates OD-nodes approximately where most people live. As a representative OD-node, the road node that lies closest to the centre of gravity was chosen for each OD region. The OD-nodes are depicted as red nodes in Fig. 5.

The definition of OD-nodes that represent geographical areas of traffic flow OD follows the idea of de Dios Ortúzar and Willumsen (2011). The authors consider the access distances from rural districts to the most proximate highway network node in their model. This depicts the total distances driven by EV more accurately than just looking at the distances travelled on highway roads. To incorporate the OD-nodes into the existing highway network graph, two directed edges between

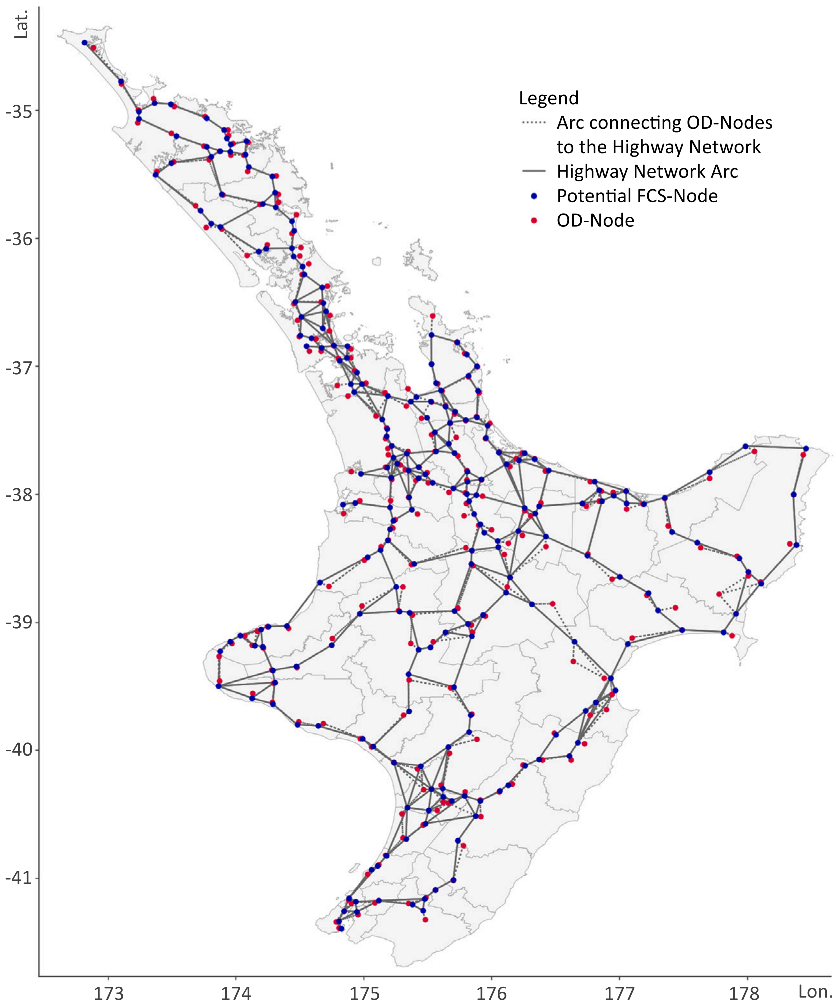

Fig. 4. Highway network graph with potential FCS nodes and OD-nodes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

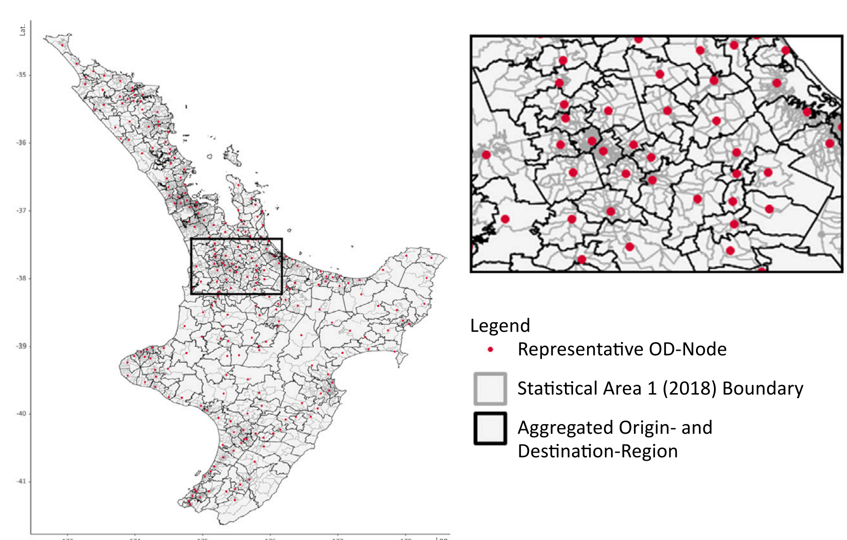

Fig. 5. Identification of OD-regions and OD-nodes.

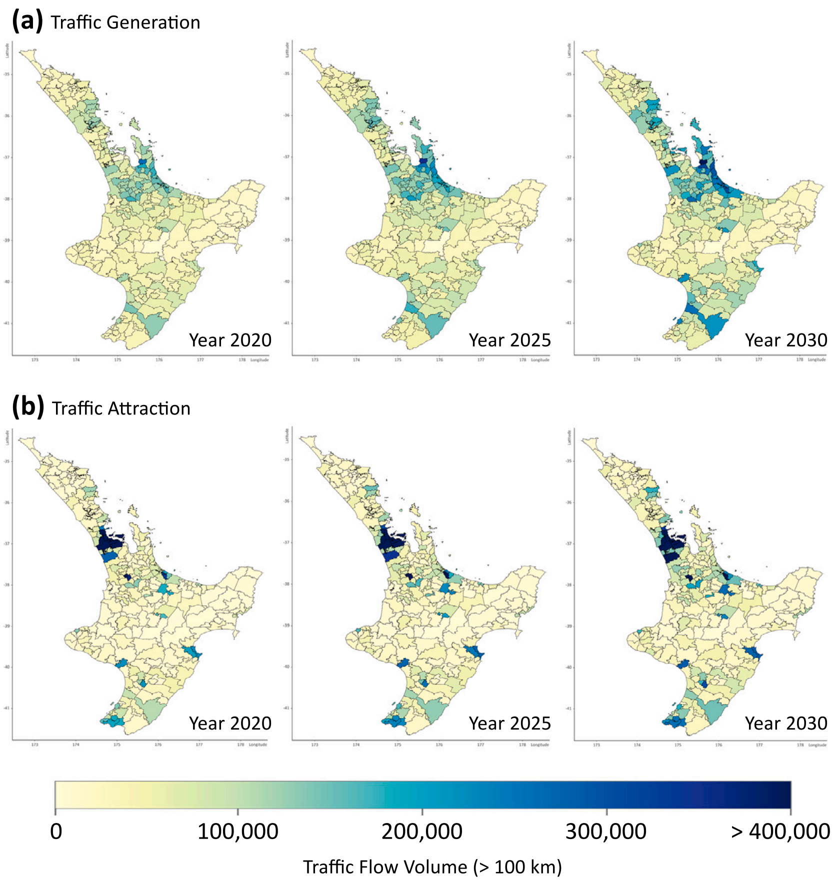

Fig. 6. Traffic flow volume generation (a) and attraction (b) (> 100 km) per OD region.

each OD-node and each FCS-node or other OD-node that is directly reachable via the road network are added to the graph. All nodes and an unweighted and undirected representation of all arcs are depicted in Fig. 4. Solid arcs indicate edges from the previously built highway network graph, while dashed arcs depict the connections from OD-nodes to the graph. The blue nodes are the potential FCS nodes and the red nodes represent OD of traffic flows.

For any two adjacent nodes, the fastest route between them including the corresponding duration and driving distance were requested from Open Route Service (ORS) cf. OpenRouteService, 2020. The fastest paths and associated total driving distances between any pair of OD-nodes were calculated using the shortest-path algorithm of Dijkstra (1959). An OD-path is thus defined by the single origin node, the single destination node and the FCS-node sequence on the graph to be taken to drive in the fastest possible manner from the origin to the destination. The resulting data table stores the total driving distances between any two non-identical OD-nodes including the node-path taken for the fastest possible connection between them and the individual driving distances of the individual arcs. This sums up to a total number of 55,932 paths.

Appendix C. Traffic flows

In order to evaluate the approach to calculate OD flow volume described in Section 4.1.1, a comparison to two simpler methods is conducted in the following.

In total, an absolute error of 175,517 counts between actual traffic counts and traffic obtained from calculated flows is yielded with our approach. Since no statement can be made on how valuable this result is without a comparative value, two more applications of the optimization model (cf. Eq. (15)) were made for comparison that include a simpler formulation of the Gravity Model T_q.

First, the classical Gravity Model (cf. Eq. (14)), where only the unweighted number of residents in each region as well as the squared distance between regions serve as a data basis, was inserted in Eq. (15) for T_q to determine flow volumes. Here, only the scaling constant k could be adjusted to meet traffic counts. In the optimized case, k amounts to $k = 29.53$ and a total absolute error between calculated to actual traffic counts of 301.494 is yielded.

In the second case, the Gravity Model including a variety of characteristics per region (cf. Eq. (14)), where all weighting factors of the region characteristics are equal to one and the distance is squared, was used to define T_q in Eq. (15). Again, only the proportionality constant k could be adjusted. In this case, k amounts to $k = 934$ and a total absolute error of 358,540 is obtained.

In the first comparative case, the obtained error is 71.78% higher than the error obtained from inserting Eq. (14) with optimized calibration parameters into Eq. (15) for T_q. In the second comparative case, the error is more than two times higher than the optimized error of the suggested formulation including the calibration of weighting factors. Thus, the suggested optimization method developed here yields significantly better results to depict OD traffic flows on New Zealand‘s highways concerning observed traffic than more basic approaches. Consequently, the obtained OD traffic flow volumes can be assumed to resemble actual traffic flows for New Zealand much more accurately than flows obtained from simpler forms of the Gravity Model.

In addition, the traffic originating from and destinating in the same region in 2020, 2025, and 2030 is visualized. Fig. 6 shows in Part (a) the yearly total aggregated traffic volume of paths that exceed 100 km distance and originate from the same region for all three time periods. Additionally, Part (b) depicts the sum of traffic volumes of all paths

Table 2
Fixed and variable (i.e. size-dependent) costs of components for FCS installation.

	Component	Costs [$]
Fixed Costs per station		
	Underground cable (11 kV)	141,700 $/km[a 1]
	Overhead line (11 kV)	35,970 $/km[a 1]
	Transformer (11 kV to 400 V)	25,070 $ (for 2.5 MW capacity)[a 1]
	Permit	2200 $[b]
	Load centre and meter	7100 $[b]
	On-site cables	10,700 $[b]
	Additional material and installation costs (e.g. for lighting, concrete, signage, …)	50,000 $[b]
Variable Costs per charging unit		
	Charging unit hardware (for a 100 kW unit)	65,800 $[b]
	Installation and electrical equipment	6000 $[b]
	Additional material and installation costs (further lighting, concrete, signage, …)	11,000 $[b]

[a] Estimate based on CONSENTEC (2006).
[b] Estimate based on Francfort et al. (2017), p.17.
[1] Exchange Rate: 1 € = 1.09 $.

longer than 100 km that terminate in the same region for every OD region in each year under consideration (see Fig. 6).

Appendix D. Detailed approach to determine grid connection costs

In the following, a more detailed outline of realistic cost values for the installation of FCS that can be found in the literature is provided. Additionally, the approach applied in this work to determine the costs for individual grid connections is explained in detail.

Further assumptions and details for the grid connection and installation costs

In comparison to Level 1 or Level 2 charging stations, FCS show higher costs due to their hardware specific costs and more complex grid connection (Element Energy Ltd., 2009). While the costs for the equipment of each charging station unit are basically the same for each location, installation costs vary substantially between different sites (Nicholas and Hall, 2018). The proximity of a site to existing electrical infrastructure has been found in former installation projects to be the largest differentiating factor between locations (The E.V. Project, 2015). Accordingly, the following costs are taken from literature and resulted in our assumptions presented in Table 2.

For a FCS with a single charging unit, Schroeder and Traber (2012) found total investment costs of 103,550 $ (95,000 €) for a 62.5 kW and 136,250 $ (125,000 €) for a 250 kW station, while Hall and Lutsey (2017) state that costs ranged from 40,000 $ to 100,000 $ in former infrastructure programs. Comparable values were also found by Wiederer and Philip (2010) with cost estimates between 40,000 $ and 75,000 $ and Markkula et al. (2013) who estimate a total investment of 45,780 $ (42,000 €). Similarly, the estimated cost of a single charging unit station is approximately 38,150 $ (35,000 €) in NPE (2015) and 40.000 $ in the considerations of Wood et al. (2018). Furthermore, Khan et al. (2018) assumed costs ranging from 50,000 $ to 160,000 $ and Funke et al. (2019) point to expenses for a single unit station of 49,050 $ (45,000 €) for a 50 kW station and 130,800 $ (120,000 €) for a 150 kW station. For lower power stations with 25–50 kW costs of 25,000 $ - 85,000 $ are estimated based on installer information (CCRPC, 2014), and for higher power stations of more than 50 kW values of 62,000 $ (50,000 £) to 124,000 $ (100,000 £) are assumed to be realistic (Element Energy Ltd., 2009). Hecht et al. (2022) identified costs of 110,000 up to 220,000 $ for FCS including installation costs.

Looking only at the costs of installation excluding expenses for charging unit equipment, the highly cited 'The E.V. Project (2015)' identified costs of 111 station installations ranging from 8500 $ to more than 50,000 $ with an average value of 23,662 $ (The E.V. Project, 2015). While Ducharme and Kargas (2016) state significantly higher costs of 18,000 $ - 100,000 $, other sources report lower costs ranging from 21,200 $–28,500 $ (CCRPC, 2014) and 9000 $ for construction and grid connection (Markkula et al., 2013). Moreover, installation costs for fast chargers in UK required 21,200 $–28,500 $ (Nicholas and Hall, 2018).

In addition, the costs for the charging unit hardware can vary widely depending on the type of product purchased and its power supply. Francfort et al. (2017) report the equipment of a 100 kW charger to amount to 60,000 $ - 70,000 $. In the 'The E.V. Project (2015)', installed chargers accounted for 10,000 $ - 40,000 $, depending on their power supply, the type of mounting, ability to communicate and additional features (Smith and Castellano, 2015). Moreover, typical purchase prices for a fast charging unit have been indicated with 20,000 $ - 50,000 $ (U.S. Department of Energy, 2012) as well as with 49,660 $ (40,000 £) to 99,200 $ (80,000 £) for a 60–120 kW charger (Element Energy Ltd., 2009).

These huge differences in identified costs and the wide cost ranges provide an indication of the difficulty to determine valid cost values and the vast differences between sites.

In the case of underground cables, trenching is assumed to take place in urban environments with sealed underground and low traffic volume. The costs for the trench thus account for 119,900 $/km while the cable itself is assumed to cost 21,800 $/km (CONSENTEC, 2006) on average. In the case of overhead lines, an average cost value of those available is assumed to represent the used cable and its installation here. For the installed dedicated transformer, a capacity of 2.5 MW load capable to serve 25 EV at a time with costs of 25,070 $ is assumed. All further estimated values are calculated based on data from Francfort et al. (2017) as a projection to a 100 kW station. Accordingly, material and installation costs for a station with six 100 kW units would account to approximately 116,000 $. It is assumed that 50,000 $ of these are fixed costs for installing the station, while each of the six units adds 11,000 $ of further material and installation costs.

According to Table 2, costs for opening a charging station amount to 95,070 $ without considering individual grid connection costs plus 82,800 $ for each charging unit. In total, the costs for opening a charging station with a single charging unit at a location with existing grid connection and sufficient transformer capacity amounts to 152,800 $.

Connection to the grid and resulting line costs

For every potential FCS node, the closest substation on the 33 kV voltage level is identified (i.e. it is assumed that each FCS can be connected by a straight line). For this a Python based code is applied.

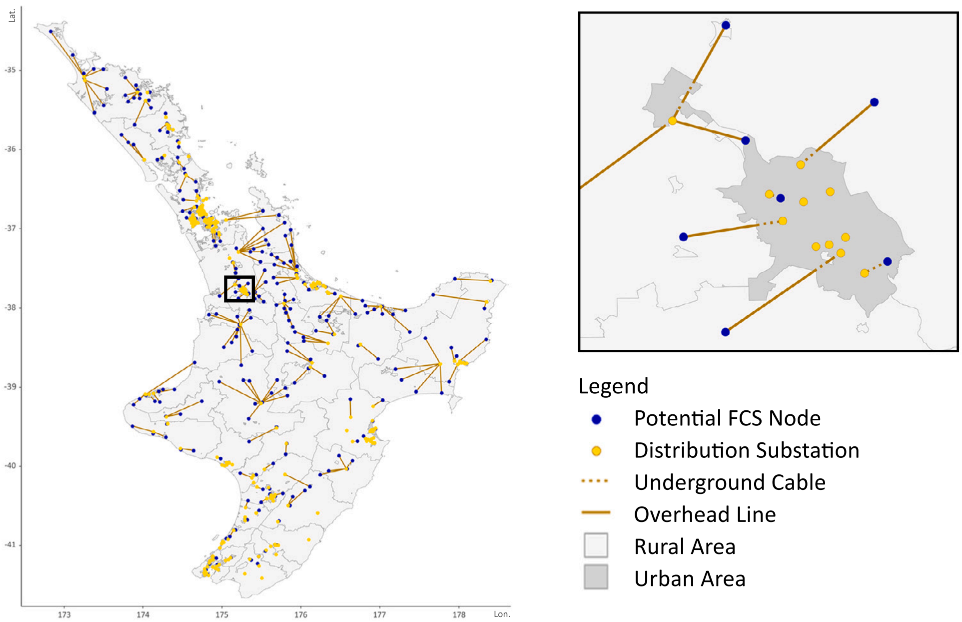

Fig. 7. Illustration of overhead and underground electricity lines in rural and urban environments.

The locations of the substations are taken from OSM. All 'distribution substations' (224 substations) and substations that are explicitly stated to transform from 33 kV to 11 kV (6 additional substations) are taken for the northern island of New Zealand. Furthermore, substations that transform from 50 kV to 11 kV and are tagged as 'distribution' substations in OSM are added to the set (11 further substations), but are treated identically as the substations on 33 kV level. All in all, 241 substations on 33 kV level (or 50 kV level) were identified that might be used to connect a FCS via a newly built 11 kV line.

To estimate installation costs of a newly built line appropriately, local conditions concerning urban or rural environment must be assessed for deciding whether an overhead line can be built or underground installation is necessary for each line and line segment. This evaluation is highly uncertain and can be severely influenced by local conditions. However, in order to obtain an assessment as accurate as possible, this approach assumes that underground cables are built in urban areas (cf. city of Christchurch approximately 40% of power cables are laid underground) whereas overhead lines are installed in rural environments (cf. region of Northland, operates 95.7% of its distribution lines as overhead installations). The classification of geographic areas in urban or rural environment is taken from Stats NZ (Stats N.Z. Geographic Data Service, 2018b). The defined geographical areas are divided into nine region types: rural settlements or other rural areas (in the following referred to as rural areas), major, large, medium, and small urban areas (in the following referred to as urban areas) as well as inland water, water inlets and oceanic regions. The classification of island regions into these types is based on equivalent characteristics in terms of population density or coverage with residential or commercial buildings, respectively, an should thus give a well-founded approximation to determine the line type required. For each potential FCS node, the set of the five most proximate substations is determined, and a straight line is assumed as the corridor for the electricity line connection. This straight line is cut into line segments wherever it crosses the boundary of any of the defined urban or rural boundary areas. For the resulting line segments, it is determined whether they are located in a rural or urban area. For any rural line segment, overhead lines and the corresponding costs are assumed whereas for line segments in urban regions underground cables and their associated costs are set. Line segments that run across lake or sea areas are assumed to be built as overhead lines. An example of potential grid connections is depicted in Fig. 7. The light-grey areas represent rural environments while all urban regions are coloured dark-grey. The electricity lines that connect each FCS-node to the most cost-efficient substation are built as overhead lines as long as they run through rural areas (depicted as solid lines) and as underground cables (depicted as dashed lines) as soon as they enter urban regions.

For each potential FCS node, the most cost-efficient connection to one of the relevant substations is chosen for its grid connection. This does not need to be necessarily the shortest connection. Since overhead lines are significantly cheaper than underground cables, bridging a longer distance with overhead lines can be the more cost-efficient choice than laying underground cables over a shorter distance. All in all, for 211 potential FCS nodes the most proximate substation is also the cheapest possible connection point. In 14 cases, the second nearest substation offers the most favourable connection and for five nodes the third-nearest station is the cheapest connection point. Furthermore, seven potential FCS nodes should preferably be connected to their fourth-closest substation and one remaining node to its fifth-nearest one. It cannot be excluded beyond doubt that these are the most cost-effective connection alternatives. The connection to an even more distant substation might by advantageous in terms of costs. In practice, however, there might be many other influencing factors and it seems undesirable to construct excessively long electricity lines through a country although sufficient infrastructure is available at a closer point. Hence, our estimations are providing only first indications.

The obtained costs for the most cost-efficient connection option of all potential FCS nodes vary between 9575 $ to 2.68 million $ with an average value of approximately 695,000 $ and a median value of 530,000 $. The distances to cover range from 0.07 km to approximately 74 km with an average distance of 16.67 km and a median of 11.76 km. 31% of potential FCS nodes require an electricity line of less than 5 km. Considering the most favourable connection option of all potential FCS nodes (irrelevant of the fact whether they are built or not), 94.6% of the potential lines lie in rural environments and would thus be built as overhead lines while the remaining 5.4% lie in urban areas and would require underground cables. This is in line with existing line installations of distribution network operators as stated earlier.

Further bottleneck induced investments by FCS in the upstream grid is not considered. Slednev et al. (2021) showed that these impacts are

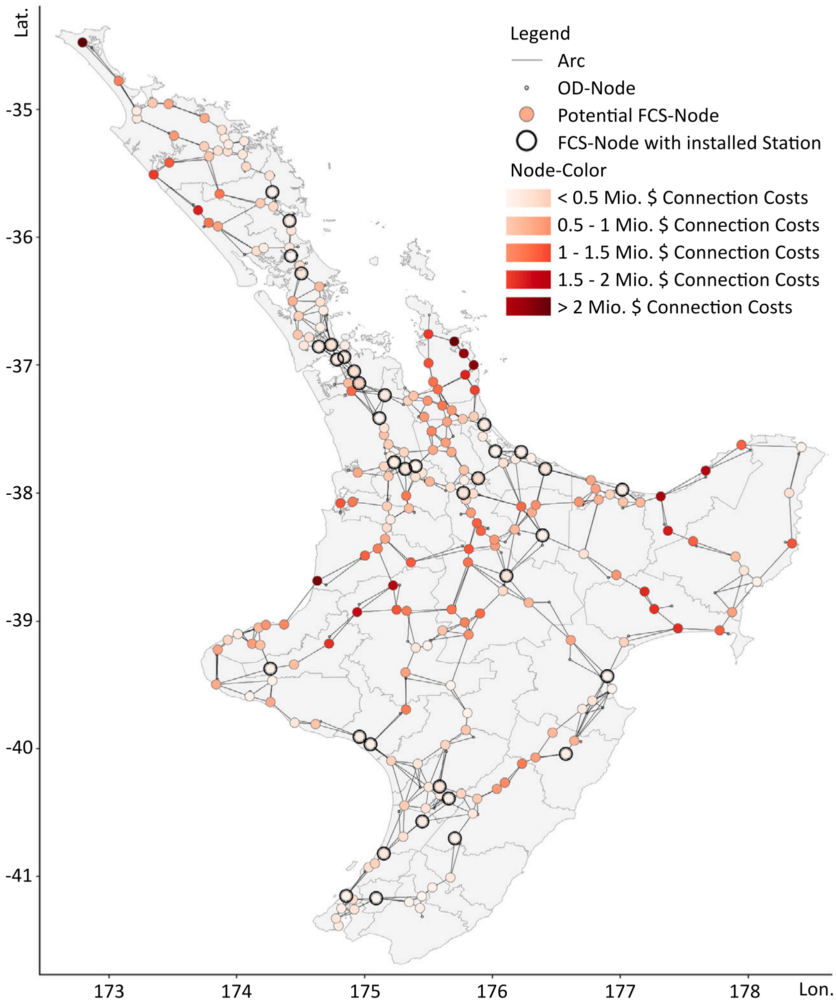

Fig. 8. Illustration of the costs to connect each (potential) FCS-node to the grid.

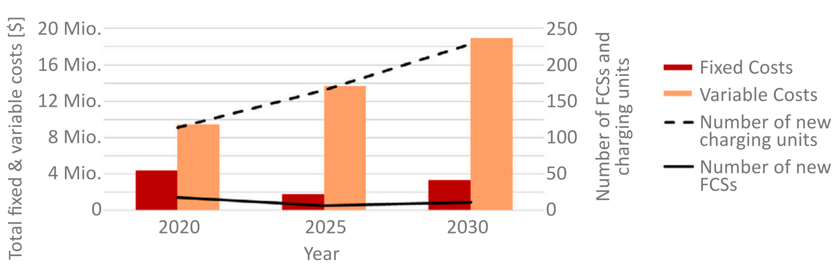

Fig. 9. Relationship between fixed (i.e. preparing locations) and variable (due to increasing the number of charging units per location) costs (left vertical axis) and the number of FCS and charging units (right vertical axis).

rather marginal. Furthermore, local electricity generation or batteries may help to overcome these challenges (Nicholas and Hall, 2018; Srdic and Lukic, 2019; Funke et al., 2020).

Appendix E. Further visualization of results

Fig. 8 depicts the grid connection costs for all potential FCS identified on New Zealand North Island. The selected locations where FCS should be installed according to the results of the IO-MP-C-AC-PC model are marked with a black circle.

The resulting relationship between fixed and variable costs and the number of FCS and charging units over time are given in Fig. 9.

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