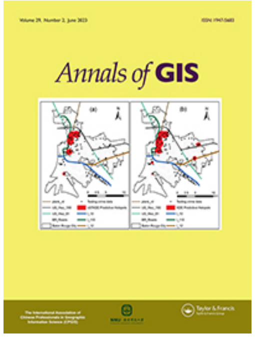

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Regional allocation of EV chargers' grid load

Bardia Mashhoodi [a] and Pablo Muñoz Unceta [b]

[a]Landscape Architecture and Spatial Planning Group, Department of Environmental Sciences, Wageningen University & Research, Wageningen, Netherlands; [b]Fab Lab Barcelona, Institute for Advance Architecture of Catalonia, Barcelona, Spain

ABSTRACT

This study develops a multiscale model for allocation of EV infrastructure to accommodate residents' demand during nights and that of residents and visitors during days under two scenarios: maximum 40% or 80% increase in load on the electricity grid. Developing a mixed-integer linear optimization model including regional traffic flow, local electricity demand and parking availability in Amsterdam Metropolitan Area (AMA), the scenarios' optimal solutions offer different spatial strategies. This study shows that multiscale allocation of EV chargers substantially improves the efficiency of use: in both scenarios, more than 53% of EVs can charge at their daily destination. However, in the 40% scenario, the extra electricity load is homogeneously allocated across the towns and villages around the AMA centre. In an 80% scenario, in contrast, the load is concentrated in a few areas (1) accessible for substantial numbers of EVs at the regional scale, (2) with relatively low annual consumption, (3) reasonably high number of registered EVs to use chargers in the nights. The manuscript ends with a discussion of the results and their policy implications and offers further studies.

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KEYWORDS
Electric vehicle; Charging infrastructure; regional infrastructure; grid load; spatial optimization

1. Introduction

1.1. Upcoming demand for electric vehicle charging infrastructure and the necessity of grid load allocation

The further adaptation of electric vehicles (EV), a globally fast-growing and celebrated development as one of the cardinal solutions to mitigate climate change, urges for spatial allocation of a vast number of new EV chargers. The possibility for the latter, however, is severely confined by the energy grids' shortage of capacity, which can render the allocation of new chargers in areas with a high density of cars and congested energy grid impossible. The point of departure of this study is to develop and introduce a novel model which optimally benefits from the left-over capacities of the energy grid at the regional scale. The intention is to use real-world data on the existing load on the energy grid and travel survey among the neighbourhoods of a large-scale region and seek the neighbourhoods that can serve all of the region during days or nights. The following paragraphs of this section elaborate on the above-mentioned trends, necessities, and the objective and approach of this study.

The number of electric vehicles (EVs) is rapidly growing in the Netherlands. The share of battery electric vehicles (BEV) of cars sold has increased from 1.1% in 2016 to 20.5% in 2020. The share of registered BEVs of total passenger vehicles enlarged from 0.16% to 1.98% in the same period (Netherlands Enterprise Agency 2020). The trend is expected to amplify, given the ambitions of the Dutch government to achieve a climate-neutral mobility system. The Green Deal on Electric Transport aims for 50% of all cars sold in 2025 to have an electric powertrain and at least 15% to be fully emission-free (Government of the Netherlands 2015). The Dutch climate agreement aims for 100% of cars sold in 2030 to be electric and emission-free (Ministry of Economic Affairs and Climate Policy 2019). A projection suggests that by 2030 will be more than 3 million EVs registered in the Netherlands (The Netherlands Knowledge Platform for Charing Infrastructure 2017).

The rapid growth in the number of EVs is parallel with a substantial increase in demand for EV charging infrastructure and the limited electricity grid capacity. Between 2016 and 2020, while the absolute number of passenger BEVs grew 13 times in the Netherlands, public EV chargers have increased only four times (Netherlands Enterprise Agency 2020). In 2018, the number of EVs per every public charger in the Netherlands was the fourth highest among the European Union (EU) and European Free Trade Association (Tsakalidis and Thiel 2018). The

CONTACT Bardia Mashhoodi bardia.mashhoodi@wur.nl Landscape Architecture and Spatial Planning Group, Department of Environmental Sciences, Wageningen University & Research, Wageningen 6700 AA, Netherlands

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urgent need for new EV charging infrastructures is reflected in the EU and Dutch policies. The European Parliament's Directive, 2014/94/EU on the deployment of alternative fuels infrastructure, calls for the development of a minimum of one charging station per every 10 EVs in the member states (Official Journal of the European Union 2014). 'Improving and expanding the charging infrastructure for EVs' is the first of the goals put forward by Electric Transport Green Deal 2016–2020 (Government of the Netherlands 2015, 4). Dutch climate accord aims to expand EV charging infrastructure by 2025 and develop spatial plans for allocation of such infrastructure specifically in the three major metropolitan areas of the country, among them Amsterdam Metropolitan Area, AMA (Ministry of Economic Affairs and Climate Policy 2019).

The need for expansion of EV charging infrastructure coincides with the shortage in the electricity grid capacity. Network operators in the Netherlands, companies that run the electricity grid in different parts of the country estimate that there is no or limited capacity left to meet additional electricity demand in most locations. For instance, Liander, a network operator, estimates that it is short of capacity in most operating areas, including the AMA (Figure 1). Doubtlessly, the capacity of the electricity grid needs to be expanded in the coming decades. The challenge is how the allocation of new EV infrastructure should consider the grid load and, in line with the Dutch climate accord's ambitions, seek optimal solutions at the regional scales.

This study proposes and implements a novel method to face the above-mentioned challenge of the electricity grid capacity shortage and the development of new EV infrastructure. The location-allocation model put forward by this study incorporates the real-world data on the actual electricity consumption within the neighbourhoods of a large-scale region and introduces constraints on the maximum extra grid load caused by new EV chargers. Such an approach is unprecedented in the existing studies on EV charger allocation, possibly due to the unavailability of data in most countries. Seizing the opportunity to access such data in the Netherlands, the richest EU country in terms of publicly available data on energy (Eurostat 2013), this study shows that incorporating data on the electricity grid helps optimally meet a 4000% increase in charging demand at the regional scale. Using the transport survey in the Amsterdam Metropolitan Area, the study seeks the optimal solutions in which EV chargers are only allocated in the areas with leftover grid capacity while all the EVs of the region have access to a charger during the day or night: an unprecedented approach. In the following parts of the manuscript, a knowledge gap in existing studies is introduced, and the study's approach is presented. Subsequently, data and the method of the study are explained, results are presented and discussed, and potential policies are recommended. The manuscript ends with a series of suggestions for further exploration.

1.2. Previous studies and knowledge gaps

A growing body of literature discusses models for the optimal allocation of EV charging infrastructure. The models use several types of data and constraints to define optimal locations, including data related to technology – e.g. battery life, charging technology, behaviour – e.g. range anxiety, route, and destination patterns, and EVs'energy demand (He et al. 2018). Various studies have developed numerical models for the allocation of EV chargers (Souley et al., 2021; Davidov and Pantoš 2017; Hung & Michailidis, 2015). A brief overview of the previous studies is presented in the next paragraph, and the knowledge gap mentioned above is elaborated.

Given the geographic scale of analysis, previous studies on the optimal allocation of EV charging infrastructure could be classified into three main types. The first type is large-scale studies searching for optimal solutions at the metropolitan, regional or national scales. Neubauer and Wood (2014) used Puget Sound Regional Council's traffic behaviour data to analyse the sensitivity of EV drivers to range anxiety and developed various scenarios of working or home charging. Pearre et al. (2011) used driving records of 484 instrumented gasoline vehicles in the US over one year to analyse potential travel behaviours of EVs at a large scale. Kuby et al. (2009) developed a spatial decision support system to allocate hydrogen stations in the Orlando metropolitan area. Similar large-scale approaches were adapted by Xi, Sioshansi, and Marano (2013) on the central-Ohio region, and by Galus et al. (2012) to study the metropolitan area of Zurich. Several studies developed or tested EV charging infrastructure location models along long-distance corridors (Alhazmi, Mostafa, and Salama 2017; Chen, Liu, and Yin 2017; Ghamami, Zockaie, and Nie 2016). The second type is studies on a small town or a neighbourhood. Napoli et al. (2021) analysed spatial potentials for electricity generation to meet the demand of EVs' last-mile travel in Capo d'Orlando, a 13,000 inhabitants city located in Sicily (Italy). Two previous studies on a district in the city of Amsterdam, with a population of 60,000 inhabitants (roughly 7% of the city's population) tested the impact of an increase of walking distance between destinations and charging stations from 2,5 to 5 minutes (Mashhoodi et al., 2021), and the influence of drivers range anxiety (Mashhoodi and van der Blij, 2021) on the overall cost of

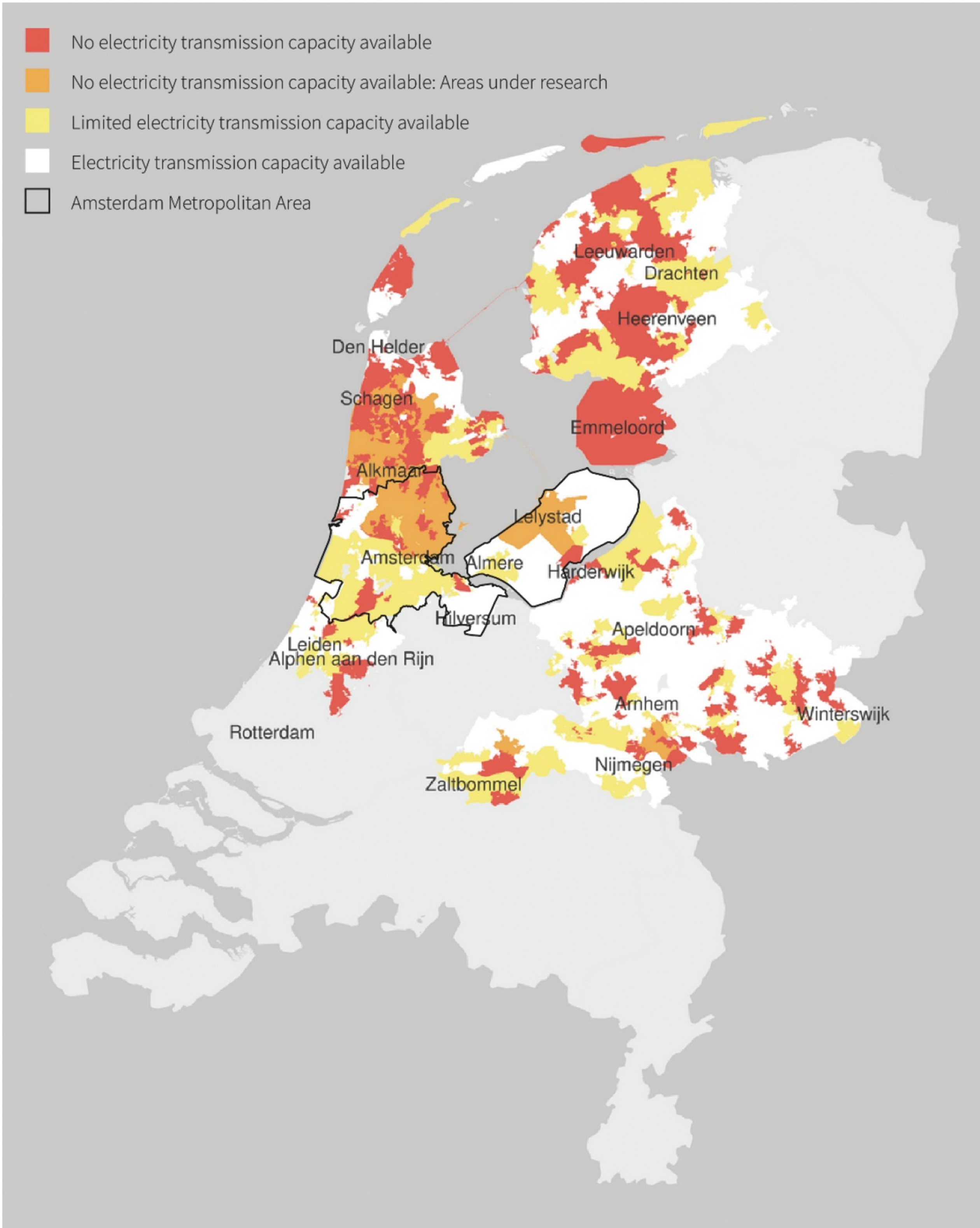

Figure 1. Electricity transmission capacity per areas covered by Liander, a network operator company, and the location of AMA (Liander 2021).

EV infrastructure. The third type of studies involves those with a multiscale approach to allocating EVs charging infrastructure (Fredriksson, Dahl, and Holmgren 2019; Shahraki et al. 2015).

There is lack of a model in previous studies which integrates actual load on the energy grid and travel survey at the local and regional scales and seeks multi-scalar optimal solutions for EVs' grid load allocation. The major shortcoming of the models described above is neglecting the real-world data on the existing grid congestion. Although various factors are incorporated in the models, e.g. battery life, charging technology, range anxiety, route, destination patterns, EVs'energy demand, the capacity of the energy grid which needs to fuel the allocated charging stations is not considered. Considering the multiscale approach of the previous studies, three knowledge gaps in the three types of studies mentioned above are eminent. Regarding the large-scale studies, the results are often determining the share of chargers allocated at work or home at the regional scale. The studies neglect the spatial and temporal dimension of regional electric mobility, i.e. one's workplace during the day can be the living location of another during the night. In other words, by neglecting the charging demand and household energy consumption at the neighbourhood level of scale, such studies do not benefit from the potential synergies between regional and local demands. On the contrary, studies on the local scale often miss the overall picture of the regional infrastructure network, such as the availability of large-scale parking areas and the regional traffic flow during the days. Such studies, consequently, miss the opportunity of the shared use of infrastructure by the EV drivers of different districts. Ultimately, although benefiting from multi-scalar synergies, the previous studies combining the different scales did not consider the EVs' grid load. Multiscale allocation of EVs opens new opportunities for controlled distribution of the new load on the energy grid. Previous studies, however, did not seize the opportunity.

1.3. Approach of this study and research design

This study aims to bridge the gap in previous studies by developing a model for the allocation of EV chargers and grid load at multiple levels of scales. To do so, the study is designed based on three principles:

Principle 1. Allocation of EV chargers should consider both local and regional scales. At the local scale, the allocation of EV chargers responds to local demand during nights by serving the residents of a neighbourhood. At the regional scale, the allocation of EV chargers responds to regional demand during days by serving both residents and visitors from the region. This principle is in line with Article 26 of Directive 2014/94/EU of the European Parliament on the deployment of alternative fuels infrastructure, which urges to plan EV infrastructure based on estimated of both residents and visitors demand (Official Journal of the European Union 2014). It also corresponds to the Dutch climate accord emphasis on spatial allocation of EV infrastructure at the regional scale (Ministry of Economic Affairs and Climate Policy 2019).

Principle 2. Allocation of chargers needs to consider the additional load on the electricity grid. This principle is in line with Article 30 of the EU Directive, which emphasizes the importance of considering electricity grid capacity in the planning of EV infrastructure (Official Journal of the European Union 2014). It is also in line with the shortage of capacity in the current electricity grid in the Netherlands.

Principle 3. Chargers can have multiple plugins, in line with Article 33 of the EU Directive (ibid).

Principle 4. Allocation of the chargers aims to meet the upcoming charging demand of an extra 40% of the total vehicles. Due to lack of data, the study does not include the number of existing chargers, serving less than 1% of the existing vehicles. It, however, includes the load of existing chargers on the electricity grid. The analysis focuses on the allocation of the 'new chargers' based on the assumption that the existing EVs are already provided with a charger, given the current approach of the Dutch municipalities to provide a charger on request. This approach could not be continued because of the lack of electricity grid capacity, which triggered the basic idea of this manuscript.

To achieve a multiscale model for allocation of EV chargers, i.e. regional in days and local at nights, this study is designed based on the specification of EVs and travel behaviour in the Netherlands. Table 1 shows the average EV battery capacity and consumption of the ten most common BEVs sold in the Netherlands in 2018 – the year prior to the dataset used in this study (Rijksdienst voor Ondernemend Nederland 2019). Accordingly, the average battery capacity is 48.3 kWh and, given the average driving range of 252.7 km, the average electricity consumption is 191.1 Wh/km.

According to the data on travel behaviour, in 2019, 8.53 million passenger cars in the Netherlands (CBS

Table 1. Battery capacity, driving range, and consumption per kilometre of the ten most popular BEVs sold in the Netherlands in 2018.

	Battery [kWh]	Driving range [km]	Consumption [Wh/km]
BMW I3	33	183	180
Tesla Model S	90	426	211
Hyundai Ioniq	28	200	140
Jaguar I-Pace	90	377	239
Nissan Leaf	30	172	174
Opel Ampera	18.4	85	216
Smart Fortwo	16.7	108	155
Tesla Model X	100	475	210
Renault ZOE	41	300	137
Volkswagen Golf	36	201	179
Average	**48.3**	**252.7**	**191.1**

2021a) have travelled 110,227 million Kilometres (CBS 2021b). This shows that every passenger car in the Netherlands travels an average of 12,922 Kilometres per year. Given the average consumption of EVs sold in the Netherlands, this implies that an EV consumes an average of 6,762 Wh per day. Setting drivers' range anxiety, i.e. the percentage of battery being empty before a driver decides to charge her/his EV, at 70%, EVs would need to be charged every five days for 33.81 kWh. This would take roughly 40 minutes using a fast charger with a capacity of 50 kWh. Assuming that every charger is unused for 20 minutes between two charging sessions, a fast charger would be able to charge 15 EVs during a day between 6 am to 9 pm (see Figure 2a). During the nights, using multiple plugins and avoiding wasting time between charging two EVs, the same fast charger can charge 13 EVs (Figure 2b).

This study aims to elaborate and test a multiscale model for day and night charging demands at the regional and local scales by allocating chargers described in Figure 2. To do so, two scenarios for allocation of EV grid load are elaborated:

- Scenario #1: the extra load on the electricity grid after allocation of EV chargers should not exceed 40% of current electricity use by buildings.
- Scenario #2: the extra load on the electricity grid after allocation of EV chargers should not exceed 80% of current electricity use by buildings.

2. Data and case study area

2.1. Case study area

The case study of this research is the Amsterdam Metropolitan Area (AMA). According to Metropoolregio Amsterdam, AMA is one of the five top economic regions in Europe and has a population of 2.5 million. The region comprises urban and rural landscapes and includes 32 municipalities, Schiphol airport, port of Amsterdam, multiple universities, business districts, a media park, and a considerable concentration of tourism and leisure activities (Metropoolregio Amsterdam 2019). There is an intense traffic flow between the areas of the AMA. According to the travel survey in 2019, 89% of the car trips that originated from a Postcode 3 (PC3) in AMA was aiming for another AMA PC3, accounting for the trips aiming to stay at destinations between 30 and 60

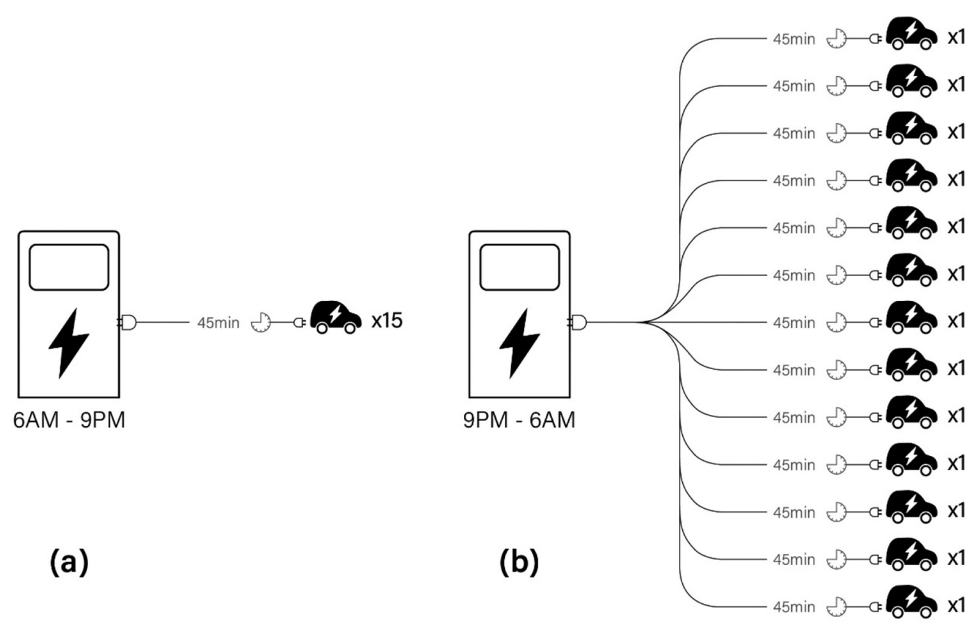

Figure 2. Capacity of a fast charger using a single plugin during days, 6 am to 9 pm, (a) and multiple plugins in nights, 9 pm to 6 am (b).

minutes (authors computation based on DANS 2020). Additionally, the Dutch climate accord designated AMA as one of the three major Dutch metropolitan areas with the urgent need for spatial planning for the allocation of EV infrastructure (Ministry of Economic Affairs and Climate Policy 2019). In this respect, AMA is a suitable case study for the objectives of this research.

2.2. Number of EVs, electricity consumption, and parking capacity

The number of EVs in AMA is set based on a projection that suggests there will be 3 million EVs in the Netherlands by 2030 (The Netherlands Knowledge Platform for Charing Infrastructure 2017). Given that there were 7.64 million passenger vehicles in the Netherlands in 2020 (CBS 2020), it suggests that by 2030 about 40% of vehicles in each PC3 will be electric (Figure 3a). Besides the expected number of EVs in each PC3, three other datasets were prepared as input for this study, including available parking areas, the percentage of visitors travelling to each PC3, and the annual electricity consumption also at PC3 level. To obtain the total number of parking lots available for allocation of EV chargers in each PC3, using the Open Street Map (Geofabrik 2021), the areas designated as car parking are selected. The number of parking lots is calculated based on 3×5.5 m space necessary for each lot and 33% circulation space (Figure 3b). To calculate the fraction of parking lots that can be used for allocation of EV chargers, using travel survey in AMA, 2019 (DANS 2020), the percentage of visitors of each PC3 who travel from an origin inside AMA and stay at their destination between 30 and 60 minutes are obtained (Figure 3c). To control the maximum percentage points of increase in electricity consumption in a PC3 after allocation of EV chargers, the annual electricity consumption of residential and non-residential buildings in PC3 of AMA in 2018 (CBS 2019) are obtained and mapped (Figure 3d).

2.3. Travel behaviour of car drivers in AMA

To estimate the maximum number of EVs from a certain PC3 which can charge in another PC3 during days, the Dutch travel survey in 2019 is used (DANS 2020). The survey includes the records of trips with origin and destination inside AMA and a weight factor for each trip. There are not enough records to estimate the traffic flow between all PC3 of AMA. The data, however, can provide insights into the length of car travels inside AMA. Table 2 shows the deciles of trip length with origin and destination inside AMA.

3. Method

To find optimal solutions, this study employs a linear integer programming model for optimal allocation of EV chargers annually. The model's objective function is minimizing the total number of new EV chargers in AMA (Equation 1). The optimization model includes four types of constraints. The first type of constraint (Equation 5) ensures that all the EVs of a PC3 area are assigned for charging between 6 am and 9 pm in either another or their PC3 between, or between 9 pm and 6 am in their PC. The second type of constraint (Equation 5) controls the daily capacity of chargers. This constraint ensures that every charger gives service to not more than 15 EVs between 6 am and 9 pm. The third type of constraint (Equation 5) controls for the night-time capacity of chargers. These constraints ensure that every charger gives service to not more than 13 EVs between 9 pm and 6 am. The fourth type of constraint (Equation 5) puts a cap on the maximum percentage of increase in electricity consumption in PC3 code *i* after allocation of EV chargers. The constraints allow for a maximum 40% and 80% increase in consumption scenarios.

Regarding the upper bounds of the variables, the maximum number of cars from PC3 code *i* charging in PC3 code *j* during the day (D_{ij}) is a function of the distance between the centroids of the PC3s. (Note that the model also allows for the possibility of an EV charging in its PC3 during days, reflected by decision variables D_{ii}.) According to the travel survey in AMA, only a fraction of cars in a PC3 travel for a certain distance (see Table 2). This is used for the calculation of the upper bounds of D_{ij}. The upper bound of the number of EVs charging in their own PC3 during nights is the expected number of EVs in 2030, equal to 40% of total cars nowadays. The upper bound of the number of chargers in a PC3 is equal to the total number of parking lots divided by 13 (given that each charger can serve up to 13 EVs during nights) multiply the fraction of the visitors of the PC3 coming from other areas of AMA and stay in their destination between 30 and 60 minutes. The latter constraint is proposed to ensure that enough parking area is reserved for different travel purposes.

The novelty of the proposed spatial optimization model is (1) incorporating the real-world data on the existing load on the electricity grid and (2) introducing caps for the increase in the grid load relative to the existing load of PC3 zones in different scenarios. The approach is unprecedented among the existing models and is novel. In terms of the formulation of the model, the model novelistically includes Ci, i.e. annual electricity consumption in PC3 code i (kWh), and λ, i.e. the maximum percentage point of increase in electricity

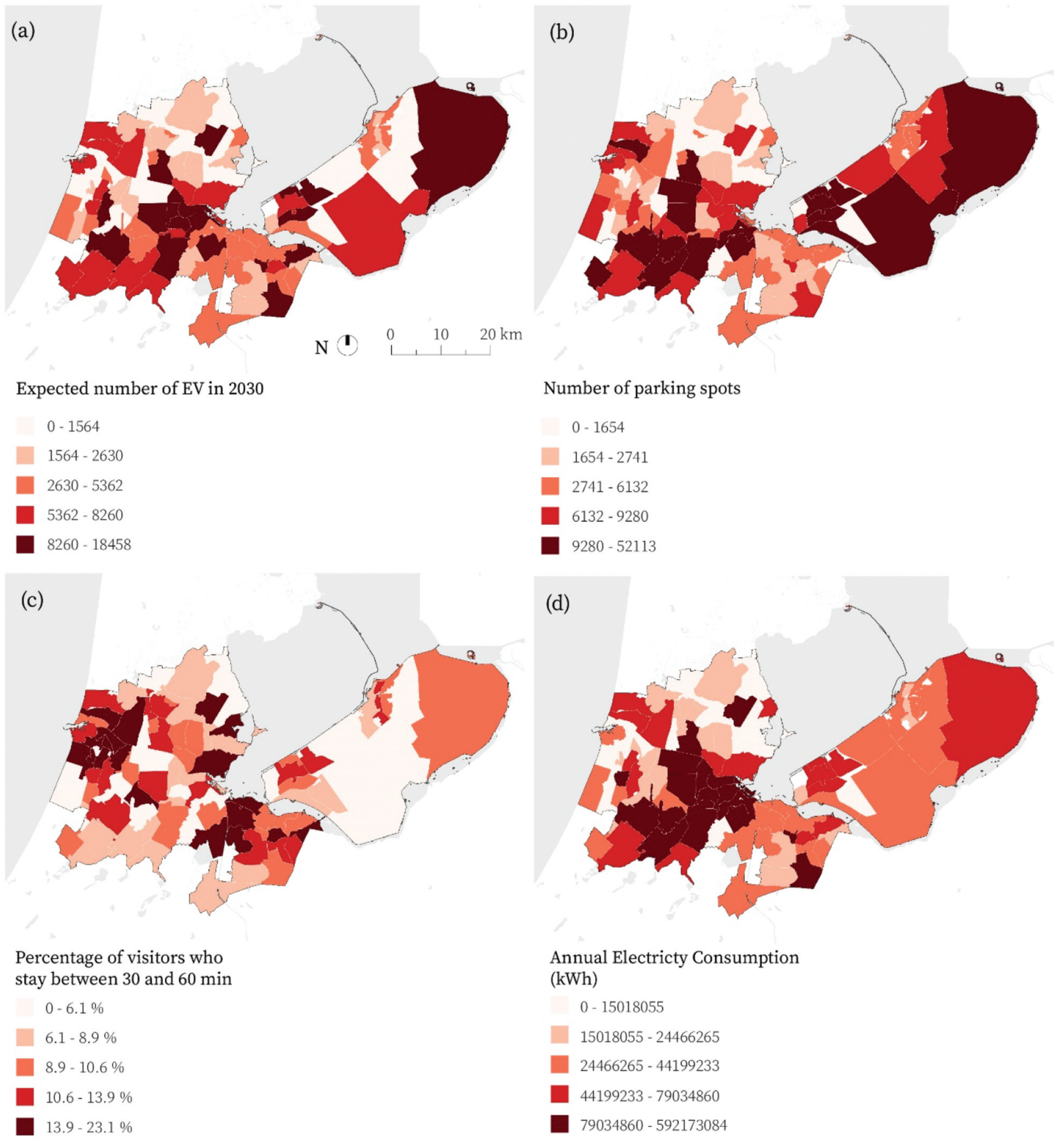

Figure 3. The basic data used for the optimization model includes the expected number of EV in 2030, i.e. 40% of total registered cars (a), number of public parking lots, excluding street parking (b), percentage of visitors from an origin in AMA staying in PC3s between 30 and 60 minutes (c), the annual electricity consumption of residential and non-residential buildings (d).

consumption in PC3 code i after allocation of EV chargers (40% or 80% in different scenarios). The model introduces caps on the additional load on the electricity grid as the maximum percentage point of increase in the existing load, that is λCi. The additional load is the sum of (1) day-time new load, i.e. the product of electricity consumption of an EV, C(EV), and the total number of day-time EVs that the model assigns to a PC3 $\left(\sum_{i=1}^{79} D_{ij}\right)$; and (2) night-time new load, i.e. the product of electricity consumption of an EV, C(EV), and the total number of night-time EVs that the model assigns to a PC3 $\left(\sum_{i=1}^{79} N_j\right)$. Overall, the novelty of the model is comprised in Equation 5 (the fourth constraint of the

Table 2. Deciles of car travels distance with origin and destination inside AMA.

Percentile	Max. travel distance [km]
10	1,70
20	2,70
30	4,00
40	5,00
50	8,00
60	11,00
70	16,10
80	25,00
90	40,00

model) as follows: $C(EV)\sum_{i=1}^{79} D_{ij} + C(EV)N_j \leq \lambda C_i$. The optimization model is formulated as follows.

Minimize

$$\sum_i X_i \tag{1}$$

Subject to:

$$\sum_{j=1}^{79} D_{ij} + N_i = EV_i \tag{2}$$

$$\sum_{i=1}^{79} D_{ij} - 15X_j \leq 0 \tag{3}$$

$$N_i - 13X_i \leq 0 \tag{4}$$

$$C(EV)\sum_{i=1}^{79} D_{ij} + C(EV)N_j \leq \lambda C_i \tag{5}$$

$$i \in [1, 79]$$
$$j \in [1, 79]$$

$$D_{ij} \in \left[0, f\left(L_{ij}\right)EV_i\right]$$

$$N_i \in [0, EV_i]$$

$$X_i \in [0, S_iP_i/15]$$

$$X_i, D_{ij}, N_i : integer$$

The decision variables of the model are as follows.

X_i: number of new chargers allocated at PC3 code i
D_{ij}: number of EVs from PC3 code i charging in PC3 code j during days (6 am to 9 pm)
N_i: number of EVs from PC3 code i charging in their own PC3 during nights (9 pm to 6 am)

The constants included in the model are as follows.
EV_i: number of registered EVs in PC3 code i, i.e. 40% of the total number of cars
L_{ij}: Walking distance between the centroids of PC3 code i and that of PC3 code j
$f(L_{ij})$: maximum percentage of EVs in PC3 code i which may charge in PC3 code i during days, 32 based on L_{ij} and the travel survey
P_i: number of available public parking spots in PC3 code
S_i: percentage of visitors to PC3 code i from other areas of AMA using car and staying at their 35 destination between 30 to 60 minutes
C_i: Annual electricity consumption in PC3 code i (kWh)
$C(EV)$: A constant showing annual electricity consumption of an EV (2,468,130 kWh)
λ: The maximum percentage point of increase in electricity consumption in PC3 code i after 39 allocation of EV chargers (40% or 80% in different scenarios)

The optimization models are developed using the MATLAB package for mixed-Integer Linear programming (MathWorks 2019).

4. Results

After running the mixed integer linear programming models for the two scenarios, the optimal solution of the maximum 40% increase scenario is found. In the case of the scenario 80% increase, a suboptimal solution with a 0.07% gap with the lower bound (i.e. the problem relaxing the requirement of finding integer solutions) is found. Given the marginal gap between the suboptimal solution and the lower bound (2.15 charger), the solution is accepted and used for the 80% scenario. In the following sections, the results of the models are presented.

4.1. *Total number of EV chargers and the distribution of charging during days and nights: similarities between scenarios*

The results show that the optimal solution of the scenarios with a maximum of 80% and 40% increase in electricity demand are similar in terms of the total number of allocated chargers and the share of car charging during days and nights. In the case of the scenario that allows up to an 80% increase in electricity demand, the optimal solution requires only four chargers less than the scenario of 40% (account for 0.1% decrease). According to the U.S. Department of Energy, the cost of each fast charger is 25,000 euros, and 13 plugins will cost about 147,000 euros, a total of 172,000 euros per charging station (Smith and Castellano 2015). This suggests that allowing the load on the electricity grid to be up to 40% higher saves 688 thousand euros out of almost 514 million euros. In other words, although the financial benefit of relaxing the constraints on electricity load is considerable in absolute terms, it is marginal relative to the total cost of the new infrastructure. The day and night charging shares are similar in both scenarios, with more than 53% of EVs travelling to other

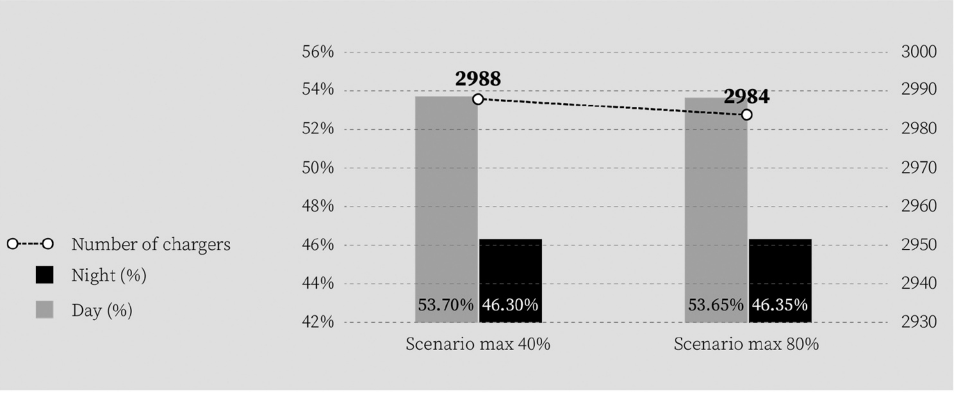

Figure 4. Similarities between the two scenarios, including a similar night and day share and the total number of chargers.

neighbours to charge during the day. This shows that multiscale allocation of EV chargers can vastly benefit from the regional flow of vehicles. In the max. 80% scenario, the share of charging in nights is 0.05% higher, which presumably contributes to fine tuning the optimal solution and the slight decrease in the number of chargers (Figure 4).

4.2. Spatial distribution of EVs' electricity demand: variations between scenarios

Although the difference between the total number of chargers and the difference between the distribution of charging across days and nights in the two scenarios are marginal, the distribution of extra electricity load substantially differs. The optimal solution for the scenario allowing for up to an 80% increase in electricity demand suggests a mixture of high and low allocation of extra load in different PC3s. In almost one-fourth of PC3s, the extra load outnumbers 40% of current electricity demand. In almost one-fifth of the PC3s, the extra load is higher than 50%. In return, in 40% of the PC3s the extra load is smaller than 20% of current electricity demand, and in 6% the extra load is zero. On the contrary, a more homogenous allocation of the extra load is achieved in the scenario that limits the extra electricity load to the maximum of 40%. In 40% and 34% of the PC3s, the extra load is only 2% to 5% short of the upper limit. In two-fifths of the PC3s, the maximum amount of allowed extra load is allocated. In return, only one-fourth of the PCs enjoy an extra load smaller than 20%, and in only one PCs no extra load is allocated (Figure 5).

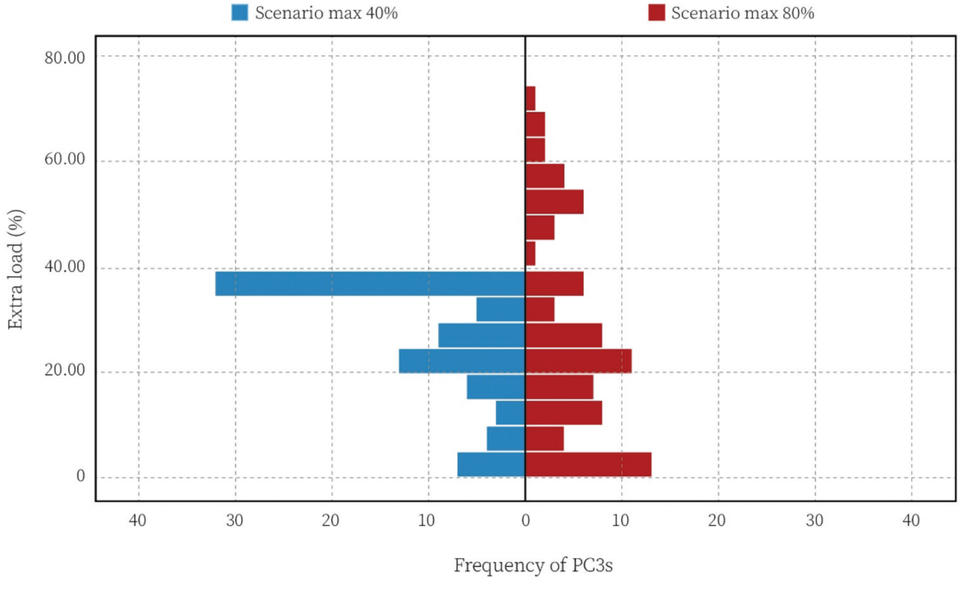

Figure 5. Percentage of extra grid load in the two scenarios (max 40% and max 80% of increase).

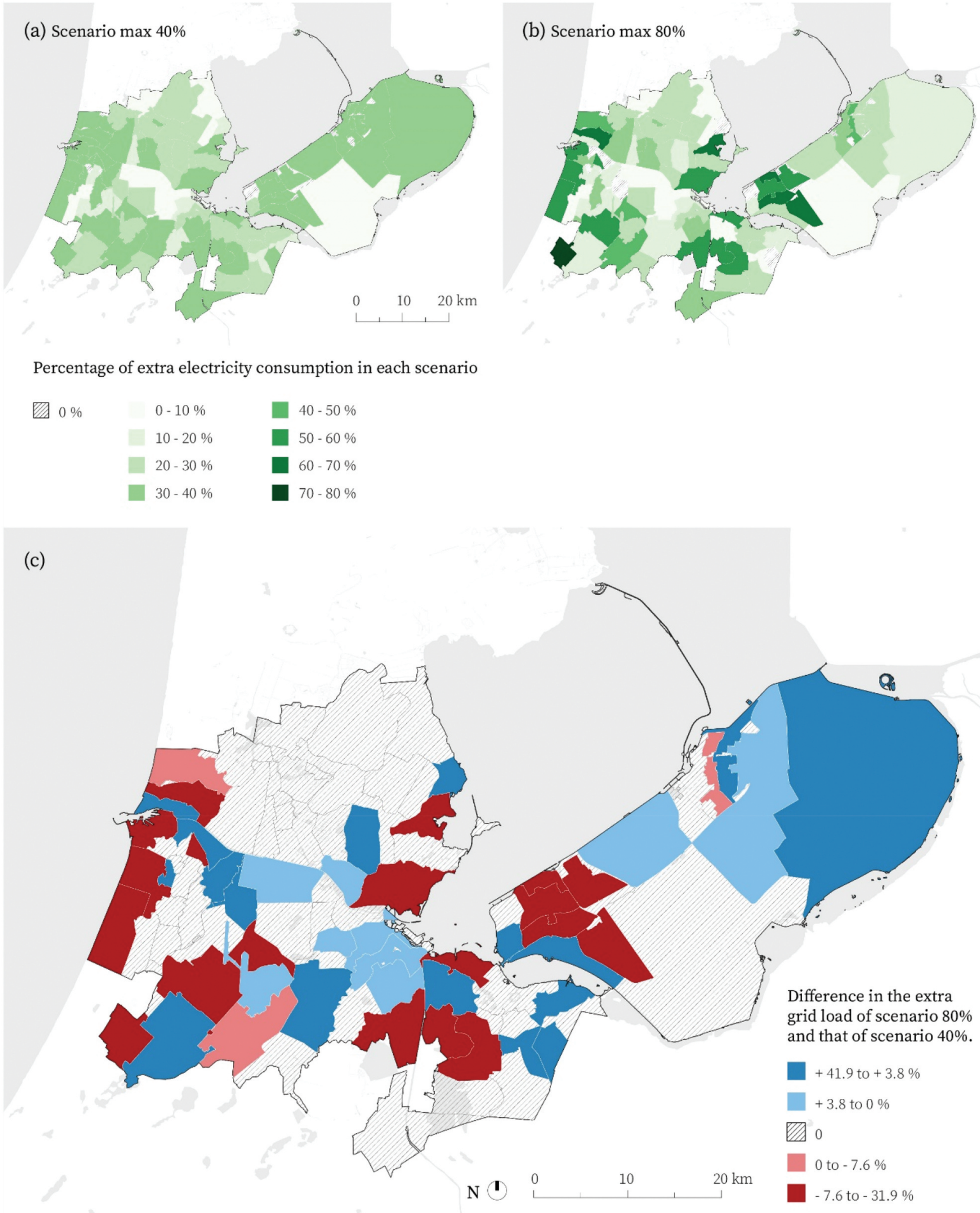

Figure 6. Distribution of extra electricity consumption for scenario 40% (a) and scenario 80% (b), and the difference in the extra grid load of scenario 80% and that of scenario 40% (c).

The spatial distributions of the extra loads across the PC3s in the scenarios with 80% increase and 40% increase represent two different solutions for meeting the electricity demands of EVs. In the scenario which only allows up to 40% increase in electricity demand, the extra load is shared between energy-intensive and non-energy-intensive PC3s (Figure 6a). In contrast, in the scenario which allows for up to 80% of extra load, EV charging infrastructure is concentrated in the PC3s with three characteristics: (1) accessible for substantial numbers of EVs at the regional scale; (2) with relatively low annual consumption; (3) reasonably high number of registered EVs to use chargers in the nights (Figure 6b). The difference between the extra grid load allocation of the 80% and 40% scenarios shows that in the former case, the load is concentrated in the areas adjacent to the main population centres. In contrast, in the latter case, the new electricity demand is diffused to various areas, among population centres in Northeast of AMA such as Lelystad and Dronten (Figure 6c).

The spatial distribution of extra grid load shows that multiscale allocation of EV infrastructure helps avoid allocating new chargers in Amsterdam city centre, the area with the most scarcity of space, in both scenarios. This is presumably due to the central location of Amsterdam city centre in AMA and accessibility of a large number of areas for daily charging. In the 40% scenario, the extra electricity load is homogeneously allocated across the areas around Amsterdam city centre. In an 80% scenario, however, the demand is

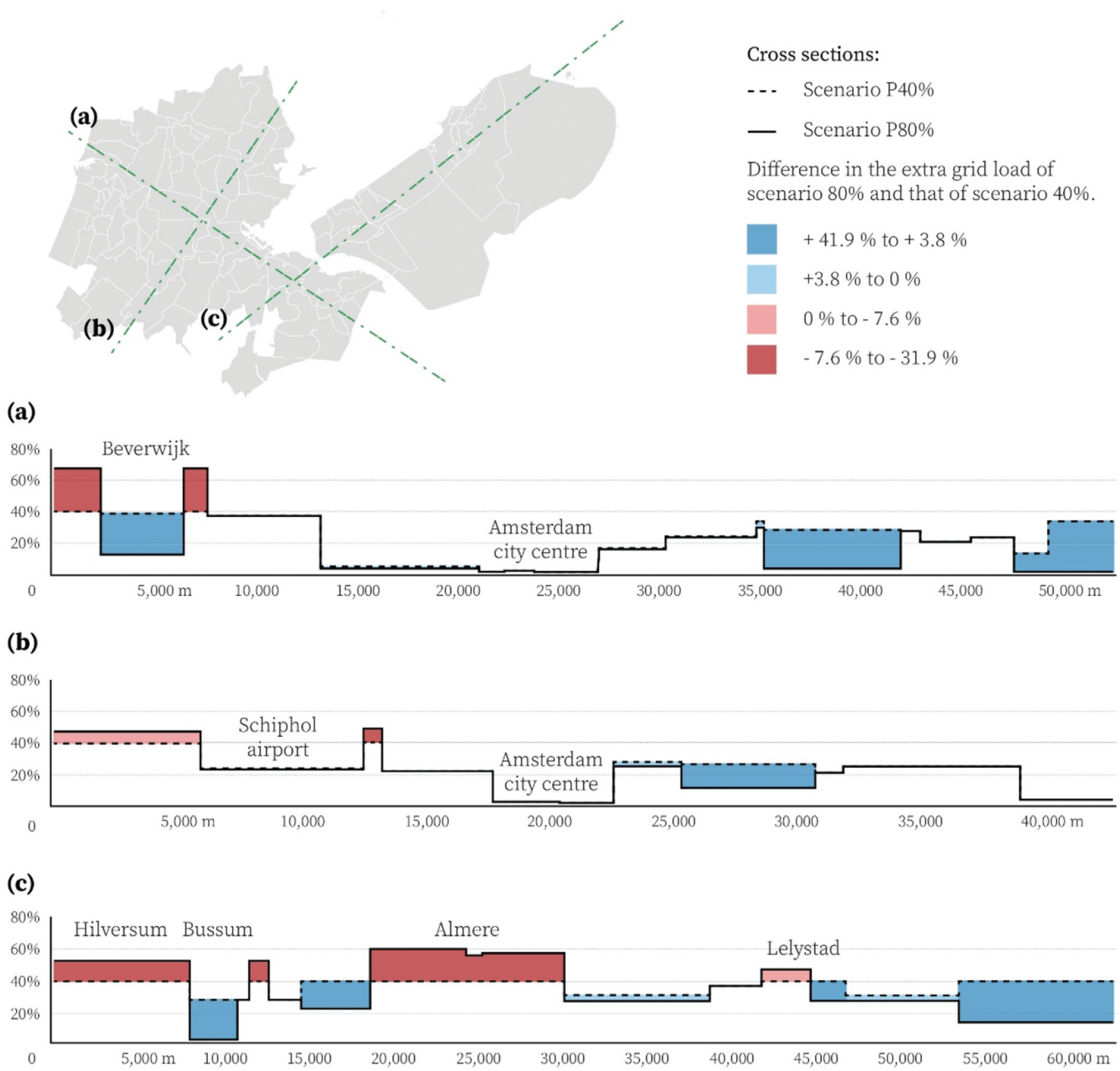

Figure 7. Difference in the extra grid load of scenario 80% and that of scenario 40% expressed on three cross-sections.

concentrated in the furthest possible areas from the centre (Figure 7a, Figure 7b). Among the peripheral areas of AMA, scenario 40% spread the extra load across the towns and villages in the region. In scenario 80%, in contrast, the load alternates between the most central and the most marginal towns, among them Hilversum, Almere, and Lelystad (Figure 7c).

5. Discussion and policy implications

The fast-growing adaptation of EVs puts a vast amount of effort into developing further charging infrastructure in motion. However, the development of such infrastructure is confined by the limited capacity of the electricity grid, which can render the allocation of new chargers in areas with a high density of cars and congested energy grid impossible. The previous studies on the optimal allocation of EV chargers failed to introduce an effective approach for tackling this challenge, mainly due to not including the real-world data of the load on the energy grid, a shortcoming presumably related to lack of data and limited spatial scope of their analysis. This study puts a novel approach to tackling this challenge forward. By incorporating the actual data on grid load at the local levels of scale, the approach allows controlling the increase in the grid load while allocating new charging stations. Such a novel component in the location-allocation models opens the opportunity for finding more realistic optimal solutions than the existing models that allocate EV stations regardless of the circumstances of the grid which need to fuel them. The multiscale approach introduced by this study opens new opportunities for the neighbourhoods with a congested grid and high density of cars, too. Incorporating the data on grid load at the regional scale help spotting the neighbourhoods with relatively lower pressure on the grid. Combined with travel survey data on the daily commute between the region's neighbourhoods, such an insight help to concentrate the new chargers in the areas visited by a relatively high number of EVs during the day and with leftover grid capacity. The approach adopted by this study, in short, opens a new opportunity for meeting the demand of a large amount of EVs in a region by optimally allocating chargers in only a fraction of neighbourhoods and offers new prospects for optimal distribution of grid load. This study shows that multiscale allocation of EV chargers substantially improves the efficiency of use, given that more than 53% of EVs can charge at their daily destination. The results also suggest that different scenarios for allocating extra grid load offer substantially different spatial patterns. In the following paragraphs, these results are further discussed.

5.1. Multiscale allocation of EV chargers: benefits and necessities

This study shows that the multiscale approach to electric mobility, i.e. allocation of day demand at the regional scale and night demand at the local scale, can substantially increase the efficiency of the use of EV infrastructure. In both scenarios examined by this study, more than 53% of the capacity of chargers of an area is used by the EVs from other areas during days. Lacking a comprehensive analysis of traffic flow at a regional or metropolitan scale, the current approach to EV infrastructure cannot guarantee the efficient use of the allocated chargers during days. The multiscale approach proposed by this study can offer innovative solutions for meeting future demands. To realize the multiscale approach, two types of interventions are essential. First, for the governance of the EV infrastructure, a new decision-making body with authority at the regional scale needs to be established. The decision-making body needs to include different stakeholders, including municipalities, energy companies, network operators, and regional governments. To achieve the goals set by Dutch Climate Accord, thirty energy regions in the Netherlands have been defined, along with specific goals and spatial plans. The regional energy strategies need to be appended with public authorities operating at the similar scale.

Second, charging in areas other than one's neighbourhood of residence could cause individual dissatisfaction, the so-called range anxiety. Range anxiety is the fear of an EV driver being stranded with an empty-battery vehicle before researching his or her destination or a charging point (Tate, Harpster, and Savagian 2008). It is likely that multiscale allocation of charging infrastructure, in which more than half of the EV is supposed to charge in other neighbourhoods, will trigger resistance among EV drivers. To tackle this problem, multiscale allocation of EV infrastructure needs to be coupled with the development of ICT infrastructure, which informs drivers of their options and effectively reduces their level of range anxiety. A study on travel behaviour of a group of EV drivers over six months shows that drivers' range anxiety is a subjective matter, to a substantial extent. What causes anxiety is the driver's perception of lacking enough charge before finding an empty charger or the shortage of 'useable range' (Franke et al. 2012). Provision of data on accessible chargers in different neighbourhoods helps drivers to have an objective understanding of their 'useable range' and reduces range anxiety among them (Du and De Veciana 2013). Smartphone applications can collect data on real-time traffic, destinations and useable ranges of all EV and tailor the most energy-efficient routes for each EV driver. The applications could plan EV charging in advance and reserve a charging spot at a specific time to assure drivers of their charging opportunities at their destination (Yaqub and Cao 2012).

5.2. *Allocation of EV grid load: two strategies*

The scenarios considered in this study show two spatial strategies for allocating EVs' charging load across a region. The first strategy is to concentrate a large amount of electricity demand in the areas where current electricity demand is low. It is necessary to consider vast developments in the electricity grid capacity to implement such a strategy. This may require direct connection of fast-charging stations to electricity substations to avoid imposing an extra load on the electricity grid. Direct connection to electricity substations must account for connectors' power and development costs. The distance between the charging stations and electricity substations, affecting the cost for new cables, should also be considered (Anonymized for review – b, Sadeghi-Barzani, Rajabi-Ghahnavieh, and Kazemi-Karegar 2014). Additionally, the possibilities of generating solar photovoltaic electricity to meet the EV demand could be studied (Verma et al. 2020). Regional allocation of EV infrastructure also opens opportunities for the use of wind energy to meet the electricity demand in the transportation sector (Mehrjerdi and Hemmati 2020). Models including solar and wind energy need to consider various geographic factors: solar radiation, wind speed, energy demand in different seasons, facilities for electricity storage, distance from natural areas, and social acceptance of windmills.

The second strategy for allocation of EV load is to put a cap on the maximum increase in electricity demand and to distribute the extra load across different areas. Similar to the first strategy, it requires an increase in the capacity of the electricity grid. Nevertheless, this strategy opens opportunities to utilize the current capacity by adapting demand-response strategies. The EU legislation paves the way for introducing demand-response mechanisms by regulating charging fees and access to charging facilities. Article 15.4 of the Directive 2012/27/EU on energy efficiency allows members states to adjust 'tariffs that are detrimental to the overall efficiency (including energy efficiency) of the generation, transmission, distribution, and supply of electricity [. . .]. Member States shall ensure [. . .] that tariffs allow suppliers to improve consumer participation in system efficiency, including demand response, depending on national circumstances' (Official Journal of European Union 2012. pp. L 315/22). Article 26 of the European Parliament directive on the deployment of alternative fuels infrastructure allows authorities to control the use of 'recharging or refuelling point[s] accessible to the public [. . .] through registration cards [. . .] which allow [. . .] private users physical access with an authorization or a subscription' (Official Journal of the European Union 2014. pp. L 307/4). These legislations open opportunities to apply demand-response mechanisms by dynamic pricing rate and direct control (Albadi and El-Saadany 2008). By adopting dynamic pricing mechanisms, authorities can charge different electricity fees to regulate the overall grid load in distinct locations. The direct control mechanism grants the authority to limit access to a charging facility, unplugging vehicles, or levying fine if and when the EV load exceeds a certain amount (Bonges and Lusk 2016).

6. Further studies

Further studies could benefit from detailed travel surveys, including the exact numbers of travels between every origin and destination at the regional scale. Moreover, further studies can benefit from data collected from smartphone apps used by a large and representative group of inhabitants. Alternatively, they can also benefit from the apps used for parking payments. Further studies can also use existing travel surveys to simulate traffic flows, which can subsequently provide information to elaborate optimization models. Further studies may consider the allocation of various types of chargers: slow-chargers (Level I), semi-fast chargers (Level II) and fast-chargers (Level III). The allocation of different types of chargers and plugins (see the model adopted by Baouche et al. 2014) allows for finding the most cost-efficient solutions offering visitors with different lengths of stay with charging opportunities.

Further studies can consider seasonal variations in the charging and electricity demand. Additionally, further studies in the Netherlands would need to consider the ambitions of the Dutch Government for phasing out gas consumption in dwellings before 2050 (Ministry of Economic Affairs and Climate Policy 2019) and a potential increase in electricity demand in cold seasons. Moreover, the intensity in electricity consumption could further increase due to climate change and urban heat islands in warm seasons (Mashhoodi, 2020), and potential inequality of global warming (Mashhoodi, 2021) which can create new dimensions of energy- and transport poverty. Therefore, further studies could combine the allocation of EV chargers and climate adaptation models for efficient management of overall electricity load on the grid.

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ORCID

Bardia Mashhoodi http://orcid.org/0000-0002-7037-3932
Pablo Muñoz Unceta http://orcid.org/0000-0003-1670-2691

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