35th International Electric Vehicle Symposium and Exhibition (EVS35)
Oslo, Norway, June 11-15, 2022

Forecasting Residential Charging Demand for Public Charging Stations in Urban Areas: A Spatial-Temporal Approach

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Summary

We present a novel method to forecast public residential charging demand over a longer time horizon at a detailed spatial level. Our method relies on initial EV adoption data, socio-economic attributes, and GIS data, and is applied to the city of Brussels. One-year-ahead predictions are validated against an independent dataset of real-world charging sessions at 253 public charging stations. While the model shows considerable variability in its errors, its performance is comparable to existing models proposed in the literature. We furthermore find that correcting predictions for off-street parking availability does not improve model performance in the current adoption phase.

Keywords: charging, infrastructure, demand, prediction

1 Introduction

Electric vehicles (EVs) have a great potential to reduce the impact of climate change and improve local air quality, which has led many cities to set ambitious electrification targets for passenger cars. However, the availability of sufficient EV charging infrastructure (EVCI) is vital for electric vehicles to become adopted by the vast majority of consumers [1]. Predicting the charging demand for public EVCI is a fundamental step in expanding the existing infrastructure.

Existing research typically uses data mining techniques [2, 3] or simulation methods [4, 5] to forecast the spatial-temporal charging demand of EVs. However, the temporal resolution in existing studies is often limited to a 24-hour time span, while urban planners would benefit from spatial-temporal forecasts on longer time horizons (i.e., 5 to 10 years) to develop their EVCI roll-out strategies. In this paper, we propose a new method to forecast residential charging demand based on EV adoption data, socio-economic attributes, and GIS data. Our method builds upon previous research on the spatial-temporal distribution of technology diffusion as proposed in [6]. To the best of our knowledge, this is the first study to forecast charging demand over a longer time horizon at a detailed spatial level and to validate the results with independent, real-world charging data.

2 Methodology and Data

The conceptual model in Figure 1 demonstrates the three steps of the proposed method. First, the static spatial-temporal technology-diffusion model (STDM) as proposed in [6] is used to forecast EV adoption. Second, land-use variables from GIS databases, combined with data on the EV driver's travel behaviour are used to transform adoption forecasts to public residential charging demand in kWh. Third, the predicted charging demand is validated with an independent dataset of real-world charging data measured at 253 public charging stations.

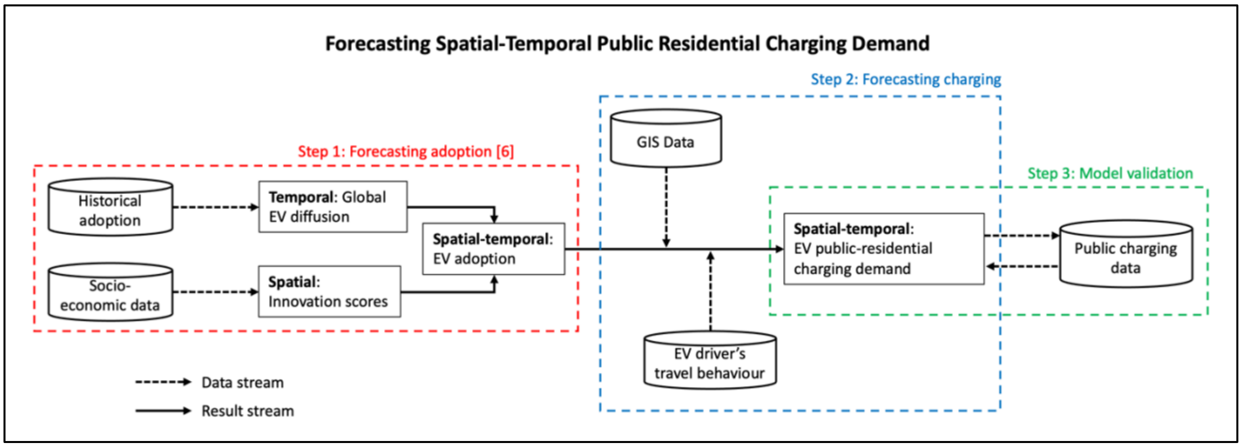


Figure 1: Conceptual model.

The city of Brussels is taken as a use case to validate the model. Brussels is an interesting use case as it is a large city (1.2 million residents, 160km^2 area), with a diverse population living in different degrees of urbanization. Furthermore, Brussels has ambitious electrification targets and is in the process of expanding its public charging infrastructure. Hence, this research demonstrates how initial data on EV adoption, socio-economic attributes and land-use data can be used to support cities in the expansion of their EV charging infrastructure. The following subsections elaborate on the three steps from the conceptual model.

2.1 Step 1: Forecasting adoption

STDM is a method proposed in [6] that can be used to forecast the diffusion of new technologies in space and time. This method will be briefly described below, however, more information can be found in [6]. The model produces a matrix $[\hat{Y}]_{t,s}$ that contains the predicted level of adoption for each spatial cell $s \in S$ at each time step $t \in T$. In the static STDM version, forecasts are made top-down in two main steps. First, a global EV diffusion forecast is made that determines the total adoption at each time step t. Second, given the global adoption at time step t, this is allocated over the spatial cells. The allocation is based on each cell's adoption preference (expressed by the 'Innovation Score' (IS)), its adoption capacity and the cell state. The cell states are the discrete steps in which adoption is assumed to take place. These are calculated as percentages (taken from an S-curve) of the cell's total adoption capacity. Figure 2 shows an example of how the adoption in 5 spatial cells (ID71 to ID31) is forecasted over time, where each cell is assumed to pass through 5 cell states. All cells are ranked according to their IS (from highest to lowest), after which cell states are filled as long as the global adoption at time t (shown in the black circles) still allows to do so.

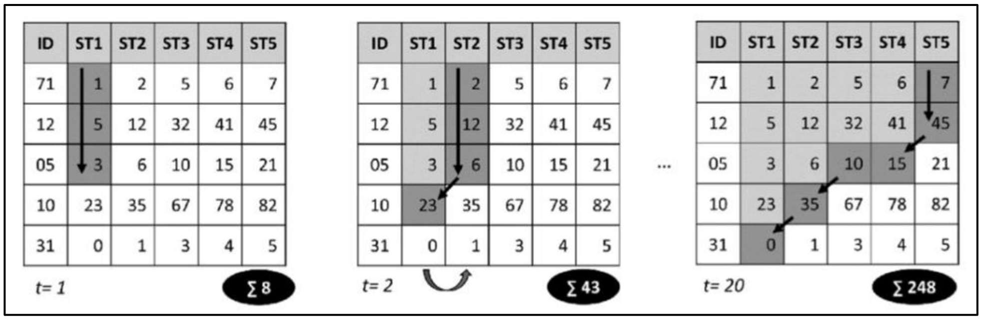


Figure 2: Example of adoption forecasts in the static STDM method. Figure is taken from [6].

2.1.1 Temporal: Global EV diffusion

Diffusion models have been used extensively in previous research to forecast EV adoption over time, of which the Bass diffusion theory received the most attention [7]. Estimating a Bass model requires three parameters: the coefficient of innovation (p), imitation (q) and market potential (M). As estimating these exact coefficients is challenging with only limited historical adoption data, this paper also relies on historical reported parameter values in literature and adoption rates in comparable cities (e.g., Oslo [8]) to fit the p and q values. The Bass model uses the parameters given in Table 1 and the following formula to calculate at each time step t the cumulative number of adopters $F(t)$ [7]:

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{p}{q} e^{-(p+q)t}} \times M \tag{1}$$

Table 1: Bass model parameters.

Parameter	Meaning	Value	Source
p	Coefficient of innovation	0.00085	Assumption
q	Coefficient of imitation	0.35	Assumption
M	Market potential	492.459	[9]

2.1.2 Spatial: Innovation Scores

The Innovation Scores (IS) represent the relative preference of each spatial cell to adopt EVs. This concept relies on previous research that has identified spatial patterns in the adoption of EVs, depending on various socio-economic variables [10-13]. This paper uses the statistical sector level in Brussels as unit of spatial cells (N = 724; μ_{area} = 0.22km^2; $\mu_{population}$ = 1,683). The adoption of new technologies is known to exhibit spatial patterns [10-12], meaning that the level of EV adoption in one neighbourhood is likely to be similar to the adoption in its surrounding neighbourhoods. Thus, the following Spatial Lag Regression model is fit to estimate the IS of each spatial cell [14]:

$$y = \alpha + \beta X + \rho W y + \varepsilon \tag{2}$$

With y representing the vector of EV registrations per thousand cars, α the intercept, β the vector of coefficients, X the vector of independent variables, ρ the spatial lag coefficient, W the spatial weights matrix and ε the vector of errors. The independent variables were selected based on previous research on the spatial adoption pattern of EVs [8-10]. The spatial weights matrix is constructed by Queens contiguity neighbourhoods. Table 2 gives an overview of all variables, including their description, summary statistics and source. All variables were collected from the Belgian statistical office (Statbel). Due to privacy, no data was provided for statistical sectors containing less than 30 residents (which mostly are non-residential areas such as parks, industrial zones, etc.), meaning that the regression model was fit on 647 spatial cells in total.

Table 2: Descriptive statistics for variables in the spatial regression model.

Variables (N = 647)	Description	Mean	Std. dev.	Min.	Max.	Source
YOUNG	Residents between 18-29 years old (%)	16.82	5.09	0.55	65.18	Statbel, 2020
MIDDLE	Residents between 30-59 years old (%)	42.14	5.54	7.14	66.91	Statbel, 2020
OLD	Residents between 60-79 years old (%)	14.62	4.91	1.31	56.86	Statbel, 2020
EDU_HIGH	Residents with post-secondary degree (%)	18.41	8.76	2.09	44.14	Statbel, 2017
OWNERS	Residents living in owned dwellings (%)	42.10	17.89	0	88.03	Statbel, 2017
INC	Median net taxable income (euro)	22,299	4,917	3,206	44,712	Statbel, 2019
HH_LARGE	Households of size 5 or larger (%)	8.69	5.22	0	27.43	Statbel, 2016
B(H)EV	Count of private BEV & HEV per 1000 cars	18.64	15.64	0	200	Statbel, 2020

2.1.3 Spatial-temporal: EV adoption

Given the global EV diffusion model and the IS for each spatial cell, the matrix $[\hat{Y}]_{t,s}$ can be constructed using the allocation method described previously (see Figure 2). This method is implemented in Python and predictions are made for T=10 years with time steps of 1 year and S=647 spatial cells. The adoption capacity for each spatial cell is set equal to the current number of ICEVs in the cell and cell states are discretised in 1-year intervals.

2.2 Step 2: Forecasting charging

The spatial-temporal forecasts resulting from step one are disaggregated from the statistical sector level to building block level. There are 4,992 building blocks in total which are all either delimited by streets or municipality borders. Figure 3 shows an example of these spatial entities in Brussels. For each statistical sector, the demand is uniformly distributed according to the number of building blocks in the sector.

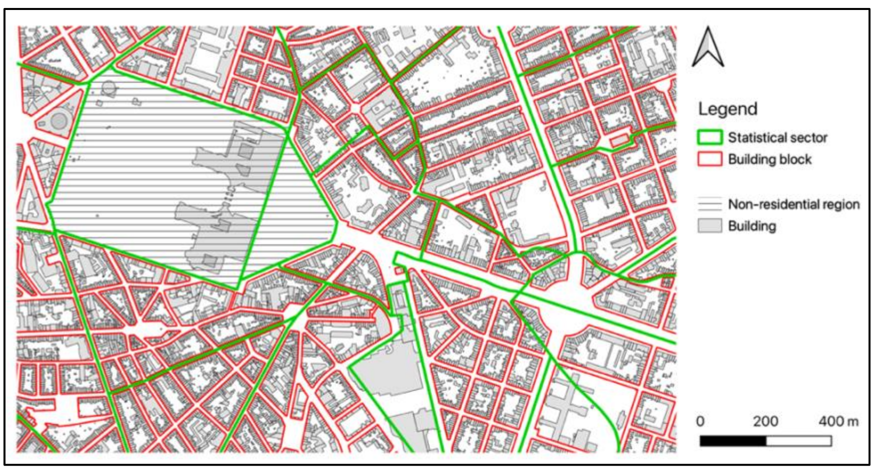


Figure 3: Overview of different spatial entities in Brussels.

Next, the forecasts on building block level are transformed to residential charging demand at public charging stations. For each EV adopter its residential charging demand is estimated via the following formula:

$$1 \text{ EV} = (ADT \times EC \times RCR \times \lambda PCR_{bb} \times 365) \text{ kWh per year} \quad (3)$$

The parameters in this formula are defined in Table 3, along with their estimated value, unit, and source. While the ADT, EC and RCR parameters are assumed to be constant over the entire study area, the PCR is calculated for each building block (bb) separately. The purpose of the latter is to correct for differences in off-street parking availability as this is expected to affect the extent to which residents rely on public charging infrastructure [15]. The λ parameter is used to control for the PCR effect.

Table 3: Assumptions on EV travel and charging behaviour.

Parameter	Meaning	Value	Unit	Source
ADT	Average Distance Travelled	25	km/day	[16]
EC	Energy Consumed	0.2	kWh/km	[17]
RCR	Residential Charging Ratio	20	%	Assumption
PCR	Public Charging Ratio	*Varies per building block*	%	Calculations based on [18]
λ	Binary variable to correct for PCR	0 (Model 1) or 1 (Model 2)	-	-

The PCR for each building block is calculated based on the ratio of off-street parking places in a building block to the number of households living in that building block, as shown in equation (4). This research uses the Public Access Road (PAR) dataset [18] to estimate the number of off-street parking places in each building block. The dataset contains points on the public road where the entrance to (one or more) off-street parking place(s) is located (i.e., a garage exit, private driveway entrance, etc.). By counting these public access points, a defensive estimation of the minimum number of off-street parking opportunities in the building block is obtained. To link each public access point to its corresponding building block, a nearest neighbour search between each public access point and the nearest address point is first conducted. Afterwards, the address points are linked to the building block they are in, and the number of off-street parking places per building block is counted. The number of households per building block is determined by uniformly distributing them from statistical sector level to building block level.

$$PCR_{bb} = 1 - \frac{\#\ \text{Off-street parking}_{bb}}{\#\ \text{Households}_{bb}} \tag{4}$$

2.3 Step 3: Model validation

In step three, an independent dataset of charging sessions at public charging stations in Brussels is used to validate the model's predictions and perform sensitivity analyses on the input parameters. The model is built by using data up until 2020, and the validation is done for the one-year ahead predictions made for 2021.

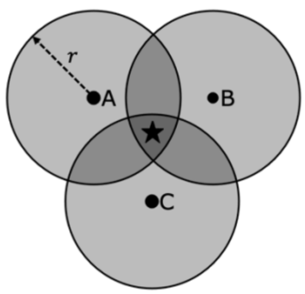
2.3.1 Data pre-processing

The data-pre-processing of the charging dataset contains multiple sequential steps. First, general data-cleaning was performed, including removing invalid charging sessions (e.g., sessions with missing data, invalid attributes, etc.), filtering out those sessions that did not start or end in 2021 and geo-referencing each session with the coordinates of its charging station. Second, filtering for including only residential charging sessions was performed. In this paper, we define residential charging as those sessions starting after 5 pm and having a duration of at least 6 hours. Third, charging stations that were active for only 30 days or less were removed from the dataset. Fourth, all charging volumes are aggregated (summed up) per charging station, resulting in a kWh measure of the observed residential charging demand at each station. After all data cleaning, 253 public charging stations are included in the validation dataset.

2.3.2 Comparing forecasts to observations

As the number of EV adopters is relatively low and public charging infrastructure is expanding rapidly, additional challenge arises when comparing the forecasted with the observed demand. First, charging demand can only be observed at those locations where existing charging stations are present. Second, many public charging stations were placed throughout the year and have only been active for a certain portion of the year.

Therefore, forecasts are compared with their observations according to the method presented in Figure 4. For each existing charging station, a buffer with radius r is constructed around the station, representing the maximum distance EV owners are willing to walk to a charging station. Next, the forecasted demand of all building blocks within the range r of the charging station (measured as the crow flies from the centroid of the building block to the charging station) are summed up, resulting in the forecasted demand for that charging station. When a building block is within the range r of two or more charging stations, its forecasted demand is equally divided over those stations, however, considering the instalment date of these stations. A numerical example is included in Figure 4. A radius of $r = 300$ meter is used in this study, as sensitivity analysis shows this gives the best model performance. This is also within the range of distances used in previous studies (e.g. 250 meter in [19] 350 meter in [20], 500 meter in [21]).



Station	Installation	Age	Weight	Forecast
A	01/01/2021	$\frac{365}{365}$	$=\left(\frac{90}{365}\times\frac{1}{1}\right)+\left(\frac{122}{365}\times\frac{1}{2}\right)+\left(\frac{153}{365}\times\frac{1}{3}\right)=55\%$	$55\ kWh$
B	01/04/2021	$\frac{275}{365}$	$=\left(\frac{0}{365}\times\frac{1}{1}\right)+\left(\frac{122}{365}\times\frac{1}{2}\right)+\left(\frac{153}{365}\times\frac{1}{3}\right)=31\%$	$31\ kWh$
C	01/08/2021	$\frac{153}{365}$	$=\left(\frac{0}{365}\times\frac{1}{1}\right)+\left(\frac{0}{365}\times\frac{1}{2}\right)+\left(\frac{153}{365}\times\frac{1}{3}\right)=14\%$	$14\ kWh$

Figure 4: Numerical example of mapping forecast to existing infrastructure.

2.3.3 Measuring performance

As the observed residential charging demand (Y) and the forecasted demand ($\hat{Y}$) are now available for each charging station, the model can be validated by comparing both. The coefficient of determination (R^2), Mean Absolute Error (MAE) and Root Mean Square Error ($RMSE$) are used to evaluate the model:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n}(Y_i - \mu)^2} \tag{5}$$

$$MAE = \frac{\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right|}{n} \tag{6}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \tag{7}$$

3 Results & discussion

3.1 Forecasting adoption

The global diffusion model resulting from the parameters presented in Table 3 is depicted in Figure 5. The Bass model was calibrated at face value with historical adoption figures from Brussels [9] (yellow line) and historical adoption rates in Oslo [8] (orange line).

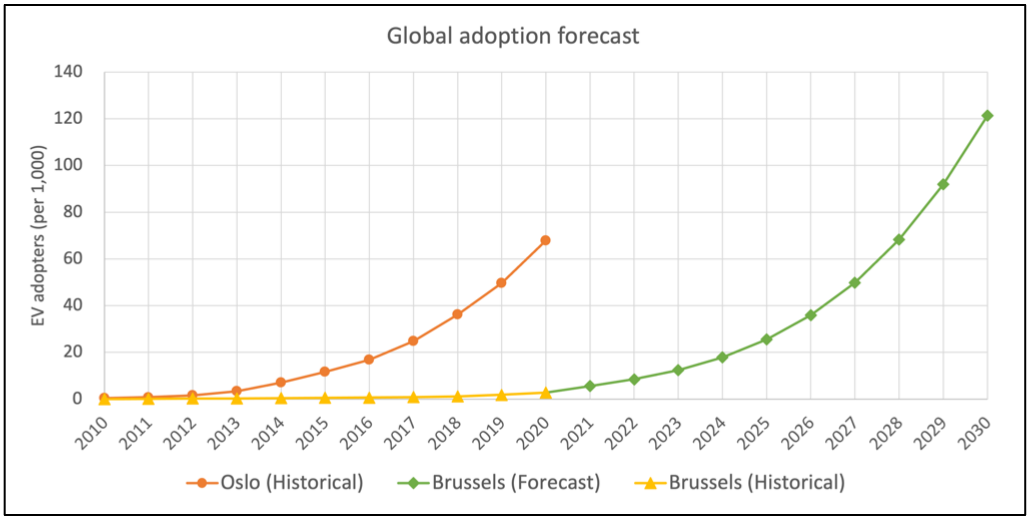


Figure 5: Global EV forecast.

The results of the spatial regression analysis are presented in Table 4. All independent variables are standardized to make their coefficients more comparable. The percentage of owners and large households are not found significant in the model, while all other variables (including the spatial lag) are significant. The association between age and the number of B(H)EV adopters is positive and highest for older aged residents (60-79 years), followed by middle-aged residents (30-59 years) and young residents (18-29 years). This is consistent with results from previous research [10]. Also, income is positively associated with B(H)EV adoption. Lastly, the proportion of highly educated residents is found to be negatively associated with adoption, which is opposite to what is found in previous studies [10, 11]. A possible explanation is the large correlation of this variable with the other explanatory variables, possibly causing multicollinearity. The highest variance inflation factor (VIF) observed is 4.65, indicating the presence of this effect, however within the threshold tolerance level of 10 [11]. The predictions from this regression model are ranked and used to determine the IS for each statistical sector (with a higher prediction corresponding to a higher IS).

Table 4: Spatial regression results.

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**p-value**
Intercept	15.866***	0.994	15.969	0.000
YOUNG	3.484***	0.775	4.497	0.000
MIDDLE	4.502***	0.957	4.706	0.000
OLD	8.827***	1.101	8.020	0.000
EDU_HIGH	-1.761*	1.031	-1.709	0.088
OWNERS	0.616	0.769	0.801	0.423
INC	5.201***	0.962	5.408	0.000
HH_LARGE	1.101	0.859	1.282	0.200
Spatial lag (ρ)	0.027***	0.008	3.333	0.001

*Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

After applying the static STDM [6], the resulting adoption forecasts at t=2021 and t=2031 are given in Figure 6 and Figure 7.

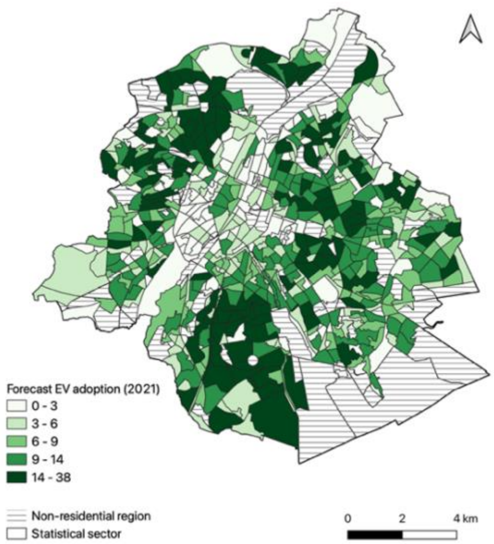


Figure 6: Forecast EV adoption 2021.

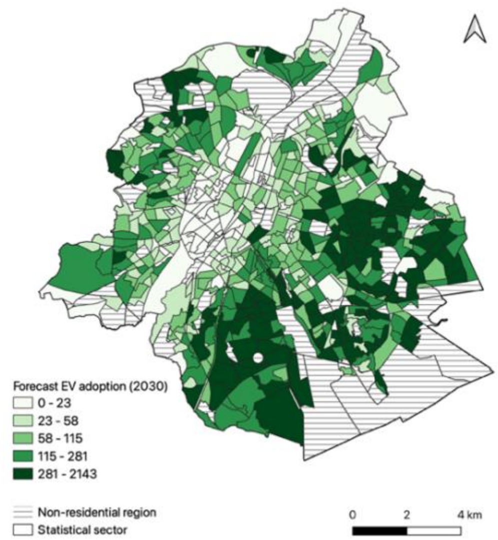


Figure 7: Forecast EV adoption 2030.

3.2 Forecasting charging

The predictions from step one are recalculated to demand for residential charging (in kWh). The calculated PCR for each building block is given in Figure 8. The predicted demand before and after applying the PCR correction at t=2021 are given in Figure 9 and Figure 10.

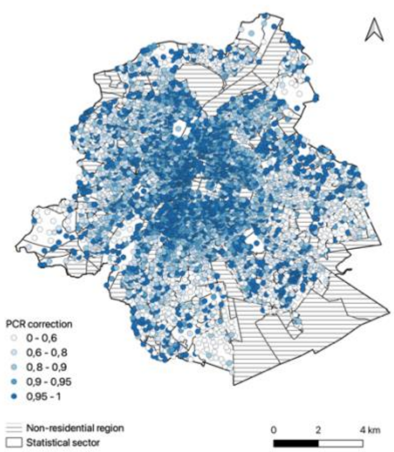


Figure 8: PCR correction per building block.

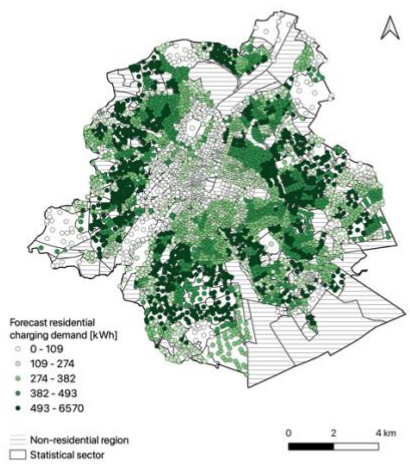


Figure 9: Predicted demand before PCR correction (t=2021).

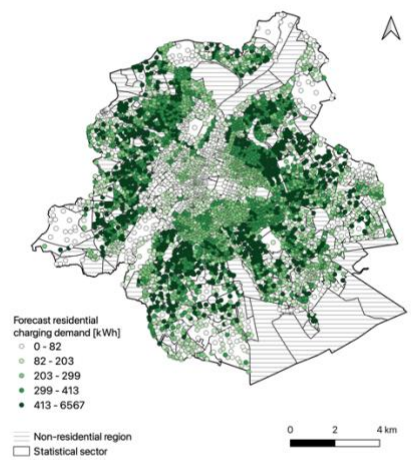


Figure 10: Predicted demand after PCR correction (t=2021).

3.3 Validation

The forecasted residential charging demand is compared to the observed residential demand at all locations where existing charging stations are present in the charging dataset. Before validating the model with the proposed performance criteria, the forecasts are first transformed so they sum up to the total observed demand. In this way, the performance of different versions of the model can be compared with each other. Table 5 presents the model performance for the model without PCR correction (Model 1) and with PCR correction (Model 2).

Table 5: Model performance with and without PCR correction.

Criteria	Model 1 ($\lambda = 0$)	Model 2 ($\lambda = 1$)
R^2	0.42	0.36
MAE (kWh)	935	979
$RMSE$ (kWh)	1,230	1,294

Two remarking results are noteworthy. First, even though our best model shows high variability (both MAE and $RMSE$ are high compared to the average observed volume of 1,940 kWh), its performance measured by the R^2 value (0.42 for Model 1 and 0.36 for Model 2) is similar with other models proposed in the literature. In [20] the authors report a R^2 value of 0.38 when using an OLS regression to predict the consumed energy at slow charging pools (i.e., slow charging stations located near each other). Using the same method the authors of [22] report a R^2 value of 0.44. Finally, the authors of [23] report a pseudo R^2 value of 0.32 when fitting a Beta regression model to predict the charge point utilization based on points of interest nearby the station. However, these models were all constructed from model fitting procedures that utilise the observed charging data to fit the model's parameters. On the contrary, the performance reported in the model presented in this paper results from one-year-ahead predictions based on initial EV adoption data, socio-economic attributes, and GIS data. The charging data used to validate our model is independent of the data used to train the model, as the former is used to quantify the model's performance. As a result, our model can be used to support the data-driven roll-out of charging infrastructure, even when EV adoption is still low and limited charging data is available.

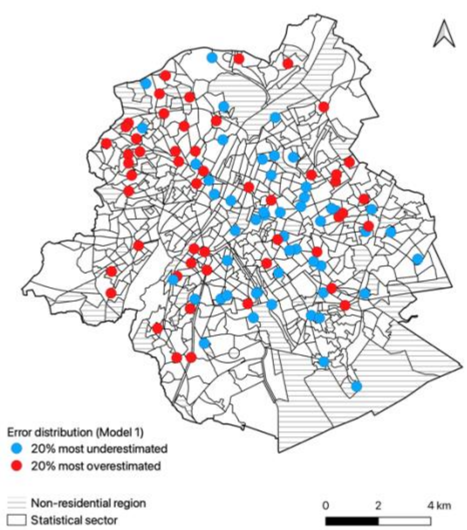


Figure 11: Spatial distribution of error (Model 1).

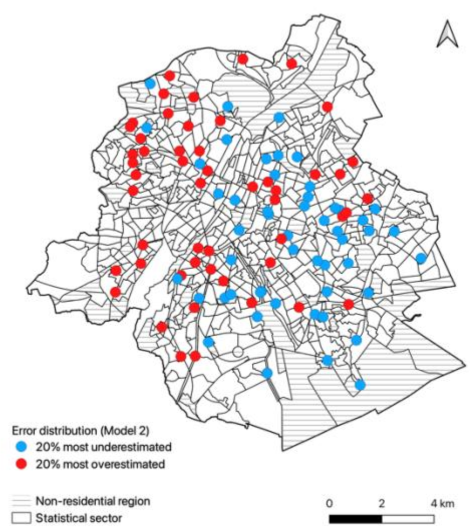


Figure 12: Spatial distribution of error (Model 2).

Second, the model's performance is surprisingly not improved when incorporating the PCR correction (i.e., $\lambda = 1$). This is unexpected as more public residential charging is expected in areas with less off-street parking availabilities [15]. A possible explanation might be found in the fact that EV adoption is still in its very initial phase. A previous survey on the Belgian e-driver [24] indicated that most EV adopters in Belgium have access to either a private charging station at home or at work to charge their vehicle. Correcting demand towards areas with less off-road parking might have no, or (as in this case) even an adverse effect because almost no EV adopters are currently found in these areas. This argument is also supported when investigating the spatial distribution of the model's error in Figure 11 and Figure 12. The 20% most over- and underestimated charging stations are depicted as red and blue points respectively. Both maps show a spatial pattern: most overestimations occur at charging stations in the northwest area of Brussels (characterized by lower-income households living in high population densities) while most underestimations occur in the southeast area (characterized by higher-income households living in low population densities). Correcting for PCR shifts demand even more towards the former area, potentially causing the increase in the model's error.

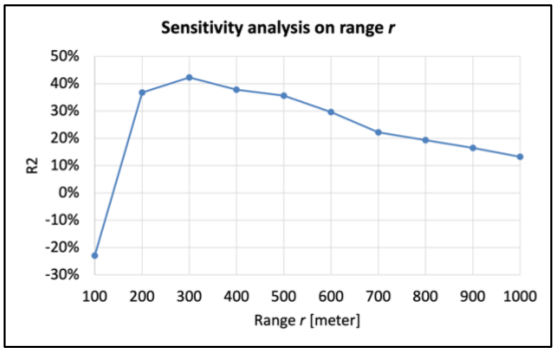


Figure 13: Sensitivity analysis on range (part 1).

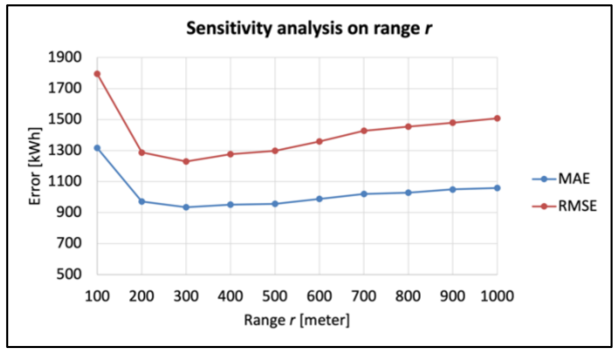


Figure 14: Sensitivity analysis on range (part 2).

Figure 13 and Figure 14 present the results of a sensitivity analysis on the maximum range r used to map the forecasts to the observations. The sensitivity analysis was done for model 1 (without PCR correction). All criteria show that model performance is highest for a range of 300 meters.

4 Conclusion

In this paper, we have proposed a method that is able to forecast the spatial-temporal distribution of public residential charging demand in large, urban areas. To the best of our knowledge, this is the first study to forecast charging demand over a longer time horizon at a detailed spatial level and to validate the results with independent, real-world charging data. The model was applied to the city of Brussels, where we used EV adoption data, socio-economic attributes, and GIS data up until 2020 to predict the spatial distribution of residential charging demand for the coming 10 years. The one-year-ahead predictions for 2021 were validated with real-world charging data. Our model showed to have considerable error rates, however, comparable to existing models proposed in the literature in terms of their coefficient of determination (R^2). Finally, we also found that correcting forecasts for off-street parking availability did not improve the model's performance. This might be due to the initial adoption stage Brussels is currently in, as previous surveys revealed that initial adopters usually have access to private charging points either at home or at work. It is expected that in the coming years, when not all EV adopters will have access to private charging points, corrections for off-street parking availability will be more influential on the model's performance.

This research has some limitations. First, the conversion of EV adopters to EV charging demand relies on strong assumptions regarding EV travel behaviour (see Table 3). The values of these parameters are likely to vary spatially and temporally. More research on these parameters is needed to better incorporate their effect. Second, this work focuses mainly on validating the predictive performance over space, not time. That is, predictions made beyond 2021 are not validated as insufficient charging data is available for validation at this moment. However, decision makers can still use the spatial-temporal predictions as a guideline to develop their long-term EVCI roll-out strategies. Future work involves forecasting opportunity charging demand, allowing to reveal the interaction effects with residential charging demand.

Acknowledgments

S.W. acknowledges a fellowship from the Research Foundation Flanders (FWO-Vlaanderen) under Grant No. 11I5122N.

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