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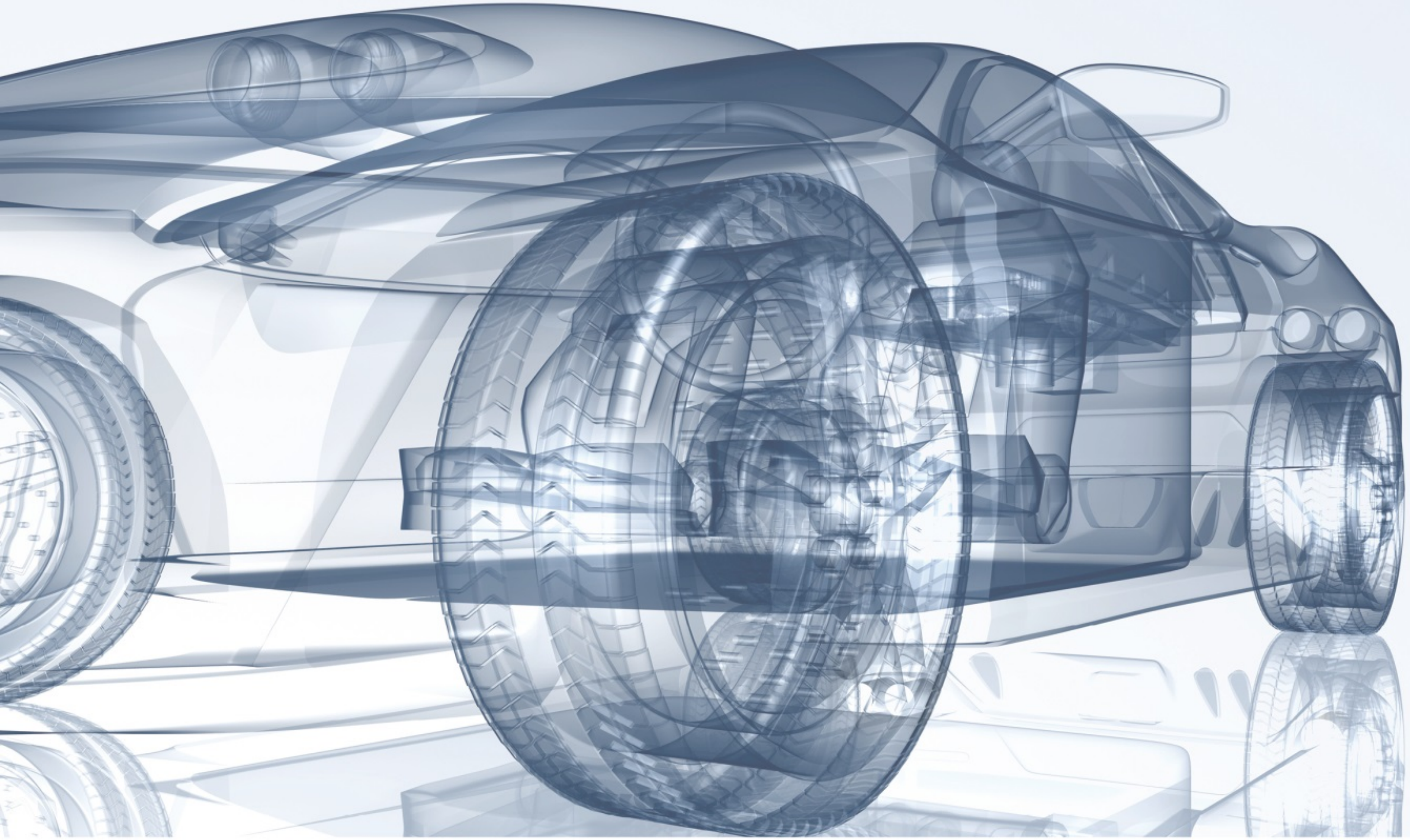

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Predicting charging infrastructure availability based on a space-time series model

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Research question

What?

What is the probability a specific charging station will be available at a given time?

How?

By using a space-times series predicting approach

Where?

Amsterdam Central district

When?

October 2016

Charging data Amsterdam Central district

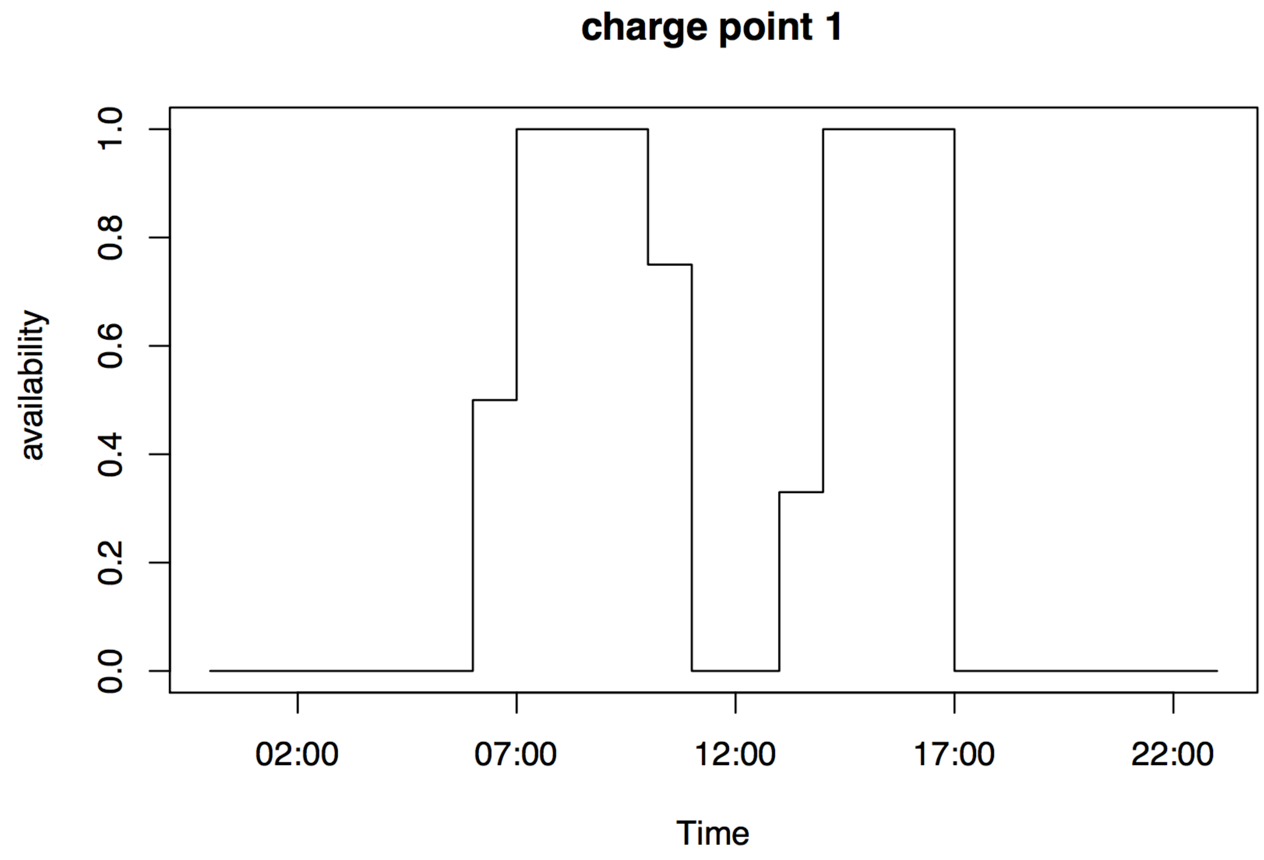
152 distinct charge points

11404 charging events

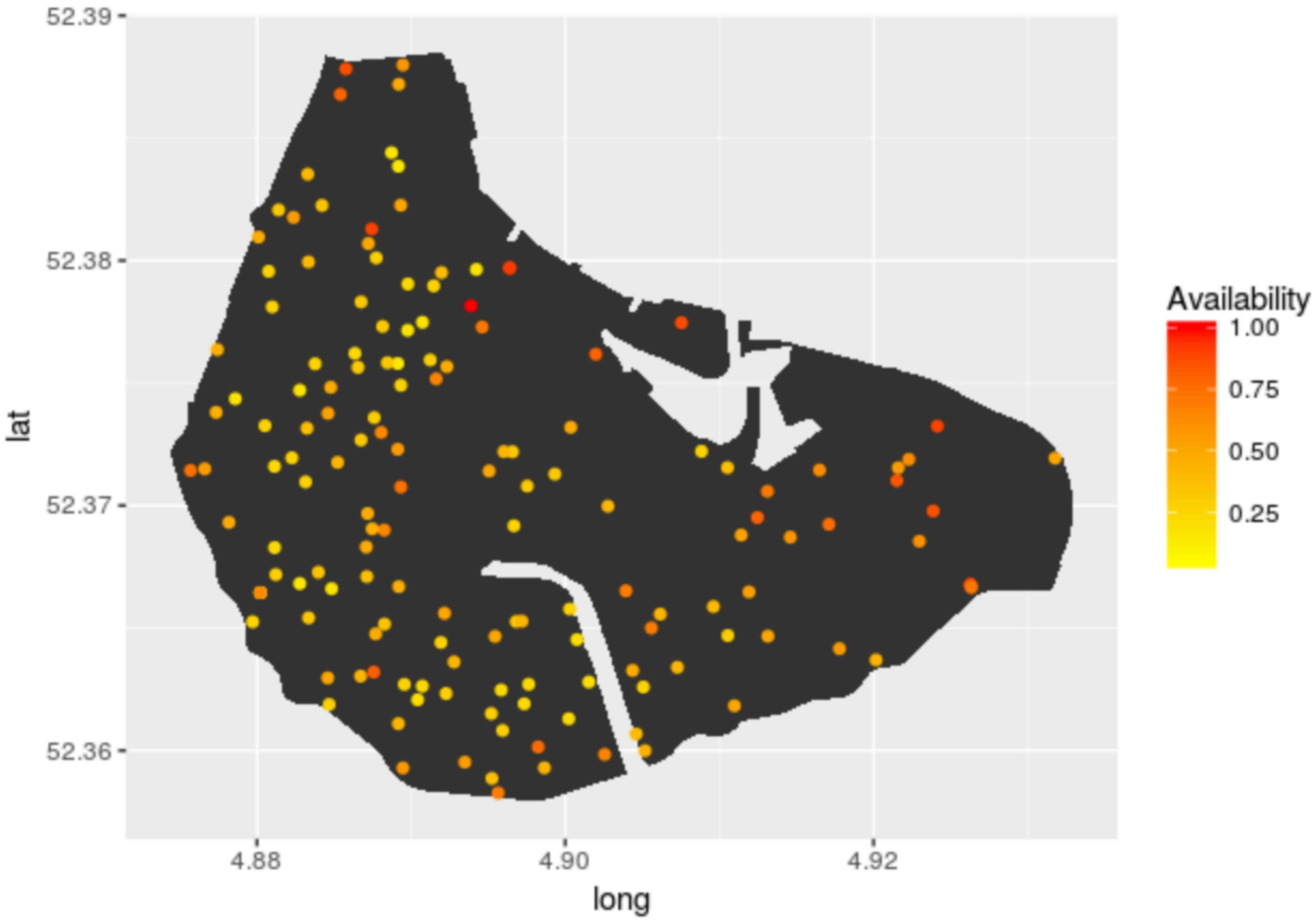
Durations

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Stand. dev.
0.006	1.558	4.698	11.520	13.250	911.600	24.744

Preprocessing charging data



Availability charging points



Space-time series modeling methods in Literature

Statistical methods:

- Space-Time Auto Regressive with Integrated Moving Average model (STARIMA) (Pfeifer & Deutsch, 1980)
- Geographical (and Temporal) Weighted Regression (Brunsdon et al., 1996; Fotheringham et al. 2015)

Machine Learning methods:

- Artificial Neural Networks (ANNs) (Kohonen, 1988)
- Support Vector Machine (SVM) (Vapnik, 2000)
- …

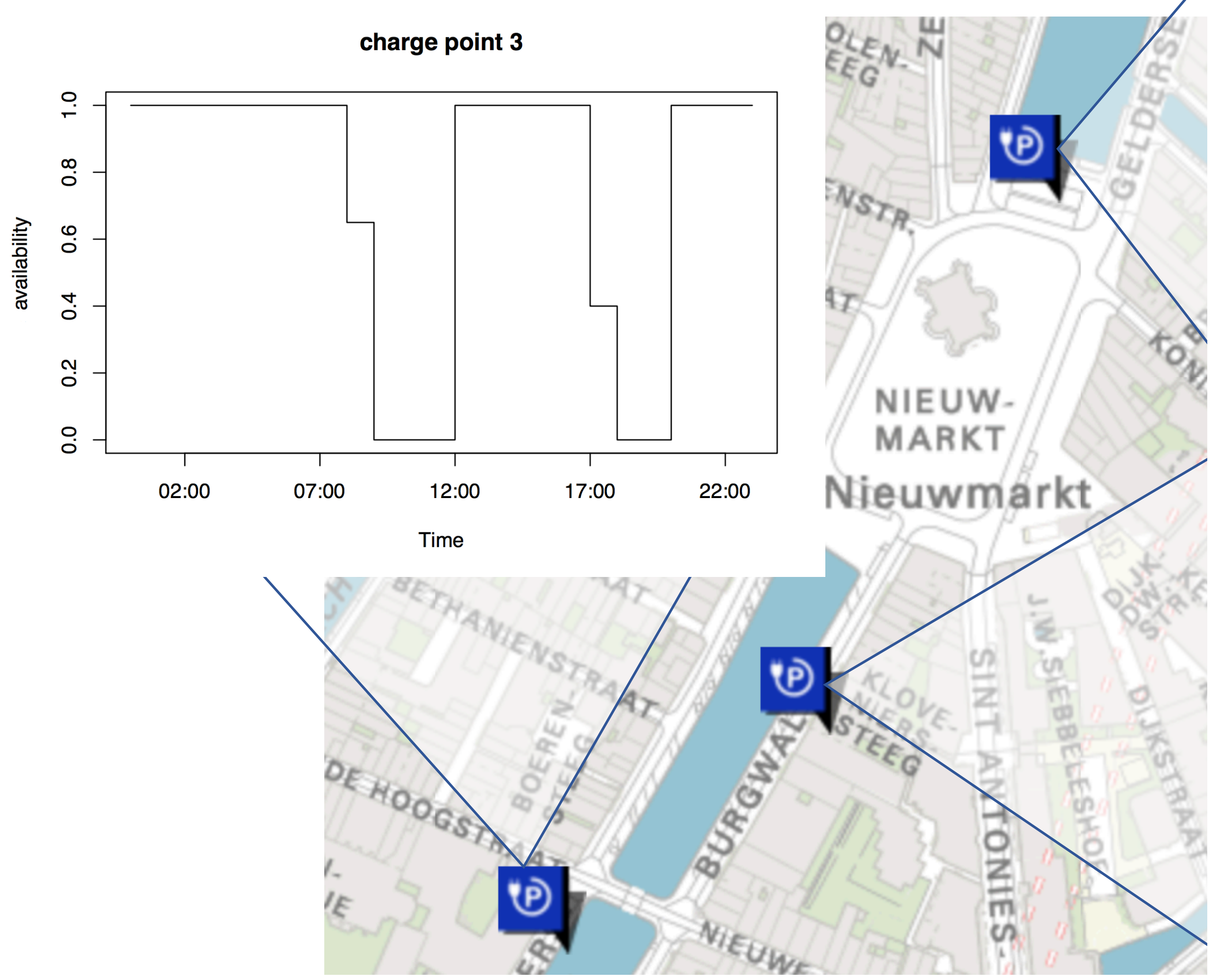
Divide-and-Conquer approach (Deng et al., 2017)

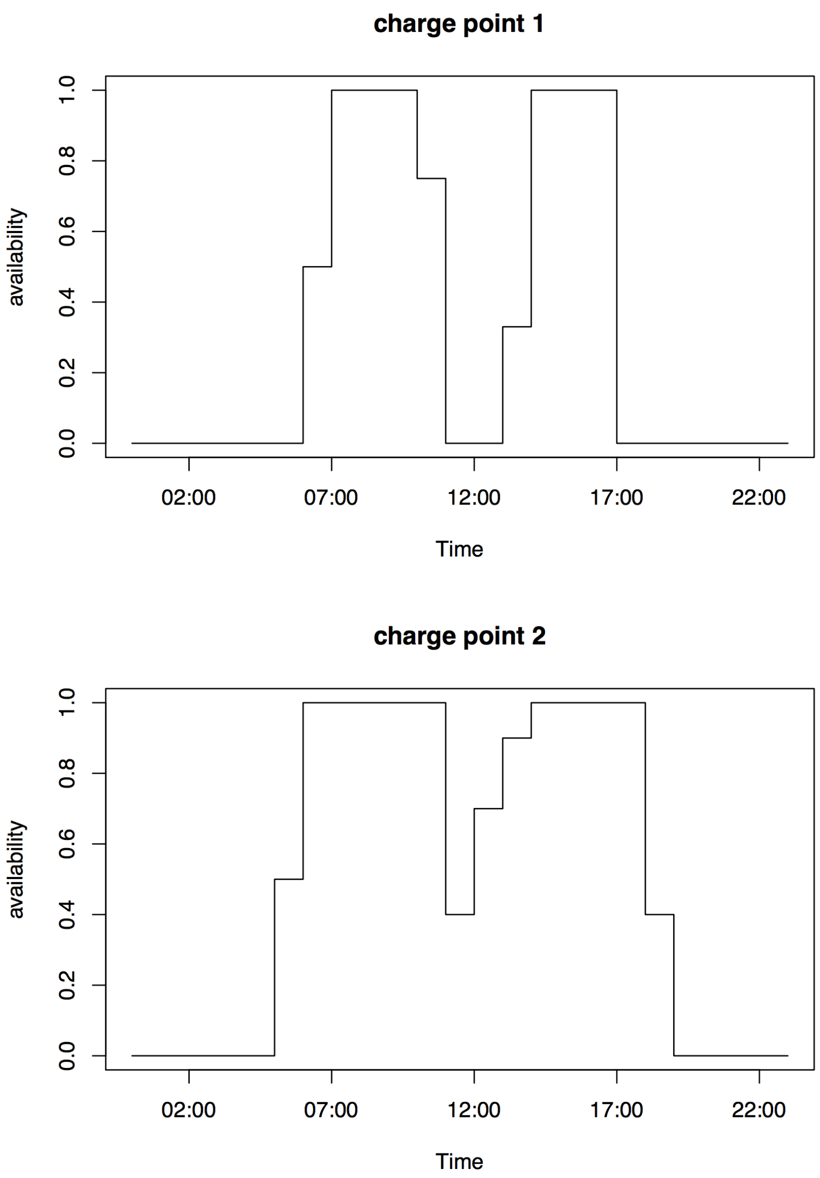
Time series consist of two space-time components
- Space-time smooth
- Space-time rough

Better predictions if space-time smooth and space-time rough are predicted separately and recombined into one prediction.

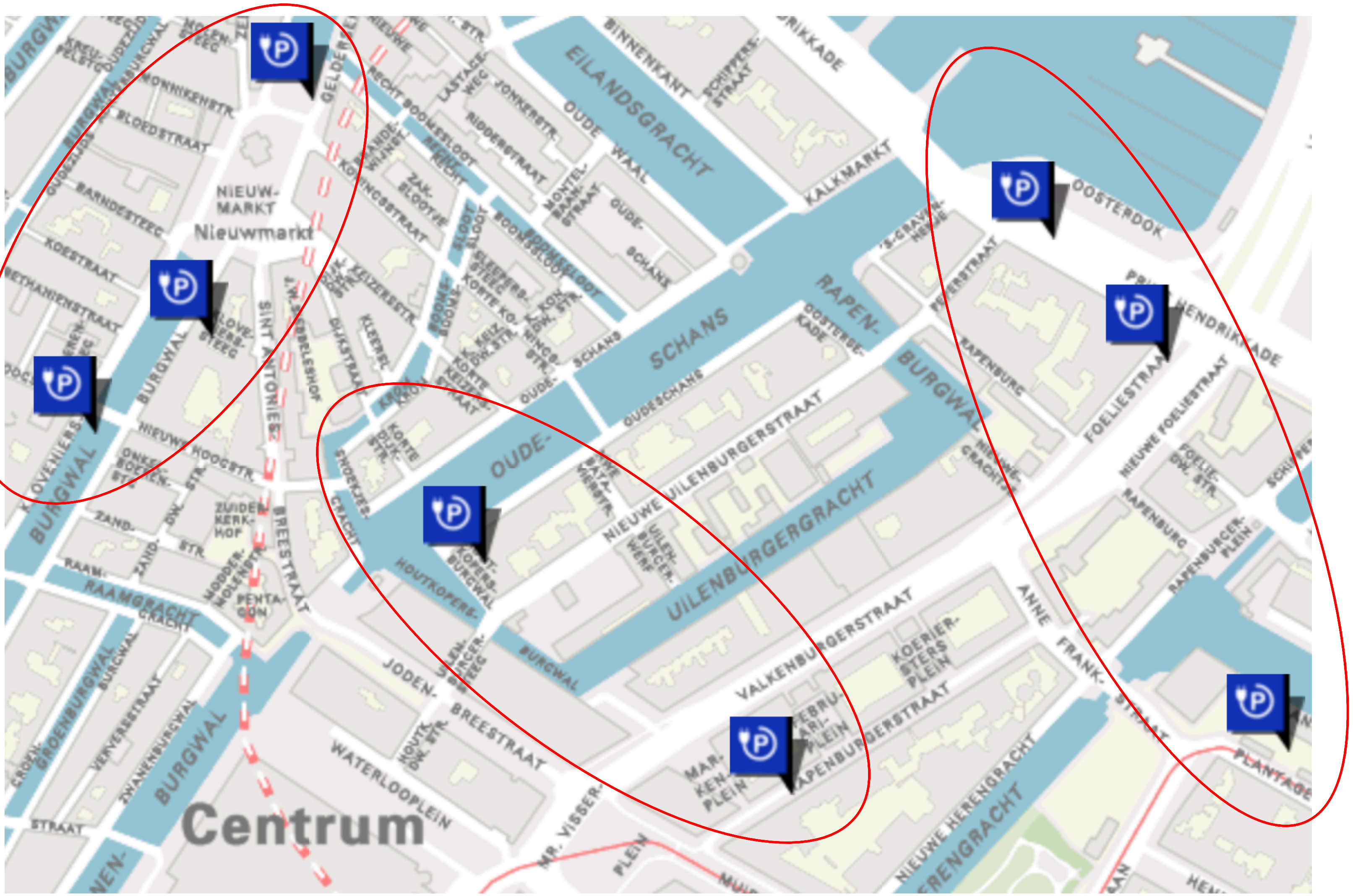
Space-time divide-and-conquer approach

Every charge point has its own activity

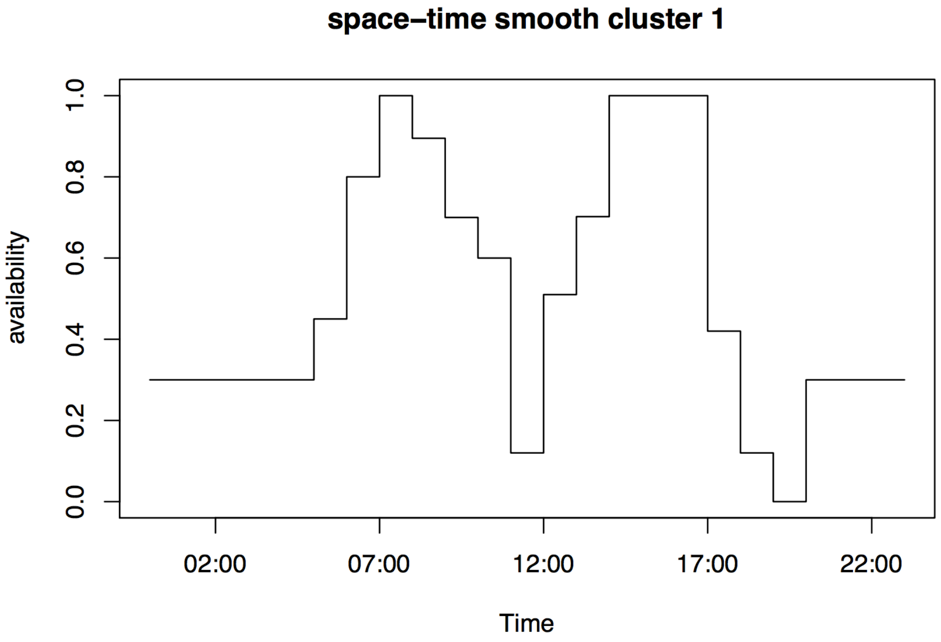




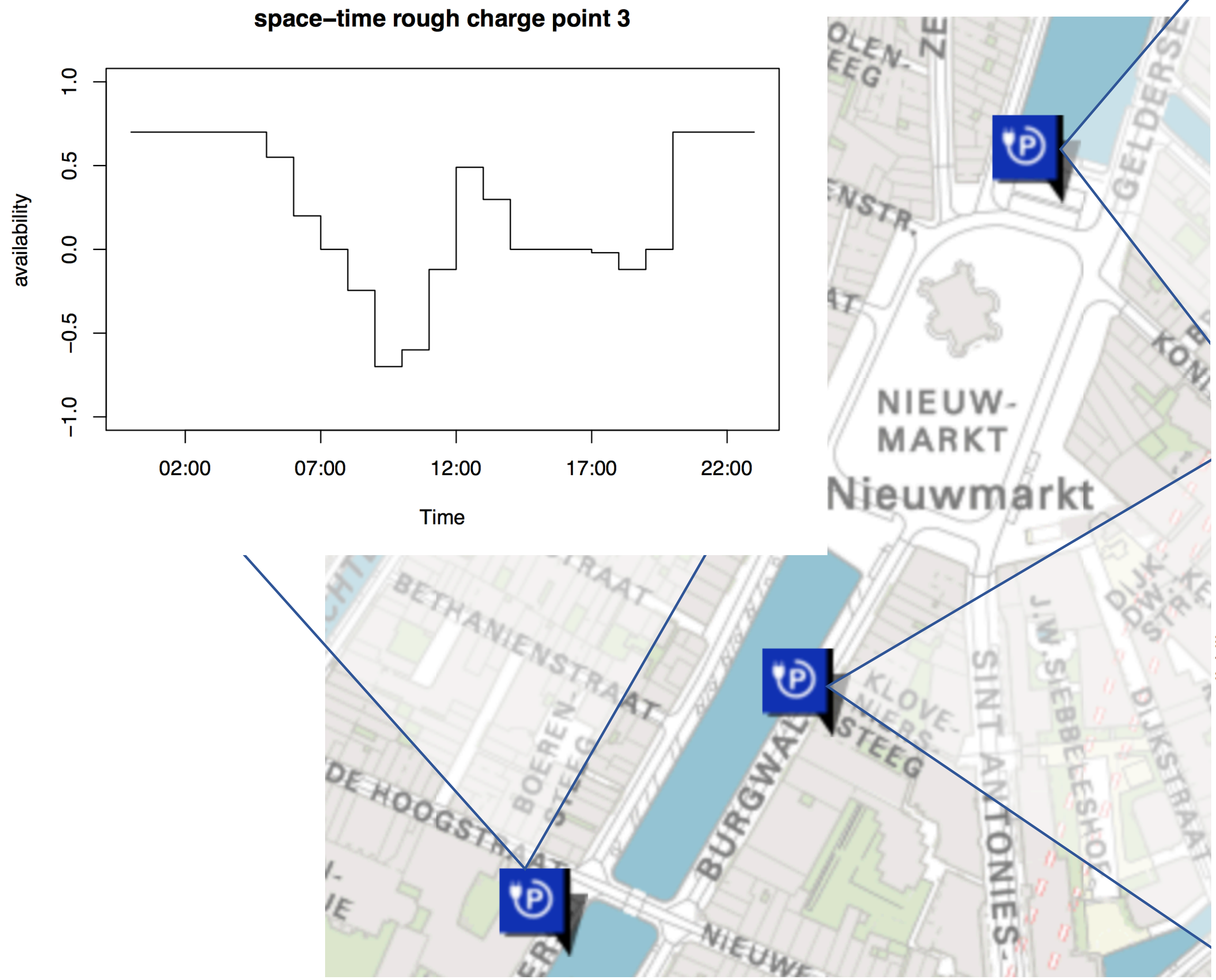
Clustering based on location and predictability

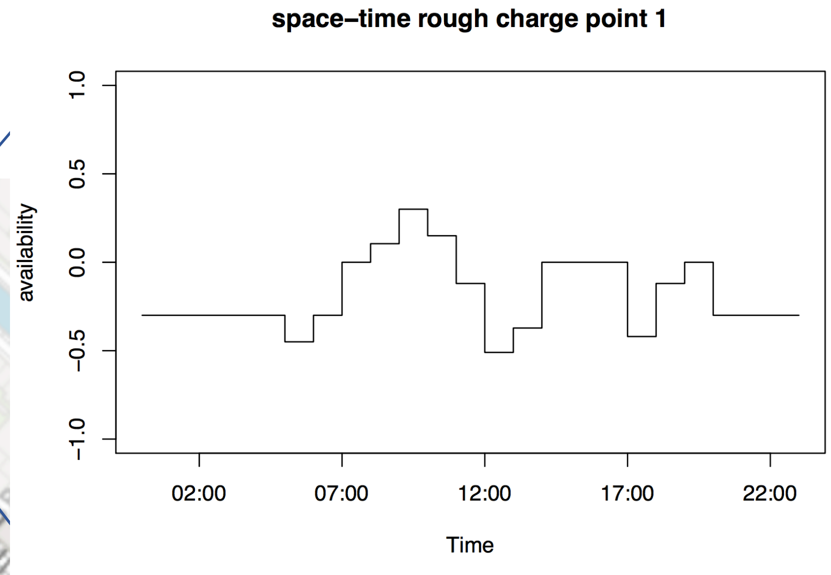


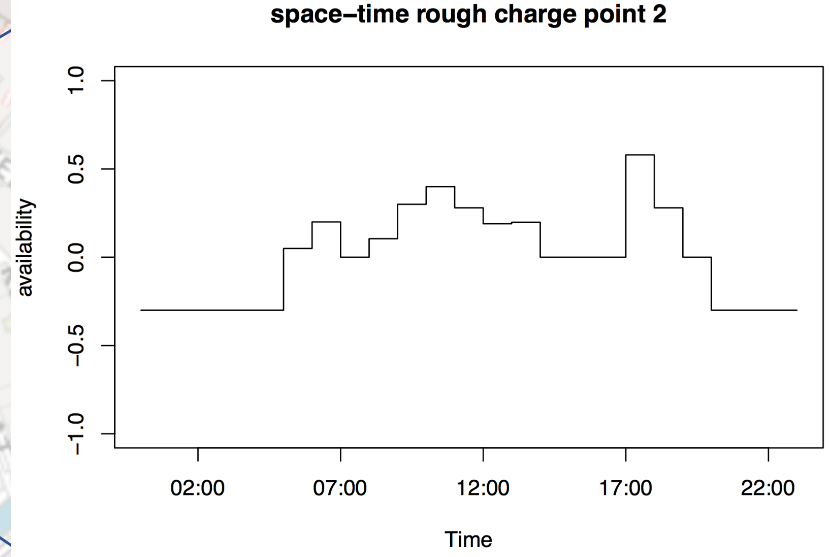
Large-scaled space-time smooth



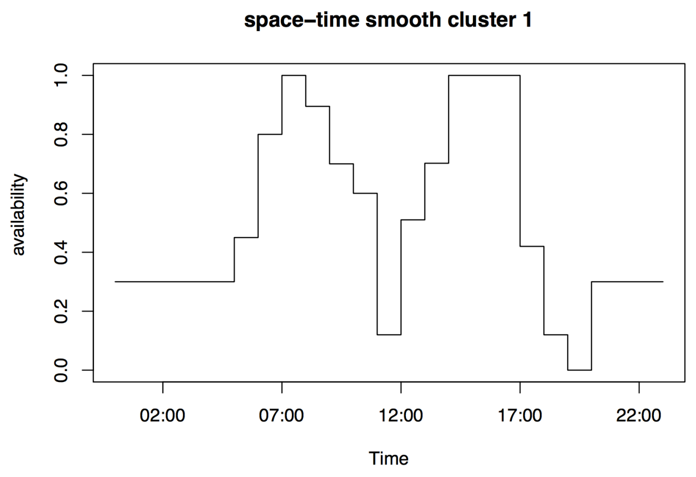
Small-scaled space-time rough

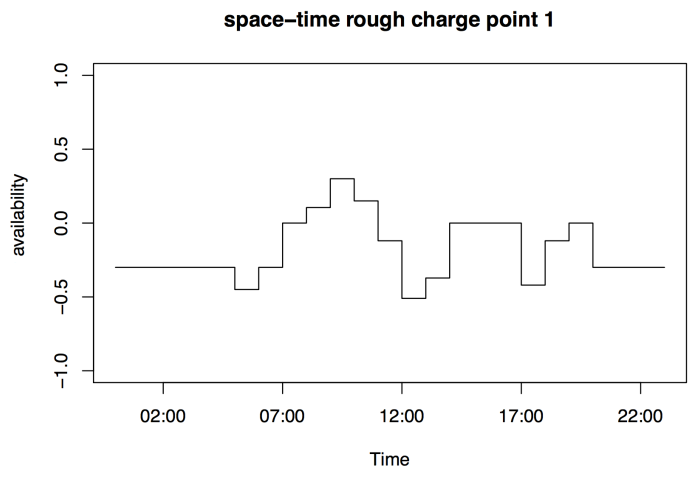






Space-time smooth and space-time rough recombination





STARIMA

Space-time smooth prediction

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Space-time series prediction

Space-time rough prediction

ANNs

Resulting accuracy of the space-time models

Method	6 hours	12 hours	1 day	2 days	1 week
Mean	0.2663	0.2697	0.2720	0.2742	0.2725
DC	0.1352	0.1812	0.2296	0.3088	0.6870
DC Corrected	0.1154	0.1593	0.2011	0.2555	0.3732
STARIMA	0.1117	0.1429	0.2028	0.2464	0.3287
STARIMA Corrected	0.0945	0.1273	0.1833	0.2241	0.3042
ANNs	0.1545	0.2024	0.2746	0.3088	1.0232
ANNs Corrected	0.1358	0.1755	0.2229	0.2800	0.4109

Conclusions

All models show better accuracy with respect to a naive method for short term predictions up to one day.

STARIMA and the Divide-and-Conquer method show better accuracy up to 2 days, but the STARIMA method has an overall better performance.

The resulting models could enable EV drivers to check in advance the predicted availability of the charging facilities at their future destination and estimated time of arrival.

References

Brunsdon, C., Fotheringham, A. S., & Charlton, M. E. (1996). Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity. *Geographical Analysis*, *28*(4), 281–298.

Deng, M., Yang, W., Liu, Q., & Zhang, Y. (2017). A divide-and-conquer method for space–time series prediction. *Journal of Geographical Systems*, *19*(1), 1–19.

Fotheringham, A. S., Crespo, R., & Yao, J. (2015). Geographical and Temporal Weighted Regression (GTWR). *Geographical Analysis*, *47*(4).

Kohonen, T. (1988). An Introduction to Neural Computing. *Neural Networks*, *1*, 3–16.

Pfeifer, P. E., & Deutsch, S. J. (1980). A Three-Stage Iterative Procedure for Space-Time Modeling. *Technometrics*, *22*(1), 35–47.

Vapnik, V. (2000). The nature of statistical learning theory. Springer, Berlin.