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Simulation of Free-floating vehicle charging behaviour at public charging points

Vincent C. Gorka[1], Jurjen R. Helmus[2,1], Michael H. Lees[3]

[1]*University of Amsterdam, vcgorka@me.com*

[2]*Amsterdam University of Applied Sciences, j.R.helmus@hva.nl*

[3]*University of Amsterdam, m.lees@uva.nl*

Corresponding author: JR Helmus, +31 6 2115 60 14

Abstract

As society has to adapt to changing energy sources and consumption, it is driving away from fossil energy. One particular area of interest is electrical driving and the increasing demand for (public) charging facilities. For municipalities, it is essential to adapt to this changing demand and provide more public charging facilities.

In order to accommodate on roll-out strategies in metropolitan areas a data driven simulation model, SEVA[1], has been developed The SEVA base model used in this paper is an Agent-Based model that incorporate past sessions to predict future charging behaviour.

Most EV users are habitual users and tend to use a small subset of the available charge facilities, by that obtaining a pattern is within the range possibilities. Yet, for non-habitual users, for example, car sharing users, obtaining a pattern is much harder as the cars use a significantly higher amount of charge points.

The focus of this research is to explore different model implementations to assess the potential of predicting free-floating cars from the non-habitual user population. Most important result is that we now can simulate effects of deployement of car sharing users in the system, and with that the effect on convenience for habitual users. Results show that the interaction between habitual and non habitual EV users affect the unsuccessful connection attempts based increased based on the size of the car-sharing fleet up to approximately 10 percent. From these results implications for policy makers could be drawn.

Keywords: simulation, car-sharing, user behaviour, charging, prediction

[1] SEVA model: Simulation of Electric Vehicle Activity model currently under review

1 Introduction

With more car brands introducing electric vehicles, the adoption of electric vehicles has grown significantly over the past years. Based on historical data, consisting of charge sessions executed in the period 2014 - 2017, a growth in the number of unique users as well as an increase in the number of used charge points (1, 2) is visible (fig. 1). An promising solution for the effective reduction of emisions has been found in the implementation of electric car sharing fleets (3, 5). While car sharing may be of potential benefit from an emission reduction point of view, it may cause inconvenience for habitual users too as increasing number of car sharing vehicles are using public charging infrastructure.

Until now research has mainly focused on the potential of car sharing (5) while little attention has been paid to the interation of car sharing EVs with other user types in the EV charging infrastructure. Moreover, having non-habitual and unpredictable modality may affect EV users convenience in terms of successful connection attempts and may thus result in unexpected and counterintuitive results (4, 6).

This research explores the effect of unhabitual users on the total charging infrastructure by simulating the typical behavioral patterns of unhabitual users. Non-habitual users are users without an evident habit. These users could be for example car-sharing users and taxies using many different charge points .

Central in this research is the predictability of free-floating vehicles. Predicting habitual users is done using the agent based model SEVA. Habitual users are simulated in SEVA as agents based on their historical data. Non-habitual and free-floating users are simulated at random. To increase the performance of the simulation non-habitual and free-floating users should be simulated differently. Therefore, predicting their behaviour should be investigated.

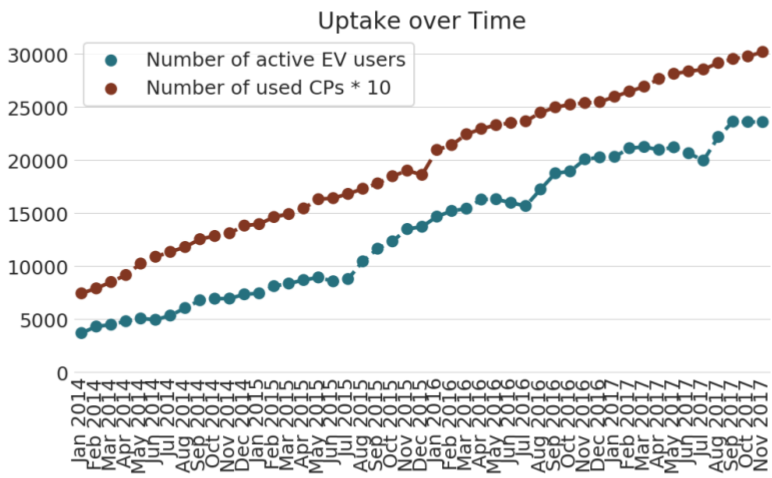

Figure 1: simulation schema SEVA

2 Definition

As stated in the introduction, two groups of users are separated; habitual and non-habitual users. A charging pattern is not determined for a unique user if it does not qualify given the following set criteria. Each unique user, distinquished by a unique card ID, should have at least 20 registered sessions. Moreover should every unique users register at least 8% of its registered sessions (with a minimum of 10 sessions) at any given charge points or group of charge points. These weighted centers of the groups of charge points are determined by using the number of sessions per charge point included in the cluster centre. To illustrate the criteria, the numbers for Amsterdam are given in table 1. The first column represents the number of unique Card ID's (card used for charging the car), the second column is the number of cars that have at least 20 sessions, the third column for the cars that have at charge points with at least ten sessions for the users. The fourth column is for those users/cars that have cluster centres with that cover at least 8% of the total sessions for the car/users.

Those cars/users that get to the fourth column have past sessions that could be used to derive a pattern. For those cars that do not get to the fourth column, a realible pattern is not feasible. Therefore, those cars that have enough (at least 20) sessions, but do not have a subset that meets the criteria are defined as free-floating users.

Table 1: Statistics Amsterdam

	#Unique Car's	> 20 sesssions	> 10 per CP	Cluster Act > 8%
Car2Go	912	879	232	5
Semi-fast	104	88	4	3
Taxi's	506	342	346	249
Uber	10	9	9	5
Connexion	11	7	8	7

3 Literature study

Human mobility models appear in research extensively and aim to simulate by reproducing the mobility trajectories of individuals (7). With research showing that it is not realistic to simulate trajectories of individuals, other models should be investigated and applied. The predictability of ones individual trajectory could be for example using a home to work pattern and other more often visited locations at given times.

Research shows that describing random behavior can be done at two different distinguishable levels, namely, on an individual level and a populations level (7). Making predicitons on an individual level allows for aggregation towards a populations level, however, deaggregation is not possible from a population level back to an individual level. With that making predictions on an individual level allows for more details in the prediction of free-floating and non-habitual electric vehicle users. Examples of models at an individual level are: Random Walk Models (e.g. biased random walks / levy flights and Preferential return model. Models on a population level are for example: Gravity based models, radiation models and markov chain models.

In Random walk models predefined discrete random steps are used, in other words, a set time period is set and the next discrete displacement step is determined (7). Many human mobility and trajectory prediction research (8,9,10) has been performed on random walk models. For example in this research paper (11) it is stated that human mobility is realistically not random and has certain predictability. Within the family of random walks models another model present is the biased random walk. In the base random walk model the probability of going to the next state is distributed uniformly, the baised random walk differs in this from the base random walk model as the probability of going to the next state is not distributed uniform. Literature has shown that biases in a populations can be of significant influence (18), research has shown that in a group of 15 a small bias can change the travel direction of a group in which the biased individual is not individually changing the population travel direction.

Another example of a random random walk model is a Levy Flight model. As describe in literature (7) a Levy Flight simulation is a random walk model in which the step length in the algorithm is given by a heavy tailed probability distribution function. In perspective of human mobility, many short-distance trips are occasionally followed by a large-distance trip. A practical applications is the travel trajectories of the wandering albatross (12). With regards to electric vehicle driving we could map this result to trips that are performed with shared cars which make many short-distance trips and occasionally travel to other regions in the supported region to charge the electric vehicle.

Different from the random walk models is a preferential return model as proposed by Song (13). A preferential return model is a model in which incorporates the preference to return to a previously visited location (e.g. charge point). Te number of times an agent in the network visits a given location, is used to define the probability for returning to a locations by the agent. Research (14) distinguish two types of travellers, those exploring and those returning to previously visited locations as part of Exploration and Preferential Return model.

Those returning to their previous location are moving between a few often visited locations, by using their radius of gyration which is defined as the root mean square distance of a set of locations from a given starting point. Exploring travellers on the other hand tend to move between a large number of locations. With that in mind, it is likely derive patterns from historical data, that can, up to a certain point predict potential future behaviour, with the tenancy to keep going to frequently visited places.

Yet another model, a population based model is the gravity based model which uses the theory of Newton's Gravitation law to determine mobility in traffic trajectory network flows (15). The gravity model tries to connect the most often used locations, with the greatest force between them. Literature concludes that Gravity-based models can predict trajectory flows, but with the many varying parameters is a drawback in terms of simulation time needed. Other downsides, as described in literature are the need of traffic data, without historical traffic data it is not possible to use the gravity model. Besides that, the model is static and will not dynamically adapt to fluctuation in for example the number of trips from origin to destination. This will decrease the accuracy in dynamically changing environments, like mobility and with that in predicting charging behaviour.

An improved version of the gravity model is the radiation model. In the radiation model improvements and extentions are made towards the gravity model. A significant difference (16) is that the model is parameter-free which makes implementation and usefulness of the model in human mobility better and easier. The radiation model uses the population at origin and destination, the distance between origin an destination and the population (within a circle radius equal to the distance between origin and destination based on the origin but without the population at the origin).

Finally, markov chain models have been looked at for trajectory/human mobility prediction. Markov chain models are models that are used for many different application, including trajectory prediction in mobility (17). A markov chain is a chain of events in which the next event is dependent on the previous state of the chain. In the case of human mobility, the current state where the car is located or charging determines the next location (state) where the car will be having its next charging sessions. This state (e.g. district, sub-district) can be the same state or a different state. Markov chain are defined as a series of states at different time steps that can have any time scale with a recurring pattern. A Markov chain is successful if it is capable of predicting future locations only based on the current location. Which in essence is what is needed in predicting behaviour in free-floating electric vehicles in which the previous trips are independent of the next to come trips. One of the downsides of Markov chain model prediction is the great dependency on historical data.

4 Methodology

To investigate the predictability of free-floating cars several models were implemented on an individual level and a population level. Evaluating the performance of prediction models metrics was done by setting up metrics. To have a fair and consistent approach to evaluating the predictionresults, the metrics were rested with the different models implemented.

The metrics were categorized in two groups, namely the activity-based statistics and other statistics. The activity-based statistics capture the charge activity at a district level, at a sub-district level and on a charge pole level. By comparing the activity from the simulation with the actual activity registered by the free-floating non-habitual users the performance could be derived, compared and evaluated. This metric presents valuable insights in the location where charge sessions happen. Evaluation on a charge point level is done differently than the evaluation of activity share on district and sub-district level because many charge points are close to each other. If evaluation is done on a charge point level, by evaluating the activity per individual charge point it would not provide meaningful results. An electric vehicle users could for example use another nearby located charge point which is not captured with the often used charge point. To evaluate the charge points predicted the minimal distance to charge points used during the specific day in the reference data. The minimal distance to a available charge point is calculated and the mean minimum distance is determined. A large distance would indicate that the sessions predicted by charge point are not close to the reference data and therefore not likely to provide useful prediction results. A smaller distance is indicating that the charge point is close to the reference data charge.

The other statistics involved are statistical measures. Included in the evaluation of the models are the jump length (eq. 1) and the average minimum distance between the predicted and known location.

$$\Delta x = d(x(t), x(t + \delta t)) \tag{1}$$

The different models are compared using these metrics. The model algorithms used in this research are: complete random, biased random, Markov Chain Network model and a Gravity Model.

5 Simulation

The models are implemented in the SEVA base model and simulation based on the implementation parameters were performed. Simulations focused on the effect on the total system based on the size of the unhabitual user fleet in the system. SEVA base model is an agent based model which takes historical sessions into account. In every simulation step, a agent is taken from the queue, the agent could be in the state of waiting to disconnect from a charge points or in the state of connecting to a charge point. If the car, taken from the queue, is connected to a charge point, the car is disconnected and a next connection time is determined whereafter it is put back in the queue. If the car was not connected to a charge point a check is performed whether it is possible to connect a charge point. If no charge point is available to connect to a new next connection time is determined and with that the vehicle is put back in the queue. In the case that a connection is possible a connection is established. A disconnection time is determined and with a next disconnection time the car is put back in the queue. A stop condition can be set to stop the simulation, this could be e.g. the number of simulated sessions. The different stepts in the simulation are visualized in the provided figure (fig. 2).

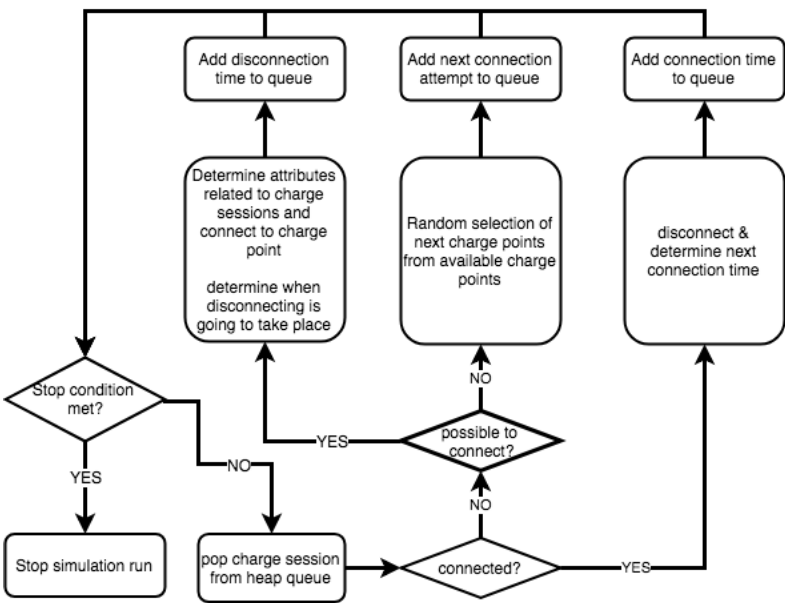

Figure 2: simulation schema SEVA

The non-habitual free-floating users are included in the simulation too, as explained, in the SEVA base model free-floating non-habitual users were simulated randomly. With the different models presented, extentions can be made to the base model. The simulation results are evaluated based on the metrics presented.

6 Simulation results

Simulation results for the different used models have been done according to the presented metrics, activity-based measured are done at both a district level and a sub-district level. For example, in Amsterdam, 8 district are at present, with on average 13 sub-district per district in Amsterdam. Predicting on a distict level, which have aggragated more sessions to base the prediction on, are easier. The different evaluation metric results are included in table 2. The data is given with regards to the reference data, e.g. the historical sessions.

Table 2: simulation results

	Avg. district distance	Average sub-district distance	Minimum distance	Jump Length
Complete Random	6.50x	0.50x	250m	5875m
Biased Random	0.09x	0.41x	35m	4100m
Markov Chain on district	0.10x	1.00x	33m	3867m
Markov Chain On Subdistrict	0.60x	14.0x	35m	4500m
Gravity model	0.49x	0.87x	300m	398m
Reference data	0.00x	0.00x	0m	3893m

District activity is measured by means of activity, both on a daily basis and on total numbers. The session activity on district level shows whether sessions take place in the expected district region or that they are distributed differently than captured in the historical sessions data. A non-habitual free-floating car has two distinct option, it has the option to leave the current district and move to another district, or it could stay in the district it is currently in. The different models have been test and ranking the used modesl based on their activity accuracy, gives the following top-3: Biased Random walk, Markov Chain on a district level and the Gravity model. The biased random predictions, which are biased on previous activity and point of interest as public transportation. The complete random prediction performed the worst, which can be explained by the fact that every district has equal probability with regards to the other districts.

The minimum mean distance, as described earlier, has performance similar to the activity measure with the biased random model again as best performing model in terms of minimum distance to the known charge points. The known charge points are on average within a small distance. The same holds for a few other models, namely, the Markov chain based on both a district level and sub-district level.

The jump length has been used to determine whether or not the characteristics in terms of certain jump lengths is different from the reference data. The jump length gives the following ranking: Markov Chain based on a district level, Biased Random walk, Markov Chain based on a Sub-district level. The Gravity model on the other hand performed worse which can be explained by the fact that the gravity model calculated a value that is inversely proportional to the distance between the two charge locations. Therefore, a similar populated charge locations closer to each other have a higher value than if they were located further from each other. This is because of the distance decay incorporated in the model. For the complete random predictions the locations are chosen randomly, and therefore, ends with a value approximately half way the total maximum distance between two locations.

The numbers, which are given as ratio with respects to the reference data, show that the biased random and Markov Chain district based network graph have similar deviation from the reference data. The biased random approximately 4 percent more, the network graph model approximately 4 percent under. The other models, but specifically the gravity model, show bigger deviation from the reference data mean squared displacement.

The best performing elaborated and evaluated models is the biased random model. This model is based on data from previous sessions combined with other point of interest information to make a biased chose where the next sessions is going to take place. Different statistics, as provided, have shown that the biased random model has the best overall performance. The other model that performed well was the network based model, the difference with the biased model is the information which is used to make predictions, in essence the Markov Chain network model is a biased model too in which trajectories numbers are incorporated in the decision to go to one place or another. Therefore, combining them in the conclusion, as biased models would make sense. The gravity model on the activity level was performing fine, due to the fact that short distance trips have a higher value for interaction between them and therefore make it more likely to travel shorter distances as soon as a free-floating car ends up in a highly populated charge point location. The other models, including the complete random has not shown signs of being a good predictor for free-floating cars. it becomes clear that taking free-floating car as complete random does not match with the real situation, therefore, it becomes clear that those free- floating vehicles do not move completely random in the network but some biases with regard to certain area's and charge points exist.

7 Case-study results

In many cities policy makers are questioning (1) whether EV car charging is feasible and (2) what the ideal size of a EV car sharing scheme would be. The agent based SEVA model used to simulate charging behaviour with adjustments to include a biased choice model for non-habitual users can provide valuable insights for policymakers. For example, the number of failed sessions can be simulated by increasing the number of vehicles added to the network. This is visualised in fig. 3 and fig. 4.

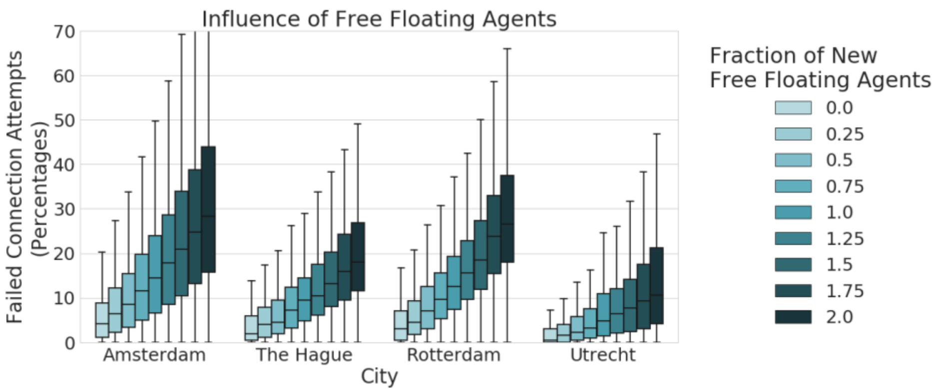

Figure 3: Influence of Free Floating Vehicles (baised random prediction)

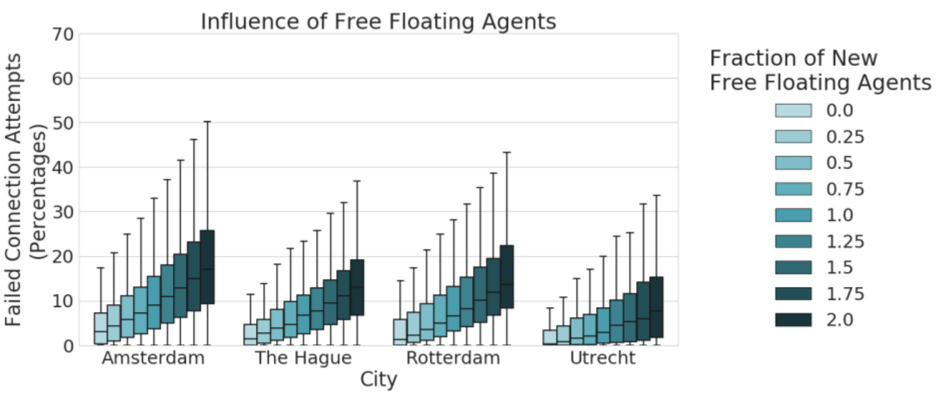

Figure 4: Influence of Free Floating Vehicles (complete random prediction)

From the figures, it becomes clear that increasing the number of vehicles in the network has a higher impact by using a more accurate simulation technique, in this case, a biased choice model versus a completely random choice model. This has provided insights into the impact that free-floating cars have on the network and could help municipalities in deciding where to place new charging infrastructure. From the simulation results, it became clear that the impact of free-floating cars increased by using a biased prediction, this could be explained by the fact that the free-floating cars are located more in the regions where habitual users are active.

In fig. 5 and fig. 6, the percentage of occupied charge points is visualized. In fig. 5 the simulation results are given for complete random predictions, fig. 6 show the results for a baised random prediction. From the figures it becomes clear that by increaring the number of free-floating agents in the system the number of occupied charge point increases.

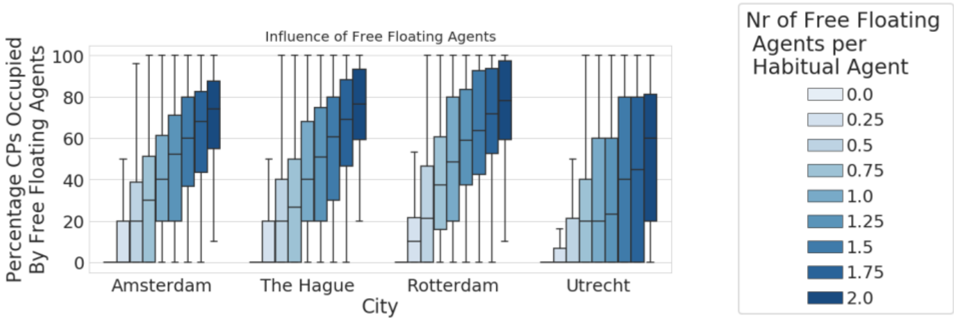

Figure 5: Influence of Free Floating Vehicles (complete random prediction)

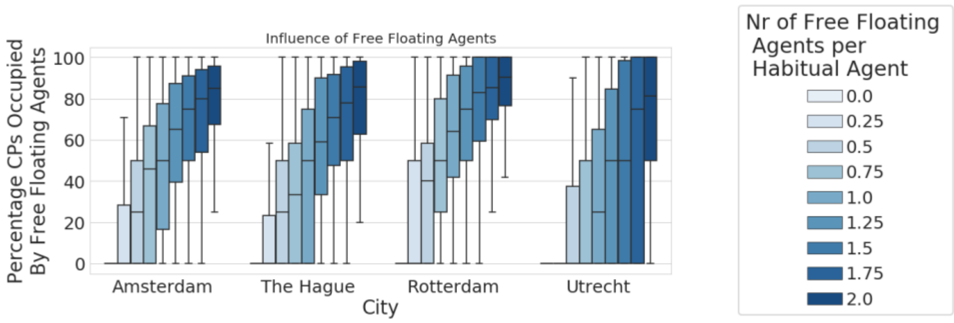

Figure 6: Influence of Free Floating Vehicles (biased random prediction)

4. Conclusions and recommendations for policy makers

Our findings show that there are possible extensions to simulate different type of users and the impact of them in the network. Increasing the number of users (e.g. the fraction of free-floating users to habitual users) show significant impact on the number of failed session attempts in the network. Our analysis shows that approximately 30% of the sessions fail if 2 free-floating cars per habitual user are added to the network. By increasing the number of cars, as people visiting the city will bring more electric vehicles to the city, higher failure rates are possible.

Policymakers should assess the possibilities simulating both habitual and non-habitual users to fully use to the potential of simulating the future behaviour and for implementing charging facilities in order to make electrical driving feasible.

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Authors

Vincent Gorka received a MSc. degree in Computational Science in 2018 from the University of Amsteredam and the VU University Amsterdam. He was working on this research for his graduation and is currently working as Data Analyst/Scientist at the Ministry of Finance performing data analysis for financial auditing.

Jurjen Helmus works at the Amsterdam University of Applied Sciences (HvA). He coordinates the minor Data Science. In addition, he is conducting a PhD research at the Computational Science lab of the University of Amsterdam, where he builds agent based simulation models for charge infrastructure electric vehicles. Jurjen holds a Msc degree in Technical Business Studies and a Msc degree Industrial Engineering at the RuG with a specialization in Chemical Engineering at the University of Groningen.

Mike Lees is Associate Professor at the Universiteit van Amsterdam in the Computational Science Lab (Informatics Institute). At the University of Amsterdam. He is the Director for the Master Computational Science. He conducts regular research visits to Nanyang Technological University (NTU), Singapore and ITMO University, St Petersburg.