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Exploring a Complex Systems Approach to Charging Infrastructure: implications for researchers and policy makers

JR Helmus[1,2], R. van den Hoed[1], M H. Lees[2]
[1]*Amsterdam University of Applied Sciences, Weesperzijde 190, 1097DZ Amsterdam,J.R.Helmus@hva.nl*
[2]*University of Amsterdam Computational Science Lab, Amsterdam*

Executive Summary

Over the last years a large growth in Electric Vehicles (EV) and charging infrastructure (CI) development has been observed. Particularly in metropolitan areas this growth has led to a system in which multitudes of interactions between EV users take place. While many researchers have focused on EV user charging behavior and deployment strategies for CI, little attention has been paid to conceptualizing the problem domain. This research provides a brief overview of complex systems theory, and derives six characterizing elements of complex systems that may be applicable for CI. The paper investigates both theoretically but also empirically how these characterizing elements apply for CI and provides implications for the further roll-out of CI for both policy makers and researchers. We illustrate our findings with preliminary results form ongoing research. Recommendations include the further development of simulation tools that are capable of exploring effects of e.g. non-linear behavior, feedback loops and emergence of new patterns on CI performance. In the end this paper aims to provide directions to enable policy makers to be better prepared for the anticipated exponential growth of EVs and CI.

1 Introduction

The suggestion that the number of Electric Vehicles (EVs) will increase exponentially in the upcoming years is becoming a realistic scenario [13,61]. Future market developments point at a large EV uptake and an increased market attractiveness due to the release of new BEV models in an affordable price range. As a result, policy makers and market parties have deployed an increasing number of private, semi-private and public charging points both AC and DC. Particularly in metropolitan areas where charging infrastructure is mainly part of the public domain, this leads to a multitude of interactions between EV users.

Since the first release of modern EVs, researchers and policy makers have shown interest in zero emission mobility [13, 61], particularly in planning charging infrastructure deployment [42]. Main questions to solve are *when* and *where* to deploy *what* type of charging infra. Research on DC Fast charging has typically focused on planning located nearby highways or corridors on semi-private locations [20,44,49], whereas AC charging has private home or office charging, semi-public in garages or in the public space [23, 60].

Despite the sheer volume of literature, little attention has been paid to the nature of the challenges of the EV systems. As a result a gap in literature is found that describes of complexity of EV user behavior in relation to an optimal deployment strategy [18].
Many studies use a demand side approach to charging infrastructure planning that involves (1) planning

using operational research methods on spatial (2) traffic density data using (3) data driven planning methods using spatio-temporal presence of vehicles (mostly non EV) data. A common optimization target is to minimize the inability of charging EVs so as to install charging stations at locations where either a trip ends or at locations that many trips have in common [42].
A drawback of these models is their linearity in scaling and lack of complex behavioral aspects. For example, the underlying assumptions of these models do not include interactions between EV users, and hence no feedback loops or adaptation of behavior in the system. Recently, predictive simulation models have shown insights in deployment strategies that include either traveling behavior or EV user charging behavior. While these models may include interactions between EV users, they pay limited attention to the simulation results in relation to the complex systems theory. Another drawback of these models is that they are not validated or only validated using small amounts of real data [27,41,45,56,59,72,74,76], which decreases the predictive certainty of the simulation results [56] and [41].

In this paper we aim to explore how knowledge from complex systems theory may enhance our understanding of charging infrastructure development for EVs, identify implications of viewing charging infrastructure as a complex system and how this may translate into policy recommendations. We do so by exploring the complex systems literature to gain insight in the general properties and typical challenges of these kinds of systems. Thereafter, we analyze and evaluate charging infrastructure on the typical characteristics of complex systems found in literature. We also provide several illustrations from ongoing research on CI using the complex systems perspective. Results contain implications for both researchers and policy makers.

2 Definition and properties of Complex Systems

Complex Systems Theory (CST) is an approach towards system analysis that focuses at emerging structures on a macro level derived from micro level behavior [33]. The methods provided in the complex system theory have proven to provide a deeper understanding of systems that are difficult to predict from a individual level [33]. The application of this field of science can be found in among others ecology, biology and social studies. Also systems in which the interaction between human behavior and technology plays an important may benefit from the complex systems approach may reveal [16, 62]. Besides, CST has proven to support in public policy making [50] and critical infrastructures [34].
In this research the following definition is *“a complex system is one whose evolution is very sensitive to initial conditions or to small perturbations, one in which the number of independent interacting components is large, or one in which there are multiple pathways by which the system can evolve.“* [65]. From this definition a set of features can be extracted that characterizes complex systems [33, 50]. Note that not all features may be required identify a system as being complex;

- Self organization
- Feedback loops and adaptation
- Non-linearity
- Emergence
- Robustness and vulnerability
- Path dependency.

A typical property of a complex system is the lack of a central control system, which means that the system is *self organized* in a bottom up manner. Each element in the system is autonomous and has a set of rules that determines its behavior [17]. Rules can be uniform for all elements or unique for each one, rules may be simple, complex or data driven. The *feedback loops* occur due to the fact that experiences of elements in the system are inputs for future behavior of other elements or itself. These experiences are caused by interactions of elements. The feedback loops may cause *adaptation* of behavior to a changing psychical environment or interaction with other individuals. For this reason different initial conditions may lead to different interactions and thus to different adaptation patterns of users. *Non-linearity* is an essential element of a complex system. A non-linear system has the property that the change in output of a system does not scale linearly with the change of the input or parameter of the system. As such, scaling the size of such a system may different regimes of behavior on micro and macro level without changing the properties of entities on the micro level.
The aforementioned interactions are the source of adaptation patterns, adaptation of rules, in the system. Literature has shown that interactions between elements may lead to unexpected spontaneous patterns of behavior such as collaboration and competitions between elements [21]. These macro level patterns are known as *emergent* behavior. This type of behavior is not part of the set of rules nor controlled as a goal of the population strive for. As with flock of birds, all the birds want to be part of the flock, but there is

no leader or centralized coordination.
The patterns of behavior are said to be *robust*, since in case of perturbations of the system the behavioral patterns tend to reoccur after recovery [33]. Though, the effect of a perturbation may be dependent on the state of the system. In an influential paper Bak, Tang and Wiesenfield discovered that elements in a complex system may self-organize into a Self Organised Critical (SOC) state, where small perturbations can have large impacts. They modeled the effect of avalanches in a simple simulation model of sand piles in which at each time step a new grain of sand was added at a random point in the system [3]. Once a pile reached a the certain threshold, it collapsed, redistributing the grains towards its neighbors, which could reach the level of threshold and so on. The emergent pattern they discovered was that the system organized itself towards a state in which the size of the avalanche, being the cascade of the propagated perturbation, displayed a power-law distribution [3]. This implies that many perturbations cause little impact, but some cause massive system scale impacts.
In literature, examples of this state of SOC in the context of infrastructure are found among others in electricity networks and traffic each with specific power law exponents [7, 32, 37, 38]. It is found that perturbations at specific nodes of the system typically cause larger effects than others, leading to the idea of *vulnerabilities* in the complex systems [1, 4, 9, 34].

Research on vulnerability of these complex networks revealed that as the load in the system increases the cascading failures are more likely to occur [9]. Research has shown that the likelihood of cascades does not gradually increase with system load, yet it reaches a critical point (sometimes called phase transition or regime shift) at which the propagation of failures suddenly increases [**?**]. Therefore, during design and operation of complex systems the system load needs to be balanced with the economic benefits of the system. A more efficiently used system may potentially lead to larger blackouts, while sub optimal operation in terms of load on the system leads to a more robust system. Likewise, intelligent rerouting of load in a complex network may decrease the effect of perturbations, but may require some form of central steering in the system.
As mentioned before, the development of behavior of the system over time is said to be *path dependent* which refers to the idea that initial conditions and therewith following interactions between elements determined that certain pathways of development are locked in or locked out. A classic example of path dependency is the railway gauge which relates to a folks tale that it is about 2 horses wide [**?**]. In practice, path dependency makes it hard to transform a system from one regime to another. This is the reason that it is difficult to reform the health care system from its current financial structure to another [50].

2.1 Modeling and analysis of Complex Systems

In literature several methods for the analysis of complex systems can be found. Particularly of interest are tools that simulate the behavior of the system using a bottom up approach of modeling the individual elements of the system with a set of behavioral rules.Typical examples are agent based models (ABM) which have been shown to be a useful tools for simulating behavior in complex systems [17,26,29,43]. In such model each agent behaves based on a set of simple rules. These rules may be based on distributions of behavior [12, 71], derived from actual data [75], cause-reaction rules or game theoretical approaches [21, 51]. An important feature of ABMs is that they allow testing interventions such as policies in these complex environments. So far, limited research has been published that realtes the use of agent based models aimed to optimize deployment of complex infrastructures to complex system features [8, 56].
Regarding analysis of the behavior in the system, behavioral patterns of agents may be analyzed in terms of distributions of performance metrics to reveal what happened in the system [17]. Yet, to gain a deeper understanding of the interactions of elements in the system complex network measures used to gain a deeper understanding in the interactions between elements in the system. Two types of networks generated from the system are of specific interest (1) a resource-to-resource network and(2) a bipartite network generated from interaction between agents and resources. The first network can reveal insight in how the system will respond to failures. The latter graph is a triplet $G_{\text{bipartite}} = (\top, \perp, E)$, where $\top \subseteq R$ is a subset of resource access points and $\perp \subseteq U$ is a subset of the user. Each edge $e \in E \subseteq T$ is a connection between one top and bottom edge and derived from the set of transactions. Each edge e can have a strength from using different perspectives of the network, such as power distribution.
Bipartite graphs have been used extensively in computational ecology to model natural animal-food systems. From literature in this field of science, a large number of metrics on the bipartite graph can be used. Next, from each bipartite graph an upper $\top$ and lower $\perp$ projection can be made (taking into account loss of information) that reveals the relation between top a bottom elements based on the total interaction in the system. From the Bipartite graph optimal resource allocation for users to resources can be run as well to reveal the minimum configuration of the system [30, 46]. Next, bipartite graph can also reveal adoption patterns for newly deployed resources [39].

3 Charging infrastructure as Complex System

This paragraph the features that characterize complex systems are put in to the context of charging infrastructure. We elaborate on the how the features match in the context of charging infrastructure and point at future developments of from both a technology and a behavioral perspective.

A central concept to the discipline of charging infrastructure research is EV user charging behavior. Charging behavior relates to the patterns of choices (*when*) EV users make to charge their electric vehicle at a specific (*where*) charging point (CP) of the charging infrastructure. It is generally accepted that EV user decisions and preferences are independent of central coordination. Charging behavior research has revealed factors determining the decision to charge such as traveling patterns, user types, charging infrastructure density and user battery interaction [2, 24, 73]. Charging behavior may therefore be considered as *self organized*. While some researchers have modeled the potential of centrally arranged charging transactions [55, 64], in the context of public charging infrastructure scheduling this may be unfeasible for two reasons; (1) personal preferences such as walking distance to end destination and (2) environmental context such as parking pressure.
An added complexity of charging infrastructure is the heterogeneity of user types in the system. Particularly in metropolitan areas the EV user population is a melting pot of residents, commuters, taxis, car sharing vehicles and other possible modalities [24, 58, 70]. Each user type is expected to have a specific set of charging behavior properties, inherited from a generic type based on its modality. In addition, each user type in the population is expected to have a different type of adaptation pattern to the interactions with another user type.

Non-linearity applies to the EV system, since scaling effects of number of CPs and Number of EV users determine part of the emergent behavior in the system. For instance, if both numbers are equal like in private charging only, then there is no competition as emergent behavior and limited interaction between EV users. Yet, in the case of public charging infrastructure there are many more EV users of potentially different user types that using the same charging stations [23, 66–68]. As the load on the system increases, *emergent patterns* of competition between EV users for CPs, adaptation of charging strategies and collaboration between users may appear. These patterns affect the relation between perceived convenience and the ratio between CPs and EV users.
As the density of charging infrastructure increases the number of relevant alternatives within walking distance to a CP increases as well which leads to a network of alternative charging points, see Figure 1 [18]. Having more than one relevant alternative may lead to non linearity in economies of scale and a lower required ratio of CPs per EV user. A negative effect of a charging network may be the increased effect of perturbations due to the network. The concept of robustness and vulnerability of charging infrastructure has been researched in relation with the convenience for EV users [18] and will be elaborated on in 4.1.

Feedback loops are based on EV user experience and interactions during their use of charging infrastructure. EV users may adapt their behavior to a changing environment or due to past experiences of interactions. Given the expected adoption of EVs it is well expected that the number CPs will increase as well, resulting in an increased density of the charging network. It is therefore expected that due to the growth EV users shift preferences due to potentially better alternative CPs for reasons of distance between CP and end destination or experienced occupancy. The change of charging preferences is expected to be a user specific gradual process of testing and evaluation.
Experience of interactions are related to emerging patterns competition and collaboration with other EV users. It is assumed that EV users strive for the best convenience of charging and therewith adapt their behavior. Negative experiences due to occupancy of preferred CPs may thus lead to shifting behavior in *when* time and space *where*. Due to competition an EV user may decide to arrive earlier at a CP in order to increase the probability of occupying the CP. Or an EV user may reroute to different CPs that have a lower occupancy rate.
Next the feedback loop within the system there is an external feedback loop as well, since the existence of CI has found attract new EV users [**?**]. An increase of EV users will result in an nonlinear increase of interactions and hence affect the other feedback loops. On the other hand, negative experiences may result in EV users to sell their EV.

Interactions between users may lead to *emerging* patterns of collaboration or competition in the system. Particularly in densely populated areas with scarce resources EV users may form communities that share charging points. Data analysis of public charging infrastructure has shown that there is significant difference between the connection duration and charging time of a charging session [23, 60, 69], which allows for sharing CPs without decreasing the effective charging time of a session. Patterns of competition may be revealed by agent based models as they reveal the unsuccessful connection attempts of an EV user to a CP. A deeper analysis of first and subsequent unsuccessful connection attempts of an EV user to an CP within is set for relevant alternatives may reveal where pressure in on the system leads to inconvenience for EV users, see Figure 6 as illustration. By definition this number of failed sessions is **not** part of charging data, since this only contains the successful transactions.
Earlier research on vulnerability of charging infrastructure has shown that a disturbance in the system, either a malfunctioning or an unexpected occupied charging station, can cause a cascade of failures in the system [18]. Simulation models on EV user charging behavior have learned that the number of failed connection attempts EV system is sensitive to changes in the number users for a given number of size of the infrastructure under relaxed circumstances (limited users and without noise) [**?**]. Moreover, in this

research an accelerated increase of system inconveinence was found when adding irregular users [**?**]. Particularly in metropolitan areas nearby POIs there is a high probability of irregular use of CPs [23]. Next, from practice it is known that next to full occupation of CPs, there are several types of perturbations that can cause an unsuccessful connection attempt: (1) a malfunctioning CP, (2) roadblocks (e.g. due to events or repairs) (3) parking spot occupied by ICE vehicle (being ICED). In these cases we assume that EV users change their destination to a new chosen CP in their vicinity. As the charging infrastructure density increases, the network density of relevant alternatives increases as well. On one hand this may lead to an increased *robustness* of charging infrastructure, since alternative CPs are able to accommodate perturbations. On the other hand in areas with high occupation rates this may lead to a *vulnerable* system, since a perturbation in the system may lead to a large cascades perturbed CPs in the system.
Path dependency relates to the fact that the EV system is currently evolving and interacting components like EVs, CPs, stakeholders on different levels play an important role in the future state of the system [**?**]. For example, worldwide we see different versions of initial conditions due to the local context: in metropolitan areas a strong focus on public AC charging, whereas areas with more private parking location focus on DC and private charging. The final optimal mix in charging infrastructure technology is likely to be dependent on the initial roll-out strategy [23] and subsequent developments. It may be very difficult for policy makers to change the local EV system from pure AC public charging to DC only charging and vice versa due to all the interactions of charging infrastructure with users and other systems.

3.1 Future developments affecting the complex EV system

It is expected that the complexity of the EV system will increase with its maturity. Not only will the number of EVs and charging points grow in the near future, also an increase in complexity is expected due to a behavioral change is expected for four reasons.
First, the improved range of new EVs is expected to influence the behavior of users, as high battery Full Electric EVs (FEV) are expected to show a different behavioral pattern than Plugin Hybrid EVs (PHEVs) [20, 63, 63]. Second, the ongoing increase of EV users will lead new types of user groups adopting the EVs as primary transport. While during the first years, EV adoption was particularly attributed to early innovation adopters curious for new technologies and driven by environmental consciousness, the new growth is expected to contain the early majority as well. Given that this new user group will have different behaviors and expectations, this sets new requirements to charging infrastructure. This corresponds to the idea that technology maturity affects usage behavior, as seen in other fields of innovation [5, 15, 16]. Noteworthy to mention is that OEMs are actively focusing on the early majority adopters as well. A third reason is that not only user groups will differ but also other types of modalities adopting electric drive-trains as well [31, 36, 40, 48, 57]. And fourth, an increased number of users will inevitably lead to an increased number of user-user interactions in the system as well. Moreover, an increased number of different groups and modalities is expected to lead to non-trivial patterns of behavior in the system.
This leads to the idea that charging infrastructure should be regarded as a growing complex system in which the behavior is constantly changing and adapting. While not currently present, phase transitions in the system due to changes in the EV user population are expected in the coming years. This not only requires policies aimed at a continued large scale deployment of public charging infrastructure [28], but it also a holistic and user central approach for deployment of resources [52].

4 Illustrations of Charging Infrastructure as Complex System

In this section we illustrate the potential of applying the complex systems approach to charging infrastructure based on ongoing research. While results are therefore preliminary (not yet published), the concepts and thoughts have been proven meaningful illustrations.

4.1 Vulnerability of Charging Networks

Recent published research on charging infrastructure vulnerability revealed effects of perturbations at charging stations on the perceived EV user convenience [18]. The convenience of charging infrastructure can not directly be measured from charging transactions, since non successful connection attempts are by definition not part of charging data. In [18] two vulnerability metrics were defined *service vulnerability* and *inconvenience vulnerability*. The *service vulnerability* refers to a disturbance in the system at a node that cannot be accommodated by any alternative CP. The *inconvenience vulnerability* refers to the length of the cascade of charging points affected by the disturbance of the perturbed charging station.

In this research the charging infrastructure was treated as a complex network in which the CPs represented the nodes and the connections between nodes were based on the existence of a appropriate walking distance (450-750meter) between two nodes, see Fig 1. The method of this research was to perturb one charging station by removing it from the system and then for each charging session in the data at this charging station search for an alternative outlet within the network. The nearest charging station that could accommodate the session was chosen as the alternative. Thereafter, given this new accommodated charging session a recursion function was run to check on cascading effects.

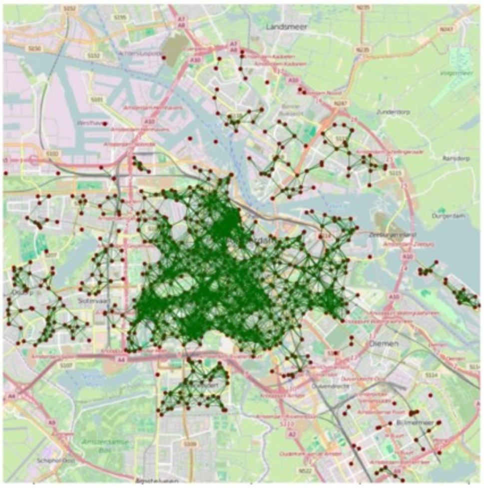


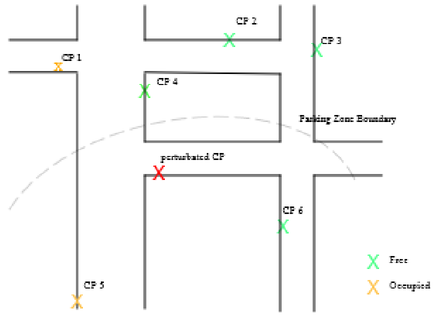
Figure 1: Complex network of alternative Charging Points from the City of Amsterdam, source: [18]

Results based on data of December 2015 for the largest 4 cities in the Netherlands show that inconvenience vulnerability was particularly present in the city centers where the network degree is high while service vulnerability was particularly present in the outskirts of the cities [18]. Cascade lengths up to 14 were found. The implications for policy makers drawn from this research were that roll-out should strategies should not only focus on general performance metrics but also take into account the potential vulnerabilities of the network.
Results from our ongoing research on this subject with charging data from 2017 to 2019 suggest that charging infrastructure may reach a critical point, as the distribution of cascade lengths seems to fit the power law distribution. These preliminary results show many short cascade lengths (0-10). incidental larger cascades (10-40) and a few extreme cascades up to length 144. It is suggested that the transition towards a power law regime may be attributed to the increased density of the network and the increased load on the network. For policy makers this implies that notice should be taken not only to the system metrics as in [53], but also systemic metrics that focus on the interaction in the system.

4.2 Nudging EV users' behavior to avoid

While complex systems typically lack a central steering mechanism, the results of [18] raise the question whether more centralized steering would be beneficial in terms of cascade reduction and therewith system convenience. Moreover, in [18] the selection of charging points was based on distance and availability, while specific user preferences were not taken into account. From this the question is raised whether the rerouting of charging sessions can be achieved to generate less impact on the total system meaning that an alternative rerouting scheme per CP is used. In ongoing research three new approaches are explored to gain insight in the effect of nudging users towards alternative CPs, see Figure 2.

In Figure 2 on the left side a map is sketched of one perturbed CP (the red cross) surrounded by 6 other CPs of which 2(number 1 and 5) are fully occupied and the others are available. The dashed line represents the boundary between 2 parking zones. On the right side of Figure 2 2 tables are shown. The upper table displays 1st to 4th preferred CP per user. The lower table shows the length of the cascade given each sessions present in the data. In this table N/A implies that the CP is occupied and this not available. Three approaches to rerouting EV users from the perturbed CP to another are researched.
In the first approach rerouting could be aimed to minimize the impact on the system, which means that service vulnerability is avoided and inconvenience vulnerability is minimized. This requires that for each alternative CP the effect of rerouting is calculated before rerouting, see table right under corner in Fig 2. A result of this rerouting could be that while less users are rerouted, the average path length of the detour may be larger than using the previous method. In a second approach, the rerouting could be performed by using the preferences of each individual user, which means that there is no central steering mechanism. In this method the users are assumed not to have real-time knowledge on the occupancy of charging points. A third approach involves a random rerouting mechanism from the CP to any alternative within range. This implies that for each session the user is rerouted to a random CP nearby regardless of whether this CP is occupied or not. Rerouting to an already occupied CP will lead to an iteration of the simulation from that point and to an increase of the inconvenience value.



		CP Preferences			
Session	User	1st	2dn	3rd	4th
1	I	5	6	4	1
2	II	4	6	1	2
3	II	4	6	1	2
4	I	5	6	4	1
5	III	4	2	3	1
6	II	4	6	1	2

	Total System Inconvenience					
Session	CP1	CP2	CP3	CP4	CP5	CP6
1	7	1	5	N/A	N/A	5
2	11	N/A	0	2	6	0
3	0	1	5	0	N/A	
4	0	6		N/A	5	4
5	5	N/A	1	0	1	2
6	2	5	N/A	N/A	1	0

Figure 2: Concept of the rerouting perspectives

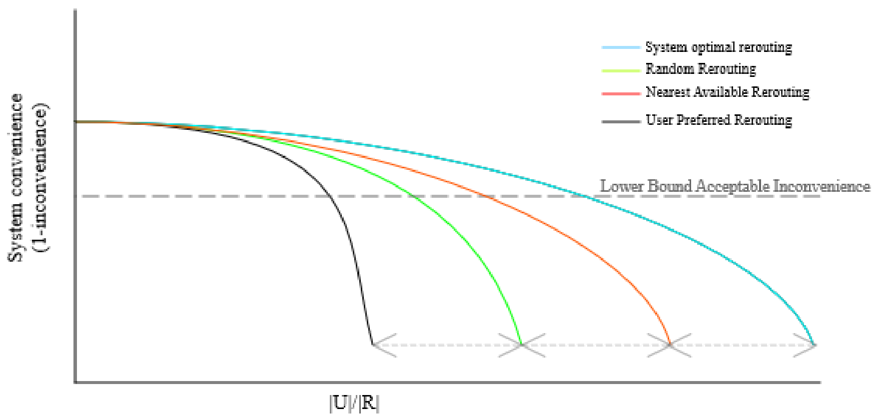


Figure 3: Hypothesized effect of system configuration on system convenience

Prelminary results of research suggest that the three perspectives result in different distributions of cascade lengths which can be related to different levels of convenience given the ratio of EV users and CPs as shown in Fig3. Moverover, the results of the first perspective generated a set that contains for each charging transaction at a specific CP the best alternative CP given its impact on the system. From this, a network of optimal alternatives may be setup with the CPs as nodes and the directions to another CP. If certain CPs consistently point at other CPs as best alternative, then a standardized reroute may be implemented in practice. This allows policy makers and CPOs to improve on system performance with simple nudging of users.

4.3 Competition between EV users for charging points

Recent advances on agent based modeling of charging infrastructure revealed dynamics of competition in the EV system that could not be examined using data analysis. An agent based model (SEVA) was created of which the behavioral rules were extracted from charging data. Rules contained start connection time, location, connection duration and distance in time and space between current session en next session. By scaling up the number of users with a constant number of charging points a relation between the growth an user convenience can be found.

In this research user convenience was related to the successful attempt of an EV user to charge their EV at their most preferred charging station at time of arrival.
In this research inconvenience was defined as an unsuccessful attempt of an EV user to connect to a specific preferred CP. This may be caused by an occupied charging station or a malfunctioning charging station. The EV user needs to divert to a second, less preferred CP. If a subsequent attempt is also unsuccessful the path of diversion increases as well.

Scaling up the number of EV users resulted in a non linear growth in used CPs versus the number of

EVs per CP in the simulation, see Fig 4. While the number of EVs per CPs (blue line) increases linearly, the number of CPs used shows a change in the slope of the line around 500. This may point at a regime change from a with a surplus of CPs to towards a system with a deficit of CPs and therewith competition. This may also relate to economies of scale due do the increased network density and therewith alternative CPs nearby.
It was also found that ~7% of connection attempts were unsuccessful given the 2,000 agents, see Fig 5. Moreover, this figure shows an increasing number of failed connection attempts as the number of users increases with a contact number of CPs. This is without perturbations in the system. Now, by definition the number of failed sessions is **not** part of charging data, since this only contains the successful transactions. This demonstrates that the system dynamics are more intricate and complex than simple data analysis would suggest.

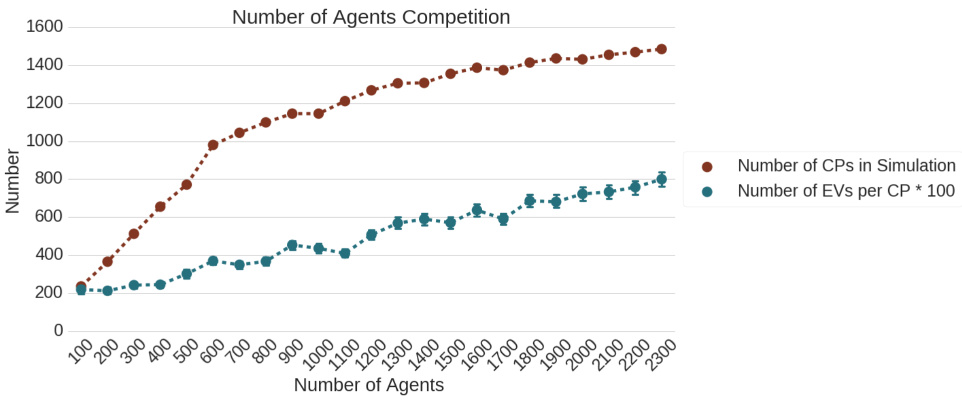


Figure 4: The number of CPs in the simulation and the number of agents per CP in the simulation for various numbers of agents in the simulation. Per value of the parameter the mean numbers with the 95% confidence interval is displayed.

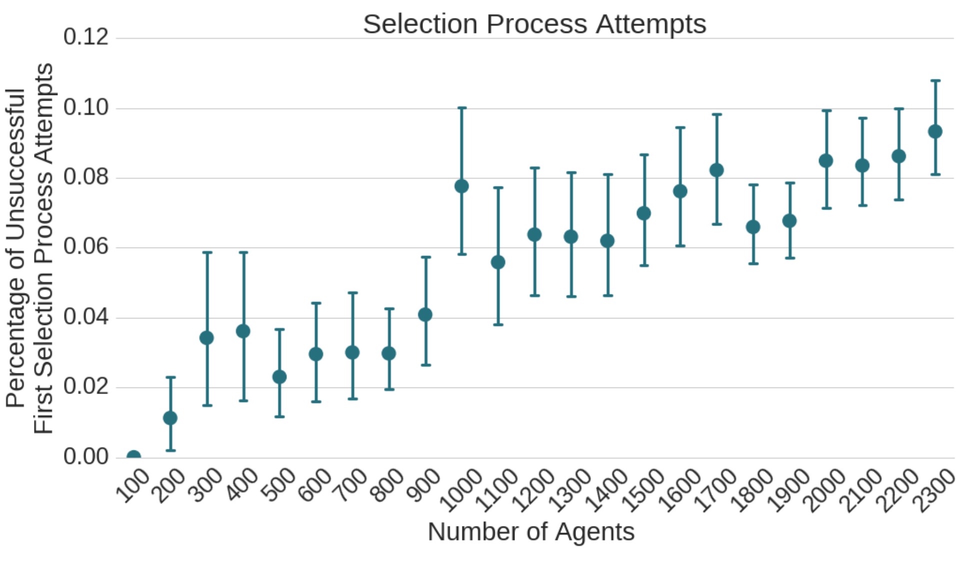


Figure 5: The percentage of failed attempts in the selection process. Per value of the number of users the mean percentages with the 95% confidence interval are plotted.

A subsequent study focused on the effects of unhabitual users on the user convenience (presented at EVS32 as well). EV users have found to be categorized into e.g. residents, commuters, visitors, taxis and car sharing. A typical difference between these user types is their charging point volatility [24]. Charging point volatility is the strength of preference for a single charging point. While residents typically use a few charging points, car sharing cars float over a whole city. As such, an increase of a user type may affect the vulnerability of the system and the unsuccessful connection attempts of EV users. Particularly, we found that the unhabitual users and visitors with semi-random patterns of start and end connection times and semi random across space have large influence on the user convenience.

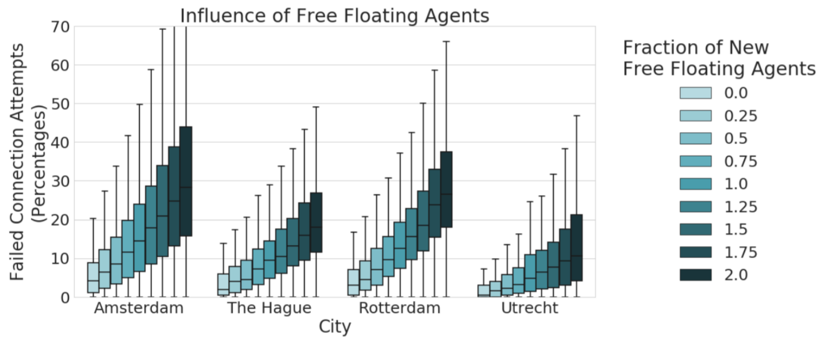


Figure 6: effect of unhabitual users on the user convenience [source Gorka]

In this ongoing study charging sessions were simulated with a different population compositions each an increasing number of ration of unhabitual users and visitors to regular users. From simulations it appears that the influence of unhabitual users appears high on the total number of unsuccessful connection attempts. The figure 6 below shows the boxplots. The box edges are boundaries of the 1st and 3rd 25% of the data and the bar in the box is the mean. It can be seen that as the number of unhabitual users increases that the distribution broadens and it increases steeply and outliers increase sharply. With this knowledge in mind, the question is raised, how to roll-out charging infrastructure in a way that focuses on user convenience and robustness rather than traditional key performance indicators. This implies that that the addition of unhabitual users has a non-linear increasing effect on the perceived convenience of EV users, which may lead to unexpected adaptation of charging behavior.

4.4 Non linear performance of CI due to tranformation of PHEV to FEV

Recent advances in market developments have shown a shift in EV technology from PHEV to FEV from 2018 onwards. This is opposite to the first EVs on the market from 2013 onward which were mostly PHEVs. Note that many of the lease contract of early EVs are ending in 2018/2019. Yet, most public charging infrastructure deployed has been done so to accommodate for many PHEVs and only a small share of FEVs. This leads to the question of whether the current public charging infrastructure is capable of accommodating the new composition of the EV fleet. To answer this question a module in an existing simulation model that incorporates the differences in charging behavior between small and large battery sized vehicles was developed. Within this simulation model the effects on charging behavior when switching from PHEV to FEV were simulated using real world data. In order to do so, a behavior transition equation had been developed to transform any PHEV user type to an equivalent FEV user based on the significant feature difference of PHEV and FEV users.

Based on behavioral properties on charging data, three types of EV-types were distilled from the data: (1) PHEV, (2) small battery FEV (low FEV) and (3) large battery FEV (high FEV). The differences in charging behavior were made explicit for modeling by drawing distributions on connection and disconnection to charging points and location-based behavior. From analysis it was found that the most significant differences were present in the time between sessions, meaning the large battery FEV users tend to skip a day, and the number of locations that were used. Intuitively this is logical since (1) the arrival patterns are known to be related to traveling patterns, (2) skipping a day or a session could imply skipping opportunity charging at non-regular locations. A Factor Transform (FT) function was developed to apply the EV transition to the time between sessions. This FT was run on all agents in the simulation model to enable modeling their transition to large batteries (70-100 kWh). Experiments were performed to simulate the effect of the transition of the EV population from current models to large battery FEVs using a varying probability.
In order to test how the EV system would react on the transition several performance indicators were analyzed from the simulation results; (1) Average connection duration per CP per week; (2) Average number of unique users per CP per week; (3) Average number of charging transactions per CP per week; (4) Average kWh charged per CP per week. Results of this case study showed that a significant drop in connection times per CP, while the kWh charged at those same poles increases. This indicates that, as a transition to higher batteries takes place, first the efficiency of charging infrastructure increases, and second less charging infrastructure would be needed to facilitate the EV population. The number of unique users per CP and the decrease in connection times would also be positive for EV users, as this implies that the CPs are available more often. the perceived inconvenience was not measured since this case particularly focused on performance accommodation. The results of these experiments show that the effects on performance indicators were not trivial, nor could be gained from extrapolating current data. The complex systems approach accommodates on the non trivial effects of system scaling.

5 Results and Implications

5.1 Implications for policy makers

In this paper we have made a case that complex systems may add to better understanding of the performance of charging infrastructure and may support policy makers in making more robust solutions for the anticipated, exponential growth of EVs. Until now, most deployment strategies were either based on actual demand of EV users or based on expected demand at strategic locations near points of interests (POIs). This approach has proven to be successful during this first phase of deployment, yet for the future growth of the system this approach may not be the most optimal. For example, economies of scale may arise due to network density or user interaction may lead to new kinds of competition for charging points.
So for deployment of resources during times of exponential growth of multitudes of user types, municipalities and other stakeholders struggle how to optimize the deployment out charging points and how to optimize the use of the current charging points [22]. The reason for this struggle is the fact that the stakeholders (such as municipalities, CPOs, DSOs) of the CI have limited insight in (1) structural performance measurement of the CI, (2) how typical behavior influences the performance of the system, (3) factors determine the user convenience the system and (4) the effect of interventions on the performance of the system [25]. Regarding these issues, this research contains several learnings.

First, due to the complex behavior in the system, policy makers should look beyond the typical key performance metrics of charging infrastructure to gain a better understanding of the interactions between users in the system. Traditionally, Key Performance Indicators (KPIs) for charging infrastructure focus on CP utilization [**?**,22]. Based on a complex network approach it is found that it is interesting to measure the interactions between EV users as well, since this may provide insight in *emerging* interaction patterns and system dynamics. Having a focus on these dynamics helps to keep track of *non-linear* behavior. This helps policy makers to be better prepared in the typical unsuspected behavior that complex systems tend to display. The bipartite network metrics may provide insight in the following dynamics of the system :

- Basic graph properties over time (diameter, degree distribution, number of connected components, average path length) may provide in the expected growth of the infrastructure versus the actual use of the infrastructure
- Bipartite graph properties related to stability of the network may provide policy maker insight in where to deploy new CPs in order to minimize user inconvenience [6, 47, 54]
- Competition between users on similar users using the user-to-user-projection of the graph
- Competition between cliques of users or resources access points may provide insight in which areas to decrease competition by adding new CPs [19]
- Supply side network robustness and vulnerability based on resource-projection of the bipartite graph as described in section 4.1
- Resource allocation and resource adoption patterns may provide insight in the differences between expected adoption and actual placement of CPs. This answers the questions are the CPs deployed for specific users really used by these users or do they swarm around other CPs as well [30, 46].

As an example, we provide in the figure below 7 the diameter (the largest connected set of competitive RFIDs) against the order (the total number of RFIDs) is shown over time for the charging infrastructure of Amsterdam between 205 and 2017. Each dot represents the value measured in a week. The diameter may be seen as the longest path of competition and with that potentially sensitivity for perturbations. The red dots show the daytime charging users, the green dot shots the overnight charging users and the blue dots represent the total network regardless of time. It can be seen that the dynamics of the different types of charging sessions have different interaction. The daytime network contains more RFIDS with about the same order as the overnight network. This means that the longest path of competition is relatively smaller for the daytime network than the overnight network. Moreover, it can be seen that the total network, has a much larger diameter. This may implay that (1) daytime and nighttime users have different interactions and (2) competition may occur in the transition time between both types of charging. For instance, EV users leaving office around 18:00 hours while others arrive at that time.
Second learning is that policy makers should embrace the use of simulation models next to using traditional data analysis. Simulations help to reveal dynamics that are not present in the data such as interactions between users. Moreover, simulation models allow testing of interventions and roll-out strategies. Particularly, simulation models allow focus on user convenience in roll-out strategies next to traditional KPIs. Results from vulnerability analysis and agent based model simulations have shown that different roll-out strategies have different effects on KPIs and user convenience and should be balanced carefully when making future deployment policies.
Third learning is that while actual individual decision making *self organization* may not be changed,

Figure 7: Diameter (the largest connected set) vs order (number of items) of graph for RFID projection of Amsterdam area based on time filter for daytime and overnight charging

nudging EV users' charging behavior may optimize the total performance of the EV system. As such, policy makers could benefit by testing different kinds of nudges in both in simulations as well as in the field. Interventions may contain, incentives to cooperate, rerouting options on CPs, apps that allow communications between EV users, or implementation of car sharing schemes.
Being conscious of learning effects and feedback loops of EV users may be key to accommodate roll-out strategies to local circumstances. For instance, based on charging data analysis policy makers may find patterns of EV user *adaptation* to local competition or collaboration.
Fourth learning is that *Robustness and vulnerability* are essential elements of complex systems and in the context of charging infrastructure they relate to convenience of EV users [18]. From literature it is known that the higher utilization of a system leads to higher tension and to higher criticality of the system. While policy makers tend to optimize on performance in terms of utilization of charging points, a balance between performance and robustness may lead to a higher total system convenience. Roll-out strategies specifically pointed at decreasing the network vulnerability may lead to an increased convenience for EV users while having marginal impact on efficiency.

Finally, while it is difficult to generalize learnings on path dependency, it is still an important factor that policy makers should be aware of. Both in research as well as in practice there seem to be two mutual exclusive paradigms for charging point technologies AC level 2 charging or DC fast charging. Technology developments of charging both on charging point and EOM are following rapidly, which results in a changing favo for each paradigm. Deploying charging infrastructure as a portfolio of several technologies may avoid that certain paths of developments become excluded. To the best or our knowledge Path dependency of charging technologies has not been researched so far.

5.2 Implications for researchers

In this paper we advocate the use of the complex systems approach to charging infrastructure researchers and policy makers. Until now, scientific literature seems to lack the relation between complex systems and charging infrastructure. As as result, limited attention has been paid to the concepts described in this research. Though, some tools like agent based models typically relate to CST have been used to gain insight in deployment strategies [56]. Given the complexity of behavior in the system, we believe that these tools are closer to real behavior than the often found Operation Research models.
We believe it would be beneficial to put research questions commonly found in complex systems theory in the context of EV charging. For example, an interesting scientific challenge would be to spot early warning signals of regime changed in charging behavior. Moreover, information theory may reveal insights into the factors that largely influence Self Organized Criticality or regime changes. From these insights interventions may be simulated that help to avoid sudden regime changes.
Since it has been found that agent based models are difficult to reproduce based upon paper writings, it would be beneficial to share ABM code and documentation online (e.g. Github) for research purposes [10]. Particularly data driven agent rules may be of interest for research worldwide, since EV maturity tends to differ. Sharing the rules themselves rather than the underlying data may avoid privacy issues as well.
Regarding complex network analysis of charging infrastructure it would be scientifically interesting to

compare the complex CP networks of metropolitan areas worldwide in relation to performance, user behavior and perceived user convenience. This may also help to gain a better understanding of path dependency in the context of charging infrastructure. Research in path dependency able to create a set of generalized insights based upon different contexts of metropolitan areas would provide a better understanding of the complex tasks of deploying any new kind of infrastructure.

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Authors

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.

Robert van den Hoed is Professor Energy and Innovation at the Amsterdam University of Applied Sciences (AUAS), part of the Urban Technology research program. Research topics include electric mobility, optimization of charging infrastructures and smart grids. Van den Hoed is board member of Dutch-INCERT and steering group member of Amsterdam Smart City and National Knowledge platform Charge Infrastruture (NKL).

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.