

# Smart grids as Common-pool Resources: Managing Electrical Vehicle Charging through Evolving institutions

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## Abstract

Urban population is responsible for 70% of greenhouse gas emissions worldwide. The production and consumption of renewable energy sources and the use of electric vehicles (EV) is promising for mitigating these emissions, but poses problems to the low voltage grid. Smart grid technology that is used to manage and thus mitigate the negative effects RES and EVs have on the grid lack acceptability because they fail to meet social requirements such as respecting privacy and minimizing user interaction.

In order to minimize interaction with users, intelligent agents can be designed to take over many user responsibilities. Artificial agents can also increase privacy by minimizing information sharing. Nonetheless, with current multi-agent system designs, a centralized management is still needed, which would require private information.

Centralized control of an agent-operated grid system can be omitted, when grids are viewed as common pool resources (CPR). Although a CPR management approach can result in the tragedy of the commons, allowing the grid to be operated by endogenous institutions can be a promising solution.

In this research, we design a multi-agent system (MAS) platform for the management of smart grids by building socially-inspired algorithms based on theories of common-pool resource management. Automated, yet bottom-up institutional arrangements for the management of smart grids proved to be a promising approach to solve existing problems of distributed control. The main finding of this research is that CPR management institutions can indeed be effective solutions to manage smart grids. Our results show that the

software agents work best when they are grouped into neighbourhoods, use borda count as a voting mechanism and the structure of the rules is simple. However, there are several computational details that need to be fine-tuned to reach optimal solutions. These including the design of the memory of agents to store effective strategies, the technical details of institutional rules and the voting mechanism. This research focused on EV users. However, given the promising results, we are extending the design to other users in the grid.

*Keywords:* smart grids, multi-agent systems, endogenous institutions, common-pool resource systems

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## 1. Introduction

Urban population is responsible for 70% of greenhouse gas emissions worldwide. Consequently, citizens hold the key to mitigate these emissions. The mitigation strategy that citizens are increasingly becoming involved in, is the adaption of renewable energy sources (RES) for houses and cars. The production and consumption of renewable energy sources and the use of electric vehicles (EV) is promising, but poses problems to the low voltage grid.

Unlike most other electricity sources, renewable energies are often integrated on the low voltage grid level. Thus, both EVs and RESs introduce massive changes in the, so far uncontrolled, low voltage grid. The grid not only has to be able to deal with the average load but more importantly the peak load, and in more recent years peak production, that can occur within a day. On the production side, PV production is dictated by the sun, PV production from distributed sources peak all at the same time and cause voltage peaks. On the consumption side the introduction of EVs increases peak load. The charging behavior of EVs is controlled by their owners, however, since most cars are used to commute to and from work, congested situation in which many people plug in their car at the same time, when they come home from work, can occur.

The concept of smart grids mostly refers to the management of the production and consumption of electricity in the low voltage grid which was not an issue until the introduction of renewable energy. With the introduction of EVs, the electricity demand increases significantly and becomes less predictable. With the uptake of PV production consumers of electricity become producers as well shifting the low voltage grid from a consumption system to

a production and consumption one. The additional demand and production is in size comparable to the already existing demand. Thus the grid will have to deal with the normal household demand plus an additional load which is just as much as the household load itself.

The easiest but also most expensive solution is to reinforce the low voltage grid to handle this new situation. It is much cheaper to manage this upcoming demand and production, than to reinforce the grid. The problem research has to deal with is how to manage a smart grid. One of the simplest ways is to use demand response and price structures. Users get feedback about their energy consumption and the current price. This way they will get a feeling for how much energy they use and hopefully adapt their behavior. This is however not guaranteed to work and has some privacy issues.

Managing the smart grid through software also shows some problems. Central management gives users the impression of losing control and is computationally heavy. Distributed solutions which use AI agents, allow independent decision making about when to switch on different household appliances or charge a backup battery of electric vehicles. However since agents work independently they either fail to find an optimal solution for the overall grid or need some outside control and incentive mechanism.

Alternatively, the grid could be seen as an common pool resource. This would mean that the reward function includes a direct feedback from the grid. This way the intelligent agent will have to strike a balance between charging the electric vehicle and not putting too much strain on the grid, instead of striking a balance between charging and cost. The rules about how and in which situation the grid constrains the behavior of the agents are set by the agents collectively through institutions.

The structure of this paper is as follows. In Section 2, we explain what smart grids are in more detail. In Section 3, we define common pool resource systems and discuss how smart grids can be viewed as such. In Section 5 we introduce our multi-agent system (MAS) design. In Section 6, we implement a model where our MAS design can be tested and illustrate the results of our simulation. Finally, in Section 8 we give concluding remarks.

## **2. Smart Grids and smart charging**

In this section we briefly go through the research that has been conducted in the area of electric vehicle charging in smart grids.

### *2.1. Technical aspects of smart grids*

Although research in the technical management of EV charging and smart grids in general can have very different scopes, the overwhelming focus is on electricity and the aim is almost always the minimization of cost and the reduction of peak load.

An interesting area is the management of the interaction between the smart homes, distributed energy resources and the electric vehicles(EV)[11]. The negative effect of electric vehicles(EV) can be mitigated by the use of smart charging or can even be beneficial to the grid through vehicle-to-grid operation(V2G). Smart charging sees the electric vehicles(EV) as a load that has to be managed to prevent higher peak loads. V2G views the battery in the EV as an active part of the grid. It can be charged when there is too much supply by PV and discharged when there is little to no PV supply present[12].

### *2.2. Distributed Approaches to smart grid*

Most approaches to find smart charging or V2G schemes involve some kind of centralized management [13][14][15]. [13] points out that any real time management of EV or smart grid has to be computationally inexpensive. In [13] the smart charging is based on a price structure incentivising people to charge their EV at times when there is otherwise little load in the grid. This still requires the user to make an active choice about in which time zone he or she would like his/her EV to be charged.

[15] proposes a solution, which has a central management but acknowledges the EVs as agents, which make autonomous decisions about what to report. The agents in this case are like intelligent sensors of a central management. They make decisions about the local situation and report this information. Which car gets to charge how much is then managed centrally based on the utility each individual car reported. The paper also mentions the possibility that agents could state incorrect values in order to seem more urgent to the system. In a congested situation in which there is too little capacity to satisfy all of the demand each agent would state the highest value to maximize its share. This is analogous to common pool resource problems, the agents try to maximize their own utility with disregard for the other agents and thus exhaust the system.

[17] has introduced a truly distributed method to deal with smart charging, where every agent makes autonomous decisions, yet the combined peak load is reduced compared to a uncontrolled charging scenario. Such decentralized

solutions are multi agent systems, composed of several agents. The agents decide about how much to charge the car on behalf of a person, without actual interaction with the person. In order for the agents to make an informed decision, they have to interact with the environment and find optimal strategies for charging. This is normally done by Q-learning. However, Q-learning does not always converge when used in a multi-agent system. Since each agent has a different reward function there is rarely a policy found which maximizes the benefits of all agents [18]. Furthermore [19] points out that if the agents in multi agent systems appropriate a real and limited resource for humans, that the agents will contribute to the depletion of this resource if not properly restricted in their behavior.

[17] solves this by making the reward, an agent gets, a combination of utility gained from electricity usage, in household or through charging, and the cost of electricity usage. Because the cost of electricity is in the reward function, agents only charge up to a certain point, and it becomes more likely to charge when the price is low. This way the Q-learning algorithm in [17] distributes the load more broadly over time and converges to a better solution than in the uncontrolled charging scenario. However the agent does not get rewarded for stabilizing the grid, it gets rewarded for being most cost efficient, the positive effect for the peak load seems to be a side effect rather than the main goal of the research. Even worse, when a surplus of renewable energy production coincides with a peak household load, the price incentive to charge at this point in time will worsen the situation rather than relieving it. This seems to be better suited for balancing the production and consumption of renewable energies than to reduce peak loads. This raises the question whether or not cost is the best indicator in the reward function to maximize the grids stability. On a broader perspective it raises the question how distributed AI systems, which do things on behalf of people should be managed.

### *2.3. Multi agent systems in Smart grids*

A subset of distributed systems are systems of distributed agents so called Multi agent Systems(MAS). [20] showed that agent systems for managing the smart grid on the low voltage level are possible and focused mainly on technical problems and implementation.

Different MAS address different problems within the smart grid. [22] addressed the problem of balancing supply and demand by coordinating agents

via market algorithms. [21] also focused on the problem of balancing supply and demand, but purely through automated demand side management, while also trying to address the problem of possible peak load resulting from too many agents trying to use too much electricity at once. Both approaches build on markets and price incentives.

As mentioned before it is not clear if price incentives to balance production and consumption also reduces peak load, and is not in fact a driving force behind peak load by creating situations in which many households want to use a lot of electricity at a time.

Instead of a market based approach there is also the possibility to see the grid as a commonly shared resource. [23] applied Ostroms theory of self-governing institutions to multi agent systems and further points out that such an approach could also be applied to agents managing the smart grid.

#### *2.4. Social aspects of Smart grids*

The social research is comprised of studies about acceptance of smart grids, management of smart grid through people commonly referred to as demand response, and the ethical problems that arise. [5] point out that the main obstacle in implementing smart grids is that most users have a feeling of loss of control over their own appliances. [7] on the other hand shows that while there is a concern over privacy and loss of control, it is outweighed once the user realizes the benefits of smart appliances.

Demand response is the idea that by giving feedback about pricing, households are more aware of energy and are thus steered towards an energy conserving lifestyle. For example, [5] showed that by giving active feedback about the households energy consumption, the power consumption is reduced by 9%. Nonetheless, [6] emphasize that electricity consumption is contributed to lifestyle factors and that consumption can be reduced by behavioral changes. The idea is that: "Technology and behavior thus have to complement each other" [6]. However others have raised moral concern about giving utility companies more power over appliances or giving them access to user data [8][9]. The fear is that utility companies or smart home appliance manufacturers could misuse or sell data to third party companies, or use price structures to influence usage behaviour [8].

### 3. Smart grids as Common pool resource systems

This section will explain what a common pool resource is, how institutions can help solve CPR problems and how the idea of institutions can be applied in multi-agent systems.

#### 3.1. Common-pool resources

Common-pool resources (CPR) are natural (e.g., forests, fisheries) or man-made resources (e.g., network infrastructure, roads) that are shared among different users [1]. The overuse of these resources often leads to their destruction. CPRs are defined by two characteristics: difficulty to *exclude* potential beneficiaries and a high degree of *subtractability* [1]. Therefore, CPRs experience properties of both public and private goods. Similar to a public good, it is hard to exclude people from CPRs. Similar to private goods the subtractability of common pool resources is very high. This differs from a public good where the subtractability is low. For instance while Wikipedia as a public good does not face subtractability, the Internet which allows access to Wikipedia is a CPR because if one person uses up all the bandwidth, it would deprive others of their access [1]. These characteristics make the management of CPRs especially complex leading to the “Tragedy of Commons” as addressed by [2].

The tragedy of the commons results from the two characteristics mentioned above. If an individual extracts value from the resource, the individual is the only one benefiting, yet the negative effect of resource depletion is shared by everyone. This incentivises individuals to extract as much as possible since their gain is greater than their loss. The behaviour is the rational behaviour of an individual but is irrational from a group perspective.

The tragedy of the commons can be avoided by using institutions [? ]. Institutions are a set of rules and norms that all users in a system consent to. By consenting to a set of rules which restrict users, the commonly shared resource can be protected and it will not deplete [24].

#### 3.2. Smart grid Commons

Research on smart grids is often limited to a top-down centralized management which can hinder the acceptance of smart grids in society [4]. By viewing smart grids as common pool resources, their users can self-organize themselves and therefore be involved in a bottom-up management of the grid [4]. This would mean that the focus of research would change away

from monetary incentives towards how to come up with rules to make the most of an existing infrastructure. In fact, Michael J. Sandel describes in his book ,”What Money can’t buy” how monetary values can crowd out moral and ethical values and undermine community engagement in general. Furthermore, [9] has urged that ethical issues should not be features that can be added to existing smart grid concepts but rather central questions that should be addressed at the very beginning. However, the first question that comes into mind, is how can smart grids actually be considered as CPRs?

The problem, in the low voltage grid can be studied from a resource perspective which in this case is the grid itself which is limited in the amount of energy it can transport. The non-excludability characteristic of the grid lies in the fact that users can simply plug their electric vehicles in based on their own needs and charge their vehicles as much as they want. This can result in the tragedy of commons because the grid can easily be overused. Like most CPR problems, the smart grid is a nested CPR problem and can be looked at as either a supply side provisional problem or an assignment problem [1]. However, in this research we only focus on the assignment problem of smart grids.

Assignment problems are a special kind of an appropriation problem, in which there is spatial heterogeneity. The spatial heterogeneity implies that the position an actor is in, affects his/her ability to access the resource. A classic example are hot and cold spots in fishing areas. In a grid, if there is a longer line between the node at which it is accessed and the main transformer, it is harder to use electricity without overloading the grid. This is also the case when there are users in serial. The last one of users will have a harder time using electricity, because the actor will add to an existing load.

### *3.3. Smart charging of EVs as a Common pool resource Dilemmas*

The charging of electric vehicles in the low voltage grid cannot just be seen as a common pool resource situation but also as a common pool resource dilemma. Ostrom distinguishes between a common pool resource situation and a common pool resource dilemma based on two properties, suboptimal outcomes and feasible alternatives[1].

1. **Suboptimal outcomes:** The strategies of the agents result in suboptimal outcomes for the agents. Strategies in this case means a set of actions to be followed by the agent.



2. **Feasible alternatives:** There exists a coordinated strategy that is possible to be followed by the agents and results in a better outcome for the individuals, than the original strategies.

Based on these properties, there has to be a high enough demand created by the agents to strain the resource and result in suboptimal outcomes for the agents, and there has to be an alternative course of actions for the agents that would result in a better outcome than the default state. To show this, a simple simulation is created. The testbed is a representation of 24 households (represented as artificial agents) connected to a main transformer. The software agents control the charging of the electric vehicles. There are some constraints on how much each individual agent can charge. The constraints are implemented based on voltage deviation. The simulation is run with rational agents each of which will charge as much as possible. Each electric vehicle arrives at home, gets reconnected to the grid and its software agent charges the battery of the electric vehicle as long as the battery is not full. The result of such a simulation run is given in figure 1. In this graph the state of charge over time is represented for different levels. The level in this case is an indication of how close or far from the electricity source the electric vehicle is situated. The higher the level the further the EV is from the source. What can be seen is that the state of charge for EVs on level 5 and 6 are not able to recover to full charge after being drained. This shows that with several rational agents trying to access a common resource, the grid, the grid will not be able to meet the requirements. Which agents are not able to charge sufficient is determined by how far they are from the power source. The farther away the more constrained they are. Their position within the system determines how well they perform. Therefore the problem is an assignment problem. This outcome is suboptimal. It is not possible to show based on one run that there are better feasible alternative strategies that the agents can follow. However it is an implicit assumption that there are better strategies and it is part of this work to show how agents can come up with better solutions, by cooperation. This system is therefore not just a common pool resource situation but also a cpr dilemma.

The smart grid design proposed in this paper addresses the three issues discussed in Section 2: ethics, acceptance and technical. The technical constraint is addressed by replacing a central management unit by artificial software agents that belong to each EV. These distributed AI agents will collaborate in some way to find a best solution for the whole grid. In order

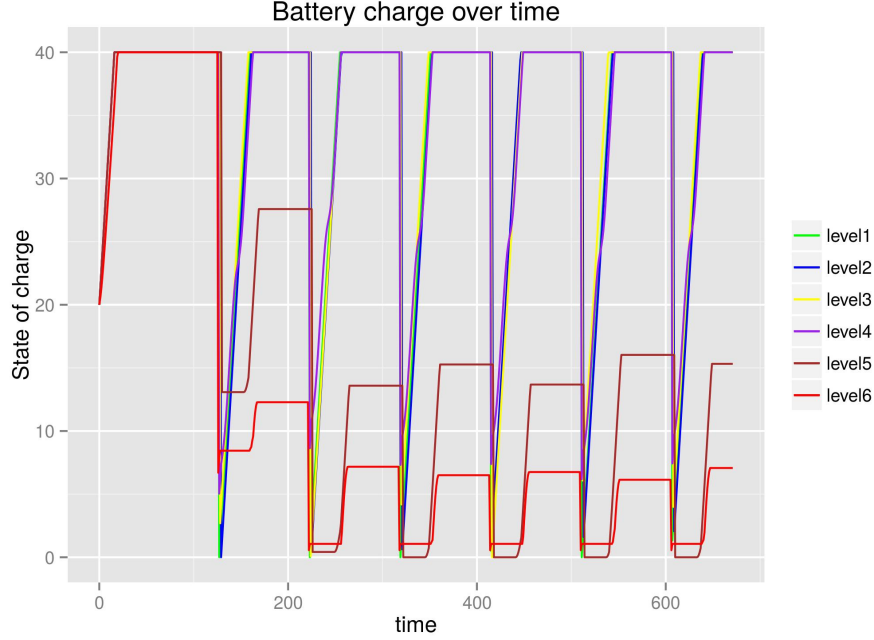


Figure 1: Tragedy of the commons in the Model

to respect privacy concerns the agent can only share limited information excluding electricity usage histories. The concept of artificial institutions for artificial societies can be helpful. The agents would optimize their behavior under the constraint of artificial institutions and evaluate how well they are doing under the given set of rules which the agents themselves define and change. The only information that has to be exchanged is the voting behavior, which says much less about the people living in the household than a complete history of electricity usage would. This could also reduce the negative feelings of loss of control that people have, because no outside utility company has to or can interfere in the management. The focus would also be on community collaboration rather than money, which can further boost acceptance.

## 4. Methodology

The goal of this research is to design and test a distributed solution to manage EV charging patterns in the low voltage grid. If the smart grid is seen as a common pool resource, then simply introducing distributed software agents to manage the grid based on the locally observable variables, will not solve the problem since the agents will simply contribute to the tragedy of the commons. Similar to human systems institutions can be used to coordinate the actions of these agents.

In this research we will design a distributed multi-agent system (MAS) that will coordinate charging behaviour for better management of the low voltage grid. The MAS design will be simulated in Python and will be tested on a model of a grid which will be implemented in PYPOWER/MATPOWER<sup>1</sup>.

## 5. A MAS design for EV charging

In this section we will introduce the design of our agent system.

### 5.1. *EV Agents*

The objective of the EV agents is to charge their electric cars. They use behavioural rules related to their state, voltage and time to decide about their actions. These behavioural rules are determined on the basis of their preference, memory and connections to others. Generally to define rules which best meet the objective, the agent evaluates the rules and assign a preference value to each one based on experience. For that, the agent keeps track of previous experiences in its memory to select the best options.

#### 5.1.1. *Agent behaviour*

Each agent has an initial learning phase which takes place for a short amount of time at the beginning of installation. During this phase, at particular intervals (e.g., every 15 minutes) the agents selects an action based on some internal rule. At the end of this time period (e.g., one week), the agent evaluates the rule it has been living with based on how high their battery state of charge over this past week was, and commits the rule and an

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<sup>1</sup>MATPOWER/PYPOWER is a software package for power flow simulations. MATPOWER/PYPOWER is available for Matlab, octave and python. The software package models AC and DC electrical networks. It will be used for the model testbed to give realistic grid responses.

associated preference value to its memory. Afterwards the agent comes up with a new rule for the next week. When the memory of the agents is not yet filled, the agents develop the rules individually.

The state of an agent is its state of charge(SOC), the voltage at its node and the current time. These behavioural rules basically map a specific combination of these variables to an action, see figure 2. The action determines how much the agent will charge in the next time step.

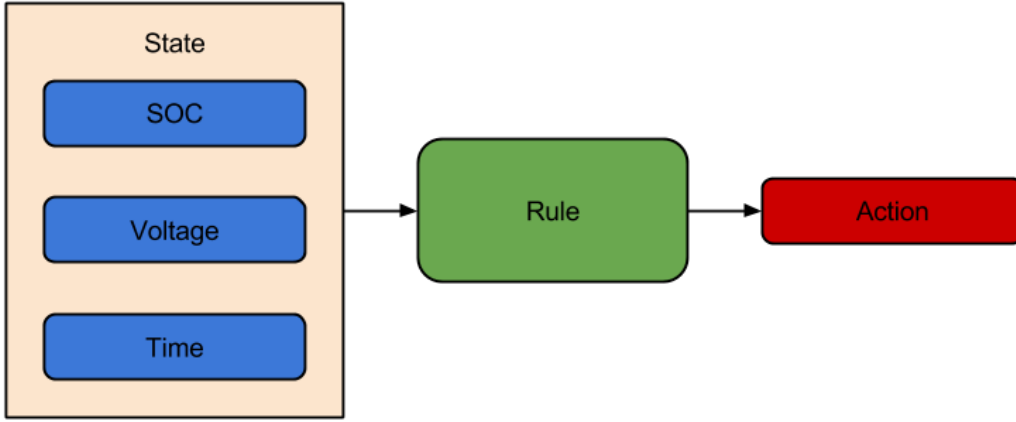


Figure 2: A behavioural rules maps agent state to agent action.

Since the agents have to be able to define the behavioural rules themselves, we define a blueprint (i.e. structure) for rules. The space of possible rules has to be rather small because the agents do not have an infinite amount of time to explore all the different combinations of behavioural rules. Rules can either be based on the current time and state of charge(soc) or on the voltage at the grid point and the state of charge(soc). Voltage based rules are indicated with a 1 and time based rules are indicated by a 2, see figure 3.

A voltage rule has a voltage and a state of charge threshold and two actions - action1 and action2. If the voltage of the agent is below the voltage threshold defined in the rule and its state of charge is above the minimum state of charge defined in the rule, the agent decides to take action1. If this condition is not true the agent takes action2.

A time rule has a similar structure. It contains two times,  $t_{begin}$  and  $t_{end}$ , to define a time interval and a minimum state of charge ( $soc_{threshold}$ ). If the agents state of charge is above the minimum, defined in the rule, and the

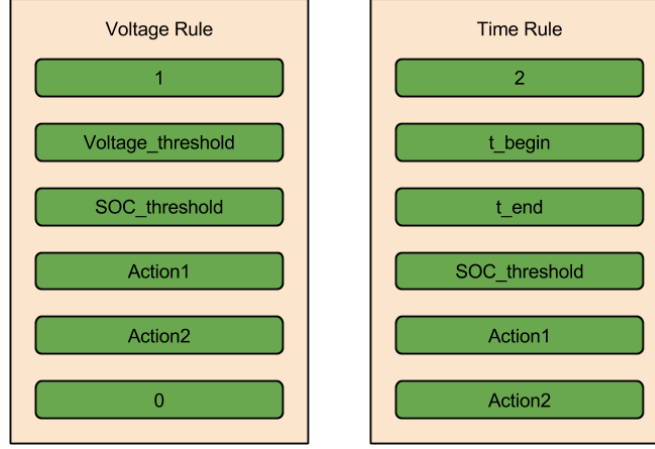


Figure 3: The structure of the two different behavioural rules.

time is within the specified time interval the agent takes action1, otherwise the agent takes action2.

Each agent has one active rule which is the best option among the behavioural rules existing in its memory.

#### 5.1.2. Memory

The memory is a private variable, each agent has. It is a matrix containing behavioural rules and preference values. The purpose of the memory is to keep track of past experiences. Experiences are rule preference-value pairs, see figure 4. Since the objective of the agent is to charge the electric vehicle, it is reasonable to take the average State of charge of the electric vehicle, over the specified time interval, as a metric for how good or bad this rule was. Preference values are determined by comparison to other existing rules in the memory. It is not possible to hold an infinite number of rules in the Memory and for this particular design we assume that this number is 5, i.e., the five best rules at a particular time are kept in memory. When the agent tries to recommit an existing rule to its memory the preference value will be set to the average of the two preference values.

#### 5.2. Institutions

In order to allow self-organization, agents define institutions. Through a voting mechanism, the agents will agree on a behavioural rule which will then be considered as the institution in the model. From that point, all agents

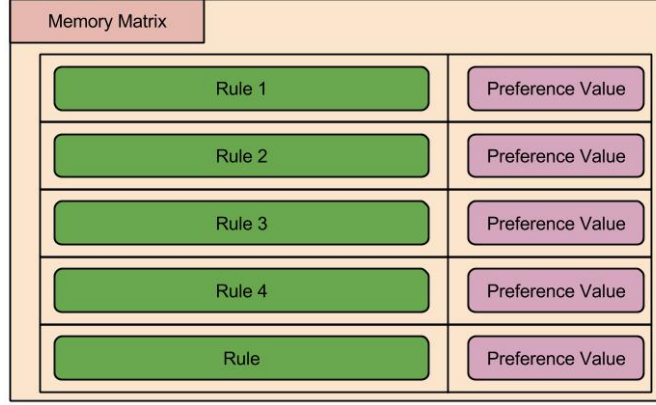


Figure 4: The structure of Memory in the agents

must comply with this institution instead of following their own behavioural rules.

When voting the agents report their ranked memory. The votes themselves are combined by borda count and then clustered.

*Border count voting.* A majority voting system only takes into account the top choice of voters. The Borda count also takes into account second and third choices of voters, this way it is more representative of the actual preferences of the voters.

Lets say there are k candidate rules  $\Omega = \{\Omega_1, \Omega_2, \Omega_3, \dots, \Omega_k\}$ . The voters then rank those k candidates from most to least favorable. Weights will be attached to the different candidates in the following manner. The best candidate gets the weight (k-1), the second best (k-2) and so on until the worst candidate receives 0. The choice with the highest weight among all voters gets selected as the institution.

*Clustering.* The K-means clustering algorithm clusters n d-dimensional data points  $x = \{x_1, x_2, \dots, x_n\}$  into k clusters,  $S_i$  with mean values  $\mu_i$ , so that the sum of square distances within the clusters is minimized.

$$\arg \min \sum_{i=1}^k \sum_{x \in S_i} \|x - \mu_i\|^2 \quad (1)$$

The algorithm consists of two steps which are repeated until the clusters no longer change. After initializing k centers of clusters randomly, all data

points get assigned to their nearest cluster center. Then the cluster centers get updated by calculating the mean of all the data points in the cluster.

The clustering is necessary, because there are so many different rules that it is very unlikely that all the agents pick one very specific rule. By clustering the rules, the rule which is closest to most votes is selected.

When the agents come up with rules without voting, the agent can come up with a new rule by either learning based on their memory, copying from the best performing other agent or randomly selecting a new rule.

At the end of this second step a new active rule is set for the agents to follow for the next week. And the process is started over again.

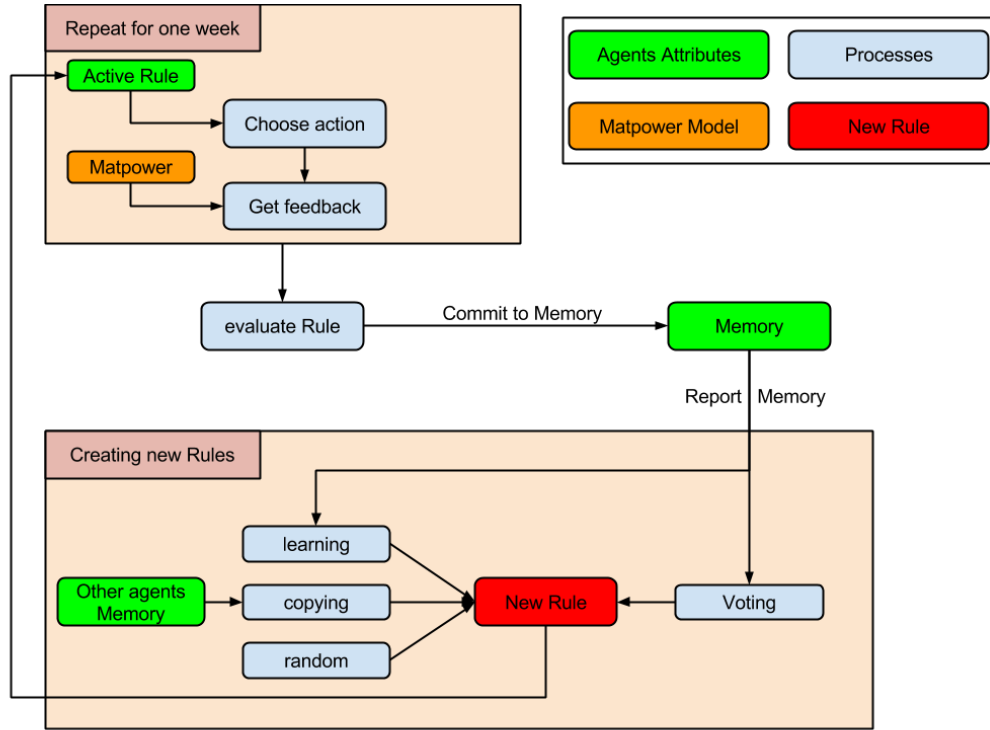


Figure 5: Model processes

For the design of our MAS, we made the following choices:

- The number of rules that dictate the behavior of the agents will be fixed to one rule

- Each agent keeps 5 previous rules and corresponding preference values in memory
- K-means clustering algorithm will be used to cluster the rules into 3 clusters
- Voting will be omitted for one week if the institutional rule is not good enough item The first five weeks the agents only develop the rules themselves.

## 6. A simulation test-bed to evaluate design

The agent system will interact with the PYPOWER model of the grid explained previously to by requesting a specific amount of power from the grid and receiving feedback about how much power they actually get. The testbed gives a realistic feedback about the actual limitations of the grid.

Each agent goes through the following process, depicted in figure 5. The process consists of two parts. The first part takes place every 15 minutes and is done for one week. The second part is done once every week. The part that takes place every 15 minutes is very simple. For one week in intervals of 15 minutes, the agent chooses an action based on their internal rule. The PYPOWER model then calculates a feedback which the agents internalize by updating their voltage and state of charge.

Each week the agent evaluates the rule it has been living with based on how high their battery state of charge over this past week was, and commits the rule and an associated preference value to its memory.

## 7. Results

The overall question that should be answered by this model is whether distributed software agents can organize in a way so that every electric vehicle can charge sufficiently while being constrained by a finite grid.

In order to explore the performance of the models, besides looking at the state of charge of each agent at different locations in the grid, we also measure the number of strong failures, i.e., whether the charge is sufficient to get someone to and from work, and weak failures, i.e., whether or not the battery is full when leaving the house.



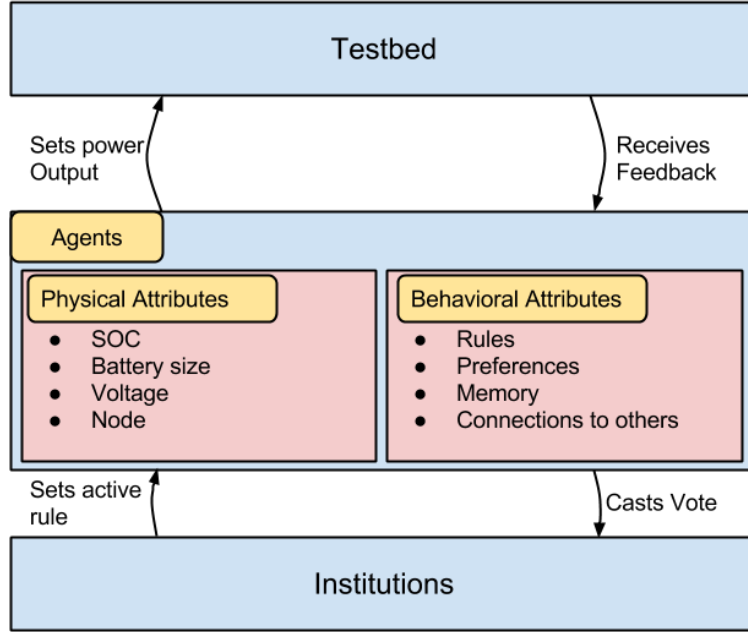


Figure 6: Model components

We first compared the model with a situation in which there is no control and every agent tries to charge as much as possible as long as its battery is not completely full.

We observed that the introduction of software agents has a big impact on managing the grid. The average SOC over all agents is increased. There is a redistribution of access from agents which would normally be not constrained (close to the source) to agents which would normally be very constrained (far from the source). The negative effects on the normally strong agents is very limited, while the effect on the very constrained agents is very pronounced. Figure 7 shows two such distributions for two different scenarios. On the left there are software agents controlling the grid and on the right the grid is uncontrolled. The number of weak failures, the cars not being charged fully when leaving the home, ranges from almost zero to a bit over 400 times in 6 months. However when the grid is uncontrolled, the number is above 1000 occurrences in every run. The case for the number of hard failures, is very similar.

In the second set of experiments, we studied the effect of the existence

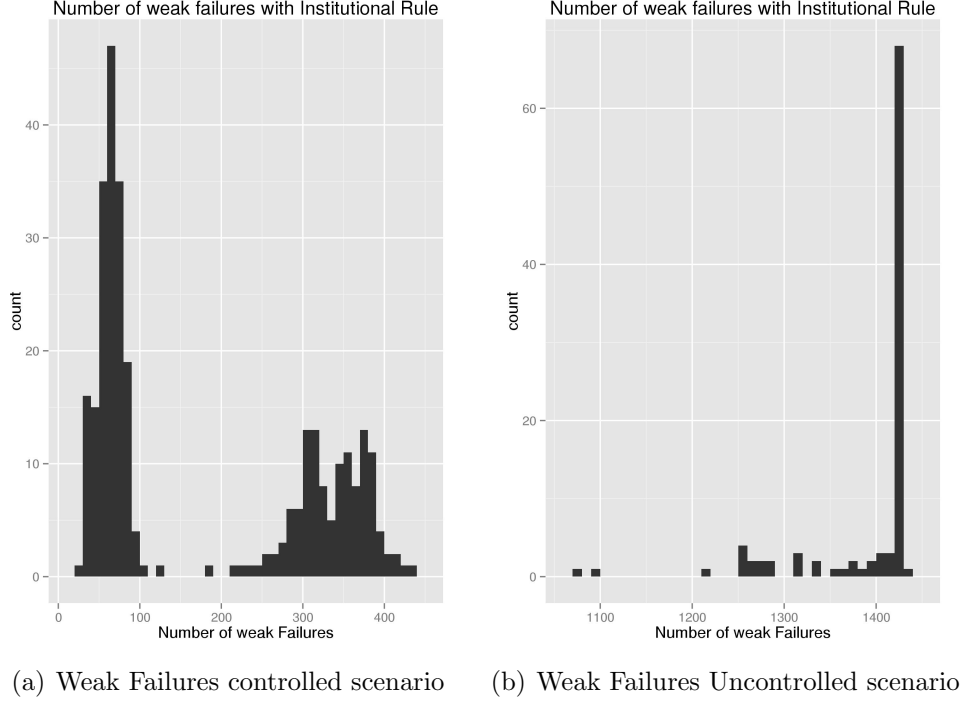


Figure 7: Number of weak Failure in uncontrolled scenario

of an institutional rule on the performance of the model. A one sided t-test for institutional rule being greater with a confidence interval of 95% reveals that the average SOC is significantly bigger when there is an institutional rule. The distribution of average state of charge of the agent on the lowest level, with and without an institutional rule is depicted in figure 8. The bin width in both graphs is the same but the axis are different. The highest value indicated in figure 8(a) is 80 whereas the highest count indicated in figure 8(b) is 30. This indicates that the weakest agents perform better when there is an institutional rule that every agent follows.

Figures 9(a) and 9(b) show the distribution of the frequency of hard failures with and without institutional rules. The number of hard failures spans from about 20 to 100 times when there is no institutional rule. Similar to the behavior of the weak failures the maximum number of hard failures is reduced and there is a portion of the runs which experience very low failure rates. Thus the introduction of an institutional rule reduces the number of

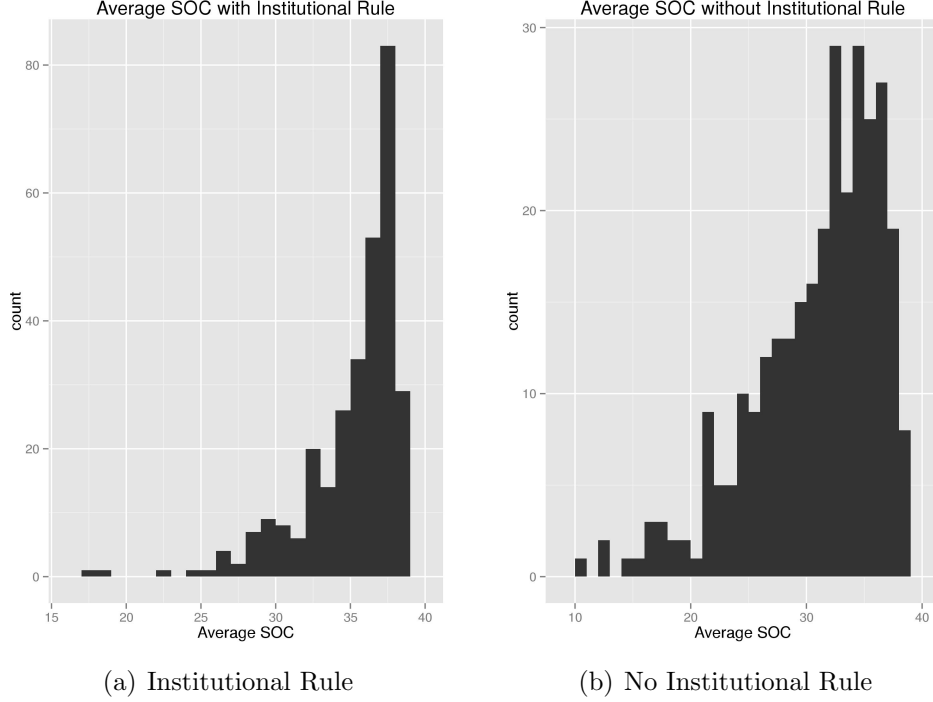


Figure 8: Average State of Charge of weakest agent

electric vehicles that fail to be able to charge sufficiently.

In summary the introduction of an institutional rule that every agent follows increases the performance of the model. The average SOC is increased. By introducing institutional rules there is a redistribution of access from the very well performing to the less well performing agents. The negative effects on the strongest agents is much less pronounced and severe than the positive effect on the weakest agents. As a result of this redistribution, the number of times electric vehicles are not able to charge fully or sufficiently is reduced.

Our third set of experiments explored the conditions under which the model performs best. Figure 10 shows the distribution of the number of hard failures for when there is an institutional rule, color coded by the kind of rule that was predominantly chosen in this run. Almost all the low failure rate runs occurred with predominantly voltage based rules. One possible explanation for this, is that the variation in the time when electric vehicles arrive at home makes it hard to come up with one specific time intervals, in

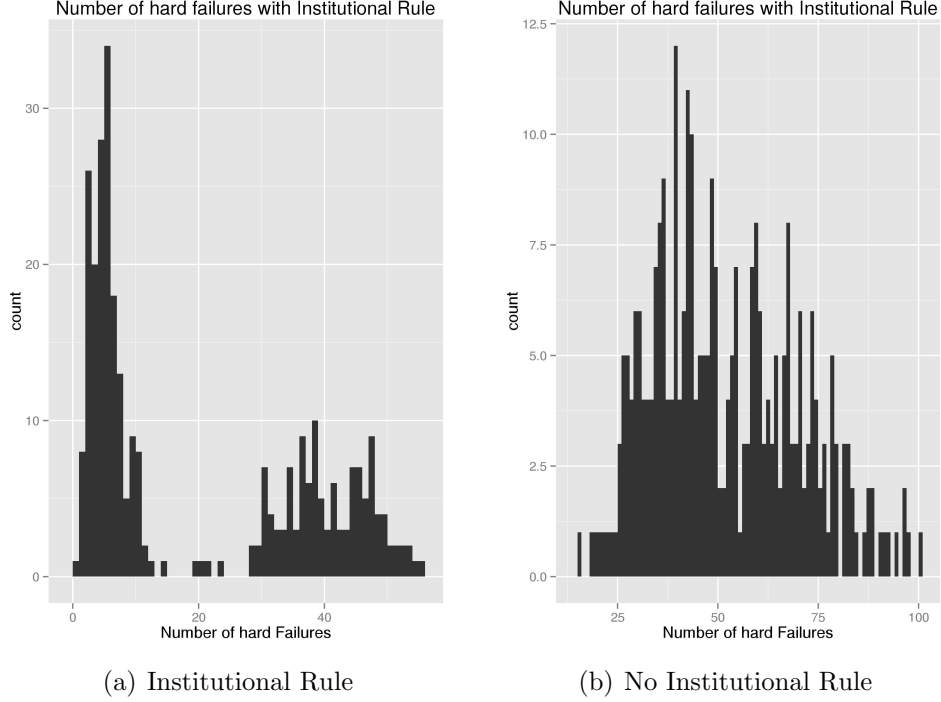


Figure 9: Number of hard Failure

which the cars should be constrained. In general, we observed that when the institutional rule is based on a voltage condition the agents perform much better.

Other experiments showed that the method of voting, grouping agents into neighbourhoods has some effect on the performance of the model while the ratio of learning and copying behaviour among agents has no significant effect.

## 8. Conclusion

The introduction of EV poses a significant problem to the low voltage grid. Charging EVs increases peak load and overloads the grid. Management systems for the charging of multiple EVs can shift the load broadly over time and prevent overload.

Central control has technical and ethical problems. On the technical side the problem is too complex and volatile for central systems to be responsive

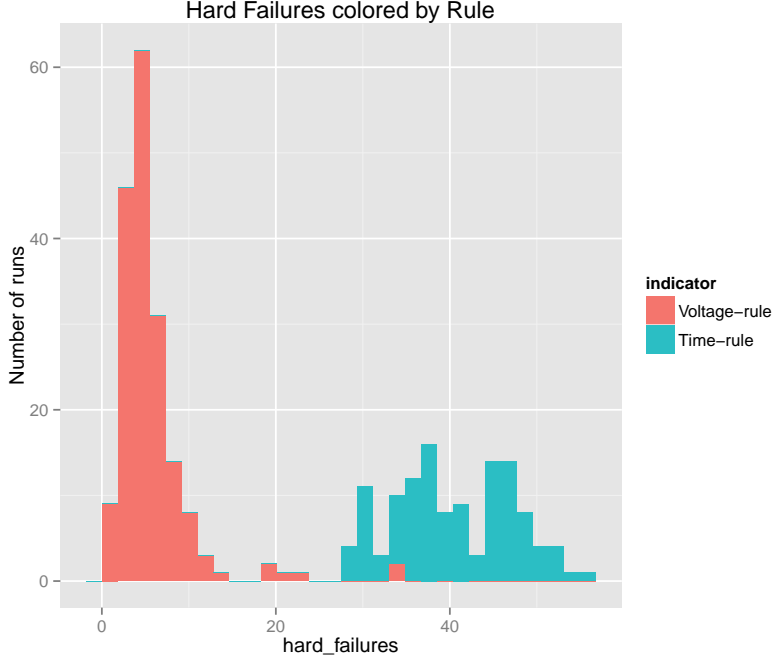


Figure 10: Number of hard Failures color coded by Rule

enough. Central systems also collect massive amounts of data or try to influence individuals behavior, which is an unacceptable violation of privacy. This research was an attempt at finding a distributed solution to manage the grid without the need for communicating private information. In order to do so a multi agent system was designed. Ostrom’s theory of self-governing institutions, which is usually applied to human systems, was applied to the software agent system.

Our results show that the software agents work best when they are grouped into neighbourhoods, use borda count as a voting mechanism and the structure of the rules is simple. However, there are several computational details that need to be fine-tuned to reach optimal solutions. These including the design of the memory of agents to store effective strategies, the technical details of institutional rules and the voting mechanism. This research focused on EV users. However, given the promising results, we are extending the design to other users in the grid.

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