Load-scheduling and PHEVs in the Smart Grid

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***Abstract*—Load peaks can have a negative impact on the stability of the power grid and maintenance costs for transmission and generation companies. Currently, increasing use of plug-in hybrid electric vehicles (PHEV) further proliferates the problem because charging patterns are expected to coincide with peak demand hours, especially the afternoon peak hours.**

To ameliorate this problem, we have investigated two different multi-agent mechanisms for scheduling the charging PHEVs: one where the charging plans for the PHEVs are created in a centralized manner, and a decentralized mechanism where PHEV agents stochastically generate charging plans on their own accord based on a pre-defined probability distribution.

We found that both mechanisms were able to schedule the PHEVs so that aggravating peak load was avoided, but that it came at a cost of the PHEVs' capacity to recharge in the centralized version. The decentralized mechanism, on the other hand, showed promising results in terms of fairness to the end user while being able to charge PHEVs outside of peak hours.

***Index Terms*—multi-agent systems, smart grid, demand-side management, load scheduling, PHEV.**

I. Introduction

Official estimates indicate that PHEVs, EVs and hydrogen-based vehicles may account for 5% of the total car population in Norway by 2020, and that as much as 26% of the fleet may be electrified or hydrogen-powered by 2030 [1]. It is thus probable that the transport sector will add a considerable load to the Norwegian electricity consumption within the next few decades.

One of the anticipated challenges in the future smart grid is how to efficiently handle the extra load associated with charging the growing number of PHEVs. PHEV market penetration may further aggravate this situation, especially since the extra demand resulting from PHEVs recharging their batteries is expected to coincide with times at which demand is already at its highest [2].

In this paper we use a multi-agent system (MAS) to schedule PHEV battery charging in a simulated environment involving residential power consumers and PHEVs connected to a simplified distribution grid. A MAS consists of intelligent agents interacting in an environment. The agents can be computer software modules, human beings, or anything else capable of autonomous and rational actions. Multi-agent technology can be used to build systems that are scalable, fault-tolerant, secure and easy to reason about.

The contributions of this paper are twofold. First, we develop a model framework for studying the impact of electrified vehicles and their charging patterns on the power grid and peak load under various conditions, along with an open-source simulator that implements this framework. Second, through a multi-agent approach to PHEV charge scheduling, we investigate the effect of different scheduling mechanisms, and demonstrate a particularly efficient distributed and stochastic scheduling regime, based on the well-known *mixed strategy* for multi-agent systems.

The rest of this paper is structured as follows. In the next section we report on related work on MAS approaches to load scheduling. In Section III we describe our overall approach. Subsequently, Section III-A describes the models that make up our simulated environment. In Section III-B, we describe the agents that operate in this environment, and the different strategies for charge scheduling. Finally, we present experiments involving different scheduling strategies, with a special focus on their effect on peak load.

II. Related work

The simulator we have developed is inspired by Boucké and Holvoet [3]. They investigated scheduling mechanisms for the charging of PHEVs, with a focus on minimizing the imbalance cost between the real-time demand or supply, and the contracted amount on the day-ahead market. Our simulator extends upon this work by considering how such scheduling mechanisms can be used to influence peak-shaving. Furthermore, the PHEV *model* in our simulator attempts to model consumer behavior by implementing uncertainty into the usage patterns. To learn the usage patterns through experience, the PHEV *agent* implements a simple learning mechanism. By learning, it is possible for the system to better schedule PHEVs when there is uncertainty about when they will be used.

Vandael et al. [4] have studied a MAS where PHEV agents and Transformer agents coordinate the load scheduling together. They consider two different decentralized coordination mechanisms, and compare these to a centralized quadratic programming (QP) approach. They find that while the MAS mechanisms are not able to obtain optimal results, they scale and adapt better than the QP solution.

Mets et al. [5] compare centralized and decentralized load scheduling scenarios for PHEVs. However, they do not use a MAS approach, and the decentralized solution uses only local information. Mohsenian-Rad et al. [6] focus on reducing the peak-to-average (PAR) ratio by using energy consumption scheduling (ECS) devices implemented in smart meters. Similarly, Caron and Kesidis [7] investigate the effect of sharing load profiles among users.

III. Proposed Approach

We have developed a system to investigate the effect of different approaches to load scheduling for PHEV charging on peak load. This system can be logically divided into a hierarchy of three main constituents:

1) A *simulated environment* in which real-world, physical entities of the problem domain are simulated using mathematical models. This includes models for the distribution grid and its substations, regular consumers such as households, and the PHEVs.
2) A *multi-agent system* (MAS) consisting of autonomous agents that operate in this environment. This includes PowerNode agents, Transformer agents, PHEV agents, and a BRP agent.
3) Within the MAS framework, different methods for *PHEV charge scheduling*. In this paper we investigate centralized and decentralized *mechanisms*. For each of these mechanisms, two different *scheduling algorithms* are studied.

Each of the models thus have a corresponding agent in the multi-agent system. The relationship between the models and the agents can be seen in Figure 1, showing how each agent interacts with a respective model.

To compare the performance of the different mechanisms, an open source simulator was developed[1].

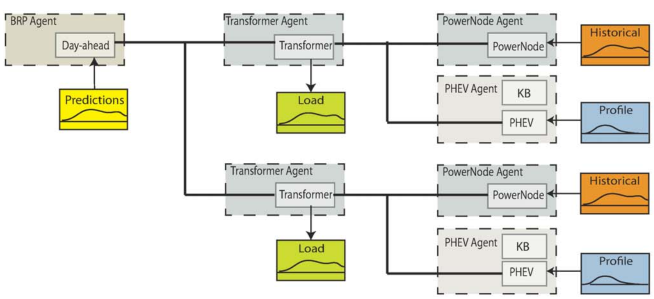


Fig. 1. An overview of the agent-model hierarchy, showing the different models and agents in the system, as well as the main channels of communication.

A. Models

1) PowerNode model: The PowerNode model represents any grid-connected entity other than a PHEV, such as a household or a distributed energy facility. Each instance of the PowerNode model thus outputs power flow as a function of time for the physical entity it represents.

In the experiments reported here, we use hourly historical consumption data from houses equipped with smart meters. Each instance of the PowerNode model thus represents one household from the dataset used. This provides for a realistic simulation of power flow in the system.

[1]SimCar, available at https://github.com/eirikdal/SimCar

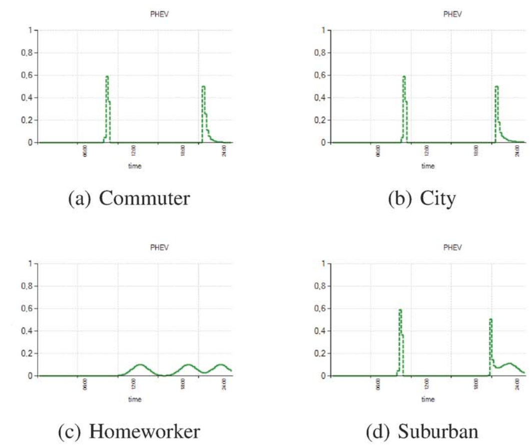


Fig. 2. The different PHEV profiles used in the simulator.

2) PHEV model: The PHEVs are modelled with an intent to reflect some of the stochasticity of human behavior. We have designed a set of PHEV *profiles*, where a PHEV profile consists of several probability distributions that determine whether a PHEV disconnects from the grid at each time step. Mapped to each probability distribution is information about the duration of the corresponding trip, and information about how much of the time was actually spent driving. Figure 2 shows the four PHEV profiles used in the experiments. Note that these profiles were designed to stress the system during peak hours, and thus challenge the ability of the PHEVs and the BRP to schedule the charging of the PHEVs.

The PHEV model also incorporates information such as average discharge rate for the PHEV while driving and average recharge rate when connected to the grid.

3) Transformer model: The Transformer model acts as a constraint in the system, in that it bound the capacity of power flow in the different parts of the grid. Each instance of the Transformer model has a defined value for the maximum capacity of energy that it can handle at any given time. In the experiments reported here, we have used typical values for distribution level transformers in Norway, with capacities of 1MVA for low-voltage transformers, and 20MVA medium-voltage transformers.

B. Multi-agent system

There are three main types of agents in the designed multi-agent system: a PHEV agent, a Transformer agent, and a BRP agent. Each of these agents interact with their respective models. Also, depending on the mechanism used, the agents may also interact with each other and the other models in the environment.

1) PHEV agent: The PHEV agent's primary responsibility is to fully charge the battery of its PHEV within the expected time of departure. Its secondary responsibility is to achieve this in the most socially economic way possible. In the decentralized mechanisms, the PHEV agent chooses its charging strategies by itself, while in the centralized mechanism it defers control of creating the charging plan to a centralized scheduler.

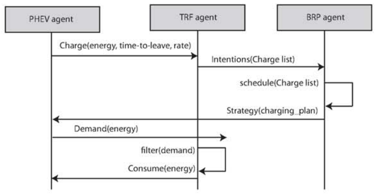


Fig. 3. An example of multi-agent interaction in the centralized scenario.

2) Transformer agent: It is the responsibility of the Transformer agent to ensure that the capacity of the physical transformer is never exceeded. To enforce this constraint, it filters demand messages made by PHEV agents.

Based on its charging plan, each PHEV agent will send a Demand message containing its current energy demand to the Transformer agent. The Transformer agent will collect these Demand messages from all of its connected PHEV and PowerNode agents. If the sum of all the Demand messages exceeds its capacity, then it will filter away Demand messages that are coming from PHEV agents until its capacity constraint is satisfied. Note that demand messages from PowerNode agents are not filtered, as these are assumed to be non-deferrable loads.

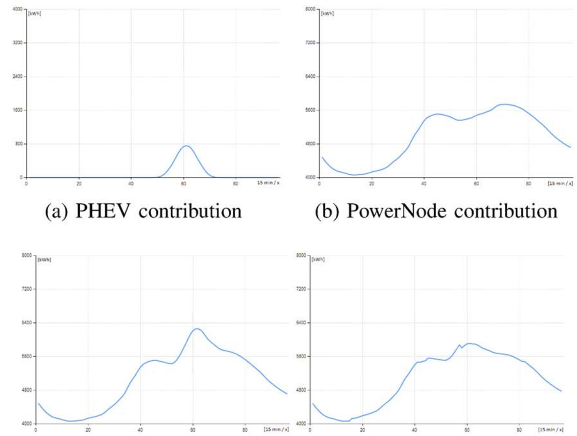
3) Balancing responsible party agent: Depending on which mechanism is used, the BRP agent has one of two responsibilities. In the centralized mechanisms, the BRP agent is responsible for scheduling the PHEV charging plans for all the PHEV agents in the grid. In the decentralized mechanism, the BRP agent is responsible for communicating updated load predictions to the PHEV agents.

Regardless of which scheduling mechanism and algorithm is used, the end result is a *charging plan* which determines when the PHEV agent should charge its batteries. The charging plan is a list containing the charging rate in kW for each 15-minute time slot between the current time and the expected departure time.

C. Centralized scheduling mechanism

In this mechanism, the BRP agent is responsible for setting up charging plans for all the PHEV agents. Charge scheduling is performed in two steps: 1) Given separate predictions about the future energy demand for non-deferrable and PHEV loads, we may create a *target load profile* that meets demand while minimizing load peaks. 2) In order to approximate the target load profile, a scheduling algorithm will plan the charging of PHEVs based on real-time information about the actual state of these. Figure 3 illustrates the inter-agent communication involved in this process.

1) Creating the target load profile: The target load profile attempts to minimize load peaks. Since most of the demand comes from non-deferrable loads, this can only be achieved by adapting PHEV charge demand. The baseline is thus determined as the expected contribution from all of the non-deferrable loads. In this paper, we have used historical data sampled from houses with smart meters for this purpose. Next, the expected contribution from the PHEVs is determined. This was done based on the expected values of the PHEV profiles, as described in Section III-A2. Finally, the baseline and the expected (deferrable) demand from the PHEVs are combined in order to yield the target load profile. In the experiments reported here, this is done with one of two methods: *peak-shaving* and *distance rule*.



(a) PHEV contribution (b) PowerNode contribution

(c) PHEV + PowerNode (d) PHEV + PowerNode – after peak-shaving

Fig. 4. Sample images from the simulator showing the different steps for calculating the target profile

Peak-shaving method: In this method, the baseline and the expected PHEV demand profile are superimposed, after which an algorithm loosely based on the Kohonen algorithm for self-organizing maps [8] iteratively shaves off the load from the highest peaks and distributes it forward in time. The effect of applying this method is illustrated in Figure 4.

Distance rule method: This is a distribution algorithm where the expected PHEV energy demand is distributed over the target profile based on a distance rule, such that troughs are filled and increased peaks are avoided while maintaining proximity to the expected PHEV charge profile.

2) The scheduling algorithms: How the PHEV agents charging plans are scheduled in the centralized mechanisms depend upon which scheduling algorithm that is used. The BRP agent can choose between two centralized scheduling algorithms: A reactive scheduling algorithm and a proactive scheduling algorithm [3]. The goal of both algorithms is to schedule the charging plans so that the overall difference between the target load profile and the realtime energy demand is as low as possible. Pseudocode for the two algorithms is listed in Algorithm 1.

Reactive scheduling: In the reactive profile, energy is balanced in a way that attempts to maintain a perfect balance between the target load profile and the actual demand, for as long as possible. Energy is reserved for as long as the prediction of a given time is less than the target load for that timeperiod, and while there is still energy left over to assign.

Proactive scheduling: This profile distributes energy in one of two ways. When the target load exceeds the predicted demand, PHEV charging is assigned to times at which the imbalance is greatest, such that real-time consumption is brought closer to the target load profile. Otherwise, energy is assigned to the times at which the imbalance is smallest. In this case, the overall real-time consumption has exceeded the net predicted load. Wherever the charge is placed, it will have a negative impact, but it will do the least harm at the time at which the imbalance is the least.

Algorithm 1 Pseudocode for the reactive and proactive scheduling algorithms, adapted from the algorithms described by Boucké and Holvoet [3].

```
function UPDATE(plan, pred, target, left, t)
    plan_t ← χ.rate
    pred_t ← pred_t + χ.rate
    left ← left − χ.rate

function CREATE-PLAN-REACTIVELY(target)
    let plan = make-empty-plan()
    left ← sum(intentions)
    for each t ∈ now ... departure-time do
        if sum(pred) < sum(target) and left > 0 then
            update(plan, pred, target, left, t)
    return plan

function CREATE-PLAN-PROACTIVELY(target)
    let plan = make-empty-plan()
    left ← sum(intentions)
    while left > 0 do
        if sum(pred) < sum(target) then
            t ← arg max_t(pred_t − target_t)
            update(plan, pred, target, left, t)
    return plan
```

D. Decentralized scheduling mechanisms

In the second approach to load-scheduling we have investigated a decentralized mechanism where no centralized schedulers are used. Rather, the PHEVs stochastically generate their charging plans on their own accord based on a pre-defined probability distribution. We have studied two different ways of creating this probability distribution, leading to two different scheduling algorithms: *uniform strategy scheduling* and *mixed strategy scheduling*. The former algorithm schedules charging based on a uniform probability distribution. In the latter, the PHEV agent creates a distribution by interacting with a central agent that provides the PHEV agents with predictions about the future energy consumption in the grid.

Uniform strategy scheduling: In the uniform strategy, each PHEV agent creates a charging plan by selecting as many 15-minute time slots as necessary to fully charge the battery. Time slots are selected with uniform probability from the present time until the expected time to leave.

Mixed strategy scheduling: In the mixed strategy, the PHEV agent creates a charging plan by drawing 15-minute time slots from a distribution that is the inverse of the normalized load prediction from the present time until the expected time to leave. This distribution has a high probability of charging when total demand is low.

Pseudocode for generating the mixed strategy is shown in Algorithm 2. Figure 6 illustrates the process. Each time the PHEV agent recognizes that it is connected to the grid and that its current battery capacity is below maximum capacity, it will ask the BRP agent for a prediction of future energy consumption based on a window from the present time and until the PHEV agent believes it will be disconnected from the grid again. Also, once the PHEV has generated its charging plan, it reports back to the BRP agent. The BRP agent will then update its own predictions by incorporating the charging plan from the PHEV agent. This prevents the PHEV agents from all generating their charging plans based on the same distribution. The interaction diagram for the mixed strategy scenario is shown in Figure 5.

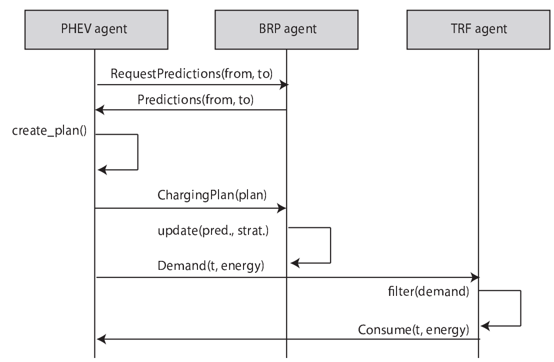


Fig. 5. An example of multi-agent interaction in the mixed strategy scenario.

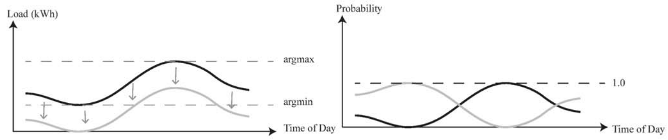
Algorithm 2 Generating a mixed strategy charging plan.

```
function CREATE-MIXED-STRATEGY
    let pred = request-prediction(brp, departure-time)
    let pred_norm = normalize(pred)
    for each x ∈ pred_norm do
        strategy_t ← 1.0 − x
    let plan = create-plan-from-strategy(strategy)
    inform(brp, plan)

function CREATE-PLAN-FROM-STRATEGY(strategy)
    let remaining = battery.max − battery.current
    for t ∈ now ... departure-time do
        if rand(0, 1) < strategy_t then
            plan_t ← rate
            remaining ← remaining − rate
    return plan
```

IV. Experiments

We have performed a total of 6 experiments in order to investigate the performance of the mechanisms. In the centralized scenario, four experiments were performed, one



(a) (b)

Fig. 6. The mixed strategy is generated in two steps. *Left:* The prediction received from the BRP is normalized. *Right:* The normalized prediction is inverted to yield the probability distribution. In both figures, the solid black line represents the initial state, and the grey line represents the result.

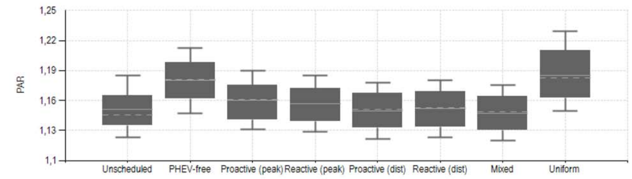


Fig. 7. Average PAR for each of the different mechanisms. Lower is better, meaning that all but the uniform strategy lead to improvements. See text for an analysis of the unscheduled case. Note that the y-axis starts at 1.1, not 0.

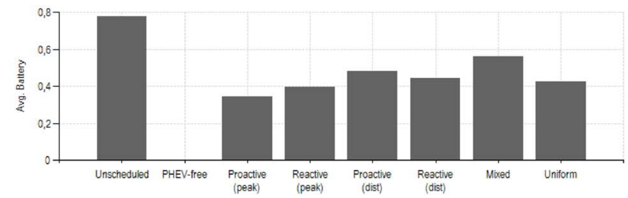


Fig. 8. Average battery capacity at departure time, showing that some of the scheduling algorithms lead to inefficient charging.

for each combination of target load profile method (*peak-shaving* and *distance rule*) and scheduling algorithm (*proactive* and *reactive*). In the decentralized scenario, two experiments were performed, one for each scheduling strategy (*uniform* and *mixed*).

Finally, we ran two control experiments that indicate lower and upper bounds on the performance of our MAS system: In the *PHEV-free* experiment there are no PHEVs in the system, only non-deferrable PowerNode loads. In the *unscheduled* experiment all PHEVs charge immediately upon connection to the grid, irrespective of input from the BRP and Transformer agents.

Each experiment consisted of running 100 days of simulation. The experiments were done on a grid composed of 1756 power nodes[2] and 616 PHEVs. Each PHEV was randomly assigned to one of the four profiles in Figure 2, with equal probability for each profile. Each PHEV was given a battery capacity of 16 kWh, an average charging rate of 2.5 kW, and a discharging rate of 8 kW[3]. For simplicity, the model assumes that the PHEV will charge its batteries fully to maximum capacity, and that it will drive entirely on batteries until the capacity is depleted.

The grid was designed such that its capacity was challenged under times of high demand: For each power node, we identified the highest load recorded during the experiment period. Power nodes were then assigned to each transformer until the sum of the maximum loads exceeded the capacity of the transformer by a certain amount. Low voltage transformers were then assigned to high voltage transformers by the same principle.

V. Results

Each experiment was analyzed with respect to load distribution, fairness, and stability.

Figure 7 shows that most of the mechanisms produce little or no reduction in peak-to-average ratio (PAR) compared to the unscheduled scenario. However, we find that the unscheduled scenario increases average daily peak by approximately 50% compared to the PHEV-free scenario (not shown). By comparison, the daily peak in all but the uniform strategy experiment is virtually identical to the PHEV-free scenario. The reduction in PAR in the unscheduled case is thus due to an increase in average load, rather than a reduction of peak load. This is confirmed by Figure 8, which shows that the average battery capacity at time of departure, and hence also the average demand, depends on which mechanism is used.

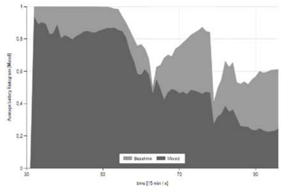
In the fairness analysis, the mechanisms were compared on how successful they were at charging the PHEV batteries. To evaluate the performance, the average ratio of battery capacity at time of departure (BCTD) for each of the PHEVs were measured. This is illustrated in Figures 8 and 9. The latter shows a histogram over the average BCTD from 07.30 and until 24.00[4]. It is apparent that the mechanism that performed best compared to the unscheduled scenario was the mixed strategy, which showed an average BCTD of 56,37%, versus 77,61% for the unscheduled case. Note that the unscheduled scenario is not subject to transformer capacity restrictions. It is also apparent that the average BCTD drops steadily from morning until evening. This is consistent with the usage patterns defined by the PHEV profiles, where the PHEVs have most of the night to recharge until the morning hours, leading to a high BCTD. However, from the afternoon and on, when the PHEVs are more active, it is more challenging for the mechanisms to recharge them in time, leading to a steady drop in the BCTD as the probability of activity increases.

Finally, we studied the stability of the different mechanisms by recording the average PHEV demand that was filtered by the Transformer agents. Figure 10 shows that the decentralized mechanisms lead to some filtering. Since the decentralized mechanisms, in particular the mixed strategy, are also successful at maintaining battery capacity, we interpret this as evidence of emergent stability caused by multi-agent

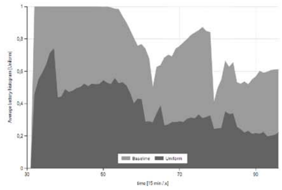
[2]The number of power nodes was given by the size of the historical data set.

[3]The battery capacity was based on the Chevrolet Volt. Charging and decharging rates were selected to give an average recharging time of 6,4 hours, and an average total driving time of 2 hours.

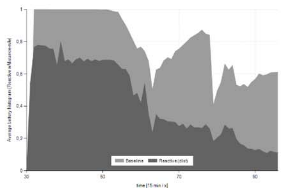
[4]The time-period between 24.00 and 07.30 was omitted from the graphs, as no PHEV profiles were given a positive probability for departing during those hours.



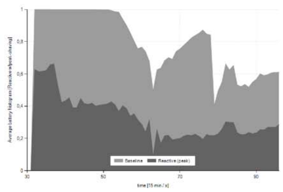
(a) Mixed strategy



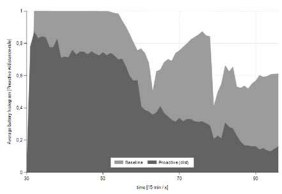
(b) Uniform strategy



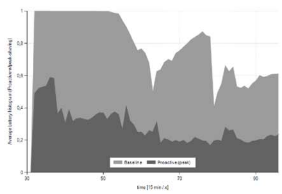
(c) Reactive scheduling, distance-rule



(d) Reactive scheduling, peak-shaving



(e) Proactive scheduling, distance-rule



(f) Proactive scheduling, peak-shaving

Fig. 9. These graphs show histograms over the average battery capacity at time of departure for each of the different mechanisms. Each mechanism is contrasted with the results from the baseline experiment for comparison.

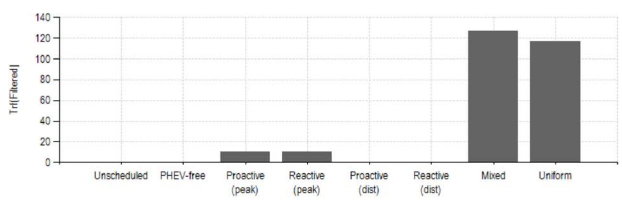


Fig. 10. A graph showing the average PHEV demand filtered (in KWh), for each of the different mechanisms. Lower is better.

interaction.

VI. Discussion

From the results, it seems the mechanism that overall proved to be the best performer was the decentralized, Mixed strategy solution, where the PHEVs generate their own charging strategies based on predictions they receive from the central BRP agent. Our results further show that the shape of the target load profile has a significant impact on the efficiency of the centralized mechanisms. We find that while the centralized mechanisms successfully reduced peak-to-average ratio and maximum peak, they showed some weakness in charging the PHEVs. The best results of the centralized mechanisms came when the target load profile was created from the distance-rule algorithm, where the largest imbalances in the target load profile was placed during the night time. In the peak-shaving algorithm, where the imbalances were placed in relative proximity to its expected original time-location, it seemed as if the highly active PHEV profiles caused the scheduling mechanism to be unable to capitalize on these imbalances. This further seems to stress the importance of how the target load profile is calculated in the centralized mechanism.

While the centralized mechanisms showed some difficulty in scheduling based on how the target load profile was created, the decentralized Mixed strategy approach showed positive results in all the experiments. This is interesting, as decentralized mechanisms have several advantages over centralized mechanisms. Firstly, if the entire mechanism depends on a centralized scheduler, the system is vulnerable if the BRP agent goes down. Secondly, scheduling algorithms are often computationally demanding and scale poorly. In contrast, in the decentralized mechanism, the only dependency is the agent that the PHEV agent receives its predictions from, and even if this agent should become unavailable for some time, the PHEV agent may default to predictions of its own. Considering all of this, the decentralized mechanism seems like a promising solution to load-scheduling.

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