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A comparison of two GIV mechanisms for providing ancillary services at the University of Delaware

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***Abstract*—At the University of Delaware, we are providing ancillary services by controlling the bidirectional power transfer between 15 EVs and the grid. To control this power transfer, a set of algorithms, models and interactions is used, called a "GIV (Grid Integrated Vehicle) mechanism". In literature, many GIV mechanisms are proposed. However, because these mechanisms are evaluated independently in specific scenarios, their differences are not always clear. In this paper, we take a first step in tackling this challenge by comparing two different GIV mechanisms in the same scenario at the University of Delaware: a decentralized and a centralized mechanism. In the decentralized mechanism, which is currently operational at our test environment, EVs decide autonomously on the amount of power available for ancillary services. In the centralized mechanism, a central server gathers all EV information and makes a decision for all EVs. In evaluation, both GIV mechanisms are compared with each other. Simulation results show that the centralized mechanism outperforms its decentralized counterpart in terms of available power for ancillary services. On the other hand, the decentralized mechanism enables large-scale integration by distributing computations across all EVs.**

I. Introduction

Growing concerns about the environment and increasing fuel prices are causing a shift towards EVs (electric vehicles). The average vehicle in the US is only used an hour per day [6] for driving 30 miles [9]. Since 30 miles of driving is less than 10 kWh, with a modest charging rate of 6 kW, only 2 hours of charging are required. Even if EVs are not near a plug all 23 hours, this simple calculation shows that EVs will offer a lot of flexibility in timing and rate of their charging power. Typically, EV aggregators are seen as the actors using this charging flexibility [1]. For an EV aggregator, a wide range of opportunities exist for intelligently controlling EV charging. Examples are day-ahead load scheduling [17], and the provision of ancillary services [4], [12].

In the GIV (Grid Integrated Vehicle) scenario at the University of Delaware, we are providing regulation service (an ancillary service) for PJM Interconnection, the largest transmission system operator in the world [5]. In this paper, we define a GIV scenario as the set of rules, regulations, market mechanisms, and infrastructural constraints under which the EVs their bidirectional power transfer is controlled. In the GIV scenario at the University of Delaware, EVs need to respond within seconds to regulation-up signals (charge less or inject more) and regulation-down signals (charge more or inject less). To control EV (dis)charging, the on-site EV aggregator uses a "GIV mechanism". In this paper, we define a GIV mechanism as the set of algorithms, models and interactions used to control the bidirectional power transfer between EVs and the electricity grid.

In current literature, several GIV mechanisms are proposed for providing ancillary serices. These mechanisms can be classified as being either centralized or decentralized [15]. In a centralized mechanism, the aggregator centrally gathers all information about its EVs. In a decentralized mechanism, EVs make local decisions, while exchanging a limited amount of information with the EV aggregator.

Centralized GIV mechanisms for providing ancillary services have been proposed in several recent articles, wherein the GIV control problem is defined as a central optimization problem. In [3], dynamic programming is used to maximize revenue for providing regulation services. In [12], a linear optimization problem is defined for buying EV energy at a spot market, and simultaneously providing two types of ancillary services (regulation and spinning reserves). The centralized GIV mechanism in this paper defines a quadratic optimization problem to comply with PJM's scoring mechanism, a variable POP (preferred operating point), and combines the EVs' asymmetric regulation power to a combined symmetric regulation power, introducing complex coupling constraints.

Decentralized GIV mechanisms for ancillary services are proposed in [8], in which EVs autonomously control their charging to locally measured frequency deviations. In [16], EVs react to frequency deviations, while flattening transformer load. In this paper, we present the current model of our own GIV mechanism, first introduced in [4], in which EVs autonomously decide upon their amount of regulation power.

While many centralized and decentralized GIV mechanisms exist, it is often unclear how these mechanisms compare to each other, because they have been evaluated in different GIV scenarios. To take a first step in addressing this challenge, we compare a decentralized and centralized GIV mechanism in the same GIV scenario at the University of Delaware. The main contributions of this paper are:

1) Description of the GIV scenario at the University of Delaware, wherein a decentralized GIV mechanism is operational (section II and III).
2) Description of a centralized GIV mechanism for EVs in the PJM regulation market (section IV).
3) Comparison of both GIV mechanisms in simulations of the GIV scenario at the University of Delaware (section V).

II. Description of the GIV scenario at the University of Delaware

In this section, we give an overview of GIV scenario at the University of Delaware. In this scenario, an EV fleet is controlled by an EV aggregator, which operates in the regulation service market of PJM. First, the structure of this market is described (section II-A). Afterwards, the physical EV infrastructure is described (section II-B).

A. PJM regulation market

PJM (Pennsylvania-New Jersey-Maryland) Interconnection is the largest TSO in the world, servicing 13 states in the Northern and Midwestern US. PJM itself is part of the larger Eastern Interconnection, one of the two major synchronized grids in North America. As for any TSO, PJM's two main objectives are (i) to maintain its grid infrastructure, and (ii) assure a continuous balance between generation and demand. To achieve the latter goal, PJM operates several power markets.

Each PJM power market contributes to the grid balance by providing a different type of power: *baseload power* is provided for the typical daily demand, *peak power* is provided during periods of exceptionally high demand, *spinning reserves* are activated for reacting to an unplanned event (e.g generator failure) and *regulation power* is used to keep the grid frequency and voltage within acceptable limits. Spinning reserves and regulation power together make up the largest value of the ancillary service markets. In these markets, GIV competes most strongly, because of a capacity payment to be online and available [7]. At the University of Delaware, we bid on the regulation market, because of its typical highest value in the ancillary service market.

To provide regulation services for PJM, bids need to be submitted via the online eMKT platform [10]. Each bid contains an amount of regulation power P_h^{bid} for hour h, and an offer price. A bid needs to be submitted at least 60 minutes before its operating hour, when the market for the respective hour is cleared (figure 1). According to PJM market rules, bids need to contain a symmetric regulation power (equal regulation-up and regulation-down) in multiples of 100 kW. In the UD scenario, the offer price is kept low (because marginal costs are low), which results in an almost certain acceptance of our bids.

Once a bid is submitted and accepted, the EV aggregator needs his EV fleet to follow an online regulation signal during hour h, which is limited by the bid's regulation power (figure 2a). According to conventional regulation performed by generators, a positive regulation signal represent regulation-up, and a negative signal regulation-down. The regulation signal changes on a 2-4 second base, and should be followed around a chosen operational midpoint, called the POP (preferred operating point). In figure 2b), the actual power transfer of the EV fleet is depicted, which is the POP superposed by the regulation signal. The quality of the response to a regulation signal is quantified by PJM through a performance score, and is used to compute a participant's revenues. This score is based on the difference between signal and response in terms of absolute difference (i), delay time (ii) and correlation (iii). All three factors are equally weighted in the performance score.

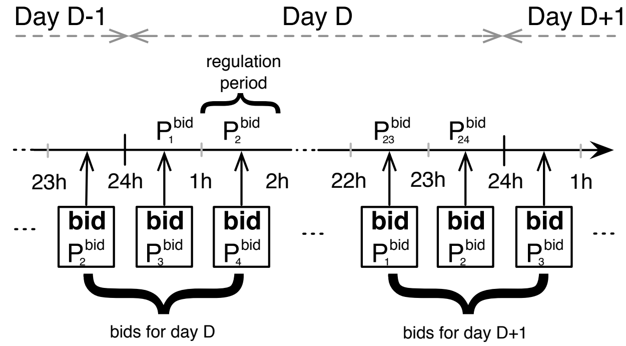

Fig. 1. Bidding process in the PJM regulation market.

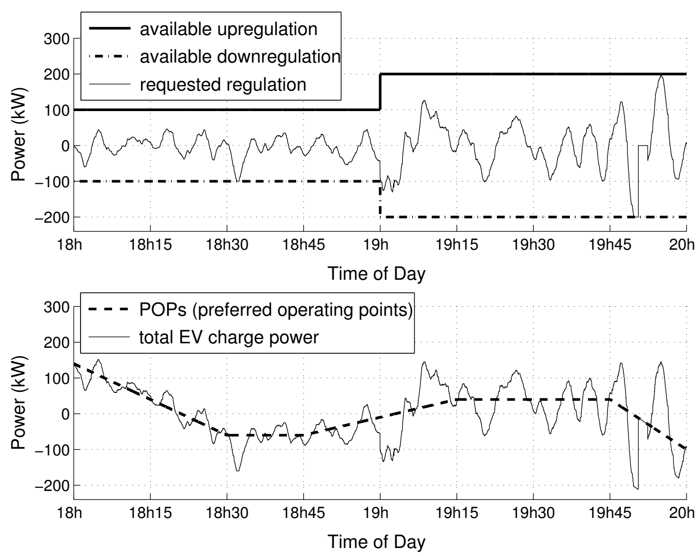

Fig. 2. (a) Regulation bids for two hours, and PJM's resulting online regulation signal. (b) Matching regulation response of the EV fleet, around the POPs.

B. EV infrastructure

Currently, the EV fleet at the University of Delaware consists of 17 Mini-E's [14], and 3 eBoxes [11]. These EVs have a battery of 35kWh and have a maximum power transfer (both charging and discharging) of 12 kW. To be able to charge the EVs simultaneously, the campus is equipped with 15 EVSEs (Electric Vehicle Supply Equipment) connected to the local power grid. Each EVSE enables communication between its connected EV and the aggregator server (on which the EV aggregator agent is running).

In figure 3, the agent architecture is shown. Each agent represents an autonomous decision making element, which is reponsible for achieving the goals of its respective owner. All the agents and their goals:

- EV aggregator agent
  The goal of the aggregator agent is bidding in the PJM market, and complying with these bids by dispatching regulation power in response to PJM's online regulation signal.
- EV agent
  The primary goal of the EV agent is charging its EV battery before departure time, and the secondary goal is providing regulation power to the aggregator agent.

During the clearing phase for a bid hour h, PJM looks at the advertised bids and picks the resources to provide regulation for the given hour. For each selected resource, PJM assigns a regulation power to the resource (aggregator) that may be up to the amount bid by that resource:

$$0 \leq P_h^{\text{assign}} \leq P_h^{\text{bid}} \tag{1}$$

At UD, we choose an offer price below the average clearing price, which typically results in full assignment of our bid by PJM. During the actual regulation hour h, PJM sends a regulation request P_t^{req} to the aggregator that may vary on a 2-4 second cycle. Each time the aggregator receives this regulation request, a fraction of each EVs' regulation power is dispatched, based on a division factor μ (figure 3). This division factor is calculated at each regulation time t in hour h:

$$P_t^{\text{req}} > 0 \qquad \Rightarrow \qquad \mu = \frac{P_t^{\text{req}}}{\sum_{i=1}^{N_{\text{ev}}} {}^{i}P_t^{+}} \tag{2}$$

$$P_t^{\text{req}} < 0 \qquad \Rightarrow \qquad \mu = \frac{P_t^{\text{req}}}{\sum_{i=1}^{N_{\text{ev}}} {}^{i}P_t^{-}} \tag{3}$$

In these formulas, ${}^{i}P_t^{+}$ and ${}^{i}P_t^{-}$ represent the respective regulation-up and regulation-down power each EV i makes available at time t. This information is stored by the EV aggregator in a "regulation matrix" (table I).

TABLE I. REGULATION MATRIX (TIME t, NUMBER OF EVS N)

${}^{1}P_t^{+}$	${}^{2}P_t^{+}$	${}^{3}P_t^{+}$	...	${}^{N-1}P_t^{+}$	${}^{N}P_t^{+}$
${}^{1}P_t^{-}$	${}^{2}P_t^{-}$	${}^{3}P_t^{-}$	...	${}^{N-1}P_t^{-}$	${}^{N}P_t^{-}$

The regulation power each EV makes available is calculated differently in the centralized and decentralized mechanism. In the decentralized mechanism, EV agents autonomously decide upon their regulation power. Consequently, each EV agent has to offer symmetric regulation power to assure the sum of their individual regulation is also symmetric ($\forall n \in \{1,\ldots,N\}$, ${}^{n}P_t^{+} = {}^{n}P_t^{-}$). In the centralized mechanism, the aggregator agent decides the regulation-up and regulation-down power of each individual EV. In this mechanism, individual EVs can provide assymetric regulation power, because the aggregator can combine them to provide symmetric regulation power.

III. A DECENTRALIZED GIV MECHANISM

The GIV mechanism used by the EV aggregator in our GIV scenario is a decentralized (agent-based) mechanism, first introduced in [4]. In this section, the current model of this solution is presented.

In the decentralized mechanism, an EV agent autonomously calculates its regulation-up and regulation-down power. In figure 4, this calculation method is shown in an artificial example. In this example, the EV has a battery capacity of 25 kWh, and an initial SoC (State of Charge) of 5 kWh. The EV is plugged in for 5 hours, and the maximum power transfer is 10 kW. The primary goal of the EV is ensuring sufficient charge in its battery for the next trip. In our example, the driver requires 20 kWh for his next trip. To determine the regulation-up and regulation-down power the EV can offer in each hour, we use a POP calculation method.

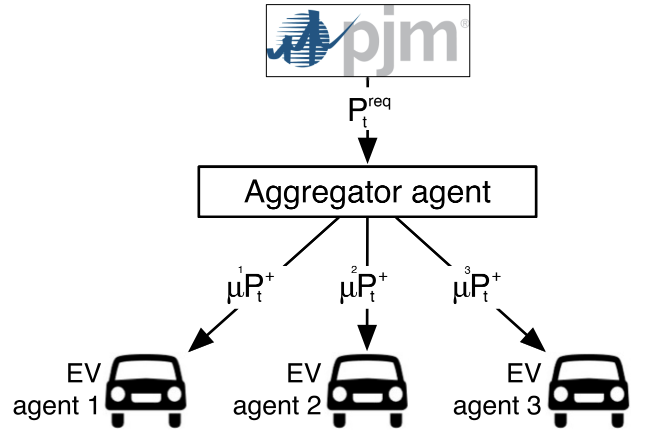

Fig. 3. PJM continuously sends a regulation signal to the aggregator agent, which divides the signal between EVs.

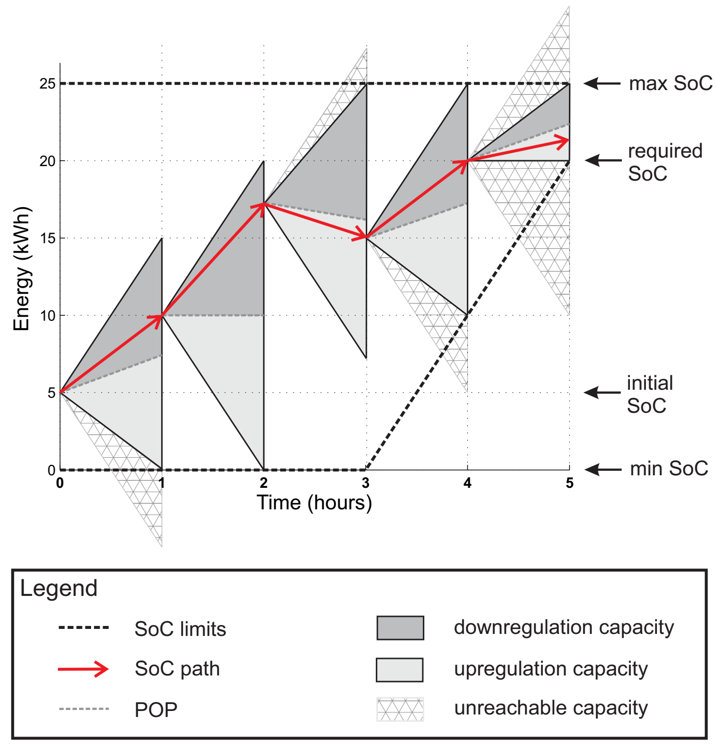

Fig. 4. Example of calculating regulation-up and regulation-down power by a single EV.

Before each hour (this control granularity Δt is a parameter that can be chosen), the POP calculation method will be used to calculate the provided regulation power. In the first hour, the SoC can advance to 0 kWh (discharge at 5 kW) or to 15 kWh (charge at 10 kW) and every value in between. Consequently, during the first hour, the EV can choose a charging power between +5kW and -10kW. To provide symmetric regulation power (required by PJM), the POP is chosen in the middle of 5kW and -10kW, at -2.5 kW. Finally, The regulation power provided by this EV is 7.5 kW around its POP of -2.5kW. Once the hour ends, the SoC has progressed to a value inbetween 0 and 15 kWh, depending on PJM's regulation signal (red arrow). For each consecutive hour, the POP and regulation power are determined in the same way. The example was chosen to cover all type of constraints on the regulation power (table II).

TABLE II. FIVE DIFFERENT TYPE OF CONSTRAINTS.

Hour 1 (0h - 1h)	Discharging limited by minimum SoC.
Hour 2 (1h - 2h)	No limitations.
Hour 3 (2h - 3h)	Charging limited by maximum SoC.
Hour 4 (3h - 4h)	Discharging limited by required SoC.
Hour 5 (4h - 5h)	Charging limited by maximum SoC. Discharging limited by required SoC.

The inclusion of constraints based on the required SoC (hour 4 and 5) differs from the initial description of the decentralized mechanism [4]. As we are continuously improving our decentralized mechanism, inclusion of these constraints maximizes regulation power.

IV. A CENTRALIZED GIV MECHANISM

In this section, a centralized GIV mechanism is presented. This mechanism gathers information about all EVs, and solves an optimization problem which optimizes the collective symmetric regulation power. The result of this optimization is the individual regulation power and POP for each EV. The complete quadratic optimization problem:

$$\min_{P_t^{\text{tot}}} \sum_{t=1}^{t_{\text{end}}} \left(P_t^{\text{bid}} - P_t^{\text{tot}}\right)^2 \tag{4}$$

subject to:

$$^{i}E_t^{\text{min}} \leq {}^{i}E_t^{\text{path}} \leq {}^{i}E_t^{\text{max}}, \tag{5}$$

$$^{i}E_t^{\text{path}} - {}^{i}E_{t-1}^{\text{path}} \leq {}^{i}P_{max}\Delta t, \tag{6}$$

$$0 \leq {}^{i}P_t^{-}\Delta t \leq {}^{i}E_t^{\text{max}} - \left({}^{i}E_{t-1}^{\text{path}} - {}^{i}P_t^{\text{pop}}\Delta t\right), \tag{7}$$

$$0 \leq {}^{i}P_t^{-} \leq {}^{i}P_{\text{max}} + {}^{i}P_t^{\text{pop}}, \tag{8}$$

$$0 \leq {}^{i}P_t^{+}\Delta t \leq \left({}^{i}E_{t-1}^{\text{path}} - {}^{i}P_t^{\text{pop}}\Delta t\right) - {}^{i}E_t^{\text{min}}, \tag{9}$$

$$0 \leq {}^{i}P_t^{+} \leq {}^{i}P_{\text{max}} - {}^{i}P_t^{\text{pop}}, \tag{10}$$

$$- {}^{i}P_{\text{max}} \leq {}^{i}P_t^{\text{pop}} \leq {}^{i}P_{\text{max}}, \tag{11}$$

$$^{i}E_t^{\text{min}} \leq {}^{i}E_{t-1}^{\text{path}} - {}^{i}P_t^{\text{pop}} \leq {}^{i}E_t^{\text{max}}, \tag{12}$$

$$^{i}E_t^{\text{path}} - {}^{i}E_{t-1}^{\text{path}} = {}^{i}P_t^{\text{pop}}\Delta t + \alpha\, {}^{i}P_t^{-} + \beta\, {}^{i}P_t^{+}, \tag{13}$$

$$\forall t \in \left\{0, \ldots, {}^{i}t_{\text{dep}}\right\}, \forall\, i \in \mathcal{F}_{c,t}$$

$$0 \leq P_t^{\text{tot}} \leq \sum_{i}^{\mathcal{F}_{c,t}} {}^{i}P_t^{-} \qquad \forall t \in \{1, \ldots, t_{\text{end}}\} \tag{14}$$

$$0 \leq P_t^{\text{tot}} \leq \sum_{i}^{\mathcal{F}_{c,t}} {}^{i}P_t^{+} \qquad \forall t \in \{1, \ldots, t_{\text{end}}\} \tag{15}$$

$\mathcal{F}$ is defined as the set of all EVs, and $\mathcal{F}_{c,t} \subset \mathcal{F}$ is the subset of EVs which are grid-connected at optimization time t. Newly arrived EVs are taken into account by repeating the optimization at intervals of length Δt.

Equation 4 defines the objective function as the minimization of the quadratic difference between the bids P_t^{bid} and collective regulation power of all EVs. The difference is chosen quadratically to divide the error over the scheduling period. This is done to make sure that the response does not fall back to zero, to maintain correlation between request and response. Notice that P_t^{bid} has a granularity of Δt, which is the hourly bid (figure 1) divided into intervals wherein the optimization is repeated.

Constraint 5 defines the SoC path for each EV between a minimum and maximum SoC limit (equivalent as shown in figure 4). These energy limits enforce an arrival SoC at $t = 0$, and a range of possible departure SoCs at $t = t_{\text{dep}}$. Furthermore, constraint 6 enforces the slope of this charging path to be limited by the EVs' maximum power transfer.

Constraints 7- 8 define the regulation-down power of the EVs. In constraint 7, the regulation power is limited by the minimum and maximum SoC limit. In constraint 8, the regulation power is limited by the maximum charging power. Constraints 9 and 10 define these limits for the regulation-up power of each EV. Constraint 11and 12 define the POP, which is limited by an EV's maximum power transfer and energy limits.

Constraint 13 expresses the change in SoC, which depends on the POP and the regulation signal followed. Because the regulation signal is not known beforehand, the change in SoC caused by the regulation signal has to be estimated. This estimation depends on the EV's offered regulation-up and regulation-down power (e.g when an EV only offers regulation-up power, the SoC will decrease). For the PJM case, we were able to use a linear model with parameters α and β. In case of a less predictable regulation signal, more complex models are possible, e.g a probabilistic model [12]. Deviations in these models are accounted for by repeatedly solving the optimization problem.

Finally, the decision variable in our optimization problem is constraint by the sum of available regulation-up and regulation-down power (coupling constraints 14 and 15). The definition of one decision variable within these constraints enforces a symmetric regulation power.

V. EVALUATION

In this section, the decentralized and centralized mechanism are compared with each other. First, both mechanisms are compared in terms of their ability to offer regulation power (section V-A). Then, the computational scalability of both mechanisms is analyzed (section V-B).

A. Comparison of regulation capabilities

For comparing both mechanisms in terms of regulation capabilities, we evaluate both mechanisms in simulations of the operational GIV scenario at the University of Delaware (section II). As 15 EVSEs are available in this scenario, 15 of the mini-E's are simulated. Currently, these EVs are driven on-campus at irregular times. In this evaluation, we assign each EV the same artificial probability distribution for arrival and departure times (figure 5). For both mechanisms, 15 minutes is chosen as the optimization step Δt (instead of an hour in the example of figure 4).

In our GIV scenario, the EV aggregator has to decide when to bid for regulation power. Since 15 EVs are being controlled, each with a maximum power transfer of 12 kW, the total maximum power transfer is 180 kW. However, not all EVs are continuously available. For example, at the end of the first hour, an average 50% of all EVs is available (≈90 kW). As

PJM only allows regulation bids in increments of 100 kW, different bid scenarios with 100 kW bids are defined, ranked from low-risk to high-risk (figure 6).

In the first experiment, both mechanisms are compared in bid scenario 3 with mini-E's of varying degrees of charging flexibility. In this experiment, the mini-E's have an arrival SoC of 17.5 kWh with a standard deviation of 10 kWh, and a required SoC based on daily commuting trips in the US [2]. These parameters amount to a wide range of charging flexibility. In figure 7, the fractions of regulation power for 100 simulations per mechanism are shown. While the centralized mechanism was able to provide 96 to 100 percent of the regulation power requested in bid scenario 3, the decentralized mechanism achieved a lower performance.

In the second experiment, both mechanisms are compared in all 5 bid scenarios. To focus on the variations between these scenarios, the EV charging flexibility is kept in a smaller range, by setting the arrival SoC of each EV at 17.5 kWh. In figure 8, the resulting total regulation power for each scenario is shown. While the decentralized mechanism's regulation power drops in scenario 3, the centralized mechanism was still able to provide this regulation power. Consequently, the centralized mechanism is able to provide symmetric regulation power of 100 kW for 4 hours (400 kW-h [1]), while the decentralized mechanism can only guarantee 300 kW-h.

In the third experiment, both mechanisms are compared in a scenario wherein any bid size is allowed (cfr. 100 kW bids in previous experiments). The goal of this experiment is comparing both mechanisms in terms of their maximum attainable regulation power. Figure 9 shows the offered regulation capacity in 100 simulations with 15 EVs (same charging flexibility parameters as in the first experiment). The amount of regulation capacity in this experiment (500 - 750 kW-h) is significantly higher than in previous experiments. The average regulation capacity provided by the decentralized mechanism is 630 kW-h, while the centralized mechanism provides an average regulation capacity of 664.5 kW-h.

B. Comparison of computational scalability

In this part of the evaluation, both mechanisms are compared in terms of computational scalability. Computational scalability is important for large-scale integration of GIV mechanisms in a scenario with more electric vehicles. In the US alone, around 250 million vehicles are currently registered [13].

In the decentralized mechanism, each EV agent calculates its own regulation power. This allows for calculations to be distributed among all EV agents. The only calculation dependent on the number of EVs is a simple summation of all regulation power values by the EV aggregator.

In the centralized mechanism, the GIV control problem is solved as a convex optimization problem (formula 4- 15). This type of optimization problem is known to be bound by a polynomial. In an experiment, the GIV control problem was solved for 1 to 1,000 EVs (figure 10). Results show that the execution time is bound by a cubic polynomial. A critical limit

[1]The unit for regulation capacity is kW-h; the ability to provide one kW of regulation power for an hour.

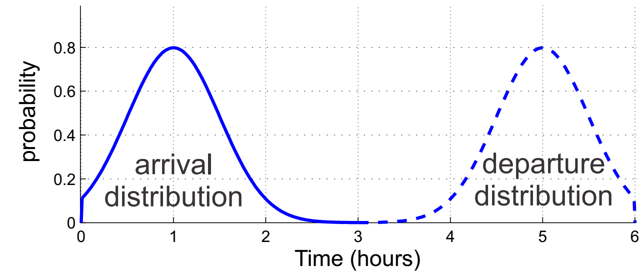

Fig. 5. Probability distributions of EV arrival and departure times.

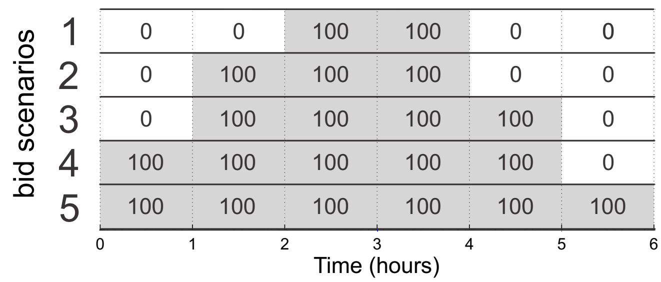

Fig. 6. Different bid scenarios. For each hour in a scenario, the EV aggregator bids for 0 or 100 kW regulation power.

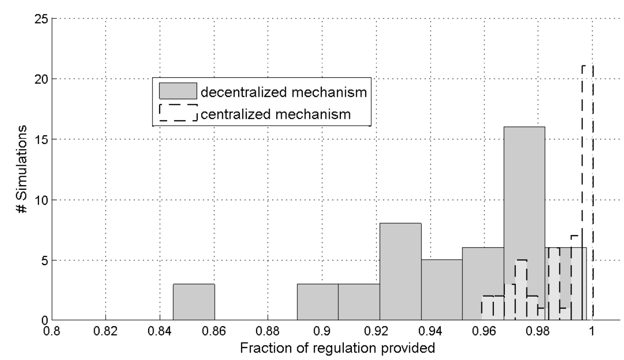

Fig. 7. Experiment 1: EVs wich a varying degree of charging flexibility.

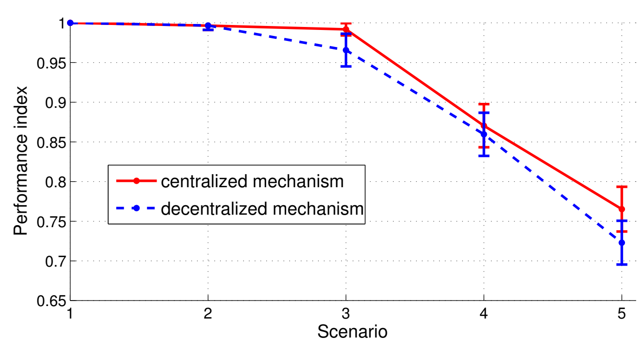

Fig. 8. Experiment 2: different bid scenarios.

is 1 hour, reached around 160 EVs, which is the duration of a bid in PJM's regulation market[2].

[2]Simulations are performed using a workstation with Intel Xeon processor (3.46 GHz, 12 MB cache, 4 cores) and 12 GB of ram.

In summary, the centralized mechanism outperforms the decentralized mechanism in terms of regulation power. This was shown in three simulation experiments: EVs with a varying degree of charging flexibility in a single bid scenario, different 100 kW bid scenarios, and an unconstrained bid scenario. Nonetheless, the practical applicability of the centralized mechanism is questionable, due to its limited computational scalability.

VI. Conclusion

At the University of Delaware, researchers are controlling the bidirectional powerflow between EVs and the grid to provide regulation power. To choose between diffent GIV mechanisms, an in-depth comparison between these mechanisms is necessary. In this paper, a first comparison was made between a decentralized and centralized GIV mechanism. Simulations show that the centralized mechanism could be beneficial in the current small-scale scenario (15 EVs), but the lack in computational scalability could hinder large-scale roll out.

Current and future work focuses on further comparison of centralized and decentralized GIV mechanisms in terms of various criteria. Furthermore, we are continuously improving our decentralized GIV mechanism by integrating centralized scheduling features in a distributed manner.

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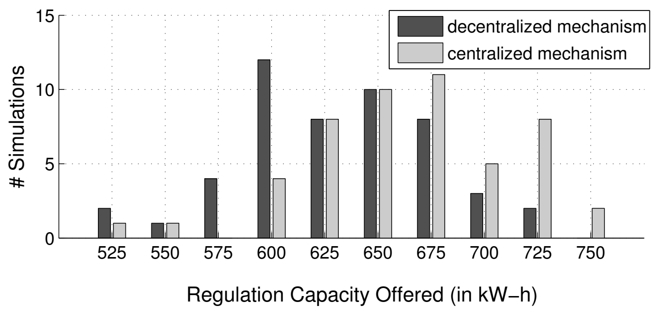

Fig. 9. Regulation maximization without a 100 kW bid restriction (x-axis represents the center of equidistant bins).

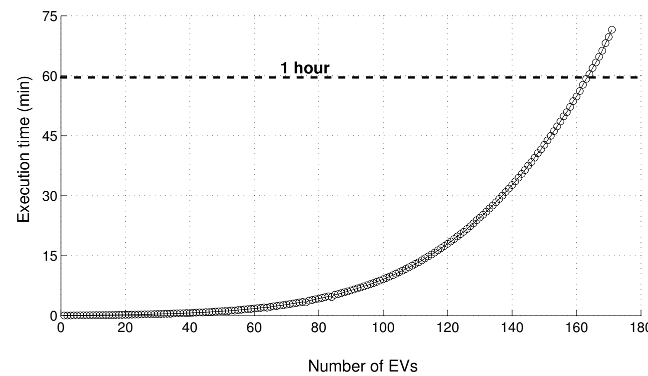

Fig. 10. Execution time of centralized mechanism for an increasing number of EVs.

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