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Real-time Scheduling of Electric Vehicles for Ancillary Services

Frederik Juul[1], Matias Negrete-Pincetic[1,2], Jason MacDonald[3], and Duncan S. Callaway[1]

[1]University of California, Berkeley
[2]Pontificia Universidad Católica de Chile
[3]Lawrence Berkeley National Laboratory

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Lawrence Berkeley National Laboratory

One Cyclotron Road | Berkeley, California 94720

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Disclaimer

Real-time Scheduling of Electric Vehicles for Ancillary Services

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***Abstract*—This work is part of a project that aims to demonstrate the concept of Vehicle-to-Grid (V2G) with an operational fleet. A fleet of electric vehicles is operated with the objective of providing regulation services to the grid. The focus of this paper is on the real-time operation of the fleet. Specifically, given an optimal trajectory for the vehicle state of charge, schemes for distributing the regulation power commands among the vehicles are tested. A scheme based on a convex optimization problem is proposed. Several numerical illustrations and simulations show the effectiveness of the scheme respect to common scheduling heuristics in terms of accuracy.**

***Index Terms*—Electric Vehicles, Resource Scheduling, Ancillary Services Market, Vehicle to Grid Control**

I. Introduction

The uncertainty and intermittency of some renewable sources require new policies for the operation and control of the grid. The usual procedures for balancing the grid in which supply is modified to follow demand should be reconsidered. An alternative approach focuses on tailoring demand for following supply by using the flexibility associated to certain loads. A type of load that possesses a potential for flexibility is electric vehicles (EVs). Usually, EVs have idle time in parking lots in which they could be used to provide additional ancillary services to the grid. Among those services, short-term fast-response regulation services emerge as an interesting possibility.

The scope of this work is to investigate the use of the storage capability of a fleet of EVs to provide frequency regulation services. The fleet is part of a real implementation of the Vehicle-to-Grid (V2G) concept at the Los Angeles Air Force Base (LAAFB). The pilot takes advantage of CAISO's[1] non-generating resource (NGR) model to enable market participation and to exist in the day-ahead and real-time market systems. EVs are given the limited energy storage resource (LESR) designation in the NGR model groups, which allows them to provide both positive power (discharging) and negative power (charging) to the grid when commanded. Communications of telemetry is accomplished through the OpenADR 2.0b protocol via its reporting mechanism. Once collected by the DR automation server, this telemetry is sent to CAISO via a standard controls protocol over their ECN network. While expensive, this approach has allowed the system to enter the CAISO market under the provisions of their tariff.

FJ, MNP and DC are with the Energy Resources Group at the University of California, Berkeley. MNP is also with the Electrical Engineering Department at Pontificia Universidad Catolica de Chile. JM is with the Lawrence Berkeley National Lab. Supported in part by Robert Bosch LLC through its Bosch Energy Research Network funding program.

[1]California Independent System Operator.

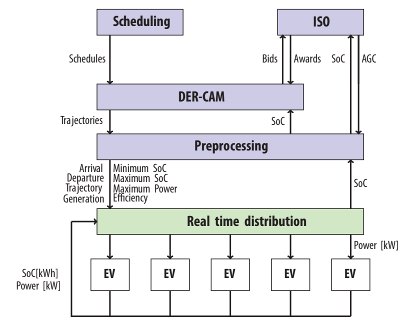

Fig. 1: Overview of the project. The focus of this paper is the development of the real time distribution.

The compensation for regulating reserve markets has recently been altered to comply with the FERC's [2] Order 755 [1] so that fast and accurate response is compensated alongside capacity payments. In particular, new performance-based payments are being introduced into the ancillary services markets.

The project uses an optimization platform: Distributed Energy Resources Customer Adoption Model (DER-CAM) which according to [2] optimizes DER operation over economic and environmental objectives. DER-CAM is used for generating bids for day ahead and real time markets for bulk energy and ancillary services, based on forecasts about the usage of the vehicles, by calculating vehicle state of charge. Additional details about the project can be found in [3].

However, DER-CAM is not fast enough to respond to uncertain Automatic Generation Control (AGC) signals within a few seconds, which is key for achieving an accurate response to such AGC signals. In this paper we focus on such real-time operation of the fleet and we develop scheduling methods subject to the realization of uncertain AGC signals. A schematic diagram of the LAAFB project, showing the interaction of the real-time distribution developed in this work with the rest of the project, is depicted in Fig. 1.

In the literature, the concept [4], [5] and impact [6], [7] of using EVs for grid stabilization has been extensively investigated. While [8] shows that EVs can indeed be used to track frequency regulation signals, no method of tracking is proposed. Though implementation projects have been done, both in industry [9] and academia [8], none of these propose a method for distributing power in real time.

Contributions of this work include the development of a framework for modeling single vehicles requirements tailored to the needs of the frequency regulation problem. By characterizing the ability of a single vehicle for providing regulation,

[2]Federal Energy Regulatory Commission.

we find expressions that capture the aggregate ability of the complete fleet. We then investigate algorithms for real-time scheduling. In particular, we analyze two common heuristics for scheduling: Earliest Deadline First (EDF) and Least Laxity First (LLF). However, the performance of these policies is not effective given the objective of distribute power among vehicles for following frequency regulation signals. As an alternative, we propose a scheme constructed around the idea of distributing the power among the vehicles by minimizing the deviation from pre-specified optimal charging schedules absent frequency regulation calculated by DER-CAM. Several simulation and numerical experiments are performed. The results reflect the effectiveness of the approach for accurately following frequency regulation signals, minimizing penalties from performance payments.

The paper structures as follows. In Section II, models are presented. Section III is devoted to developing the real-time resource allocation schemes. Simulations and numerical results are provided in Section IV. Finally, concluding remarks and extensions are presented in Section V.

II. Models

The charging scheduling of the electric vehicles fleet is done in two stages. In the day-ahead and then again in hour-ahead, based on forecasts of arrival and departure times, trip requirements and AGC signals, a set of charging trajectories is constructed. In real-time, based on the realization of the different uncertainties including the regulation signals, a dynamic re-scheduling of these trajectories must be performed. In this paper, we focus specifically on the real-time stage of this procedure taking as an input the scheduled trajectories. We consider the real-time scheduling of the fleet subject to frequency regulation requirements over an operating period $[0, T]$, time is indexed by $k = 1, \ldots, T$. At each operational time, we are interested on finding how to modify the pre-specified charging trajectories of each vehicle.

A. Vehicle Battery Modeling

We start by considering the problem of allocating power to a single electric vehicle in discrete time. Let the set of all vehicles be denoted $\mathbb{V}$. A vehicle, V_i, can store energy between a lower bound, β_i^-, and an upper bound, β_i^+ given by the physical characteristics of the vehicle battery. The highest amount of power which can be charged to the battery is denoted m_i^+ while the highest amount that can be discharged is denoted m_i^-. Let p_{ik} be the power delivered to vehicle V_i at time step k. Define Δt as the time of each time step k. We assume that power is kept constant between time steps, such that the energy charged to the vehicle from time k until $k+1$ is equal to $p_{ik}\Delta t$. We assume that p_{ik} can take any value in the continuous interval $[m_i^-, m_i^+]$.

When charging a vehicle the charging is subject to efficiency losses. Efficiency of charging is denoted η_i, defined as $0 \leqslant \eta_i \leqslant 1$. Since there can be different efficiencies when charging and discharging these are denoted η_i^+ and η_i^- respectively. Let $x_{ik}\Delta t$ be the energy necessary from a source to charge the battery of vehicle V_i with $p_{ik}\Delta t$. This implies the relationship $p_{ik} = x_{ik}\eta_i^+$. Conversely, when discharging, such that the vehicle now acts as a source $p_{ik} = \frac{x_{ik}}{\eta_i^-}$.

From this, the relationship between p_{ik} and x_{ik} can be described as:

$$p_{ik} = \left(\frac{\eta_i^+}{2} + \frac{1}{2\eta_i^-}\right) x_{ik} + \left(\frac{\eta_i^+}{2} - \frac{1}{2\eta_i^-}\right) |x_{ik}| \tag{1}$$

The inverse relationship is defined by $F(p_{ik}) = x_{ik}$ and can be easily derived from (1).

B. Charging Trajectories

Consider the case of an operator performing the real-time scheduling of the vehicles. A vehicle, V_i, arrives back from a trip at time a_i with a known state of charge, E_{ia_i}, and is scheduled to leave at time d_i. For every time step k, V_i has an energy state, E_{ik}. At the time d_i the vehicle must be charged to a minimum state of charge, E_i^-. If $E_{ik} < E_i^-$ there is a time where the vehicle must be charged at its maximum charge rate to satisfy $E_{id_i} \geqslant E_i^-$. The time until this time is known as the laxity, ϕ_{ik}.

Definition 1: The laxity, ϕ_{ik}, is defined as the amount of time left until a vehicle must charge at its maximum charge rate to reach its minimum state of charge, E_i^- at time d_i. This is calculated as (2).

$$\phi_{ik} = d_i - k - \frac{E_i^- - E_{ik}}{m_i^+} \tag{2}$$

From this we introduce the concept of charging trajectories. A feasible charging trajectory, $\mathbf{t}_i$, is any trajectory which goes from (a_i, E_{ia_i}) to $(d_i, [E_i^-, \beta_i^+])$ without exceeding the boundaries. In general these trajectories are fixed in the hour ahead scheduling and the real-time scheduling updates them in a feasible way. Two examples of charging trajectories (Trajectory Ex. 1 and Ex. 2) from a given state of charge, E_{ia_i}, to a state of charge between E_i^- and β_i^+, the boundaries defined by the battery parameters and the laxity can be visualized in Fig. 2. We can model the problem of charging a vehicle as a task, following the approach introduced in [10].

Definition 2: A task, T_i, can be defined by its parameters (E_i^-, E_i^+, m_i^+, m_i^-, η_i^+, η_i^-, a_i, d_i, β_i^+, β_i^-, $\mathbf{t}_i$) with states E_{ik}, ϕ_{ik}. Let $\mathbb{T}_k$ be the set of all tasks and N_k be the number of tasks in set $\mathbb{T}_k$ at time k. In the rest of the paper, for notational simplicity, we will equal the maximum state of charge at departure E_i^+ with the maximum energy level given by the physical characteristic of the battery, β_i^+.

C. Ancillary services

The fleet participates, in aggregate, in two markets: The energy market and the frequency regulation market. From these, the aggregate resource receives a power dispatch signal every four seconds which must be distributed among the individual vehicles. The aggregate power dispatch is composed of a known quantity that results from the energy market award, B_k at time k, and a variable regulation quantity, r_k at time k, falls between the range of values $[r_k^-, r_k^+]$, with with $r_k^- \leqslant 0$ and $r_k^+ \geqslant 0$. r_k^+ and r_k^- are the hourly ancillary services market awards for regulation up and regulation down, respectively.

For the fleet to participate in the regulation services their total load must follow the combination of the energy signal and the regulation signal as accurately as possible. We call their sum the generation signal and we denote it by g_k at time k. We define the difference between the load associated with the vehicles and the generation signal as

$$e_k = \sum_{i \in \mathbb{T}_k} x_{ik} - g_k \tag{3}$$

Therefore any algorithm which desires to follow the regulation signal must aim to minimize $|e_k|$.

D. Performance Metric

Based on the new rules associated with ancillary services markets, compensation for providing regulation services is done in two parts: Capacity and Performance Payment. The capacity compensation is calculated simply as the price per unit of capacity times the amount of regulation. The performance payment depends on the accuracy of the load following. The accuracy as defined in the CAISO market rules is calculated as

$$\mathrm{ACC} = 1 - \left(\sum_{k=1}^{T} |e_k|\right)\left(\sum_{k=1}^{T} |g_k|\right)^{-1} \tag{4}$$

We use also the accuracy as a metric to measure the performance of the proposed scheduling algorithms.

E. Limits

If a task is close to its boundaries and the energy state approaches its upper bound, as shown in Fig. 2, it is possible that the charging rate may need to be reduced. The limits for charging which guarantees that no boundaries are violated are denoted Γ_{ik}. The amount of energy charged to the battery for a given time k is bounded by $m_i^-, m_i^+, E_i^+, E_i^-, E_{ik}$ and β_i^-. The maximum load a vehicle can deliver at time k, Γ_{ik}^+, is defined as

$$\Gamma_{ik}^+ = \min\left[m_i^+, \frac{E_i^+ - E_{ik}}{\Delta t}\right] \tag{5}$$

While the minimum, Γ_{ik}^-, is defined as:

$$\Gamma_{ik}^- = \min\Big[\max[m_i^-, \frac{\beta_i^- - E_{ik}}{\Delta t}, (1-\phi_{ik})m_i^+], \Gamma_{ik}^+\Big]$$

From this it can be seen that the fleet is able to meet any generation signal within the bounds of the fleet, $e_k = 0, \ \forall g_k \in \left[\sum_{i \in \mathbb{T}_k} F(\Gamma_{ik}^-), \sum_{i \in \mathbb{T}_k} F(\Gamma_{ik}^+)\right]$.

III. Real-Time Scheduling

A. Benchmark Algorithms

We consider two common heuristics for resource allocation: Least Laxity First (LLF) and Earliest Deadline First (EDF) as a benchmark for comparison to the proposed scheduling algorithm.

1) Least Laxity First: At each time k this heuristic creates a merit order list ordered by laxity. If a task is charging at its full power, its laxity stays constant. However any task which is not charging will decrease its laxity by one. Due to this fact, tasks will fluctuate between fully charging and not charging, as their laxities converge towards the same value. While this is undesirable the approach is still considered.

The algorithm in essence prioritizes finishing the tasks with the least laxity first. This in turn means that the task with the highest laxity is considered the task with the lowest priority. To allow the algorithm to work for discharging, we therefore discharge the vehicles with the highest laxity first.

2) Earliest Deadline First: Earliest Deadline First will fully charge the vehicles with the earliest deadline and allow vehicles with the latest deadlines to remain at a low state of charge until sufficient resources are available to charge them.

To allow this algorithm to work for discharging as well, we consider the vehicle with the latest deadline to have the least priority, and is therefore discharged first.

However, this approach prioritizes charging some vehicles to their maximum capacity while allowing others to discharge to their minimum capacity. As hitting these capacity boundaries limit the capacity of the fleet to absorb the regulation signal this is undesirable. We therefore propose a method based on following a predetermined charging trajectory charging for each vehicle.

B. Trajectory Following

We wish to distribute the generation signal across the vehicles in such a way that the deviation from the predetermined charging trajectory is minimized for each individual vehicle. The deviation from the predetermined charging trajectory, $\mathbf{t}_i$, for the next time step can be formulated as:

$$\sigma_{ik+1} = t_{ik+1} - (E_{ik} + p_{ik}\Delta t) \tag{6}$$

in which E_{ik} is the state of charge of the battery at time interval k. The minimization of the deviations can be formulated as a convex optimization problem which minimizes the ℓ_2 norm of the vector of deviations.

By defining the cost matrix $\boldsymbol{W}$ and the cost M (usually with large values to penalize deviations) and the vectors $\boldsymbol{\sigma}_{k+1} = [\sigma_{1k+1}, \ \sigma_{2k+1}, \ldots, \sigma_{N_k k+1}]$, $\boldsymbol{p}_k = [p_{1k}, p_{2k}, \ldots, p_{N_k k}]$ we can state the optimization problem:

$$\begin{aligned} \min_{\boldsymbol{p}_k} \quad & \boldsymbol{\sigma}_{k+1}^T \boldsymbol{W} \boldsymbol{\sigma}_{k+1} + |e_k| M \\ \text{s.t.} \quad & \sum_{i \in \mathbb{T}} x_{ik} - e_k = g_k & (7) \\ & p_{ik} \leqslant \Gamma_{ik}^+, \quad p_{ik} \geqslant \Gamma_{ik}^-, \quad \forall i \in \mathbb{T}_k & (8) \end{aligned}$$

For the optimization problem to be efficiently solved by packages such as CVX for MATLAB, the problem must be a disciplined convex programming problem [11]. However, since the definition of the deviation includes the conversion from x to p, which includes an absolute value as seen in expression (1), the problem is no longer disciplined as it breaks the "no products" rule of disciplined convex programming [12]. Therefore, a disciplined convex optimization problem is proposed by modifying the objective function of the previous optimization problem. By defining the vectors $\boldsymbol{x}_k = [x_{1k}, x_{2k}, \ldots, x_{N_k k}]$, $\boldsymbol{E}_k = [E_{1k}, E_{2k}, \ldots, E_{N_k k}]$, $\boldsymbol{t}_{k+1} = [t_{1k+1}, t_{2k+1}, \ldots, t_{N_k k+1}]$, the problem can be defined as follows

$$\min_{\boldsymbol{x}} \ (\boldsymbol{t}_{k+1} - (\boldsymbol{E}_k + \boldsymbol{x}_k \Delta t)^T \boldsymbol{W} (\boldsymbol{t}_{k+1} - (\boldsymbol{E}_k + \boldsymbol{x}_k \Delta t) + |e_k| M$$

$$\text{s.t.} \quad \sum_{i \in \mathbb{T}} x_{ik} - e_k = g_k \tag{9}$$

$$p_{ik} \leqslant \Gamma^+_{ik}, \quad p_{ik} \geqslant \Gamma^-_{ik}, \quad \forall i \in \mathbb{T}_k \tag{10}$$

In the objective function of the disciplined convex problem, we remove the efficiency term and approximate the energy put into the battery by the energy taken from the grid.

C. Uncertainty Handling

As the arrival and departure times, a_i and d_i, as well as the arrival state of charge, E_{ia_i}, are dependent on uncertain factors such as human behavior, weather, failures, etc., these are considered estimations of stochastic variables. The realization of the arrival and departure times are denoted by a_i^r and d_i^r, respectively. Given that the optimization algorithm considers the trajectory at the next time step, this information must be available. Because d_i is the time in which the vehicle is expected to be no longer available, if a vehicle is available after this time, $d_i^r \geqslant d_i$, it is treated as it is just about to leave, and the trajectory is kept constant at the expected departure value. Similarly, if a vehicle arrives early, $a_i^r < a_i$, its trajectory is kept constant at its expected arrival value until a_i. Thus, as depicted in Fig. 2, outside the estimated interval the trajectory is kept at a constant value equal to the first or last values.

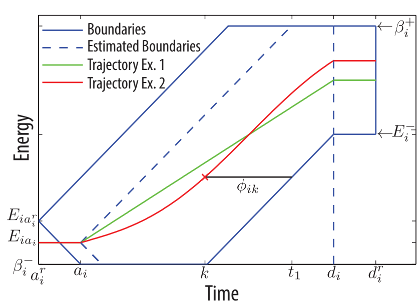

Fig. 2: To handle the realization of the uncertainties, the trajectory values are held constant outside the interval $[a_i, d_i]$.

Another uncertainty might be unforeseen limitations in power by the charging circuitry in the vehicles. However this can be mediated by feeding the maximum power back to the optimization algorithm as a new limit and running the optimization again because there is no communication with on-board vehicle charging control.

D. Examples

We use some examples to illustrate advantages and issues of the approaches explained before. In particular, we focus on EDF and trajectory following. As the examples illustrate, trajectory following can handle better situations in which constraints are binding.

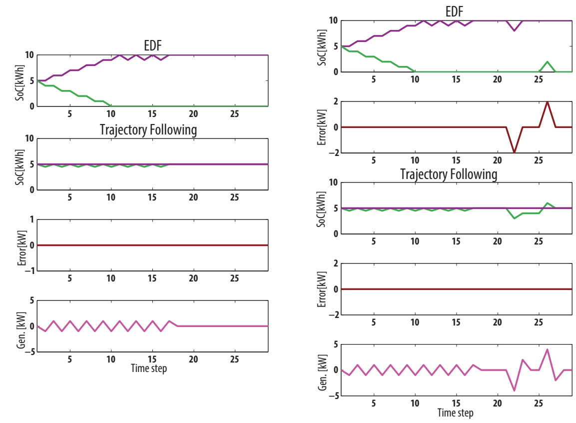

Fig. 3: (Left) An example realization of the AGC signal, handled by the different distribution algorithms. The algorithms are equally capable of minimizing the error. (Right) An example realization of the AGC signal, handled by the different distribution algorithms. When the SoC are at their extremes, the regulation capacity of the system is limited.

1) Example 1: Consider the case of 2 identical vehicles, V_1 and V_2, each with $E_i^+ = 10$, $E_i^- = 0$, $m_i^+ = 2$ and $m_i^- = -2$, with initial state of charge $E_{ia_i} = 5$ and with unequal deadlines somewhere in the future. The efficiency is not considered. Each of these vehicles has a trajectory $t_{ik} = 5$ for all time steps in this example.

We consider two example realizations of an AGC signal. They both share the feature that they are at all times in the range $[m_1^- + m_2^-, m_1^+ + m_2^+]$. Given that the vehicles do not hit their boundaries, they should be able to follow this signal perfectly. We wish to show that EDF distributes the power in such a way that the regulation capacity of the system is lesser that it would be with trajectory following. On Fig. 3 (Left) we see how small perturbations of the generation signal let the state of charge of the vehicles go towards different extremes for EDF. For trajectory following on the other hand the state of charge is always close to the trajectory. We also see that the algorithms are equally capable of handling the signal for this realization.

2) Example 2: Now we will focus on a case in which there are tangible differences between EDF and trajectory following. As seen in section II-E, the regulation capacity of the vehicles are diminished when near the boundaries. This can easily be seen if a large signal, still within the boundaries of the system, is introduced after the system has reached it's steady state, as seen on Fig. 3 (Right).

From this we can see that there are realizations of the AGC signal where trajectory following behaves better than EDF. As we will present in the next section, this difference has real impacts on the system performance.

IV. Simulation Studies

To analyze the performance of the different scheduling schemes in terms of effectively charging the vehicles for their trips and following the regulation signals, we perform several simulation studies. Given that the project is currently under development, we use a mixture of real and simulated data. We focus on a fleet of 18 electric vehicles. In terms of trips, we use real arrival and departure data from the

LAAF base. Vehicle parameters and charging requirements are taken from simulated data provided by the DER-CAM platform. The regulation signal is constructed by assuming a symmetric signal modeled by a random variable with an uniform distribution with support $[r_k^-, r_k^+]$. This signal is also smoothed with a moving average filter of length five. In order to compare the schemes, we quantify the performance in terms of the accuracy in following the generation signal. For each running, the same schedule and realization of the generation signal is used. The simulation period is 2 days. The implementations are run with a symmetric regulation capacity bid of 280 kW. We provide several tracking performance plots. Further, we investigate the impact of the regulation bid capacity. We perform simulations for both EDF and trajectory following schemes. Results can be appreciated in Fig. 4 (Left). The red line represents the generation signal while the blue line denotes the load from the vehicles. As expected both methods see the largest tracking errors when the vehicles are leaving and away, as they must charge to their minimum state of charge and will not be available while they are gone. However it can be seen that EDF has a noticeably larger error. To further investigate the difference between the algorithms, we see how this error behaves by simulating the behavior of the system under the exact same conditions, with the exact same generation signal, but with increased r_k^- and r_k^+. This is then averaged over 10 realizations of the signal. The result can be seen on Fig. 4 (Right). This figure shows that for regulation bids greater than 10% iof maximum resource capacity, the trajectory following approach has significantly higher accuracy than both heuristics. As the bid increases, we expect to see some tracking error due to spikes of power demand higher than the maximum charging rate of the available vehicles. As the bid further increases, we expect to see a significant drop in regulation capacity as batteries reach their limits and vehicles are unable to consume any more power. Note that the size of this error would be mitigated by reducing the regulating capacity available at times in which the vehicles were not expected to be plugged in. As it is right now, the metric for accuracy is aggregated across the two days, but it would be better to see this accuracy rating for each hour, or even in shorter periods.

V. Concluding Remarks

In this paper, we focus on the real-time scheduling of a fleet of EVs with the aim of providing frequency regulation services. We investigate several scheduling schemes. First, we consider two common scheduling heuristics, namely EDF and LLF and we show several deficiencies in terms of excessive battery cycling and limited regulation capacity. As an alternative to these schemes, we propose one based on a convex optimization model which aims to minimize the tracking error for each individual vehicle. Simulation results shows the effectiveness of the proposed schemes in terms of accuracy in following the regulation signal.

This work confirms the expectation that vehicles operated away from the physical limits of the battery perform better when subjected to uncertain power requests from the grid. This result is in a congruence with the results of economic

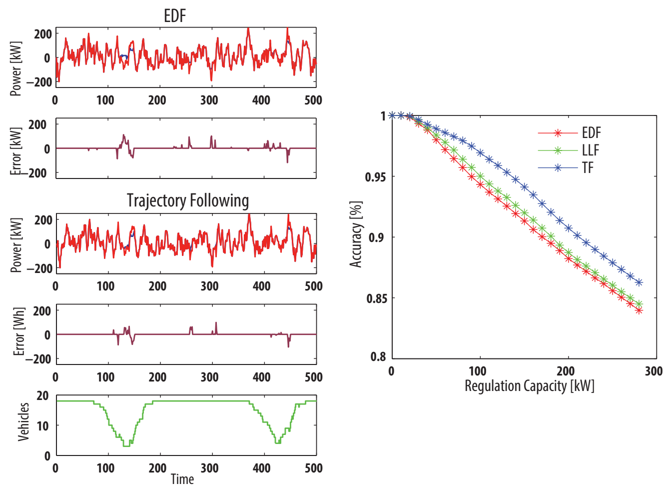

Fig. 4: (Left) The generation signal is tracked using EDF and Trajectory Following (TF). (Right) Comparison between the accuracy of TF, EDF and LLF averaged over 10 realizations of the generation signal.

optimization of vehicle resources that will preferentially place batteries with a battery C-rate, the ratio of discharge power to energy stored, less than one somewhere significantly between the minimum and maximum state of charge. An economic optimization will attempt to maximize regulation revenue by having energy storage capacity available for both discharging and charging the vehicle simultaneously. The simulation of control response suggests that participating in frequency regulation in states similar to this results in more accurate response.

Future work will explore losses in greater detail, apply model predictive control techniques to resource scheduling, evaluate the response characteristics to temporary inaccuracies in uncertain resource parameters, and evaluate in greater detail the generality of the approach.

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