Who Should Pay for the Mileage Payment?

Xingyu Gao, Kui Wang, *and* Chenye Wu†

***Abstract*—To tackle the challenges brought by the renewable's stochastic nature, activities have been picked up: FERC order 755 requires ISOs to introduce mileage payment to frequency regulation providers for more reliable and high quality services. This payment is currently being collected from the ISOs despite the fact that it is not ISOs who cause this extra payment. Therefore, we submit that it is time to reconsider a fair cost allocation. In particular, we study the impact of introducing the corresponding 'mileage cost' to the renewables for causing fluctuations in the system. We start by formulating the problem with perfect forecasting for an infinite horizon. Then, we investigate the role of information by restricting our knowledge within a window, i.e., the Model Predictive Control (MPC) approach. We prove that the MPC approach can achieve near optimal performance and further characterize the performance guarantee. Finally, we propose a hierarchical control approach to initiate the discussion on sharing, coordination, and privacy.**

***Keywords*—model predictive control, hierarchical control, fairness, mileage payment**

I. Introduction

Last decade witnessed the soar of renewable energy installation all over the world, as shown in Fig. 1. These newly installed renewable energy sources are contributing a remarkable share in the electricity sector. In Germany, with its continuous efforts towards zero operating nuclear plant by 2022, its renewable energy (in particular, wind and solar power) produced about 52 TWh, 20% of the nation's electricity, during the first half of 2014 [1]. United States and many other nations, though have not seen such remarkable market share of renewable energy, have also built up their own plans for utilizing renewables. Take United States as an example. Among the 50 states and the District of Columbia, 33 of them have set up their own renewable portfolio standards. The most ambitious one is set by California, which requires 33% of renewable energy penetration by the year of 2020 [2].

A. Reconsideration on Integrating Renewables

While the increasing penetration of renewables helps achieve a sustainable future, its stunning advances conceal deeper problems: its stochastic nature constantly stresses the power system. The current practice to avoid the disruption from renewables is to conduct curtailment. In China, the annual curtail rate is already very high: in 2015, China has curtailed 33.9 TWh wind power, with a curtailment rate of 15%; the solar curtail rate in Gansu Province, China is as high as 31% in the same year.

In US, the negative locational marginal prices for wind power appear very often. The reason why renewable energy owners accept the negative prices is because of the generous tax credits and other subsidies. The net metering policy is responsible for much of the dramatic growth of distributed photovoltaic (PV) generation. Utilities have started complaining about the concept of net metering because it poses an existential threat to their business models. In particular, under net metering, the prosumers do not need to bear the true costs of infrastructure, reserves, and reliability. That is, it is the high time for us to calm down and rethink what should be the right and necessary incentives to achieve the sustainable future that we dreamed of. Otherwise, the growing PV generation may even jeopardize our sustainable energy future.

We start by analyzing the newly introduced mileage payment for frequency regulation providers (required by the FERC Order 755 [5]). The milage payment is the total arc curve length of the regulation trace (i.e., the imbalance in the system over time). It is designed to compensate and reward those regulation providers with reliable and high quality services. While currently this extra payment is paid by the system operators, it is the high penetration of renewables that warrants such a payment. The highly stochastic nature of single PV panel outputs is demonstrated in Fig. 2. One natural approach to fairly collect the mileage payment would be to (partially) collect it from renewables. This motivates us to define the concept of mileage cost. We employ the classical Model Predictive Control (MPC) approach to understanding the impact of introducing such a cost, and characterize the renewable owners' best response under this condition.

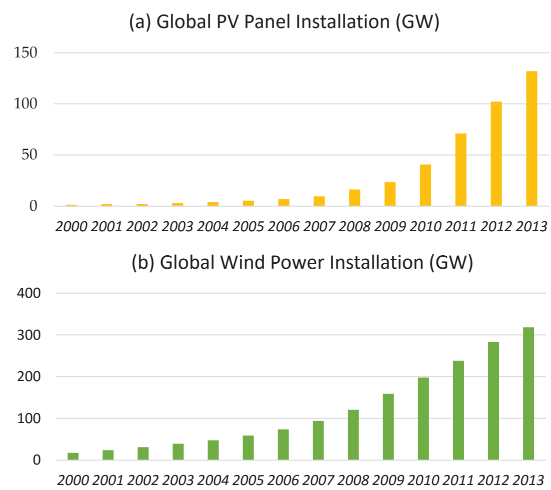

Fig. 1. Global renewable energy installation: (a) PV installation [3] (b) Wind power installation [4].

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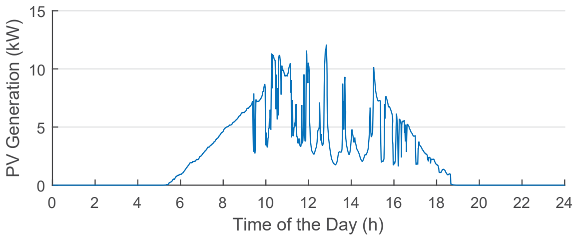

Fig. 2. Sample PV panel generation with 1 minute resolution.

In this paper, we are interested in an aggregator, where, besides the loads, a set of photovoltaic (PV) panels are distributed in the system. Apparently, before introducing any cost to integrate renewables, net metering makes it most beneficial to sell all the excess PV generation back to the grid. And this will no longer be true with mileage cost.

B. Related Works

There are two major bodies of related literature. Firstly, the control schemes to accommodate renewable energy integration have been extensively studied previously. Just to name a few, in [6], Moura *et al.* identified the important role of DSM for large scale wind power integration based on field data. Stochastic control was introduced to optimize the management of distributed renewable generators and storage units within the smart grid paradigm in [7] and [8]. Huang *et al.* furthered this research line by incorporating quality of service into the paradigm in [9]. Interesting distributed control schemes to tackle renewable energy penetration were discussed in [10] and [11]. Different from previous works, we propose to take the mileage cost into account, which fundamentally changes the nature of the problem.

To solve the new problem, we employ the MPC (also known as receding horizon control) approach, which has been widely adopted in the power system control. In this paper, we only review few of them that were proposed to smooth out the fluctuations in the system. In [12], Palma-Behnke *et al.* proposed a rolling horizon strategy-based energy management system for microgrid. Atic *et al.* presented a decentralized MPC approach to performing regulation in [13]. Camponogara *et al.* introduced the communication-based distributed MPC approach in [14]. Venkat *et al.* extensively compared various MPC frameworks, and proposed a cooperation-based MPC for the current AGC system in [15]. In [16], Roshany-Yamchi *et al.* employed a distributed Kalman filter algorithm along with the MPC scheme for frequency regulation. With the popularity of plug-in electric vehicles, interesting MPC based frequency regulation frameworks with time-varying resources (the PHEVs) were discussed in [17], [18]. In contrast, the mileage cost introduces more temporal coupling and makes the theoretical analysis more challenging.

C. Our Contributions

In seek of demonstrating the impact of 'mileage cost', our principle contributions are summarized as follows:

- *Fair Cost Allocation*: The introduction of mileage cost allows us to understand the fair cost allocation of mileage payment. We hope this will serve as the foundation to inform regulators, policy makers, as well as renewable generation owners cautiously develop renewables.
- *Performance Analysis for MPC*: We first connect MPC with the aggregator's decision making problem in an infinite horizon. Then, we establish the performance guarantee for MPC with limited window size.
- *Hierarchical Control Framework*: The MPC approach can be easily implemented in a centralized fashion. However, the hierarchical control framework enjoys the advantages that centralized one lacks. With the awareness of privacy and the success of sharing economy, a hierarchical control framework will potentially enable the privacy-preserved coordination, and the sharing economy for the electricity sector.

The rest of the paper is organized as follows: Section II introduces the problem formulation in the infinite horizon and its MPC simplifications. Then, in Section III, we analyze the MPC performance guarantee by connecting the two formulations. Section IV verifies the performance of MPC approach with simulation. We generalize the MPC approach to the hierarchical control framework in Section V. Concluding remarks and future directions are given in Section VI.

II. Problem Formulation

A. System Model

As shown in Fig. 3, the aggregator is supported by both the PV panels and the utility company. Denote the set of all end users by $\mathcal{N}$. We assume each of them is equipped with several PV panels. We denote the output of user n's PV panels by $\bar{s}_{n,t}$.

Conventionally, the aggregator will seek to solve the following optimization problem:

$$\begin{aligned} \underset{s_{n,t}}{\textbf{minimize}} \quad & \sum_{t=1}^{\infty} \delta^{t-1} C^o \left(\sum_{n \in \mathcal{N}} s_{n,t} \right) \\ \textbf{subject to} \quad & 0 \le s_{n,t} \le \bar{s}_{n,t}, \end{aligned} \tag{1}$$

where the conventional generation cost $C^o(\cdot)$ can be defined

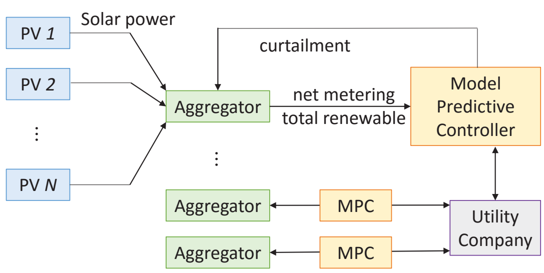

Fig. 3. System model: Role of model predictive control.

as a quadratic function:

$$
\begin{aligned}
&C^o\left(\sum_{n\in\mathcal{N}} s_{n,t}\right)\\
=&a\left(d_t-\sum_{n\in\mathcal{N}} s_{n,t}\right)^2+b\left(d_t-\sum_{n\in\mathcal{N}} s_{n,t}\right)+c
\end{aligned}
\tag{2}
$$

Here, a, b, c are the cost parameters; d_t denotes the total demand within the aggregator at time t; $s_{n,t}$ is the actual dispatched solar energy from user n at time t. We use the quadratic cost function to capture the case when the aggregator acts as a microgrid operator. Net metering is just a special case by setting a and c to be zero. Obviously, when d_t is always greater than the total solar power (which is often true for solar power), the optimal solution to (1) is to fully utilize the solar energy.

Notice mileage payment is calculated based on the total arc curve length of compensating the load generation imbalance. Since the generators can track the traditional load very accurately, the renewables should now be responsible for major imbalance. Therefore, we introduce the mileage cost in response to mileage payment, which is proportional to the arc curve length of renewable generations.

In the subsequent analysis, we first formulate our problem in an infinite horizon under an idealized assumption, which serves as the benchmark for optimality. Then, we relax this assumption, and turn to a more realistic scenario by employing a model predictive control (MPC) framework. In particular, we show that the employed MPC approach is in fact ϵ-close to the performance of the benchmark.

B. Infinite Horizon Problem Formulation

To cast our problem in an infinite horizon, we make the following idealized assumption:

Assumption 1: All the predicted demand profiles d_t's for all $t = 1, \cdots, \infty$, and all the predicted solar panel outputs $s_{n,t}$ for all $n \in \mathcal{N}$ and $t = 1, \cdots, \infty$ are available to the aggregator.

To indicate that the aggregator may not have the perfect predictions, when taking the future information into account, we always use a discount factor δ, where $0 \le \delta < 1$. Therefore, in this case, the aggregator may seek to minimize the following cost:

$$
\begin{aligned}
\underset{s_{n,t}}{\textbf{minimize}} \quad & \sum_{t=1}^{\infty}\delta^{t-1}C\left(\sum_{n\in\mathcal{N}} s_{n,t}\right)\\
\textbf{subject to} \quad & 0\le s_{n,t}\le \bar{s}_{n,t},
\end{aligned}
\tag{3}
$$

where

$$
C\left(\sum_{n\in\mathcal{N}} s_{n,t}\right)=C^o+\beta\left|\sum_{n\in\mathcal{N}} s_{n,t}-\sum_{n\in\mathcal{N}} s_{n,t-1}\right|. \tag{4}
$$

The first term is the conventional generation cost, the second term stands for the mileage cost, and β is the design parameter (price) for mileage cost. With mileage cost, it is self-evident that it may not always be beneficial to inject the maximal available renewable energy into the power system. For example, when $\beta \to \infty$, one optimal solution could be to curtail all the renewable energies.

C. MPC Formulation

In practice, the prediction in an infinite horizon is impossible and most importantly, very inaccurate. Therefore, intuitively, there is no need to consider the problem in an infinite horizon in particular for time slots in the far future. The MPC approach is a widely accepted approach to tackling this kind of problem. At each time slot h, we only consider the information within a window size of T, and conduct the scheduling. In particular, only the schedule of the current time slot is implemented, i.e., the schedule for time slot h. And this process keeps going as h increases. Thus, the MPC approach motivates us to relax Assumption 1:

Assumption 2: At time slot h, the predicted demand profiles d_t's for all $t = h, \cdots, h+T-1$, and the predicted solar panel outputs $s_{n,t}$ for all $n \in \mathcal{N}$ and $t = h, \cdots, h+T-1$ are available to the aggregator.

Under this assumption, at time h, the aggregator seeks to solve the following problem:

$$
\begin{aligned}
\underset{s_{n,t}}{\textbf{minimize}} \quad & \sum_{t=h}^{h+T-1}\delta^{t-h}C\left(\sum_{n\in\mathcal{N}} s_{n,t}\right)\\
\textbf{subject to} \quad & 0\le s_{n,t}\le \bar{s}_{n,t},
\end{aligned}
\tag{5}
$$

Unlike the infinite horizon version, problem (5) can be easily solved using convex optimization techniques (e.g., using CVX solver [19]).

III. MPC Performance Guarantee

In this section, we try to understand the performance guarantee of the MPC approach. The analysis largely relies on the fact that the generation of each PV is bounded.

Denote the maximal capacity of solar panel n by $\bar{s}^m_{n,t}$. Then, for any two feasible solutions to problem (5), denoted by $(s^1_{n,t}, \forall n, \forall t)$ and $(s^2_{n,t}, \forall n, \forall t)$, respectively, we know that for all $t = h, \cdots, h+T-1$,

$$
\begin{aligned}
&C\left(\sum_{n\in\mathcal{N}} s^1_{n,t}\right)-C\left(\sum_{n\in\mathcal{N}} s^2_{n,t}\right)\\
=\;& a\left(\sum_{n\in\mathcal{N}} s^1_{n,t}-\sum_{n\in\mathcal{N}} s^2_{n,t}\right)^2+b\left(\sum_{n\in\mathcal{N}} s^1_{n,t}-\sum_{n\in\mathcal{N}} s^2_{n,t}\right)\\
&+\beta\left|\sum_{n\in\mathcal{N}} s^1_{n,t}-\sum_{n\in\mathcal{N}} s^1_{n,t-1}\right|-\beta\left|\sum_{n\in\mathcal{N}} s^2_{n,t}-\sum_{n\in\mathcal{N}} s^2_{n,t-1}\right|\\
\le\;& a\left(\sum_{n\in\mathcal{N}} \bar{s}^m_{n,t}\right)^2+b\left(\sum_{n\in\mathcal{N}} \bar{s}^m_{n,t}\right)+\beta\sum_{n\in\mathcal{N}} \bar{s}^m_{n,t}\\
\doteq\;& A.
\end{aligned}
\tag{6}
$$

By further analysis, we can prove that

Theorem 1: The proposed MPC approach is ϵ-close to the original problem (3), where

$$\epsilon = \frac{\delta^T A}{1-\delta}. \tag{7}$$

Proof: We prove this theorem by induction. For each time slot h, the MPC approach provides the solution for time slots $h, \cdots, h+T-1$. The energy dispatch outcomes at time slots $1, \cdots, h$ have already been determined by previous optimizations. For the rest energy dispatch outcomes, we simply use the energy dispatch outcomes given by a greedy approach, which uses all the renewable energy. Thus, we can denote $(s_{n,t}^{h,*}, \forall t)$ the energy dispatch outcomes given by the MPC optimization at time slot h. We prove that this series of energy dispatch outcomes is ϵ-close to the energy dispatch outcomes $(s_{n,t}^*, \forall t)$ given by problem (3).

Base Case: When $h=1$, if we implement $(s_{n,t}^{1,*}, \forall t)$, then we know

$$\begin{aligned}
&\sum_{t=1}^{\infty}\delta^{t-1}\left(C\left(\sum_{n\in\mathcal{N}}s_{n,t}^{1,*}\right)-C\left(\sum_{n\in\mathcal{N}}s_{n,t}^{*}\right)\right)\\
=&\sum_{t=1}^{T}\delta^{t-1}\left(C\left(\sum_{n\in\mathcal{N}}s_{n,t}^{1,*}\right)-C\left(\sum_{n\in\mathcal{N}}s_{n,t}^{*}\right)\right)\\
&+\sum_{t=T+1}^{\infty}\delta^{t-1}\left(C\left(\sum_{n\in\mathcal{N}}s_{n,t}^{1,*}\right)-C\left(\sum_{n\in\mathcal{N}}s_{n,t}^{*}\right)\right)\\
\leq&\sum_{t=T+1}^{\infty}\delta^{t-1}\left(C\left(\sum_{n\in\mathcal{N}}s_{n,t}^{1,*}\right)-C\left(\sum_{n\in\mathcal{N}}s_{n,t}^{*}\right)\right)\\
\leq&\frac{\delta^T A}{1-\delta}.
\end{aligned} \tag{8}$$

The first inequality comes from the fact that $(s_{n,t}^{1,*}, t = 1, \cdots, T)$ is the optimal solution to problem (5), and the second inequality is a direct result from (6).

Inductive Step: Suppose at time slot $h=k$, the energy dispatch outcome $(s_{n,t}^{k,*}, \forall t)$ is ϵ-close to the optimal energy dispatch outcomes. Then, at time slot $h=k+1$,

$$\begin{aligned}
&\sum_{t=1}^{\infty}\delta^{t-1}\left(C\left(\sum_{n\in\mathcal{N}}s_{n,t}^{k+1,*}\right)-C\left(\sum_{n\in\mathcal{N}}s_{n,t}^{*}\right)\right)\\
=&\sum_{t=k+1}^{k+T}\delta^{t-1}\left(C\left(\sum_{n\in\mathcal{N}}s_{n,t}^{k+1,*}\right)-C\left(\sum_{n\in\mathcal{N}}s_{n,t}^{k,*}\right)\right)\\
&+\sum_{t=1}^{\infty}\delta^{t-1}\left(C\left(\sum_{n\in\mathcal{N}}s_{n,t}^{k,*}\right)-C\left(\sum_{n\in\mathcal{N}}s_{n,t}^{*}\right)\right)\\
\leq&\sum_{t=1}^{\infty}\delta^{t-1}\left(C\left(\sum_{n\in\mathcal{N}}s_{n,t}^{k,*}\right)-C\left(\sum_{n\in\mathcal{N}}s_{n,t}^{*}\right)\right)\\
\leq&\frac{\delta^T A}{1-\delta}.
\end{aligned} \tag{9}$$

Again, the first inequality comes from the fact that $(s_{n,t}^{1,*}, t = k+1, \cdots, k+T)$ is the optimal solution to problem (5) at time slot $h=k+1$, and the second inequality uses the inductive assumption. Thus, we complete the proof. ■

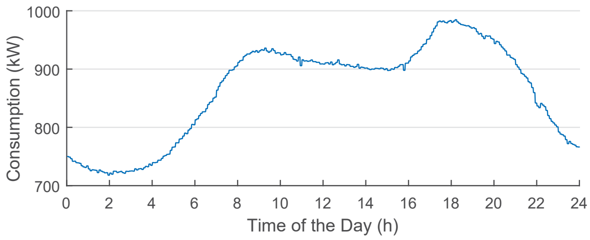

Fig. 4. Load profile.

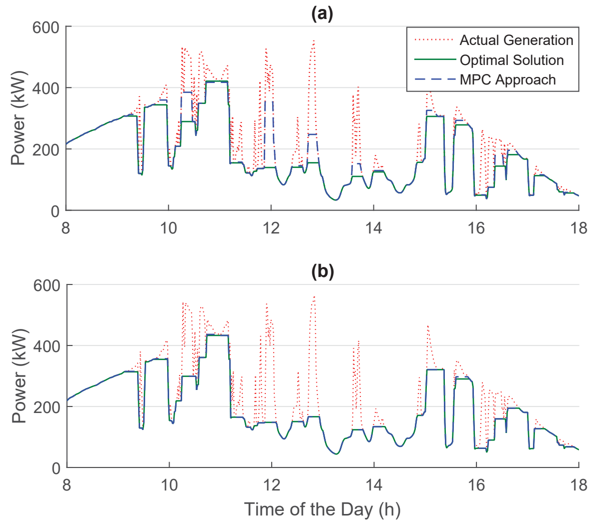

Fig. 5. Impact of window size W.

IV. Simulation Results

In this section, we conduct the simulation to verify the performance of our proposed approach. The total load profile within the aggregator is shown in Fig. 4, with 1-minute resolution. Suppose the aggregator controls 50 PV panels. For simplicity, the conventional generation cost parameters are set as follows: $a = 5$ \$/MW^2, $b = c = 0$. The mileage cost parameter β is set to be 100 \$/MW. We set the discount factor to be 1 in the simulation.

Fig. 5(a) demonstrates the MPC performance (dashed blue line) with $T = 10$ min. It largely follows the optimal control schedule (solid green line), but still fluctuates from time to time. Fig. 5(b) shows the results when the window size is 15 minutes. Surprisingly, in this case, there is already almost no difference between the MPC performance and the optimal control schedule. This means that if we can obtain the reliable solar energy forecasting in 15 minutes, the aggregator can already conduct the optimal control.

V. Generalization

We have avoided discussing the fact that there could be infinitely many solutions to problem (5). Though every solution performs the same curtailment to the aggregator, different solution means significantly different to each PV panel. Hence, in this section, we will first discuss the coordination of PVs within the aggregator.

A. Coordination within the Aggregator

Note that, in problem (5), the variables $s_{n,t}$'s appear in the objective function only in its aggregate form, i.e., $\sum_{n\in\mathcal{N}} s_{n,t}$. This motivates us to define

$$l_t = \sum_{n\in\mathcal{N}} s_{n,t}, \tag{10}$$

and thus, problem (5) can be simplified to

$$\begin{aligned} \underset{s_{n,t}}{\textbf{minimize}} \quad & \sum_{t=h}^{h+T-1} \delta^{t-h} C\left(l_t\right) \\ \textbf{subject to} \quad & 0 \leq l_t \leq \bar{l}_t. \end{aligned} \tag{11}$$

In fact, this formulation is more desired, since $\bar{l}_t$'s are often more predictable to the aggregator.

With such a simplification, we can show that problem (11) has a unique solution:

Theorem 2: Problem (11) has a unique solution when the cost parameter $a > 0$.

Proof: The proof directly follows from the facts that the objective function is strictly convex and the constraint set is convex.

It is not hard to observe that problem (5) may have infinitely many optimal solutions. Therefore, it is natural to ask, is the unique minimizer to problem (11) corresponds to the set of solutions to problem (5) in their aggregate form? Since the constraints in both (5) and (11) are not coupled in time, we can design a round-robin fashion greedy algorithm to efficiently construct a feasible solution to problem (5) using the unique minimizer to problem (11). Then, apparently, this feasible solution is one of the solutions to problem (5). We can formally state this argument in the following theorem.

Theorem 3: There exists at least one solution $(s^*_{n,t}, \forall n, t = h, \cdots, h+T-1)$ to problem (5) in response to the aggregate form solution $(l^*_t, t = h, \cdots, h+T-1)$ provided by problem (11).

In fact, we can show that all the optimal solutions to (5) correspond to $(l^*_t, t = h, \cdots, h+T-1)$, which achieve the same goal of minimizing the cost. However, not all solutions are equally desired by the end users (the owners of the PV panels). For example, injecting more solar power to the system may help the end user obtain more profits through net metering. Therefore, certain fairness metric should be pursued to avoid the bias in the curtailment. One possible example could be

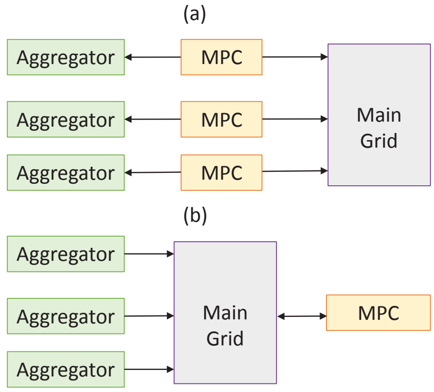

Fig. 6. MPC controller coordination.

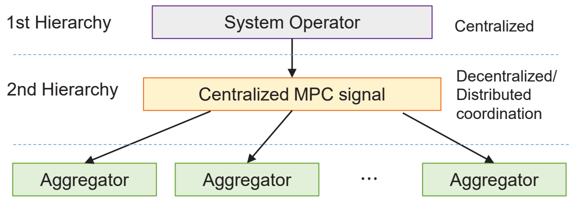

Fig. 7. Hierachical control framework.

$$\gamma = \sum_{t=h}^{h+T-1} \sum_{n\in\mathcal{N}} \left(s_{n,t} - \frac{l^*_t}{N}\right)^2. \tag{12}$$

Note that, we do not consider the discount factor here because the solution $(l^*_t, t = h, \cdots, h+T-1)$ has already taken the discounting effect into account. To pursue this kind of fairness metric while maintaining the goal of minimizing cost, the following optimization problem needs to be solved:

$$\begin{aligned} \underset{s_{n,t}}{\textbf{minimize}} \quad & \sum_{t=h}^{h+T-1} \sum_{n\in\mathcal{N}} \left(s_{n,t} - \frac{l^*_t}{N}\right)^2 \\ \textbf{subject to} \quad & \sum_{n\in\mathcal{N}} s_{n,t} = l^*_t, \\ & 0 \leq s_{n,t} \leq \bar{s}_{n,t}. \end{aligned} \tag{13}$$

Problem (13) can be efficiently solved in a centralized fashion. If privacy is a concern, (e.g., $\bar{s}_{n,t}$ could be confidential information), the problem can also be solved in a privacy preserving distributed way. A detailed discussion, however, is beyond the scope of this paper.

B. Coordination between Aggregators

We have discussed how to conduct the MPC within each aggregagtor. From the system operator's point of view, however, without coordination (as shown in Fig. 6(a)), this cannot achieve the most effective curtailment. Instead, the global most effective curtailment can be conducted in a centralized fashion, as suggested by Fig. 6(b). This motivates us to discuss the coordination between aggregators in this section. In particular, we propose a hierarchical control framework which will further enable the privacy preserve and peer-to-peer coordination.

In the first hierarchy, the system operator makes forecasting on the total PV generation (or more generally, the total renewable generation) within its control. Note that, in our Assumption 2, we assume the aggregator has perfect information about the total PV generation within the window, which is not very practical. However, the total solar power generation forecasting can be rather accurate to the system operator. It will compute the global control signal based on this information, in a fully centralized way, as suggested by Fig. 7. In the second hierarchy, the coordination between aggregators can be achieved in many ways. For example, the system operator could assign the participation factors to the each aggregator, just as the case for frequency regulation. The more interesting alternatives will ask the aggregators to communicate with each other, and make the decisions on their own. We imagine there are at least two very distinct ways to enable the communication:

- One approach requires the system operator's own estimation on the mileage cost parameter β, then the system operator could employ the distributed control and enable the communication between aggregators. There is a very rich body of research on distributed control for networked systems, see [20] for a detailed survey. The system operator can also enforce the privacy preserving techniques when gathering the information [21].
- The other approach reveals the mileage cost parameter from the market. For example, the system operator could employ an auction for the curtailment. Each aggregator will simply submit the supply bids to sell its solar energy. We note that, auction is only one possible way to achieve such a market. A detailed discussion, however, is beyond the scope of this paper.

VI. Conclusion

In this paper, we target the fair cost allocation issue. Particularly, we introduce the 'mileage cost' in response to the mileage payment. Based on this cost, we cast the problem in the MPC approach and analyze its performance guarantee rigorously. With simulation, we surprisingly observe that after the introduction of mileage cost, it is possible to conduct the optimal control with the reliable forecasting only for the next 15 minutes.

We believe that our analysis will initiate many interesting subsequent discussions. For example, mileage cost is a natural counterpart to mileage payment. This, however, does not mean mileage cost is the best way to incentivize the renewables to help the system operation. In fact, FERC Order 755 only requires the system operators to design performance payment to compensate for the high quality frequency regulation. The only reason for introducing such a cost is because PJM and several other ISOs have already implemented mileage payment, but it remains unclear if mileage payment is among the best choices to optimally utilize the frequency regulation providers. On the other hand, Section V shows a general hierarchical control framework to enable the coordination and sharing between different aggregators. It will be interesting to further rigorously understand this dynamic process and storage system's impact on the process.

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