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Electric Vehicle Load Management: An Architecture for Heterogeneous Nodes

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ABSTRACT Integrating electric vehicle (EV) charging infrastructures into the utility grids requires solutions for coordinated charging of EVs. Load management systems aim at computing coordinated charging schedules for electric vehicles based on predetermined charging objectives. Contributions on coordinated charging for EVs predominantly assume that the EVs or the charging stations are controllable entities in the load management systems. However, in practice, charging infrastructures may consist of controllable and uncontrollable entities. This paper proposes architecture and control strategies for EV charging infrastructures consisting of controllable and uncontrollable entities. Simulations based on real-world charging sessions show how the share of uncontrollable entities in a charging infrastructure affects the performance of different control strategies in the system architecture. We show that a certain number of uncontrollable entities in a charging infrastructure does not affect the scheduling objectives significantly. EV fleet and charging infrastructure operators can develop pragmatic investment and operation strategies based on the proposed control strategy and architecture.

INDEX TERMS Electric vehicles, scheduling strategy, aggregator, control architecture.

I. INTRODUCTION

Electric vehicles (EVs) provide an environmentally friendly transportation form. Compared to combustion engine vehicles, EVs emit negligible air pollution. Furthermore, the environmental EV usage benefits grow even more if the power supply comes from renewable resources [1]. However, range anxiety¹ aggravates consumers' willingness to purchase EVs, despite governmental incentives and increased awareness. Li *et al.* [2] show that consumers' increased desire to buy EVs depends on charging infrastructure deployment and corresponding public investment. Globally, the awareness rises that charging availability is a barrier to EV diffusion. Therefore, different countries target charging infrastructure deployment (e.g., [3]).

With EV adoption increasing rapidly, the power grid is facing new challenges. For example, uncoordinated charging can drastically alter the immediate demand shape [4]. Undesired demand shapes pose concerns both on a local scale, such as overloading the transformer [5], [6] and on a broad scale,

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¹Range anxiety is a driver's concern that the EV does not have enough energy storage to get to his or her destination, especially if charging station is not always available.

such as the power grid's voltage instability [7], [8]. On the other hand, EVs are also mobile energy storage systems [9], [10]. Furthermore, intelligent EV charge scheduling enables grid load shaping (reshaping undesired grid load peaks or valleys) [11], [12]. Contributions on EV charge scheduling have mostly covered control algorithms, control architectures, and control strategies (see [13]–[18] for recent reviews on these topics).

A. CONTROL ALGORITHMS AND ARCHITECTURES

With a defined scheduling objective and the corresponding constraints, mathematical optimization techniques such as (mixed-integer) linear programming [19]–[22] and quadratic programming [23]–[26] or heuristic optimization approaches such as reinforcement learning [27]–[30] are applied to find the optimal schedule. These algorithms are usually integrated with a centralized control architecture. In a centralized architecture, as shown in Fig. 1(a), the centralized aggregator gathers charging behavior *information* from all the electric vehicle supply equipment (EVSE)/EV nodes and computes the charging *schedules*. However, using centralized architectures entails potential risks. For example, the computation at a central node may cause a single point of failure, i.e., if the centralized aggregator fails, the whole EV fleet will stop

charging. Besides, the centralized aggregator requires private *information*, i.e. the arrival times (AT), departure times (DT), and energy demands (ED), to compute the charging *schedules*. Moreover, an increased node number calls for more computational power.

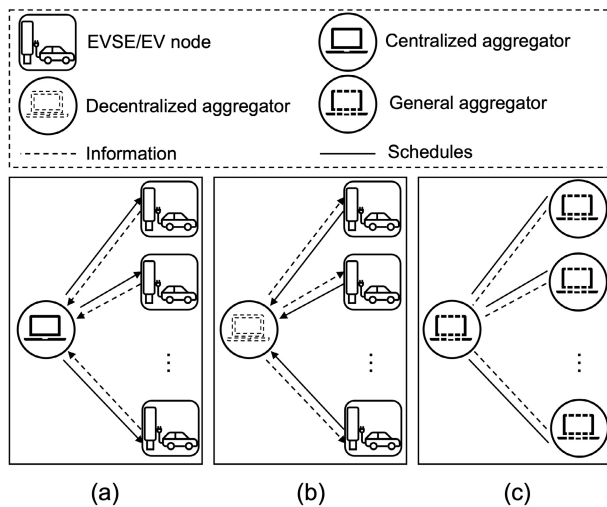


FIGURE 1. Control architectures for EV charge scheduling: (a) centralized; (b) decentralized; (c) layered.

Decentralized architectures can overcome these disadvantages. Decentralized architectures employ distributed or decentralized algorithms such as the optimal decentralized control [31], [32], the game theory approach [33]–[37], or multi-agent reinforcement learning [38], [39]. Fig. 1(b) shows that EVSE/EV nodes determine their schedule in a decentralized architecture. The decentralized aggregator then collects the charging *schedules* from all the nodes, based on which it will regulate and publish the control signal, such as virtual pricing *information*. The EV fleet can generally determine the optimal schedule in a few iterations.

Layered architectures often apply for EV fleets with a large node number. Fig. 1(c) outlines a three-layer control architecture (the bottom layer consists of centralized and decentralized nodes, not shown). Each general aggregator can operate either in a centralized or decentralized manner in this architecture. For example, Yao *et al.* [40] presented a three-layer control architecture where the top and middle layers are centralized aggregators. References [41], [42] employed the same architecture. In [43]–[45], the top layer is a decentralized aggregator: the nodes are aggregated by centralized aggregators, and then distributed algorithms, more specifically, the game theory approach is applied to regulate the centralized aggregators. In contrast, Shao *et al.* [46] kept the top layer as centralized but the middle layer as decentralized aggregators. In [47], [48], both top and middle layers are decentralized aggregators. Although it is common to have purely centralized or decentralized aggregators in the middle layer, in practice, depending on the node types, it may require both types of aggregators in the middle layer. Wang *et al.* [34]

illustrated a three-layer architecture, where the top layer is centralized, and the middle layer combines a centralized and a decentralized aggregator.

B. CONTROL STRATEGIES

Control strategies determine how to execute EV fleet charge scheduling under the chosen control algorithm and architecture. We distinguish between the following charging control strategies: uncontrolled, oracle, offline and online. The uncontrolled and the oracle strategies provide the worst and the best benchmark performance, respectively. The offline strategy is usually applicable with day-ahead predictions of charging behavior, and the online strategies are more applicable since they get updated information upon the new time index.

1) UNCONTROLLED STRATEGY - NO CONTROL

EVs start charging immediately upon their arrival. It is currently the most frequently used control strategy. This strategy maximizes the likelihood of a full state-of-charge on departure and does not require any additional a priori knowledge about the AT, DT, and ED. The disadvantage of this strategy lies in the high probability of peak demands due to simultaneously charging EVs. The presented dataset from [49], [50] showed the flexibilities reside in real-world charging sessions, and there are potential benefits to applying controlled scheduling.

2) ORACLE-BASED CONTROL STRATEGY

The AT, DT, and ED are three crucial input parameters for charge scheduling algorithms. An oracle-based strategy has the perfect a priori knowledge about ATs, DTs, and EDs over the entire scheduling horizon. The perfect AT, DT, and ED knowledge are not available in a practical scenario. Nevertheless, the oracle strategy is helpful as a benchmark strategy.

3) OFFLINE STRATEGY

The offline control strategy determines a schedule once at the beginning of a predetermined complete scheduling horizon [31], [35], [36]. It assumes that it has imperfect a priori knowledge about the ATs, DTs, and EDs within the horizon. This imperfect knowledge can either come from the users' self-predicted charging behavior or from a prediction the charging station has carried out learning from historically available data (e.g., [51]–[53]). Compared to uncontrolled strategies, offline control strategies have the advantage that they enable intelligent charging by employing peak shaving, valley filling, or cost-optimized scheduling. The disadvantage of the offline strategy lies in the AT, DT, and ED prediction uncertainty.

4) ONLINE STRATEGY

Alternatively, online control strategies can overcome these offline strategy-related reliability limitations. The online strategy updates the charging schedule iteratively for each

time index defined within the scheduling horizon [27], [31], [54]–[58]. We further differentiate between two subcategories:

- 1) **Naive Online:** The naive online strategy refers to a strategy that only has the information revealed to date, i.e., the arrived EVs’ DTs and EDs (e.g., [31], [34], [56]).
- 2) **Predictive Online:** The predictive online strategy refers to a strategy that, apart from the information revealed to date, employs the predicted ATs, DTs, and EDs of EVs to arrive in the future (e.g., [27], [54], [55], [57]–[59]).

C. OPEN CHALLENGES AND NOVEL CONTRIBUTIONS

Available smart EV charge scheduling contributions focus mainly on responsive EVSE/EV nodes, i.e., decentralized and/or centralized nodes, as shown in the above subsections. However, in practice, infrastructures include uncontrolled nodes. Uncontrolled nodes can neither compute a schedule nor provide the scheduling interface to a central entity. Besides, some users would prefer to control the charging window by themselves. We also refer to this node type as an uncontrolled node.

To the authors’ best knowledge, intelligent EV charge scheduling contributions rarely consider the existence and integration of uncontrolled nodes. Xydas *et al.* [60] modeled the uncontrolled nodes as unresponsive EV agents in their multi-agent framework. They identified the importance of forecasting the EDs from those uncontrolled nodes to achieve the scheduling objective. We consider a practical charge scheduling problem that includes three node types: decentralized, centralized, and uncontrolled nodes. Furthermore, we adapt the layered control architecture to handle the heterogeneous nodes. Wang *et al.* [34] designed the control architecture where the top layer is a centralized aggregator, and the middle layer consists of a centralized aggregator and a decentralized aggregator. There are, in total, three aggregators in their control architecture. Besides, the top layer is a centralized aggregator, bringing in the disadvantages of the centralized architecture. To overcome this disadvantage, we propose a different layered architecture variant. The top layer is a decentralized aggregator; the middle layer contains a centralized aggregator, decentralized nodes, and uncontrolled nodes; and the bottom layer consists of centralized nodes. The detailed description is in Section II.

In this paper, we provide numerical results for the proposed control architecture to tackle the challenges with the following contributions:

- We propose the control architecture introduced in Section II for an EV fleet containing heterogeneous nodes, i.e., uncontrolled, decentralized, and centralized nodes.
- We present detailed mathematical formulations for decentralized, centralized charge scheduling, including uncontrolled nodes (Section III).

- We assess the proposed control architecture and analyze the simulation results to answer the following:

- 1) **What are the performance differences if we apply different online control strategies?** The oracle strategy provides benchmark performance, whereas the naive and predictive online strategies are practically applicable. The performance difference will indicate if the predictions are necessary or not.
- 2) **To which percentage the responsive nodes should be to achieve acceptable performance?** Less responsive nodes mean less initial investment cost and less communication traffic and computational demand during operation.

We present the result focusing on a specific scheduling objective: load flattening.² However, we can explore other objectives with the same approach.

II. AGGREGATOR DESIGN

We propose a variant of the layered architecture to handle an EV fleet with heterogeneous nodes, as shown in Fig. 2.

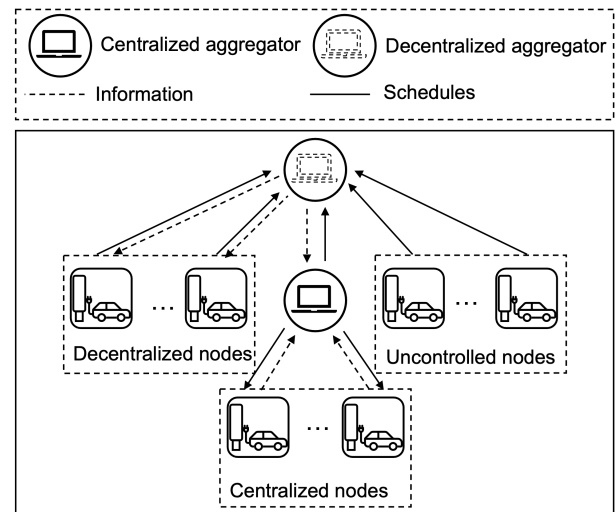


FIGURE 2. Proposed control architecture for an EV fleet containing heterogeneous nodes, i.e. uncontrolled, decentralized, and centralized nodes.

The bottom layer consists of the centralized nodes, aggregated by the centralized aggregator at the middle layer. Additionally, we have the uncontrolled and the decentralized nodes at the middle layer. Furthermore, a decentralized aggregator lies on top. The uncontrolled nodes are not responding to any control signal, but they can share their (fixed) charging schedules (*schedules*, solid arrows). The decentralized nodes iteratively update their charging schedules based on the received control signal (*information*, dashed arrows) from the decentralized aggregator. The centralized nodes must share their charging behavior with the centralized aggregator, i.e., ATs, DTs, and EDs (*information*, dashed arrows). Then,

²The objective is to distribute the load from EVs over time evenly.

the centralized aggregator iteratively updates the charging schedules based on the received control signal (*information*, dashed arrow) from the decentralized aggregator. For the decentralized aggregator to compute the control signal, it must collect charging schedules (*schedules*, solid arrows) from the centralized aggregator, the uncontrolled and the decentralized nodes.

Control strategies formed based on the mix-layer control architecture are mix-layer oracle, mix-layer offline, mix-layer naive online, and mix-layer predictive online control strategies. Due to the reliability concern in the offline strategy, we will not cover it in this paper. The decentralized aggregator collects the initial schedules from the centralized aggregator and decentralized and uncontrolled nodes to compute the schedule based on the mix-layer oracle control strategy. The centralized aggregator gathers the charging behavior from centralized nodes and initializes the charging schedules. Based on the initialized charging schedules, the decentralized aggregator calculates the control signal, such as the virtual pricing information for each decision time slot in the scheduling horizon. If the deviation of the control signal is significant, the decentralized nodes will reschedule and resend the charging schedules to the decentralized aggregator. Meanwhile, the centralized aggregator will reschedule on behalf of the centralized nodes. The rescheduling will result in a new control signal. On the other hand, the stabilized control signal means the EV fleet has reached the optimal charging schedules. Then, the centralized aggregator will transfer the charging schedules to the centralized nodes. Fig. 3 shows the flow chart of the processes when applying the mix-layer oracle control strategy.

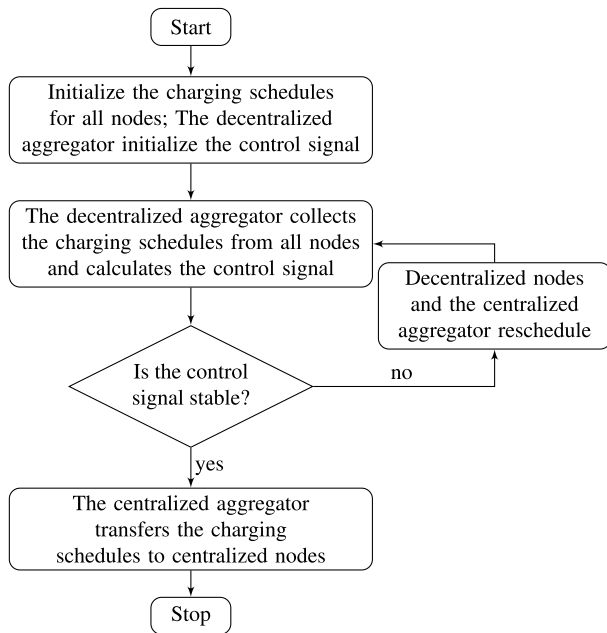


FIGURE 3. Flow chart of the processes when apply the mix-layer oracle control strategy.

When applying mix-layer online strategies, the iterations depicted in the flow chart in Fig. 3 occur at each time

index within the scheduling horizon. The charging schedules computation relies on the information revealed to date when applying the mix-layer naive online control strategy. If the prediction is available and we apply the mix-layer predictive online control strategy, the computation also considers the future charging behavior.

III. PROBLEM FORMULATION

This Section presents the mathematical formulation for computing the charging schedules for uncontrolled and responsive nodes.

We denote vectors by lower case boldfaced letters, and we denote the vector's k th entry as $\bullet(k)$, where \bullet is the corresponding lower case letter. Further, let $\langle \bullet, \bullet \rangle$ denote the scalar product, let \otimes denote the Kronecker product, let \leq denote element-wise smaller and equal to. Further, let $\bar{\bullet}$, $\hat{\bullet}$, $\tilde{\bullet}$, and $\|\bullet\|$ denote historical mean, predicted values, hypothetical values, and the Euclidean norm, respectively.

Let N , N^u , N^r , N^d , and N^c represent the number of all, uncontrolled, responsive, decentralized, and centralized nodes, respectively. Further, let H represent the scheduling horizon, and τ the decision time slot duration. Thus, we have in total $K = \lfloor H/\tau \rfloor$ slots.

For charging behavior, let t_n^a , t_n^d , and e_n represent the n th node's true AT, DT, and ED for all nodes $n \in \{1, \dots, N\}$, respectively. We let p_n^{\max} represent the n th node's maximum charging rate, and $\mathbf{p}_n = [p_n(1), \dots, p_n(K)]^T \in \mathbb{R}_{\geq 0}^{K \times 1}$ the final charging schedule. The charging schedule for responsive nodes depends on the EV connection times. We define the k th binary connection status vector $\mathbf{c}_n = [c_n(1), \dots, c_n(K)]^T \in \mathbb{B}^{K \times 1}$ entry for the n th EV as:

$$c_n(k) = \begin{cases} 1, & \text{if } t_n^a \leq k\tau \leq t_n^d \\ 0, & \text{else.} \end{cases} \quad (1)$$

To facilitate a convenient matrix vector representation, we stack the charging rates for all nodes in $\mathbf{p} = [\mathbf{p}_1^T, \dots, \mathbf{p}_N^T]^T$ (same for uncontrolled, responsive, and centralized nodes: \mathbf{p}^u , \mathbf{p}^r , and \mathbf{p}^c); and we stack the connection time vectors, energy demands, and maximum charging rates for responsive nodes in $\mathbf{c}^r = [\mathbf{c}_1^T, \dots, \mathbf{c}_{N^r}^T]^T$, $\mathbf{e}^r = [e_1, \dots, e_{N^r}]^T$, and $\mathbf{p}^{r,\max} = [p_1^{\max}, \dots, p_{N^r}^{\max}]^T$, respectively (same for centralized nodes: \mathbf{c}^c , \mathbf{e}^c , and $\mathbf{p}^{c,\max}$). We define the auxiliary matrix \mathbf{A} as

$$\mathbf{A} = \mathbf{1}_{1 \times N} \otimes \mathbf{I}_K \quad (2)$$

to express the summations over the charging schedules \mathbf{p}_n for all $n \in \{1, \dots, N\}$ as

$$\mathbf{A}\mathbf{p} = \sum_{n=1}^N \mathbf{p}_n. \quad (3)$$

In the same way, we define the auxiliary matrices \mathbf{A}^u , \mathbf{A}^r , and \mathbf{A}^c for uncontrolled, responsive, and centralized nodes, respectively.

For online control strategies, the available information and the computed charging schedules change over the time,

and we let \bullet^κ denote the value at the time index κ , where $\kappa \in \{1, \dots, N\}$. For example, e_n^κ denotes the n th node's (unfulfilled) energy demand at the time index κ ; \mathbf{p}^{κ} denotes the computed charging schedules over the scheduling horizon for responsive nodes at the time index κ .

A. UNCONTROLLED NODES

In the uncontrolled case, the node starts charging immediately with the maximum charging rate p_n^{\max} . The charging stops, if the EV is fully charged. To ease the calculation and performance comparison, we assume that the charging rate does not change within a decision time slot. Let M denote the number of required time-slots to reach the demand e_n . Then the EV will charge with p_n^{\max} for the duration $M\tau$. Though, to finish charging, the charging rate at the last decision time slot may be smaller than p_n^{\max} . Thus, the k th entry of the charging profile vector \mathbf{p}_n for an uncontrolled node $n \in \{1, \dots, N^u\}$ is:

$$p_n(k) = \begin{cases} p_n^{\max}, & \text{if } t_n^a \leq k\tau < t_n^a + M\tau \\ \frac{e_n - p_n^{\max}M\tau}{\tau}, & \text{if } t_k = t_n^a + M(\tau + 1) \\ 0, & \text{else,} \end{cases} \quad (4)$$

where, $(e_n - p_n^{\max}M\tau)/\tau$ is the charging rate for the last decision time slot to achieve the ED e_n .

B. RESPONSIVE NODES

For an arbitrary target total load profile in the scheduling horizon $\mathbf{p}^t = [p^t(1), \dots, p^t(K)]^T \in \mathbb{R}_{\geq 0}^{K \times 1}$, we find the optimal charging schedules, \mathbf{p}^t , given that there exists uncontrolled nodes:

$$\begin{aligned} \mathbf{p}^t &= \arg \min_{\tilde{\mathbf{p}}^t} \frac{1}{K} \underbrace{\|\mathbf{A}^u \mathbf{p}^u + \mathbf{A}^r \tilde{\mathbf{p}}^t - \mathbf{p}^t\|_2^2}_{L(\tilde{\mathbf{p}}^t)} \\ \text{s.t.} \quad &\begin{cases} \mathbf{0} \leq \tilde{\mathbf{p}}^t \leq \mathbf{c}^r \odot (\mathbf{p}^{r,\max} \otimes \mathbf{1}_{K \times 1}) \\ \tau (\mathbf{I}_{N^r} \otimes \mathbf{1}_{1 \times K}) \tilde{\mathbf{p}}^t = \mathbf{e}^r \end{cases} \end{aligned} \quad (5)$$

where $\tilde{\mathbf{p}}^t$ is the hypothetical charging schedule, and $1/K$ is a constant and does not contribute to the solution. The inequality constraint limits the individual charging rate at each time index. The equality constraint targets fulfilling the ED.

To flatten the load, an intuitive way to form the problem is to minimize the load variance over the scheduling horizon. We can then set the target load profile to the estimated average load:

$$p^t(k) = \frac{1}{K} \langle \mathbf{A} \hat{\mathbf{p}}, \mathbf{1}_{K \times 1} \rangle, k \in \{1, \dots, K\}, \quad (6)$$

where $\hat{\mathbf{p}}$ denotes the estimated future charging load. The optimal solution will minimize the deviation between the load at each decision time slot and the average load, achieving the flattest overall load. Though, a more common formulation to achieve the load flattening is to set the target load as $\mathbf{0}$, which

has been proven to be equivalent [15]. From here on, we apply the latter formulation.

We adapt the algorithm proposed in [31] to iteratively update the responsive nodes' charging schedules at each time index κ , and the detailed algorithm is shown in Algorithm 1. For the specific L defined in (5) and $\mathbf{p}^t = \mathbf{0}$, the virtual price signal is:

$$\mathbf{v}_{i+1}^\kappa = \frac{2\gamma}{K} \mathbf{A} \mathbf{p}_i^\kappa / (N^{d,\kappa} + b^\kappa). \quad (7)$$

Algorithm 1 Online Scheduling for Decentralized Nodes

- 1: **Initialization:** Set the iteration index i to 0 at time index κ . Initialize the charging schedules for all nodes by a random control strategy (eg., uncontrolled strategy), denoted by \mathbf{p}_i^κ . The aggregator initializes the virtual price signal $\mathbf{v}_i^\kappa \in \mathbb{R}_{\geq 0}^{K \times 1}$ (eg., to $\mathbf{0}$).
- 2: At the $(i + 1)$ th iteration, the aggregator calculates the virtual price signal \mathbf{v}_{i+1}^κ by [31]:

$$\mathbf{v}_{i+1}^\kappa = \gamma L'(\mathbf{p}_i^{\kappa}) / (N^{d,\kappa} + b^\kappa), \quad (8)$$

where the parameter γ satisfies $0 < \gamma < \beta$, and β is the Lipschitz constant for the derivative function of the objective function $L'(\mathbf{p}_0^{\kappa})$, $N^{d,\kappa}$ denotes the number of considered decentralized nodes at time index κ , and b^κ is a binary number, defined as:

$$b^\kappa = \begin{cases} 1, & \text{if } N^{c,\kappa} > 0 \\ 0, & \text{else,} \end{cases} \quad (9)$$

where $N^{c,\kappa}$ denotes the number of considered centralized nodes at time index κ . The \mathbf{v}_{i+1}^κ is then broadcast to the decentralized nodes.

- 3: If $\|\mathbf{v}_i^\kappa - \mathbf{v}_{i+1}^\kappa\| < \varepsilon$ (ε is a small constant), stop. Otherwise, the decentralized node n computes its updated schedule, $\mathbf{p}_{n,i+1}^\kappa$, by:

$$\begin{aligned} \mathbf{p}_{n,i+1}^\kappa &= \arg \min_{\tilde{\mathbf{p}}_{n,i+1}^\kappa} \langle \mathbf{v}_{i+1}^\kappa, \tilde{\mathbf{p}}_{n,i+1}^\kappa \rangle + \frac{1}{2} \|\mathbf{p}_{n,i}^\kappa - \tilde{\mathbf{p}}_{n,i+1}^\kappa\|_2^2 \\ \text{s.t.} \quad &\begin{cases} \mathbf{0} \leq \tilde{\mathbf{p}}_{n,i+1}^\kappa \leq p_n^{\max} \mathbf{c}_n^\kappa \\ \tau \mathbf{1}_{1 \times K} \tilde{\mathbf{p}}_{n,i+1}^\kappa = e_n^\kappa, \end{cases} \end{aligned} \quad (10)$$

where $\mathbf{p}_{n,i}^\kappa$ is the latest schedule from prior iterations, \mathbf{c}_n^κ denotes the n th node's connection status at time index κ , and the e_n^κ denotes the (unfulfilled) energy demand. The objective is to achieve the lowest virtual cost, and the regularization part (least-square part) encourages smaller update of the schedule, which makes convergence of this algorithm more likely [31]. Set the iteration index i to $i + 1$ and go to Step 2.

For centralized nodes, the centralized aggregator computes the charging schedules on behalf of them. Indeed, the centralized aggregator resembles a decentralized node. The difference is that the centralized aggregator computes the optimal

charging schedules for multiple nodes, i.e. $\mathbf{p}_{i+1}^{c,\kappa}$, instead of one, and the formulation is as following:

$$\begin{aligned} \mathbf{p}_{i+1}^{c,\kappa} = \arg \min_{\tilde{\mathbf{p}}_{i+1}^{c,\kappa}} & \langle \mathbf{v}_{i+1}^{\kappa}, \mathbf{A}^c \tilde{\mathbf{p}}_{i+1}^{c,\kappa} \rangle + \frac{1}{2} \|\mathbf{A}^c (\mathbf{p}_i^{c,\kappa} - \tilde{\mathbf{p}}_{i+1}^{c,\kappa})\|^2 \\ \text{s.t.} & \begin{cases} \mathbf{0} \leq \tilde{\mathbf{p}}_{i+1}^{c,\kappa} \leq \mathbf{c}^{c,\kappa} \odot (\mathbf{p}^{c,\max} \otimes \mathbf{1}_{K \times 1}) \\ \tau (\mathbf{I}_{N^c} \otimes \mathbf{1}_{1 \times K}) \tilde{\mathbf{p}}_{i+1}^{c,\kappa} = \mathbf{e}^{c,\kappa}. \end{cases} \end{aligned} \quad (11)$$

For the naive online control strategy, the above variables depending on the time index κ consider only arrived EVs and their charging behavior. If we are to apply the predictive online control strategy, we also take the predicted future to be arrived EVs and their charging behavior into consideration. As for oracle control strategy, we simply eliminate the superscript κ .

IV. SIMULATION AND RESULT ANALYSIS

A. SIMULATION SCENARIO AND DATA PREPARATION

To simulate a realistic scenario, we take advantage of the publicly available charging sessions collected by Caltech ACN [50]. We downloaded the charging sessions within the 10 weeks starting from 1 Feb 2021 at the site JPL. Among the attributes in one charging session, four are of our concern:

- **“userID”**: the identification for each individual EV user
- **“connectionTime”**: the time when the user connects the EV (mapped to the AT)
- **“disconnectTime”**: the time when the user disconnects the EV (mapped to the DT)
- **“kWhDelivered”**: the delivered energy to the EV in this session (mapped to the ED)

We set the maximum charging rate to 7 kW and the scheduling horizon (H) for one day (24 h). Some EV users have two or more charging sessions per day, and the intervals between the sessions vary from minutes to hours. We combine the sessions from the same user ID within a day for simplicity. We decided to start the scheduling horizon at 9 am since the dataset shows there was the least amount of EVs connected. We trim a charging session if it spans over 2 scheduling horizons. If a charging session spans over 2 scheduling horizons, we cut it to the scheduling horizon where the EV had a longer connection time. The often-used decision time slot τ in the literature is 0.25 h (15 min) [15], [61], [62], which corresponds to the typical communication time between the energy management units and the grid [63]. However, to reduce the computation complexity and time, we set τ to 0.5 h.

To apply the predictive online control strategy, we need to provide the predicted future charging behavior. To ease notation, we vectorize the true AT t_n^a , historical mean AT \bar{t}_n^a , and predicted AT \hat{t}_n^a , where $n \in \{1, \dots, N\}$, into \mathbf{t}^a , $\bar{\mathbf{t}}^a$, and $\hat{\mathbf{t}}^a$, respectively. The same applies to DT and ED. For the future charging behavior prediction, we directly use the first moments of the historical charging behavior, i.e., the mean values: $\bar{\mathbf{t}}^a$, $\bar{\mathbf{t}}^d$, and $\bar{\mathbf{e}}$. Among the 10 weeks' charging sessions, we treat the first 9 weeks as historical charging behavior. We then evaluate the performance from different control strategies on 3 days from the 10th week. There were

26, 19, 25 charging sessions on those day, respectively, and we assume it is known. The “connectionTime”, “disconnectTime”, and “kWhDelivered” represent the true AT, DT, and ED, respectively. And we assume that the EV can publish the true DT and ED upon arrival.

Table 1 summarizes the simulation parameters and their values.

TABLE 1. Simulation parameters.

Parameters	Value
N	{26, 19, 25}
H	2021-04-05 9:00 - 2021-04-06 9:00 (24 h)
τ	0.5 h
$\hat{\mathbf{t}}^a$	historical mean AT, $\bar{\mathbf{t}}^a$
\mathbf{t}^a	true AT, “connectionTime”
$\hat{\mathbf{t}}^d$	historical mean DT, $\bar{\mathbf{t}}^d$
\mathbf{t}^d	true DT, “disconnectTime”
\mathbf{p}^{\max}	7 kW
$\bar{\mathbf{e}}$	historical mean ED, $\bar{\mathbf{e}}$
\mathbf{e}	true ED, “kWhDelivered”

B. RESULT AND ANALYSIS

To answer the research questions from Section I, we need to include the uncontrolled nodes in the simulation settings. For responsive nodes, since a decentralized node can achieve an optimal charging schedule [31], centralized nodes can also achieve optimal charging schedules because the centralized aggregator is a decentralized node. Thus, responsive nodes can achieve the optimal schedule whether they are purely decentralized nodes, purely centralized nodes, or a mix of both nodes. So, we randomly distribute the responsive nodes while varying the number of uncontrolled nodes. The following presents the answers and analyses to the research questions:

1) What are the performance differences if we apply different online control strategies?

Fig. 4 aims to show an example total system load on one test day ($N = 26$) from different control strategies where there are 20%, 40%, 60%, 80%, and 100% responsive nodes.

The purely uncontrolled strategy assumes no control over nodes and gives the worst load profile (highest load variance). When all nodes are responsive, as shown in Fig. 4 (e), the mix-layer oracle control strategy forms the optimal load profile since it assumes the complete knowledge of the future charging behavior. The mix-layer naive online depends solely on the published charging behavior from the EVs that have arrived. The mix-layer predictive online control strategy computes the charging schedules also based on the predicted future charging behavior if the EV has not arrived at that decision time slot.

As we see from Fig. 4, the final load profile depends on how many nodes are responsive. Nevertheless, the load profiles from the mix-layer predictive online control strategy only differ slightly from that of the mix-layer oracle. The reason is that we used the historical mean as the predicted future charging behavior, and the prediction is accurate

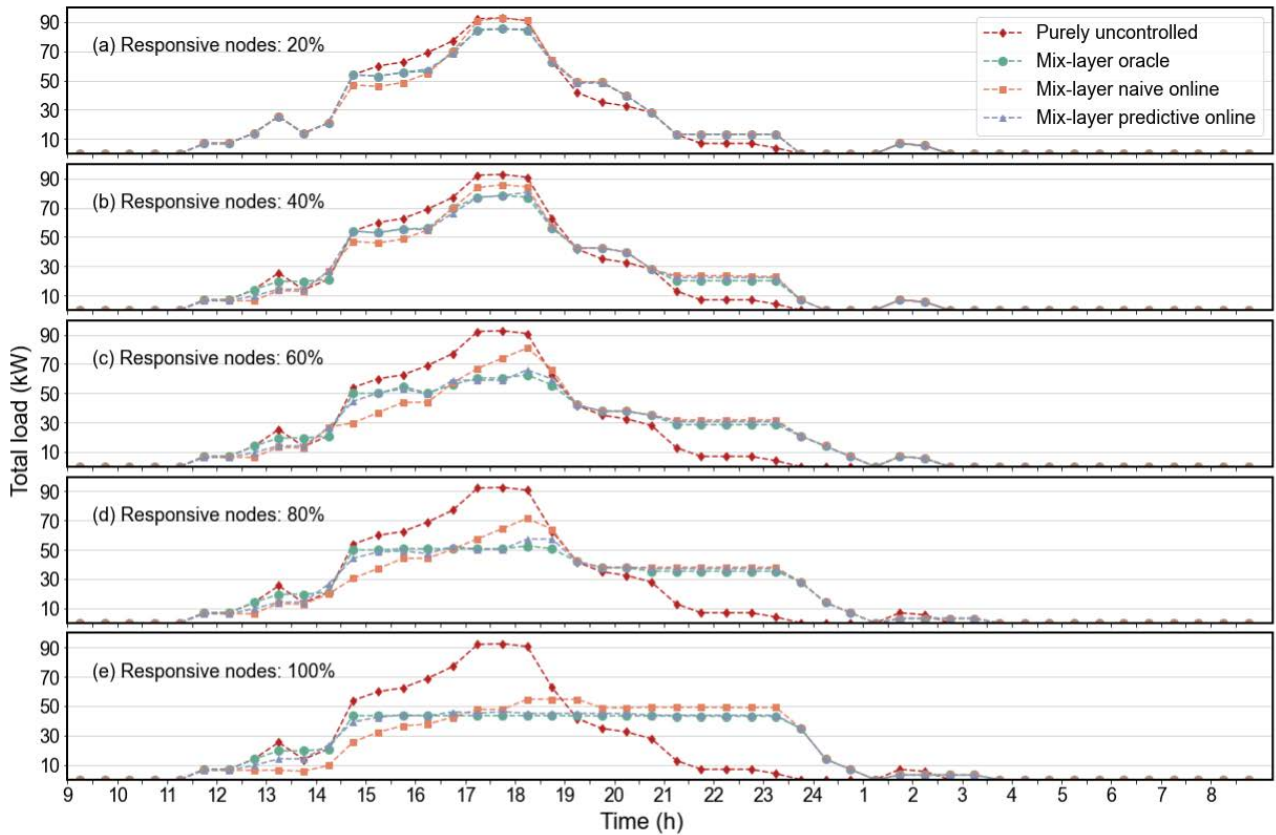


FIGURE 4. The total system load on the day from different control strategies and with the percentages of responsive nodes at: (a) 20%; (b) 40%; (c) 60%; (d) 80%; (e) 100%. The figure shows that more responsive nodes achieves less load variance and that predictive online control strategy in general outperforms naive online.

enough for the mix-layer predictive online control strategy to achieve a good performance. The overall load profile from mix-layer naive online control strategy differs the least from the mix-layer predictive online control strategy when the responsive nodes' percentage is the lowest (Fig. 4 (a)). With the increasing percentage (Fig. 4 (b)-(e)), we can see a difference in the total load. The reason is that when the responsive nodes' percentage is small, the inflexibility lying in uncontrolled nodes overtakes the impact on the overall scheduling. Then, with the majority being responsive nodes, the mix-layer naive online control strategy has significantly worse performance. The reason is that the responsive nodes initially have low scheduled charging rates due to no predictions for future charging behavior. Then, the scheduled charging rates may increase dramatically depending on the newly observed charging behavior. The resulting load variance is high.

Though, the final load profile depends also on which nodes are responsive due to the nodes' different charging behavior. Consequently, we conduct further experiments by running each experiment J (we set J to 30) times with randomly chosen individuals as responsive nodes and compute the load variance as per the defined objective function in (5). For a fixed percentage of responsive nodes, we denote the load

variances by L_j^π , where j is the j th simulation, and π varies with the control strategies, i.e., the uncontrolled, mix-layer oracle, mix-layer naive online, and mix-layer predictive online control strategies. Moreover, the purely responsive nodes with the oracle control strategy assume control over all nodes with complete knowledge, and it provides the lowest load variance, denoted by L^{opt} . For a fair comparison, we normalize the load variances from other control strategies by L^{opt} . Fig. 5 shows the final normalized load variance comparison for the 3 test days.

The result confirms the previous findings: the load variances from the mix-layer predictive online control strategy, compared to the naive online, are much closer to the oracle control strategy. Besides, the mix-layer naive online control strategy differs the least from the mix-layer predictive online and oracle control strategy when the responsive nodes' percentage is the lowest. The higher the responsive nodes' percentage, the higher the difference.

2) To which percentage the responsive nodes should be to achieve an acceptable performance?

We conduct further experiments with an increased resolution to answer this question: we choose the test day with $N = 26$, and we conduct 27 experiments by varying the number of responsive nodes (0 – 26). Further, we run each

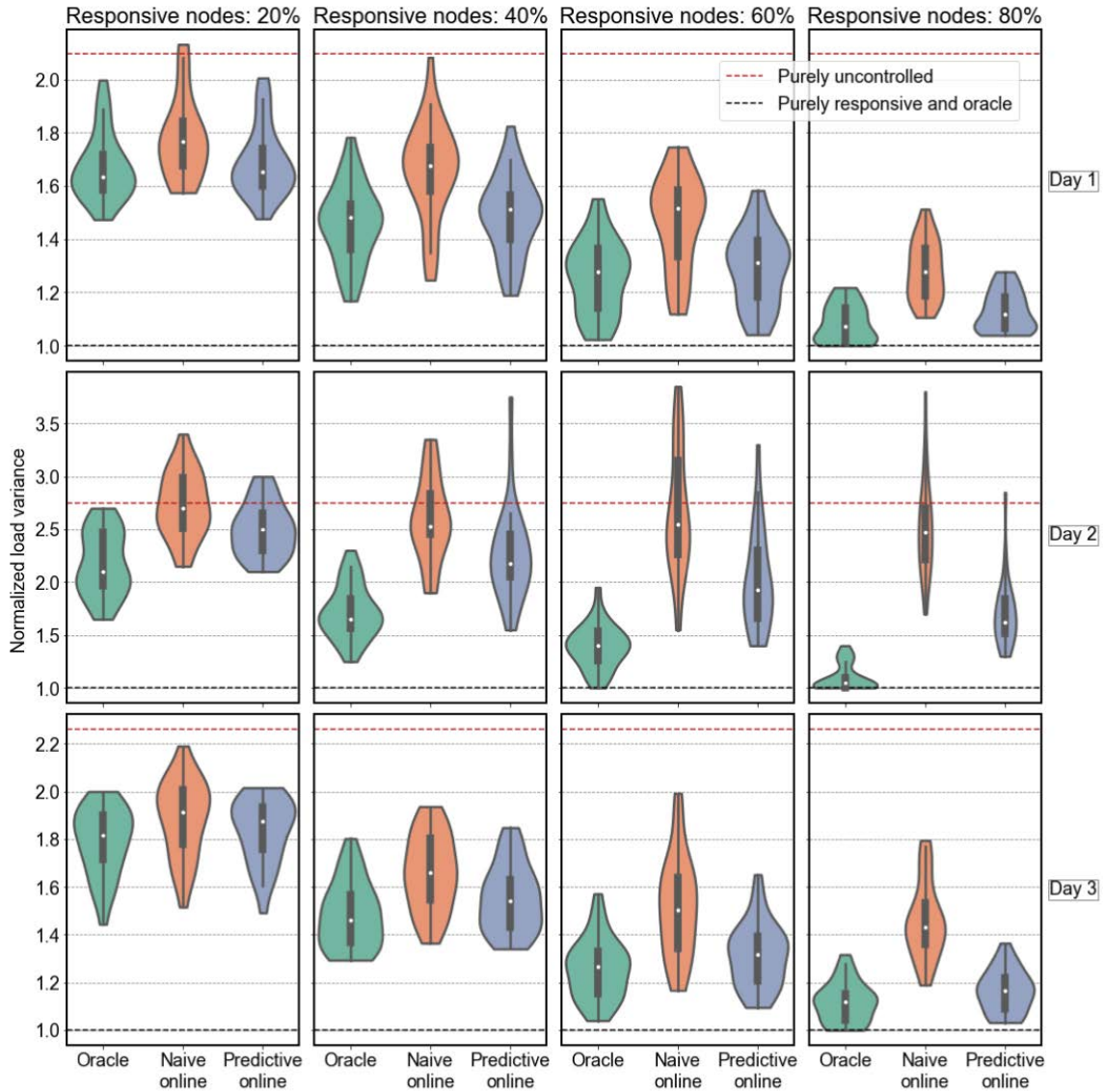


FIGURE 5. The violin plots of the load variances for the 3 test days from different control strategies where the percentage of responsive nodes varies. The variances are normalized by that from the purely responsive and oracle control strategy, i.e., L^{opt} . The violin plots show the absolute load variance distributions. They indicate that the mix-layer oracle outperforms the mix-layer predictive online and the mix-layer predictive online outperforms the mix-layer naive online control strategy for all test days.

experiment J ($J = 30$) times with randomly chosen individuals as responsive nodes and compute the mean load variance as per the defined objective function in (5):

$$\bar{L}_i^\pi = \sum_{j=1}^J L_{i,j}^\pi, i \in \{0, 1, \dots, N\}, \quad (12)$$

where i is the number of responsive nodes, j is the j th simulation for a fixed i , π denotes the control strategies, i.e., the uncontrolled, mix-layer oracle, mix-layer naive online, and mix-layer predictive online control strategies. We normalize the mean load variance from other control strategies by L^{opt} :

$$w_i^\pi = \frac{\bar{L}_i^\pi}{L^{opt}}, i \in \{0, 1, \dots, N\}. \quad (13)$$

Fig. 6 shows the final normalized mean load variance comparison.

As shown, the load variances from the mix-layer control strategies generally decrease when the number of responsive nodes increases. Moreover, we notice that the load variances get close to L^{opt} (purely responsive nodes with oracle control strategy), even with uncontrolled nodes. We observe that we only need to control approximately 61.5% (here 16 nodes out of 26) to stay below a 125% of the optimal load variance L^{opt} (gray dashed line in Fig. 6) if we apply the mix-layer predictive online control strategy. The reason is that the flexibility in those responsive nodes can mitigate the inflexibility from those uncontrolled nodes. However, if we apply the mix-layer naive online control strategy, we would need around 22 nodes out of 26 (84.6%) to be responsive nodes.

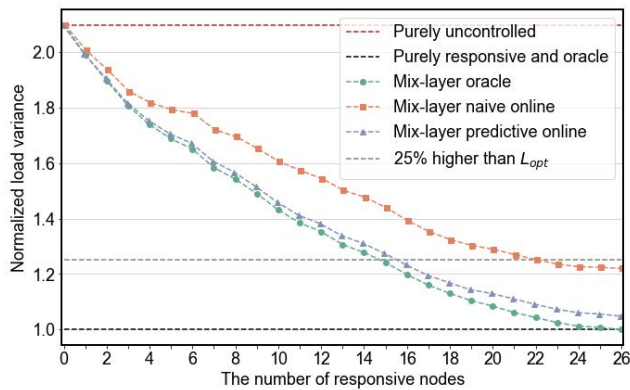


FIGURE 6. The comparison shows the mean load variances for one test day from different control strategies versus a varying number of responsive nodes. To stay below 125% of L^{opt} (gray dashed line), the predictive online strategy requires 16 nodes ($\approx 61.5\%$ of the nodes) versus 22 nodes ($\approx 84.6\%$) for the naive online strategy.

V. CONCLUSION

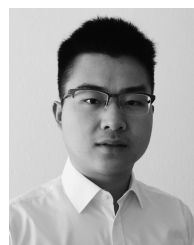
This paper investigated the charge scheduling for an EV fleet consisting of heterogeneous nodes. We proposed a variant of the layered control architecture that regulates the charging rates for responsive nodes with the presence of uncontrolled nodes. We conducted a case study based on a real-world charging session dataset. We find that the predictive online control strategy approaches the oracle control strategy. In contrast, the naive online control strategy performs worse, relatively. However, the difference is insignificant when the responsive nodes' percentages are low. Then, modeling the charging behavior to apply the predictive online control strategy will not significantly improve the performance. Besides, the simulation result shows that the mix-layer online control strategies can already achieve good results with part of the nodes responsive in an EV fleet. Applying the mix-layer predictive online or naive online control strategy in an EV fleet with a certain portion of responsive nodes can achieve a suboptimal performance ($> L^{opt}$).

In this work, we completed the computation for these simulations at a centralized computer. However, in reality, the computation is distributed to aggregators and nodes, happening asynchronously. Besides, the impact from in practice occurring communication delays and failures between the nodes and the aggregator should be investigated. Furthermore, the financial benefits from the proposed architecture and the control strategies are interesting to study as to whether it can surpass the investment in the infrastructure to ensure communication and computation. Depending on the scale of the charging network, it may require a too long time to converge to the optimal charging profile, resulting in compromised performance.

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