Validating and Improving an Aggregated EV Model for Energy Systems Evaluation

Kun Qian, Reza Fachrizal, Joakim Munkhammar, Thomas Ebel, and Rebecca Adam

***Abstract*—With the trend in transportation electrification, electric vehicle (EV) charging/discharging scheduling has become an area of concern. Scheduling can help manage EV charging/discharging activities. Besides, it is also valuable for energy systems evaluation, in which case modeling the individual EV has high complexity and requires a long computation time due to too many EVs. The aggregated model significantly reduces computation time but may sacrifice accuracy. This work investigates the trade-off between accuracy and computational time when designing intelligent EV charging/discharging scheduling by comparing the individual and aggregated models. This work first provides a detailed problem formulation. The simulation results show that the aggregated model can achieve similar energy system performance estimations from the energy-matching perspective compared to the individual model, given that the system allows vehicle-to-grid (V2G). Otherwise, the aggregated model will overestimate the performance. Thus, this work, in the meantime, proposes an extra constraint to avoid such overestimation when V2G is not allowed. Given the validated accuracy of the aggregated model and its advantage of low complexity and computation time, the aggregated model is more suitable for assessing large (e.g., city-level) energy systems.**

***Index Terms*—charging scheduling, vehicle-to-grid, energy system, aggregated model**

I. Introduction

Electric vehicles (EVs) have seen a surge in popularity in recent years due to their environmental benefits and potential to reduce dependence on fossil fuels [1]. However, as the number of EVs on the road increases, it presents new challenges on the power grid. In particular, EV charging/discharging management has become an area of concern. The charging/discharging from the increasing number of EVs can significantly affect the immediate demand shape [2], and without proper management, the grid will face instability issues [3].

The existing EV charging/discharging scheduling literature has investigated the aspects such as the scheduling objectives and the mathematical formulations. Recent reviews [4–6] provide an overview of the relevant topics. Indeed, apart from optimally managing the EVs, the charging/discharging scheduling also plays an essential role in the energy systems evaluation. Simulating various scheduling scenarios and assessing their impact on the power grid can lead to a better understanding of the energy system and facilitate planning for accommodating the growing number of EVs. This approach enables the identification of potential issues and insights into strategies for mitigating them, such as modifying the distribution network or adjusting the energy production. For example, Fachrizal et al. [7] showed the optimal solar power sizing based on the EV charging schedules; Heinisch et al. [8] investigated how various scheduling strategies affect the optimal operation and design of the electricity and district heating sectors, in conjunction with sector-coupling in the urban energy system.

Energy systems evaluation often requires considering many EVs. There are two primary approaches to designing the scheduling: Aggregated modeling, which provides aggregated charging scheduling, and individual modeling, which additionally provides individual charging scheduling. Note that the concept of individual modeling differs from distributed scheduling. To provide individual charging scheduling, individual modeling must introduce parameters for each individual. In contrast, aggregated modeling considers all chargings as a single aggregate, dramatically reducing the parameters' dimension. Thus, aggregated modeling can significantly reduce computation time but may sacrifice accuracy. González Vayá et al. [9], after describing the individual model, introduced the aggregated EV charging/discharging formulation. The aggregated model achieved good performance in the defined simulation scenarios. Compared to the individual model, the aggregated model has significantly reduced complexity. Though, they did not compare both models to verify the accuracy of the aggregated model.

Evaluating large energy systems by the individual model is unrealistic and sometimes even infeasible. The aggregated model can potentially reduce the computation time. However, there are concerns about the aggregated model. Fig. 1 helps illustrate these potential problems: suppose that one battery is at the maximum state-of-charge (SoC), one is at the minimum SoC that requires charging until departure, and the rest has an SoC between the minimum and maximum range. The resulting aggregated battery SoC will also be within the range, and there are potentially different charging/discharging options that are feasible from the aggregation perspective

- Charging at maximum.
- Discharging at maximum.
- Discharging or charging at low power.

Charging at maximum is unrealistic since b_1 is full. Similarly, discharging at maximum is unrealistic due to b_N. These unrealistic charging/discharging can undermine the result of

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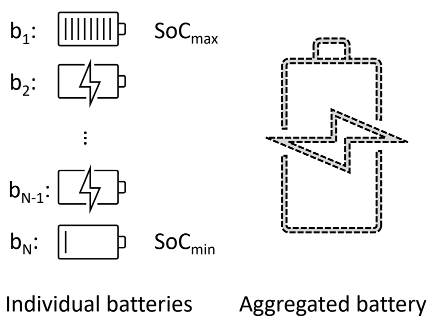

Fig. 1. The concept of aggregating the batteries from individual sessions.

the aggregated model. Discharging or charging at low power may be unrealistic for b_N since it requires charging until departure (as in the assumption). However, the aggregated model only focuses on the net charging/discharging activity, i.e., it does not capture the overlapping part, referred to as vehicle-to-vehicle (V2V). For example, a few individuals are charging while others are discharging can result in a net 0 charging power. The V2V is acceptable if the scheduling strategy allows discharging. However, the aggregated model is incorrect if the strategy allows only charging.

Consequently, this work investigates

- How much more computationally efficient is the aggregated model?
- How inaccurate is the aggregated model?
- How to avoid the unwanted V2V in the scheduling scenario which allows only charging?

The main contributions of this work are:

- The detailed EV charging/discharging scheduling formulation for both the individual and aggregated models.
- A novel constraint formulation for the aggregated model in smart charging without vehicle-to-grid (V2G) capability scenario.
- A systematic comparison between the individual model and the aggregated model.

The remainder of this paper is structured as follows. Section II provides information on the applied methods, which cover the data used in this study, the problem formulation, the energy-matching measures explanations, and the descriptions of the simulation scenarios. Section III presents the simulation results and the analysis. Section IV concludes the work.

II. Methods

This section describes the methods used in this paper. Moreover, Section II-A presents data and the assumptions used in the study. In Section II-B, the individual and aggregated smart charging/discharging optimization models are described. Section II-C presents the energy matching measures used to assess the energy performances. The simulation scenarios conducted in this study are presented in Section II-D.

A. Data and Case Study

This work aims to assess the aggregated model for energy system evaluation. Specifically, this paper investigates a city-level net-zero energy system where the renewable energy sources (RESs) generation equals the electricity demand (including EV charging) over the year. Thus, the simulations require datasets from the RES generations, the base load of the city, and the charging sessions.

This paper utilizes the mobility data from the Swedish travel survey in 2006 [10, 11], and obtains the charging sessions for a Swedish city with the assumption that all personal cars in the city are electric, and 80% of the users are charging at home [12] while the rest are at work. Depending on the population, personal car ownership percentage, and productive age percentage [13], the generated sessions cover around 37k users. For the base load, the historical data from Sweden can be found in [14], which has the data for the corresponding region to the selected city. The base load is then rescaled so the overall EV charging and base demand ratio is $0.11:1$ [15]. This work also utilizes historical data from [14] for the RES generation and rescales it so that the generation equals the consumption in the city. In the later simulations, the number of uses is much smaller than 37k, so that the individual model is applicable. The base load and the RES are then rescaled accordingly.

B. Problem Formulation

This section provides the problem formulation for both the individual and aggregated models. In the formulation, lowercase letters denote variables; uppercase letters denote constant values; lowercase boldfaced letters denote vectors; and uppercase boldfaced letters denote matrices.

Let H represent the scheduling horizon, T the decision time slot duration, and $K = \lfloor H/T \rfloor$ the total number of time slots. This paper aims to investigate the energy balance in a RES-powered system where the net energy is zero over the horizon H, i.e., RES production equals energy consumption from EV charging. The production consists of the RES, $\mathbf{p}_{\text{RES}}$, and potential discharging from the EVs, $\mathbf{p}_{\text{dch}}$, while the consumption comes from the base load, $\mathbf{p}_{\text{base}}$, and the EV charging, $\mathbf{p}_{\text{ch}}$:

$$\mathbf{p}_{\text{prod}} = \mathbf{p}_{\text{RES}} + \mathbf{p}_{\text{dch}}, \tag{1}$$

$$\mathbf{p}_{\text{cons}} = \mathbf{p}_{\text{base}} + \mathbf{p}_{\text{ch}}, \tag{2}$$

where $\mathbf{p}_{\text{prod}}$ and $\mathbf{p}_{\text{cons}} \in \mathbb{R}^{1\times K}$ denote the total production and consumption. Thus, the objective function is:

$$\min_{\mathbf{p}_{\text{ch}},\mathbf{p}_{\text{dch}}} \quad \left\| \mathbf{p}_{\text{prod}} - \mathbf{p}_{\text{cons}} \right\|^2 . \tag{3}$$

A charging session is defined as a 3-tuple $(t_\text{a}, t_\text{d}, e)$, where t_a is the arrival time index, t_d is the departure time index, and e is the energy demand. Let $\mathbf{t}_\text{a}$, $\mathbf{t}_\text{d}$, and $\mathbf{e} \in \mathbb{R}^{S\times 1}_{\geq 0}$ denote the arrival time indexes, departure time indexes, and energy demands for the considered S charging sessions. Charging sessions have two types: The minimum required charging time is equal to or smaller than the stay duration. For the sessions where the minimum required charging time equals the stay duration, the EV must charge during the whole stay, which leaves no flexibility. Otherwise, the extra stay time provides the potential for smart charging/discharging control. To quantify the inflexible charging sessions, let $\mathbf{p}_{\text{fix}} \in \mathbb{R}_{\geq 0}^{1\times K}$ denote the aggregated charging power from the inflexible charging sessions. Consequently, the total EV charging power is:

$$\mathbf{p}_{\text{ch}} = \mathbf{p}_{\text{fix}} + \mathbf{p}_{\text{fch}}, \tag{4}$$

where $\mathbf{p}_{\text{fch}}$ is the charging power for those flexible charging sessions.

The difference between the individual and aggregated models mainly lies in formulating the constraints, which cover the charging/discharging power and the energy content. The following will provide a detailed description of the constraints formulation.

1) Individual Model: In the individual model, the charging/discharging decision variable matrix $\mathbf{P}_{\text{ind}}$ has the dimension $S \times K$. Let $\mathbf{p}_{\text{ind,load}} \in \mathbb{R}^{1\times K}$ denote the summation of the load at each time index:

$$\mathbf{p}_{\text{ind,load}} = \sum_{s=1}^{S} [\mathbf{P}_{\text{ind}}]_{s,:}. \tag{5}$$

Thus,

$$\mathbf{p}_{\text{ch}} = \mathbf{p}_{\text{fix}} + \max(\mathbf{p}_{\text{ind,load}}, 0), \tag{6}$$
$$\mathbf{p}_{\text{dch}} = -\min(\mathbf{p}_{\text{ind,load}}, 0), \tag{7}$$

where $\min(\cdot)$ and $\max(\cdot)$ are element-wise comparison.

To formulate the charging/discharging power constraint, it requires a binary connection matrix $\mathbf{C}_{\text{p,ind}} \in \mathbb{B}^{S\times K}$ to indicate whether the charging session is connected:

$$[\mathbf{C}_{\text{p,ind}}]_{s,[\mathbf{t}_{\text{a}}]_s:[\mathbf{t}_{\text{d}}]_s} = 1, \forall s \in \{1, \cdots, S\}. \tag{8}$$

With $\mathbf{C}_{\text{p,ind}}$, the constraint can be formulated as follows:

$$|\mathbf{P}_{\text{ind}}| \preceq P_{\text{max}} \mathbf{C}_{\text{p,ind}}, \tag{9}$$

where P_{max} is the maximum charging/discharging power.

To formulate the energy content constraint, it requires binary connection matrices $\mathbf{C}_{\text{e,ind}} \in \mathbb{B}^{S\times K}$ and $\mathbf{D}_{\text{ind}} \in \mathbb{B}^{S\times K}$ to indicate the session's connection status before departure and the departure time index for the sessions:

$$[\mathbf{C}_{\text{e,ind}}]_{s,[\mathbf{t}_{\text{a}}]_s:[\mathbf{t}_{\text{d}}]_s-1} = 1, \forall s \in \{1, \cdots, S\}, \tag{10}$$
$$[\mathbf{D}_{\text{ind}}]_{s,[\mathbf{t}_{\text{d}}]_s} = 1, \forall s \in \{1, \cdots, S\}. \tag{11}$$

Additionally, it requires a matrix $\mathbf{E}_{\text{a,ind}} \in \mathbb{R}_{\geq 0}^{S\times K}$ to indicate when the new energy content from the arriving charging session is available.

$$[\mathbf{E}_{\text{a,ind}}]_{s,[\mathbf{t}_{\text{a}}]_s} = E_{\text{max}} - [\mathbf{e}]_s, \forall s \in \{1, \cdots, S\}. \tag{12}$$

where E_{max} is the maximum battery capacity or energy content. Then, the energy content for those charging sessions is:

$$\begin{aligned}\mathbf{E}_{\text{ind}} = \text{cumsum}(\mathbf{E}_{\text{a,ind}}) - E_{\text{max}}\text{cumsum}(\mathbf{D}_{\text{ind}}) \\ +T\text{cumsum}(\mathbf{P}_{\text{ind}}),\end{aligned} \tag{13}$$

where E_{max} also denotes the required departure energy content, and $\text{cumsum}(\cdot)$ is to compute the cumulative sum over the row. Note that, the result from the $\text{cumsum}(\cdot)$ operation has the same dimension as the original matrix. The energy content has the following constraint:

$$E_{\text{min}} \mathbf{C}_{\text{e,ind}} \preceq \mathbf{E}_{\text{ind}} \preceq E_{\text{max}} \mathbf{C}_{\text{e,ind}}, \tag{14}$$

where E_{min} is the minimum energy content.

Consequently, the optimization formulation for the individual model is:

$$\begin{aligned}&\mathbf{P}_{\text{ind, opt}} = \arg\min_{\mathbf{p}_{\text{ch}},\mathbf{p}_{\text{dch}}} \|\mathbf{p}_{\text{prod}} - \mathbf{p}_{\text{cons}}\|^2, \\ &\text{s.t.} \begin{cases}|\mathbf{P}_{\text{ind}}| \preceq P_{\text{max}} \mathbf{C}_{\text{p,ind}}, \\ E_{\text{min}} \mathbf{C}_{\text{e,ind}} \preceq \mathbf{E}_{\text{ind}} \preceq E_{\text{max}} \mathbf{C}_{\text{e,ind}},\end{cases}\end{aligned} \tag{15}$$

where $\mathbf{P}_{\text{ind, opt}}$ denotes the optimal resulting scheduling.

2) Aggregated Model: In the aggregated model, the decision variables $\mathbf{p}_{\text{agg}}$ are in vector form, and the dimension is $1 \times K$. Thus,

$$\mathbf{p}_{\text{ch}} = \mathbf{p}_{\text{fix}} + \max(\mathbf{p}_{\text{agg}}, 0), \tag{16}$$
$$\mathbf{p}_{\text{dch}} = -\min(\mathbf{p}_{\text{agg}}, 0). \tag{17}$$

Moreover, for the constraint formulation, the required parameters $\mathbf{c}_{\text{p,agg}}$, $\mathbf{c}_{\text{e,agg}}$, $\mathbf{d}_{\text{agg}}$, and $\mathbf{e}_{\text{a,agg}}$ can be directly computed from those in the individual model: by summing over the column of $\mathbf{C}_{\text{p,ind}}$, $\mathbf{C}_{\text{e,ind}}$, $\mathbf{D}_{\text{ind}}$, and $\mathbf{E}_{\text{a,ind}}$, respectively.

Consequently, the constraint for the aggregated charging/discharging power is:

$$|\mathbf{p}_{\text{agg}}| \preceq P_{\text{max}} \mathbf{c}_{\text{p,agg}}. \tag{18}$$

The aggregated energy content is:

$$\begin{aligned}\mathbf{e}_{\text{agg}} = \text{cumsum}(\mathbf{e}_{\text{a,ind}}) - E_{\text{max}}\text{cumsum}(\mathbf{d}_{\text{agg}}) \\ +T\text{cumsum}(\mathbf{p}_{\text{agg}}),\end{aligned} \tag{19}$$

which has the following constraint:

$$E_{\text{min}} \mathbf{c}_{\text{e,agg}} \preceq \mathbf{e}_{\text{agg}} \preceq E_{\text{max}} \mathbf{c}_{\text{e,agg}}. \tag{20}$$

Thus, the aggregated model's optimization formulation is:

$$\begin{aligned}&\mathbf{p}_{\text{agg, opt}} = \arg\min_{\mathbf{p}_{\text{ch}},\mathbf{p}_{\text{dch}}} \|\mathbf{p}_{\text{prod}} - \mathbf{p}_{\text{cons}}\|^2, \\ &\text{s.t.} \begin{cases}|\mathbf{p}_{\text{agg}}| \preceq P_{\text{max}} \mathbf{c}_{\text{p,agg}}, \\ E_{\text{min}} \mathbf{c}_{\text{e,agg}} \preceq \mathbf{e}_{\text{agg}} \preceq E_{\text{max}} \mathbf{c}_{\text{e,agg}}.\end{cases}\end{aligned} \tag{21}$$

where $\mathbf{p}_{\text{agg, opt}}$ denotes the optimal resulting scheduling.

3) Improved Aggregated Model for Smart Charging: The aggregated model focuses only on the net charging/discharging activity, i.e., there are potential V2V activities from the individual perspective. The unmodelled V2V is acceptable if the desired charging strategy allows the EV to discharge. When discharging is not allowed, the model should also avoid the V2V.

Thus, this paper proposes a new constraint on the overall charged power: the minimum energy the grid must have delivered should cover the required energy to fulfill the energy demand for the departing EVs, which aims to minimize or prevent the undesirable V2V entirely. Let $\mathbf{E}_{\text{d,ind}} \in \mathbb{R}_{\geq 0}^{S\times K}$ denote when the energy demand should be fulfilled for each session, and let $\mathbf{e}_{\text{d,agg}}$ denote the required energy from the grid at each time index (summation over the column of $\mathbf{E}_{\text{d,ind}}$):

$$[\mathbf{E}_{\text{d,ind}}]_{s,[\mathbf{t}_\text{d}]_s} = [\mathbf{e}]_s \,, \forall s \in \{1, \cdots, S\} \,, \tag{22}$$

$$\mathbf{e}_{\text{d,agg}} = \sum_{s=1}^{S} [\mathbf{E}_{\text{d,ind}}]_{s,:} \,. \tag{23}$$

Then the constraint for the total charged power is:

$$\text{cumsum}\left(\mathbf{e}_{\text{d,agg}}\right) \preceq T\text{cumsum}\left(\mathbf{p}_{\text{agg}}\right) . \tag{24}$$

Consequently, the optimization formulation for aggregated smart charging without V2G capability is:

$$\mathbf{p}_{\text{agg-sc, opt}} = \arg\min_{\mathbf{p}_{\text{ch}}} \left\|\mathbf{p}_{\text{prod}} - \mathbf{p}_{\text{cons}}\right\|^2 ,$$
$$\text{s.t.} \begin{cases} \mathbf{0} \preceq \mathbf{p}_{\text{agg}} \preceq P_{\text{max}} \mathbf{c}_{\text{p,agg}}, \\ E_{\text{min}} \mathbf{c}_{\text{e,agg}} \preceq \mathbf{e}_{\text{agg}} \preceq E_{\text{max}} \mathbf{c}_{\text{e,agg}}, \\ \text{cumsum}\left(\mathbf{e}_{\text{d,agg}}\right) \preceq T\text{cumsum}\left(\mathbf{p}_{\text{agg}}\right) . \end{cases} \tag{25}$$

where $\mathbf{p}_{\text{agg-sc, opt}}$ denotes the optimal resulting scheduling for smart charging without V2G capability.

C. Energy Matching Measures

This paper examines the energy balance in a net zero energy system, where the annual renewable energy production equals the electricity consumption (including EV charging). Three energy-matching measures are applicable to assess model performance [7, 16]:

- Self-consumption (SC): the ratio of the consumed renewable electricity production to the total renewable production;
- Self-sufficiency (SS): the ratio of the consumed renewable electricity production to the total EV charging consumption;
- Self-consumption-sufficiency balance (SCSB): the equilibrium between SC and SS.

Fig. 2 provides a schematic outline of the daily consumption

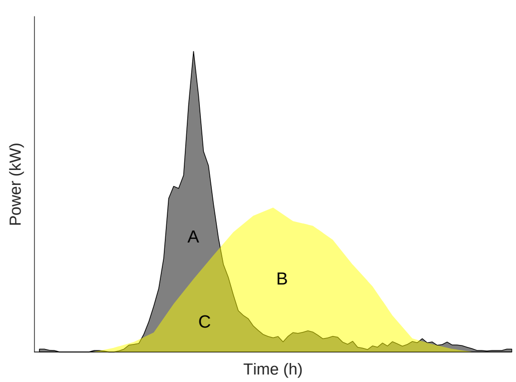

Fig. 2. Schematic outline of daily net load (A+C), net generation (B+C), and absolute self-consumed electricity (C) [7].

(A+C), generation (B+C), and self-consumed electricity (C), which helps to understand the measures [7, 16]. Mathematically, they are defined as:

$$\text{C} = \sum_{k=1}^{K} \min\left(\mathbf{p}_{\text{prod}}, \mathbf{p}_{\text{cons}}\right) , \tag{26}$$

$$\phi_{\text{SC}} = \frac{\text{C}}{\sum_{k=1}^{K} \mathbf{p}_{\text{prod}}} , \tag{27}$$

$$\phi_{\text{SS}} = \frac{\text{C}}{\sum_{k=1}^{K} \mathbf{p}_{\text{cons}}} . \tag{28}$$

High generation usually leads to low ϕ_{SC} while high consumption leads to low ϕ_{SS}. This creates an imbalance that needs to be quantified. The ϕ_{SCSB}, proposed by [7]:

$$\phi_{\text{SCSB}} = \frac{2\phi_{\text{SC}}\phi_{\text{SS}}}{\phi_{\text{SC}} + \phi_{\text{SS}}} . \tag{29}$$

which is the harmonic mean of ϕ_{SC} and ϕ_{SS}, can convey the optimal trade-off. This work will apply SCSB to evaluate the energy balance.

D. Simulation Scenarios

This study is to verify how much more computationally efficient and accurate the aggregated model is, compared to the individual model. Thus, the simulations cover both the computation time estimation and the model performance.

1) Computation Time Comprison: The number of considered users and the scheduling horizon affect the computation time. Thus, this paper evaluates the computation time from these two aspects. Consequently, the simulation has two parts:

- The scheduling horizon is with a fixed number of days (7 days in this case to cover the daily difference); then, the simulation covers a different number of users (10, 20, 100, 200, 1000, 2000 in this study).
- The number of users is a fixed value (200 users in this case to limit the computation time); then, the simulation covers a different number of days, ranging from 7 to 25, with a step of 2.

Additionally, to consider the seasonality, the starting date covers 4 months in the year: February, May, August, and November. Each simulation is repeated 20 times with different users (thus different travel and charging behavior) to count for the uncertainties.

The comparison should cover both scenarios with and without V2G capability. However, considering the similarity, this work will only compare the scenario where V2G is allowed.

2) Model Performance Assessment: As for comparing the performance of the aggregated and individual models, the scheduling horizon will not matter as both models evaluate the performance over the defined scheduling horizon. However, the number of users matters since it affects the individual model but not the aggregated model. Thus, this paper compares the performance of these two models in the simulation setting with a fixed number of days (7 days) and a varying number of users (10, 20, 100, 200, 1000, 2000 in this study).

III. Results and Analysis

This work utilizes Python and the module CvxPy [17], as a modeling language for the least-square optimization problems. This section will provide the simulation results and analyses for each scenario.

A. Computation Time

Fig. 3 and Fig. 4 show how the increasing number of days and users affect the computation time, respectively. As mentioned in the simulation setup, there are extra measures to count for the uncertainties: for each number of days and users, the simulation is repeated 20 times. Besides, the simulation covers the starting dates from the 4 different months. Fig. 3 and 4 show only the mean computation time with the dot plot. With the increasing number of days, there exhibits an exponential relationship. The fitted curves in the line plots based on exponential functions confirm it. However, with the increasing number of users, the individual model shows a linear increase in the computation time (applied log to both x and y before fitting). In contrast, the aggregated model has a fixed computation time. Note that, the intention of showing a fitted curve is to visually demonstrate the potential relationship between the computation and the number of days and users. Estimating the computation time with a high number of days or users requires much more accurate curve-fitting, which is not within the scope of this study.

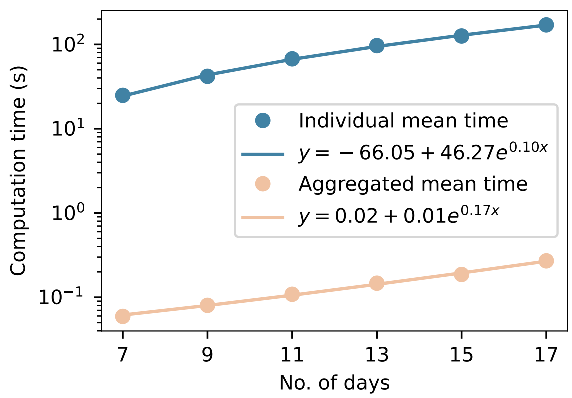

Fig. 3. Computation time increases exponentially for both models with increasing days. The line plots show the estimated relationship between the computation time and the number of days.

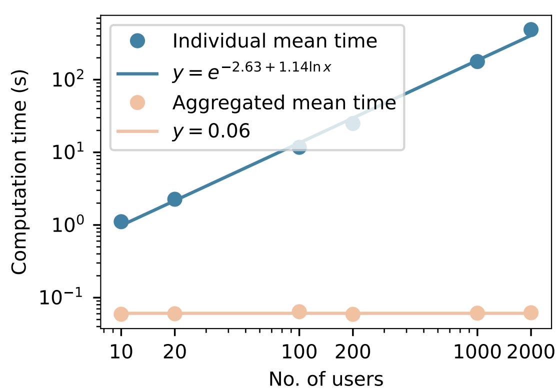

Fig. 4. In the individual model, the computation time increases linearly with the increasing number of users. The aggregated model has a fixed computation time. The line plots show the estimated relationship between the computation time and the number of users.

The increase in the number of days will extend the column length for the decision variable, which results in increased computation time for both the individual model and the aggregated mode. An increasing number of users will lead to an increased row length for the decision variable in the individual model. However, it does not directly affect the aggregated model. Consequently, only the individual model has increased computation time.

B. Model Performance

This section first shows the performance of the aggregated model on smart charging with V2G capability. Further, knowing that directly applying the aggregated model on smart charging without V2G is incorrect, this paper has proposed an extra constraint. Overestimations on the SCSB for both the original aggregated model and the improved aggregated model, compared to the individual model, are shown.

1) Smart Charging and V2G: Fig. 5 shows how the increasing number of users affects the SCSB. As seen, the aggregated model seems to provide the best accuracy when the number of users is small. This is due to the fact that, with a small number of EVs and their separate connection times, the aggregated model can only provide realistic charging and discharging power. With the increasing number of users, there is an overestimation of the SCSB from the aggregated model. However, the overestimation tends to converge, and the value is small (around 1%), as shown in Fig. 6. The overestimation is due to the unrealistic charging/discharging power since the optimization only constrains the aggregated energy content other than the individual. An increasing number of users provides more flexibility for the solver to find solutions within the boundary, making the overestimation insignificant.

Fig. 7 shows an example resulting load from the individual and aggregated models (2000 users in February). As can be seen, the aggregated model sometimes desires higher charging/discharging power, which is not feasible from the individual perspective. Though, the overall load from both models is similar.

2) Smart Charging Only: Fig. 8 shows the overestimations from the original and the improved aggregated models. As seen, the improved aggregated model has significantly reduced the overestimation. Especially during the week in May, the overestimations are too small (below 0.0001) to show.

Fig. 9 shows an example resulting load from the individual, aggregated, and improved aggregated models (2000 users in February). As can be seen, the original aggregated model can dramatically overestimate the charging ability due to delayed charging for some EVs. On the contrary, the improved aggregated model has a constraint on energy delivery, avoiding

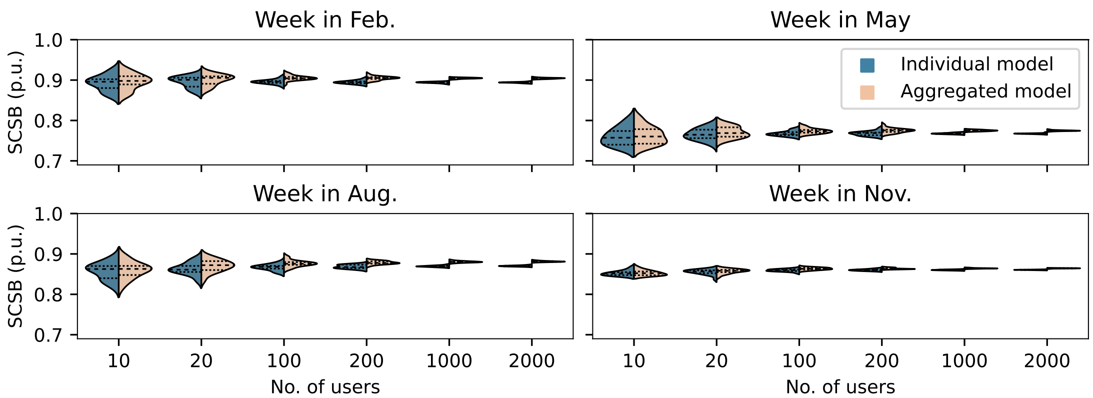

Fig. 5. The individual model provides the accurate SCSB. The aggregated model usually results in overestimated SCSB. Note that the tick labels on the x-axis are only ordinal.

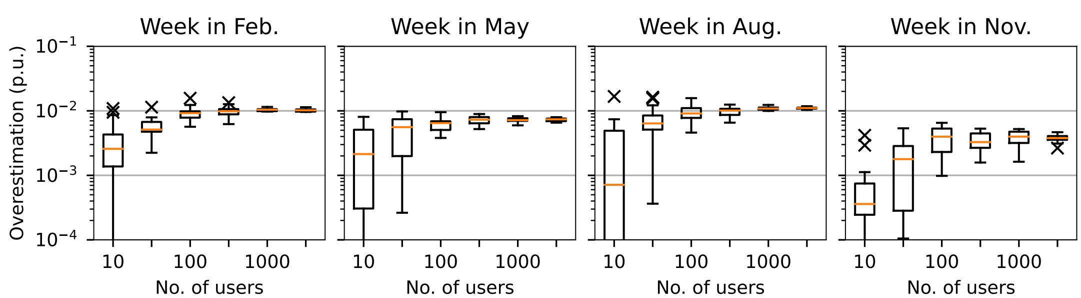

Fig. 6. Overestimation of the SCSB from the aggregated model. Note that the tick labels on the x-axis are only ordinal.

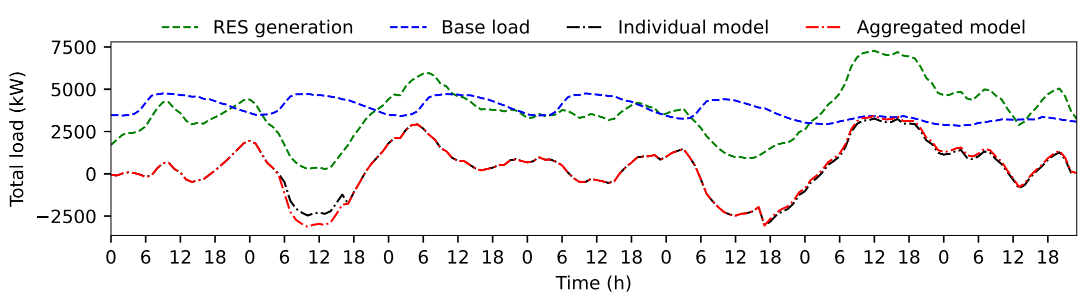

Fig. 7. The generation and load profile. The SCSB values for individual and aggregated models are 0.895 and 0.906.

delayed charging. Consequently, the overall load from the aggregated model resembles that from the individual model.

IV. Conclusion

This paper explores individual and aggregated modeling approaches and analyzes their strengths and weaknesses. The aggregated model has a significant advantage in the computation time, but it sacrifices the evaluation accuracy. The simulation shows that the extra flexibility from an increasing number of users mitigates the disadvantage of the aggregated model allowing unrealistic charging/discharging. Consequently, the overestimation converges to an insignificantly small value. On the other hand, the aggregated model is not directly applicable to smart charging without V2G as it will greatly overestimate the energy system performance. This paper has proposed a method to avoid unwanted V2V in the aggregated model by forming an extra constraint, which significantly improves the accuracy. Further studies on the energy system evaluation (e.g., load matching potential, optimal sizing of RES) involving many EVs can apply the aggregated modeling to simplify the problem and reduce the computation time, but bear in mind the potential sacrificed accuracy.

This work assumes no energy loss during charging/discharging to limit the scope of the study. In a more practical setting, charging efficiency should be considered, which brings a further challenge to the aggregated model since it cannot keep track of the V2V and thus cannot determine the

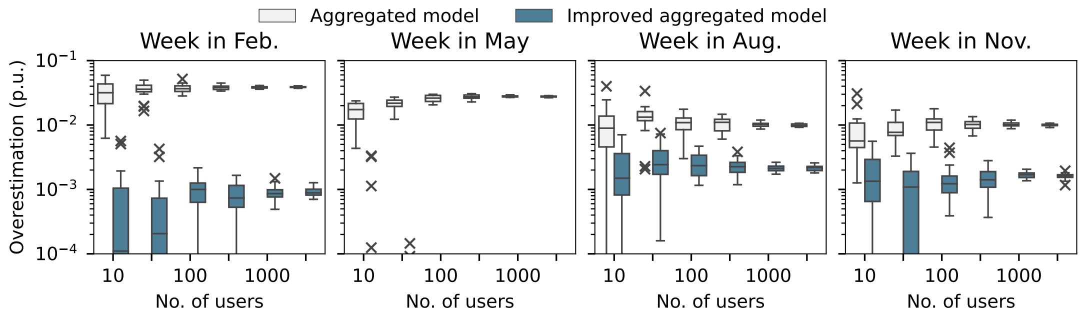

Fig. 8. Overestimation of the SCSB from both the original and the improved aggregated models. Note that the tick labels on the x-axis are only ordinal.

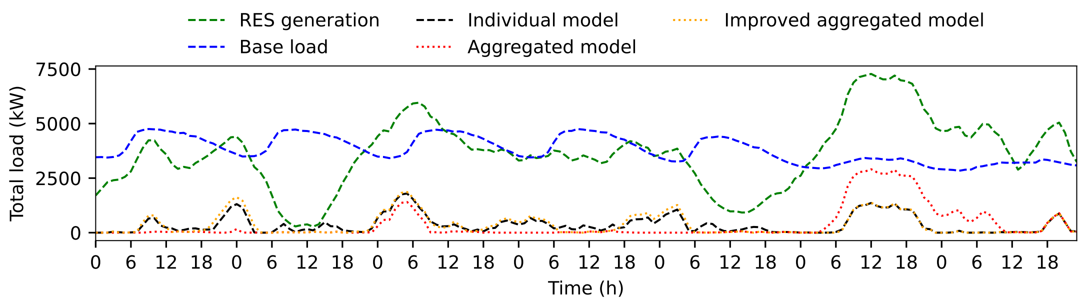

Fig. 9. The generation and load profile. The SCSB values for the individual, aggregated, and improved aggregated models are 0.819, 0.856, and 0.810.

energy loss from that. The future study includes quantifying the V2V and integrating the energy loss in the aggregated model to improve the evaluation accuracy.

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