Declaration Decision of the Adjustable Charging-Power Range for Electric Vehicles Considering Battery Degradation Cost

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***Abstract*—Electric vehicles represent a prominent category of flexible loads, and their adjustable charging power ranges can be aggregated to support system-level ancillary services. However, many existing studies do not consider the decision-making process behind declaring adjustable ranges, particularly when these ranges follow time-coupled charging requirements. This paper proposes a declaration decision model that captures the selection of adjustable charging power ranges from the EV owners' perspective while explicitly incorporating battery degradation costs and the revenue obtained from flexibility provision. Since the actual dispatch power determined by the aggregator cannot be predicted with accuracy, the resulting formulation is expressed as a quadratic robust optimization model with decision-dependent uncertainty. A master and subproblem iterative algorithm is developed to obtain exact solutions. Case studies demonstrate the practical effectiveness of the proposed model and confirm the quality of the solution method.**

***Index Terms*—Electric vehicles, charging optimization, battery degradation cost, decision-dependent uncertainty, master–subproblem iteration**

I. Introduction

With the rapid development of vehicle electrification, the number of electric vehicles (EVs) has increased considerably, which in turn has led to a substantial rise in total charging power on the grid side. Due to their controllable charging behavior, EVs possess significant potential as flexible resources that can provide ancillary services under appropriate coordination, and this capability has attracted increasing research interest [1].

Individual EVs have relatively small capacities and are geographically dispersed, which makes aggregators necessary to coordinate their participation in system-level dispatch and electricity market activities. A variety of studies have examined how to aggregate and regulate the adjustable charging power range of EVs. *Wang et al.* propose a method to characterize the aggregated adjustable power range of EV charging stations while guarantee the decomposability of aggregated power [2]. *Harsh et al.* present an approach in which EV aggregators participate in microgrid demand response, maximize revenue from demand response while ensuring that EV charging energy requirements are satisfied. These studies, however, do not consider the decision-making processes of EV owners. Instead, they either assume that the adjustable range declared by each EV is known or allow the aggregator to operate within the maximum adjustable range without explicitly modeling owner behavior [3]. Another study considers EV aggregators participating in energy and reserve markets with the EV degradation costs calculated and compensated to EVs [4]. However, the compensation method requires the collection of degradation-related parameters from EV owners, which raises concerns regarding privacy and data authenticity .

In comparison, some of the existing literature has investigated the decision-making behavior of EV owners when declaring reserve capacity [5] or frequency regulation capacity [6] under price incentives. These works provide valuable insights into how economic incentives influence participation behavior. Nevertheless, the adjustable charging power ranges considered in these studies are divided into independent time intervals and are treated as separate decision segments. This simplification does not capture the inherent time-coupled nature of EV battery operations, where charging decisions in one period directly influence the feasible charging power in subsequent periods. As a result, the flexibility modeled in these studies does not fully represent the real constraints or the intertemporal transition of EV charging states. Furthermore, accepting uncertain and potentially fluctuating power dispatch from an aggregator leads to additional battery degradation, which affects the long-term operating cost of EV owners. To address these issues, the contribution of this paper is two-fold.

- This paper proposes a declaration decision model that represents how EV owners determine time-coupled adjustable charging power ranges when interacting with an aggregator. The model includes the degradation cost and revenue from flexibility services to minimize the total cost for EV owners.
- This paper proposes a master and subproblem iterative algorithm to solve declaration decision problem, which is formulated as a quadratic robust optimization with decision-dependent uncertainty. The algorithm provides exact solutions while typical methods fail to process such problems efficiently.

The remainder of this paper is organized as follows. Section II formulates the EV adjustable charging power declaration problem as a quadratic robust optimization model with decision-dependent uncertainty. Section III presents a

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master and subproblem iterative solution algorithm. Section IV provides numerical results that verify the effectiveness of the proposed model, and Section V offers concluding remarks and discusses future research directions.

II. Problem Formulation

A. The EV Adjustable Charging-Power Feasible Set

The charging power of EVs can be adjusted, meaning it is not limited to a fixed curve but instead belongs to a feasible set $\mathcal{P}^{\text{ev}}$:

$$\mathcal{P}^{\text{ev}} = \mathcal{P}^{\text{out}} \cap \mathcal{P}^{\text{opr}} \tag{1}$$

$$\mathcal{P}^{\text{out}} = \left\{ \mathbf{p} \middle| \mathbf{1}^\top \mathbf{p} \geq (e^{\text{end}} - e^{\text{init}})/\eta^{\text{ev}} \right\} \tag{2}$$

$$\mathcal{P}^{\text{opr}} = \left\{ \mathbf{p} \middle| \begin{aligned} & p^{\min,\text{ev}} \leq \mathbf{p} \leq p^{\max,\text{ev}}, \\ & e^{\min,\text{ev}}/\eta^{\text{ev}} \leq e^{\text{init}}/\eta^{\text{ev}} + \mathbf{e} \leq e^{\max,\text{ev}}/\eta^{\text{ev}}, \\ & \mathbf{e} = L\mathbf{p} \end{aligned} \right\} \tag{3}$$

where Δt is the duration of a time slot, T is the number of time slots during which the EV remains parking and connecting to the grid, $\mathbf{p} \in \mathbb{R}^T$ is the charging power on the grid side, $\mathbf{e} \in \mathbb{R}^T$ is the charged energy, and $L \in \mathbb{R}^{T \times T}$ is a lower-triangular matrix with non zero elements equal to Δt.

Constraint (2) ensures that the EV reaches the target energy upon departure. e^{init} and e^{end} denote the initial and final battery energy, respectively, and η^{ev} is the charging efficiency. Constraint (3) imposes the upper and lower limits on EV charging power and energy.

The feasible set $\mathcal{P}^{\text{ev}}$ can be represented directly by the vector $\mathbf{b}^{\text{ev}} \in \mathbb{R}^{4T} := (\overline{\mathbf{p}}^{\text{ev}}, -\underline{\mathbf{p}}^{\text{ev}}, \overline{\mathbf{e}}^{\text{ev}}, -\underline{\mathbf{e}}^{\text{ev}})$ such that

$$\begin{aligned} \mathcal{P}^{\text{ev}} = \mathcal{P}(\mathbf{b}^{\text{ev}}) &= \left\{ \mathbf{p} \middle| \begin{aligned} & \underline{\mathbf{p}}^{\text{ev}} \leq \mathbf{p} \leq \overline{\mathbf{p}}^{\text{ev}}, \\ & \underline{\mathbf{e}}^{\text{ev}} \leq \mathbf{e} \leq \overline{\mathbf{e}}^{\text{ev}}, \\ & \mathbf{e} = L\mathbf{p} \end{aligned} \right\} \\ &= \{ \mathbf{p} | A\mathbf{p} \leq \mathbf{b}^{\text{ev}} \} \end{aligned} \tag{4}$$

where $A \in \mathbb{R}^{4T \times T} := [I; -I; L; -L]$ and $I \in \mathbb{R}^{T \times T}$ is the identity matrix.

Many studies assume that EVs provide the entire adjustable range $\mathcal{P}(\mathbf{b}^{\text{ev}})$ to the aggregator and then follow the dispatch command issued by the aggregator. In practice, when incentives are inadequate, it is more reasonable for EV owners to provide only a portion of the adjustable range to protect the battery. In this case, the declared adjustable range is a subset of the original range, i.e.,

$$(\mathbf{b} \leq \mathbf{b}^{\text{ev}}) \Rightarrow (\mathcal{P}(\mathbf{b}) \subset \mathcal{P}(\mathbf{b}^{\text{ev}})) \tag{5}$$

By deciding $\mathbf{b}$, the EV can control the adjustable range provided to achieve cost optimization.

B. EV Adjustable Range Declaration Decision Model

It is reasonable to assume that the EV needs to determine the adjustable range it is willing to offer to the aggregator. This range is represented by the power and energy boundary vector $\mathbf{b} = (\overline{\mathbf{p}}, -\underline{\mathbf{p}}, \overline{\mathbf{e}}, -\underline{\mathbf{e}})$. The corresponding optimization decision model is given as follows.

$$\begin{aligned} & \min_{\mathbf{b}} \left[-R^{\text{flex}}(\mathbf{b}) + \sigma \max_{\mathbf{p} \in \mathcal{P}(\mathbf{b})} C^{\deg}(\mathbf{p}) \right] \\ & \text{s.t. } \mathbf{b} \in \mathcal{B}^{\text{phy}} \cap \mathcal{B}^{\text{eff}} \end{aligned} \tag{6}$$

The details of the objective function and the associated constraints are presented as follows.

The objective function focuses on the revenue and cost resulted from the adjustable range declared. Electricity cost is not included to keep the analysis focused, and it can be incorporated with minor model adjustments if needed.

a) Revenue of adjustable range R^{flex}

When the EV provides its adjustable range to the aggregator, it should receive compensation revenue denoted by R_{flex}. Existing research has examined compensation mechanisms for adjustable ranges by proposing setting compensation prices for the power and energy boundaries [7]. Following the approach proposed in [7], we assume that the compensation revenue is given by

$$R_{\text{flex}}(\mathbf{b}) = (\pi^P)^\top (\overline{\mathbf{p}} - \underline{\mathbf{p}}) + (\pi^E)^\top (\overline{\mathbf{e}} - \underline{\mathbf{e}}) \tag{7}$$

The proposed declaration model and solution method are not restricted to the form in (7). As long as R_{flex} remains a convex function of $\mathbf{b}$, the proposed method can be applied.

b) Cost of adjustable range (degradation cost $C^{\deg}$)

Once the adjustable range is provided, the actual charging power $\mathbf{p}$ is determined by the aggregator, and this may increase costs, mainly battery degradation costs. Different studies adopt various methods to estimate battery degradation, and many of these estimation methods use convex functions of power, such as piecewise linear functions [8], polynomial functions [9], or rainflow counting methods [10]. In this paper, a quadratic function form is used:

$$C^{\deg}(\mathbf{p}) = \frac{C^B \Delta t}{k^{\text{aban}}} \left(k^{\deg 1} \mathbf{1}^\top \mathbf{p} + k^{\deg 2} \mathbf{p}^\top \mathbf{p} \right) \tag{8}$$

where C^B is the battery replacement cost, $k^{\text{aban}}(\%)$ is the maximum allowable battery capacity degradation percentage, typically 20, and $k^{\deg 1}$ and $k^{\deg 2}$ are degradation-related coefficients.

Since the EV does not know how the aggregator will adjust $\mathbf{p}$, the variable $\mathbf{p}$ is treated as an uncertainty variable from the perspective of the EV. Moreover, $\mathbf{p}$ is in set $\mathcal{P}(\mathbf{b})$, indicating that its feasible range depends on the decision variable $\mathbf{b}$, meaning the uncertainty is decision dependent. This paper adopts a robust optimization approach to handle this decision-dependent uncertainty by calculating the battery degradation cost under the worst-case scenario in the uncertainty set; that is,

$$\max_{\mathbf{p} \in \mathcal{P}(\mathbf{b})} C^{\deg}(\mathbf{p}) \tag{9}$$

Finally, σ is a conservativeness coefficient used to control the level of conservatism.

The decision model constraints are as follows:

a) Adjustable range within physical limits $\mathcal{B}^{phy}$

$$\mathcal{B}^{\text{phy}} = \{ \mathbf{b} \,|\, \mathbf{b} \leq \mathbf{b}^{\text{ev}} \} \tag{10}$$

b) Boundary effectiveness constraint $\mathcal{B}^{eff}$

$$
\begin{aligned}
\mathbf{b}\in\mathcal{B}^{\text{eff}}=\Big\{(\overline{\mathbf{p}},-\underline{\mathbf{p}},\overline{\mathbf{e}},-\underline{\mathbf{e}})\Big|\\
\overline{\mathbf{e}}\geq R\underline{\mathbf{e}}+\overline{\mathbf{p}}\Delta t,\quad \underline{\mathbf{e}}\leq R\overline{\mathbf{e}}+\underline{\mathbf{p}}\Delta t,\\
\overline{\mathbf{e}}\leq R\overline{\mathbf{e}}+\overline{\mathbf{p}}\Delta t,\quad \underline{\mathbf{e}}\geq R\underline{\mathbf{e}}+\underline{\mathbf{p}}\Delta t,\\
\overline{\mathbf{e}}\geq R\overline{\mathbf{e}}+\underline{\mathbf{p}}\Delta t,\quad \underline{\mathbf{e}}\leq R\underline{\mathbf{e}}+\overline{\mathbf{p}}\Delta t\Big\}
\end{aligned}
\tag{11}
$$

where

$$
R\in\mathbb{R}^{T\times T},\quad R_{i,j}=\begin{cases}1, & \text{if } i=j+1\\ 0, & \text{otherwise}\end{cases}.
\tag{12}
$$

This constraint ensures that the declared boundary vector $\mathbf{b}$ is effective, or called non-redundant in [11]. Fig. 1 illustrates two typical cases of ineffective boundary declarations. If EVs declare their boundaries in this manner, they would still receive compensation according to (7), while contributing no actual adjustable range. Therefore, it is assumed that the aggregator imposes rules to prevent this situation.

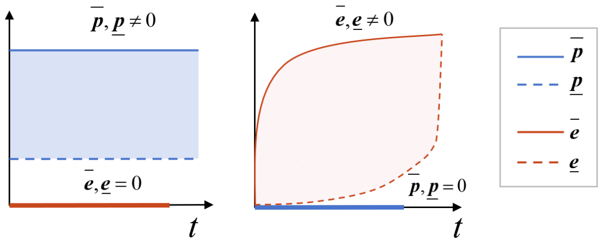

Fig. 1: Typical ineffective boundary declarations: a) left: ineffective power boundary; b) right: ineffective energy boundary

III. SOLUTION METHOD

The aforementioned adjustable range declaration decision problem (6)–(12) can be simplified as

$$
\min_{\mathbf{b}\in\mathcal{B}}\left[f(\mathbf{b})+\sigma\max_{\mathbf{p}\in\mathcal{P}(\mathbf{b})}g(\mathbf{p})\right]
\tag{13}
$$

where $f(\mathbf{b})$ is a linear function and $g(\mathbf{p})$ is a quadratic convex function. This formulation results in a quadratic robust optimization problem with decision-dependent uncertainty.

In typical studies on decision-dependent uncertainty, $g(\mathbf{p})$ is linear, allowing solutions via Karush-Kuhn-Tucker (KKT) conditions or duality-based methods [12]. However, in this paper, the inner optimization $\max g(\mathbf{p})$ is non-convex, which makes the KKT conditions insufficient and leads to a nonzero duality gap. Moreover, the feasible set of the inner variable $\mathbf{p}$ depends on the outer variable $\mathbf{b}$, which renders conventional Benders decomposition invalid.

Since typical approaches are not applicable to problems of the form (13), we propose a master-subproblem iterative solution method. The derivation and solution procedure are as follows.

First, by the property of convex functions, we have

$$
g(\widetilde{\mathbf{p}}_k)+\nabla g(\widetilde{\mathbf{p}}_k)^\top(\mathbf{p}-\widetilde{\mathbf{p}}_k)\leq g(\mathbf{p}),\quad \forall\widetilde{\mathbf{p}}_k,\mathbf{p}\in\mathbb{R}^T
\tag{14}
$$

Hence,

$$
\begin{aligned}
&\max_{\mathbf{p}\in\mathcal{P}(\mathbf{b})}\left[g(\widetilde{\mathbf{p}}_k)+\nabla g(\widetilde{\mathbf{p}}_k)^\top(\mathbf{p}-\widetilde{\mathbf{p}}_k)\right]\\
&\leq\max_{\mathbf{p}\in\mathcal{P}(\mathbf{b})}g(\mathbf{p}),\quad \forall\widetilde{\mathbf{p}}_k\in\mathbb{R}^T
\end{aligned}
\tag{15}
$$

Thus, the original optimization problem can be relaxed as

$$
\min_{\mathbf{b}\in\mathcal{B}}\left[f(\mathbf{b})+\sigma\max_{k\in\mathcal{K}}\max_{\mathbf{p}\in\mathcal{P}(\mathbf{b})}\left(g(\widetilde{\mathbf{p}}_k)+\nabla g(\widetilde{\mathbf{p}}_k)^\top(\mathbf{p}-\widetilde{\mathbf{p}}_k)\right)\right]
\tag{16}
$$

which is equivalent to

$$
\begin{aligned}
\min_{\theta,\mathbf{b}}\quad & f(\mathbf{b})+\sigma\theta\\
\text{s.t.}\quad & \mathbf{b}\in\mathcal{B},\\
& \theta\geq\theta^{\min},\\
& \theta\geq\max_{\mathbf{p}\in\mathcal{P}(\mathbf{b})}\left(g(\widetilde{\mathbf{p}}_k)+\nabla g(\widetilde{\mathbf{p}}_k)^\top(\mathbf{p}-\widetilde{\mathbf{p}}_k)\right),\quad \forall k\in\mathcal{K}
\end{aligned}
\tag{17}
$$

$\mathcal{K}$ is the index set of the selected points $\widetilde{\mathbf{p}}_k$ used for approximation, and $\theta^{\min}$ is a known lower bound of θ, for example, 0 for degradation cost. Since $\max_{\mathbf{p}\in\mathcal{P}(\mathbf{b})}\left(g(\widetilde{\mathbf{p}}_k)+\nabla g(\widetilde{\mathbf{p}}_k)^\top(\mathbf{p}-\widetilde{\mathbf{p}}_k)\right)$ is a convex optimization, it can be equivalently transformed using KKT conditions. Therefore, (17) is equivalent to

$$
\begin{aligned}
\min_{\theta,\mathbf{b},\mathbf{p}_k,\lambda_k,\forall k}\quad & f(\mathbf{b})+\sigma\theta\\
\text{s.t.}\quad & \mathbf{b}\in\mathcal{B},\\
& \theta\geq\theta^{\min},\\
& \theta\geq g(\widetilde{\mathbf{p}}_k)+\nabla g(\widetilde{\mathbf{p}}_k)^\top(\mathbf{p}_k-\widetilde{\mathbf{p}}_k),\quad \forall k\in\mathcal{K},\\
& -\nabla g(\widetilde{\mathbf{p}}_k)^\top+\lambda_k^\top\mathbf{A}=0,\quad \forall k\in\mathcal{K},\\
& \lambda_k\geq 0\perp\mathbf{A}\mathbf{p}_k\leq\mathbf{b},\quad \forall k\in\mathcal{K}
\end{aligned}
\tag{18}
$$

where $\perp$ denotes complementarity, and can be handled by introducing binary variables via the big-M method, as shown in (19)

$$
\begin{aligned}
&(\lambda_k\geq 0\perp A\mathbf{p}_k\leq\mathbf{b}) && \Leftrightarrow\\
&\left(\lambda_k\geq 0,\ A\mathbf{p}_k\leq\mathbf{b},\ \lambda_k^\top(A\mathbf{p}_k-\mathbf{b})=0\right) && \Leftrightarrow\\
&\begin{cases}0\leq\lambda_k\leq M\delta_k,\\ -M(1-\delta_k)\leq A\mathbf{p}_k-\mathbf{b}\leq 0,\\ \delta_k\in\{0,1\}^{4T}\end{cases}
\end{aligned}
\tag{19}
$$

M is a sufficiently large positive constant, and δ_k is a binary vector. Therefore, the optimization problem (18) can be formulated as a mixed-integer linear programming (MILP) problem and solved using commercial optimization solvers. The objective value of (18) provides a lower bound of the original problem (13). Optimization (18) functions as the master problem in the master-subproblem iteration. Let $\widetilde{\mathbf{b}}_k$ be the solution of the master problem in the k-th iteration. The corresponding subproblem is then formulated as follows.

$$
\max_{\mathbf{p}\in\mathcal{P}(\widetilde{\mathbf{b}}_k)}\ g(\mathbf{p})
\tag{20}
$$

The subproblem is a non-convex quadratic optimization, which can be solved exactly using commercial solvers such as Gurobi. If $g(\mathbf{p})$ takes other forms of convex functions, it can be approximated by piecewise-linear functions, and then

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the subproblem is transformed into an MILP.

Let the solution of the subproblem be $\widetilde{\mathbf{p}}_{k+1}$; then $f(\widetilde{\mathbf{b}}_k)+\sigma g(\widetilde{\mathbf{p}}_{k+1})$ provides an upper bound on the optimal value of the original problem. The computation terminates once the upper and lower bounds are iteratively updated through the repeated master–subproblem iterations and converge. The overall procedure of the solution algorithm is presented in Algorithm 1.

It is noteworthy that $f(\mathbf{b})$ can be a convex function rather than strictly linear, and $g(\mathbf{p})$ may also take general convex forms beyond the quadratic case. The proposed algorithm remains applicable because its derivation relies solely on the fundamental properties of convex functions.

Algorithm 1 EV Flexibility Range Declaration Decision Model Solution Algorithm

Input: Termination tolerance $\varepsilon > 0$, maximum iteration number $K_{\max}$, relevant parameters in the EV decision model
Output: Optimal declaration decision $\mathbf{b}=(\overline{\mathbf{p}},-\underline{\mathbf{p}},\overline{\mathbf{e}},-\underline{\mathbf{e}})$

Initialize: set convergence flag $F_{\text{con}}=\text{False}$, $\mathcal{K}=\emptyset$, UBD $=+\infty$
for $k=0$ to $K_{\max}$ **do**
  [MASTER]: Solve the master problem (18), obtain $\mathbf{b}$, denoted as $\widetilde{\mathbf{b}}_k$.
  [LBD]: Record the objective of master problem as LBD.
  [SUB]: Solve the subproblem (20), obtain $\mathbf{p}$, denoted as $\widetilde{\mathbf{p}}_{k+1}$.
  [UBD]: Compute $f(\widetilde{\mathbf{b}}_k)+\sigma g(\widetilde{\mathbf{p}}_{k+1})$. If it is less than UBD, update UBD with this value.
  Compute $g(\widetilde{\mathbf{p}}_{k+1})$ and $\nabla g(\widetilde{\mathbf{p}}_{k+1})$, update $\mathcal{K}=\mathcal{K}\cup\{k+1\}$.
  [GAP]: Update *gap* as $|(UBD-LBD)/LBD|$
  if $gap\le\varepsilon$ **then**
    Set $F_{\text{con}}=\text{True}$
    break
  end if
end for
return $\widetilde{\mathbf{b}}_k$, *gap* and F_{con}

IV. Numerical Results

A. Simulation Setup

Consider each time period to be 1 hour (Δt = 1h). The parameters of the electric vehicle are listed in Table 1.

TABLE I: Electric Vehicle Parameters

Parameter	Value	Unit
$p^{\max,\text{ev}}$, $p^{\min,\text{ev}}$	20, 0	kW
$e^{\max,\text{ev}}$, $e^{\min,\text{ev}}$, e^{init}, e^{end}	60, 0, 10, 55	kWh
η^{ev}	0.90	-
C^{B}	10000	\$
k^{deg1}	1.09×10^{-4}	%/kWh
k^{deg2}	3.86×10^{-7}	%/(kW·kWh)

The degradation coefficients are estimated based on degradation test results obtained from a commercial 1.5 Ah 18650 lithium-ion cell (UR18650W) reported in Reference [13] and on typical EV parameter values. The conservativeness coefficient is set as $\sigma=0.9$, and the solution accuracy is ϵ = 0.01%. Simulations are performed on a personal computer with a 16-core i7-13700 processor and 32GB of memory, using MATLAB as the computation platform, YALMIP for modeling, and Gurobi as the solver.

B. Simulation Results

1) Declaration Results under Different Price Scenarios

To analyze the impact of price on the EV's declaration of adjustable range, the declaration results are computed under three different price scenarios. The duration of stay is set as $T=4$. The three scenarios are defined as follows:

- **Scenario 1**: Prices π^{P},π^{E} are all set to 0, representing no or low incentive for the adjustable range.
- **Scenario 2**: Prices π^{P},π^{E} are all set to 0.05, representing adequate incentive for the adjustable range.
- **Scenario 3**: Prices π^{P} are set as shown in Table II, and π^{E} are set to 0, representing time-dependent incentives at different levels.

TABLE II: Prices at Different Time Periods

Time	1	2	3	4
Price (\$)	0.0024	0.0027	0.0004	0.0027

Figure 2 shows the algorithm convergence curve for Scenario 1 as an example. After a certain number of iterations, the algorithm reaches the predefined convergence accuracy.

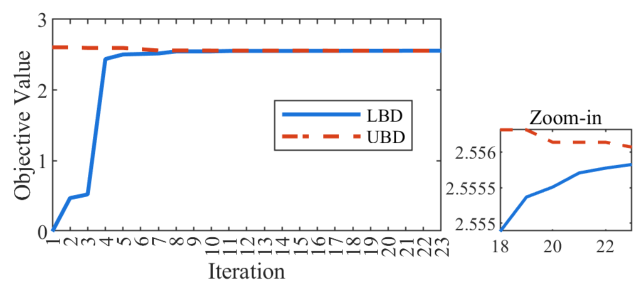

Fig. 2: Algorithm Convergence Curve under Scenario 1

Figures 3 illustrate the declaration ranges under the three scenarios. Comparatively, in Scenario 1, without incentives for adjustable range, the EV declares a zero adjustable range, and the charging power remains almost constant, minimizing battery degradation cost. In Scenario 2, the high price incentivizes the EV to declare its maximum adjustable range. In Scenario 3, due to the low price at time 3, the corresponding power adjustable range is declared smaller. This demonstrates that the proposed algorithm effectively considers time-dependent incentive prices and can declare an adjustable range that minimizes total cost based on price.

Table III summarizes the computation details under the three scenarios. It can be observed that different adjustable ranges correspond to different maximum battery degradation costs. Ignoring degradation cost leads to reporting the maximum adjustable range equal to that in Scenario 2, resulting in high degradation. Accounting for the trade-off between revenue and degradation, the proposed method lowers degradation cost by 11.8% in Scenario 1 and 10.6% in Scenario 3.

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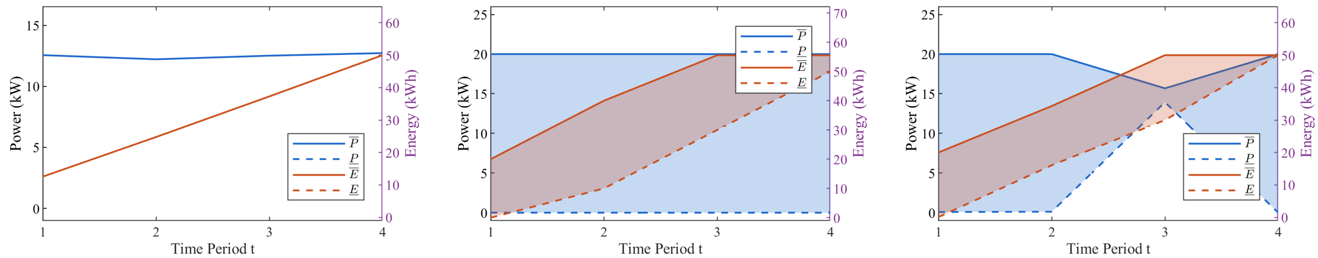

Fig. 3: Declaration Results of Adjustable Range under Scenario 1, 2, and 3

TABLE III:
Computation Results under Different Price Scenarios

Scenario	1	2	3
Objective value ($)	2.56	-5.16	2.44
Worst-case degradation cost ($)	2.84	3.22	2.88
Computation time (s)	38.48	0.78	71.05
Iterations	23	3	21

2) Different Lengths of Parking Period T

The price π^{P} is set to 0.003 for all time slots, and π^{E} is set to 0. The solution accuracy is $\epsilon = 0.5\%$, and the maximum computation time is 20 min. The results are shown in Table IV. It can be observed that the longer the parking period, the lower the total cost for the electric vehicle. However, the computation time of the algorithm increases significantly with the parking period length because more integer variables are introduced in each iteration. Future research will focus on how to simplify and accelerate the solution process.

TABLE IV:
Computation Results under Different Parking Period Lengths

Parking Period T	3	4	5	6
LBD ($)	2.51	2.36	2.30	2.23
Iterations	2	9	13	16
Computation Time	0.32s	2.64s	251s	20 min
Final Gap	0.19%	0.054%	0.19%	0.76 %

V. Conclusion

This paper proposes a decision method for electric vehicles to declare time-coupled adjustable range. The objective is to minimize the total cost that combines battery degradation cost and the revenue obtained from providing adjustable flexibility. Since the charging power schedule determined by the aggregator is unknown in advance, the declaration problem is formulated as a quadratic robust optimization model with decision-dependent uncertainty. To solve the optimization problem, a master and subproblem iterative algorithm is introduced. Case studies demonstrate that the proposed model can effectively balance degradation cost and flexibility-based revenue while simultaneously verifying the effectiveness of the proposed solution algorithm.

Future research will focus on accelerating the proposed algorithm to handle problems with longer time horizons and on extending the declaration framework from a single EV to multiple EVs aggregated at the fleet or charging station level.

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