Techno-Economic Optimization of PV–Wind–Battery Microgrids for EV Charging Under Price Volatility

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***Abstract*—Large-scale transport electrification requires economically viable EV charging infrastructure with limited impact on distribution networks, especially under electricity price volatility. This paper presents a techno-economic planning and operation model for a grid-connected EV-charging microgrid integrating photovoltaic and wind generation together with battery energy storage. The proposed techno-economic model is formulated as a linear program that co-optimizes component capacities and hourly dispatch over a multi-year horizon by minimizing the levelized cost of energy (LCOE) while considering technical constraints related to power balance and energy component operation limitations. The case study considers two scenarios related to EV charging power supply: base scenario and renewable-only EV charging scenario to quantify the trade-off between costs and sustainability.**

***Index Terms*—electric vehicle charging, microgrid, photovoltaic, wind energy, battery energy storage system, techno-economic optimization, linear programming, levelized cost of energy**

I. Introduction

E-mobility is a central pillar of the green transition, yet its large-scale deployment requires economically viable charging infrastructures with limited impacts on distribution network loading. Uncoordinated EV charging can increase peak demand, increase network congestions and voltage issues, as well as raise grid usage electricity costs; these challenges become more evident under price volatility, when wholesale and retail electricity prices can reach extreme levels and directly affect the attractiveness of EV adoption. Coordinating charging with local renewable energy sources (RES) and storage operation is therefore increasingly studied as a potential direction to reduce EV charging costs, improve self-sufficiency, and mitigate grid loading.

Microgrids represent a good framework that can solve this problem since they can combine photovoltaic (PV) generation, wind generation, and a battery energy storage system (BESS) with a grid import/export to balance cost and sustainability objectives. The difficulty in implementing operational strategies is related to variable renewable output and charging demand which depends on driver behavior, given that these two factors rarely coincide in favorable manner without active coordination. Given this, a planning and operational framework is therefore required to jointly determine (i) the optimal sizing of PV/wind/BESS assets and (ii) an economically efficient dispatch strategy over time.

This paper addresses a techno-economic optimization problem for supplying EV charging through a grid-connected microgrid that combines RES, grid exchange, and BESS. The proposed formulation is a linear programming (LP) model that jointly optimizes equipment sizing and hourly operation over a long-term planning horizon by minimizing the levelized cost of energy (LCOE). In addition, the model supports an optional renewable-only EV charging requirement ("green charging") for a clear evaluation of the trade-off between economic performance and sustainability.

II. Literature Review

The literature on EV-integrated microgrids can be broadly organized into three connected themes: (i) the impacts of EV charging on distribution networks and the importance of coordinated management strategies, (ii) renewable-powered charging stations and the contribution of energy storage to system performance and flexibility, and (iii) integrated planning frameworks that jointly optimize long-term investment decisions and short-term operational dispatch.

A. EV charging impacts on distribution grids

Uncontrolled EV charging can increase demand in time windows that coincide with residential/commercial peak hours, increasing distribution feeder and transformer loading and potentially requiring network reinforcements. To reduce these negative impacts on the distribution grid, coordinated charging strategies use price signals and explicit network constraints to shift or shape aggregate charging profiles. Optimization based approaches used in some papers, usually include decentralized formulations that reduce grid impacts while respecting EV charging requirements [1], as well as pricing/market-based coordination while considering distribution network constraints. In parallel, other papers related to optimal EV scheduling also include explicit combinatorial scheduling formulations for charging sessions (assignment of charging jobs to limited chargers and time slots), as in [2]. Whether implemented through decentralized control, market mechanisms, or explicit scheduling, optimal coordination of EV charging task can significantly reduce grid loading and energy costs without compromising essential mobility requirements.

B. Microgrids for EV Charging: optimal sizing & operation

A second major category of research focuses on the synergy between charging demand and behind-the-meter renewables and storage. These methods are primarily driven by the need to reduce charging costs and associated emissions as well as to hedge against the inherent volatility of market prices. In these approaches, a common modeling choice is to treat EV charging demand as an exogenous time series or a set of scenarios. Based on these demand patterns, the algorithm determines the optimal sizing for PV, wind, and storage systems to ensure a reliable and cost-effective energy supply.

Several studies use software tools like HOMER (or HOMER Pro) to evaluate a wide range of candidate designs—combining PV, wind, storage, and diesel—to identify the most cost-effective configurations based on site-specific resource and fuel assumptions. For instance, researchers have used these tools to size solar-wind EV charging stations, illustrating how the ideal mix of PV and wind depends heavily on the local complementarity of available resources [3]. Related case studies for off-grid hybrid systems further expand on this by providing detailed sensitivity analysis workflows that account for technology costs, discount rates, and fuel prices. These analyses demonstrate a critical point: the optimal system architecture is highly sensitive to initial assumptions and can easily shift between high-renewable and diesel-assisted configurations depending on the economic and environmental context [4], [5].

Beyond simple tool-based enumeration, more advanced optimization formulations allow us to explicitly consider both reliability and complex operational requirements. For example, recent work has focused on sizing renewable microgrids for EV charging stations by carefully studying the trade-off between cost and reliability while accounting for inherent uncertainties [6]. Furthermore, studies on fully renewable autonomous microgrids have shown that the choice between single and hybrid storage technologies can fundamentally change the least-cost design. This is especially true when deep renewable penetration is enforced, as the storage system must be sized not only to balance supply and demand but also to provide sufficient flexibility to handle variability and uncertainty in renewable generation [7].

Recent literature increasingly adopts integrated models that co-optimize microgrid component sizing and operational scheduling, typically through the use of MILP or stochastic programming. In these formulations, we couple design variables—such as capacities—with time-series operational constraints like power balance, storage dynamics, and grid import/export. This integration is essential because it enables the model to consistently value flexibility and arbitrage across different time scales.

At the community or campus level, we frequently model EV adoption as either an additional flexible load or a vital flexibility provider. For instance, researchers have integrated distributed flexibility into microgrid sizing while accounting for network upgrade costs, demonstrating that explicitly valuing this flexibility can significantly reduce total system costs, especially as EV penetration increases [8]. In order to account for input data uncertainty, recent models have moved toward two-stage stochastic sizing-and-operation frameworks. These analyses show that by explicitly representing the uncertainty in both renewables and demand, more robust investment decisions can be achieved. This often leads to a different, more effective balance between renewable capacity, storage, and grid exchange than deterministic models might suggest [9]. Complementary research emphasizes that our assumptions regarding EV demand modeling and control strategies fundamentally shape planning outcomes. For example, integrating a smart EV charging framework into the sizing of PV–wind systems for net-zero-energy campuses has been shown to improve renewable utilization and reduce grid interaction compared to uncoordinated charging [10]. Even at a smaller scale, such as in marina energy systems, coordinated EV charging and discharging strategies can increase PV self-consumption and lower overall operational costs [11]. Finally, system-level formulations that jointly minimize operating costs and emissions highlight a critical trade-off: multi-objective or weighted-sum objectives can significantly shift dispatch priorities. This often means moving toward cleaner local generation and storage at the expense of higher investment costs [12]. These findings provide the primary motivation for models—such as the one we propose—that can explicitly study the economic implications of sustainability constraints, such as renewable-only EV charging, within a tractable and rigorous planning framework.

C. Research gap and contribution

The literature review indicates that (i) EV flexibility can substantially reduce costs and DN grid loading, (ii) RES and battery storage sizing decisions are highly sensitive to assumptions on tariffs, reliability constraints, and uncertainty, and (iii) tractable mathematical programming models (LP/MILP) remain attractive for multi-year, high-resolution scenario analysis.

Motivated by these insights, this paper proposes a linear programming (LP) formulation that jointly optimizes the sizing of PV, wind, and battery energy storage systems (BESS) alongside hourly dispatch over a long-term horizon. Proposed model accounts for asymmetric buy/sell prices, explicit storage dynamics, and an optional renewable-only EV charging scenario. The model finds optimal microgrid component sizing and dispatch policies while minimizing the Levelized Cost of Energy (LCOE), which allows a systematic and rigorous comparison across different considered scenarios.

III. Mathematical Model

In this section, we present the mathematical framework used to jointly optimize the sizing and operation of the microgrid. We consider a grid-connected system designed to supply both a base electrical load and a dynamic EV charging demand. The model is formulated as a linear optimisation program (LP) to ensure computational tractability over a multi-year planning horizon with hourly resolution.

A. Microgrid architecture and profiles

The microgrid architecture integrates solar and wind generation, a battery energy storage system (BESS), and a bidirectional grid connection. The figure 1 shows simplified overview of microgrid components considered in the model.

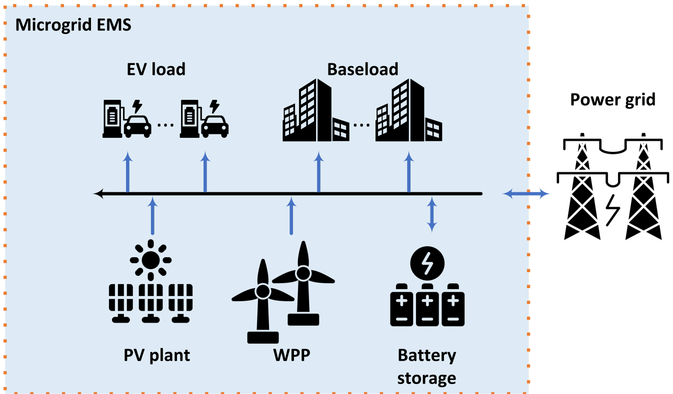

Fig. 1. Microgrid energy management system.

To ensure the generality of the approach, the model uses normalized base load and EV charging load profiles,as well as RES production profiles, which are then scaled to there real values. The planning horizon is N_y years with hourly resolution ($t \in \{1, \ldots, T_{\max}\}$, with $T_{\max} = N_y \cdot 8760$). Normalized profiles are denoted by S_t (normalized PV production), W_t (normalized wind production), L_t (base-load profile), and E_t (EV-demand profile).

The total power demand at any given hour t, $P_{\text{dem}}(t)$, is the sum of the base load and the EV charging requirements:

$$P_{\text{dem}}(t) = P_{\text{L,base}} \cdot L_t + P_{\text{E,base}} \cdot E_t \tag{1}$$

where $P_{\text{L,base}}$ & $P_{\text{E,base}}$ is a scaling parameter that converts the normalized base-load (L_t) and EV-demand (E_t) profiles into kilowatts (kW). Similarly, the intermittent nature of RES is captured through normalized solar (S_t) and wind (W_t) availability profiles, which define the actual power output based on the determined optimal installed capacities:

$$P_{\text{solar,out}}(t) = P_{\text{solar}} \cdot S_t \qquad P_{\text{wind,out}}(t) = P_{\text{wind}} \cdot W_t \tag{2}$$

B. Decision variables

Proposed optimization problem includes two distinct sets of decision variables. The design (sizing) variables determine the optimal capacity of the microgrid components: the installed solar power (P_{solar}), wind power (P_{wind}), as well as battery's power (P_{batt}) and energy (E_{batt}) ratings.

In addition to this, the operational variables define the system's behavior at each hour t over the entire horizon $T_{\max}$. These include the power purchased from ($P_{\text{grid,buy}}(t)$) or sold to ($P_{\text{grid,sell}}(t)$) the grid, the battery charging ($P_{\text{ch}}(t)$) and discharging ($P_{\text{dis}}(t)$) rates, and the resulting state of energy ($E(t)$). By distinguishing between buying and selling, we can explicitly model asymmetric grid tariffs, which is essential for realistic economic assessments.

C. Objective function: LCOE minimization

The primary goal of the proposed model is to minimize the Levelized Cost of Energy (LCOE). The LCOE provides a standard metric for comparing the economic performance of different microgrid configurations across different energy supply scenarios. The LCOE is defined as the ratio of the total discounted costs minus profits to the total discounted energy supplied to base and EV load:

$$\min \ \text{LCOE} = 1000 \, \frac{C_{\text{tot}}}{E_{\text{tot}}} \tag{3}$$

The total cost C_{tot} is the sum of the initial investment (CAPEX) and the discounted operational expenses (OPEX) reduced by the total revenue from selling excess energy back to the grid. In the model we assume that the investment cost C_{inv} scales linearly with the installed capacities of the solar, wind, and battery components:

$$C_{\text{tot}} = C_{\text{inv}} + C_{\text{op}} \tag{4}$$

$$C_{\text{inv}} = C_s P_{\text{solar}} + C_w P_{\text{wind}} + C_{b,P} P_{\text{batt}} + C_{b,E} E_{\text{batt}} \tag{5}$$

The operational cost C_{op} represents the net cost of grid interaction over the planning horizon, discounted to the present value using the factor γ_t:

$$C_{\text{op}} = \sum_{t=1}^{T_{\max}} \gamma_t \left(c_{\text{buy}} P_{\text{grid,buy}}(t) - c_{\text{sell}} P_{\text{grid,sell}}(t) \right) \tag{6}$$

By discounting both the costs and the energy served (E_{tot}), we ensure that the LCOE accurately reflects the time value of money throughout the project's lifetime. This is particularly important for long-term planning horizons, where the timing of costs and energy production can significantly influence the economic viability of different microgrid configurations.

$$E_{\text{tot}} = \sum_{t=1}^{T_{\max}} \gamma_t \left(P_{\text{L,base}} \cdot L_t + P_{\text{E,base}} \cdot E_t \right) \tag{7}$$

Discounting is applied with annual rate r by mapping each hour to a year index $y(t) = \left\lfloor \frac{t-1}{8760} \right\rfloor$ and defining

$$\gamma_t = \frac{1}{(1+r)^{y(t)}}. \tag{8}$$

D. Constraints

Power Balance: At every hour, the sum of local generation, grid interaction, and battery discharge must exactly meet the total demand. This ensures that the microgrid remains stable and reliable:

$$P_{\text{grid}}(t) + P_{\text{solar,out}}(t) + P_{\text{wind,out}}(t) - P_{\text{batt}}(t) = P_{\text{dem}}(t). \tag{9}$$

Battery Dynamics and Degradation: The battery's state of energy changes based on the charging and discharging power, adjusted for round-trip efficiency η. The proposed model also includes a battery capacity degradation which is included in simple way through fade multiplier κ_t, which represents the gradual degradation of the battery over time:

$$0 \le P_{\text{ch}}(t) \le P_{\text{batt}}, \qquad 0 \le P_{\text{dis}}(t) \le P_{\text{batt}}, \qquad \forall t \quad (10)$$

$$E(t) = E(t-1) + P_{\text{ch}}(t)\sqrt{\eta} - \frac{P_{\text{dis}}(t)}{\sqrt{\eta}}, \qquad t > 1 \quad (11)$$

$$0 \le E(t) \le E_{\text{batt}}\,\kappa_t, \qquad \kappa_t = 1 - \delta_{\text{batt}}\frac{y(t)}{N_y}, \qquad \forall t \quad (12)$$

where δ_{batt} is the total fractional capacity loss over the project lifetime.

To avoid end-of-horizon artifacts, the terminal SOC is fixed:

$$E(T_{\max}) = E_{\text{batt}} \cdot E_{\text{DoD}} \quad (13)$$

Sizing and grid constraints: installed capacities and grid exchange are bounded by:

$$0 \le P_{\text{solar}} \le P_{\text{solar,max}} \quad (14)$$
$$0 \le P_{\text{wind}} \le P_{\text{wind,max}} \quad (15)$$
$$0 \le P_{\text{batt}} \le P_{\text{batt,max}} \quad (16)$$
$$0 \le E_{\text{batt}} \le E_{\text{batt,max}} \quad (17)$$
$$-P_{\text{grid,max}} \le P_{\text{grid}}(t) \le P_{\text{grid,max}} \quad (18)$$

Renewable-Only EV Charging Constraint: For scenarios focused on maximum sustainability, the model also includes an optional constraint that mandates EV charging demand to be met by local renewable generation and BEES discharge. This ensures that the e-mobility component of the load is entirely ”green” even if the base load still relies on grid support:

$$P_{\text{solar,out}}(t) + P_{\text{wind,out}}(t) + P_{\text{dis}}(t) \ge P_{\text{E,base}} \cdot E_t \qquad \forall t \quad (19)$$

IV. Case Study and Results

The case study applies the proposed optimization model to a representative microgrid, with peak base load equal to 1000kW and peak EV load equal to 700kW. The time-series data for both the base load and EV charging demand is illustrated in Figure 2, where we use box plots alongside average daily profiles to visualize the underlying variability. To ensure that the case study use realistic EV behavior, we generated the EV demand profile using the RAMP-mobility model. This tool can be used to simulate (un)coordinated charging patterns by leveraging actual mobility data and typical consumer charging habits. Similarly, we derived the base load profile from a blend of residential and commercial consumption patterns, effectively capturing the characteristic daily and seasonal fluctuations inherent in such systems. Finally, the normalized renewable generation profiles for solar and wind are based on site-specific availability patterns. This approach is highly flexible, as these profiles can be easily adjusted to reflect the unique meteorological conditions of different geographic contexts.

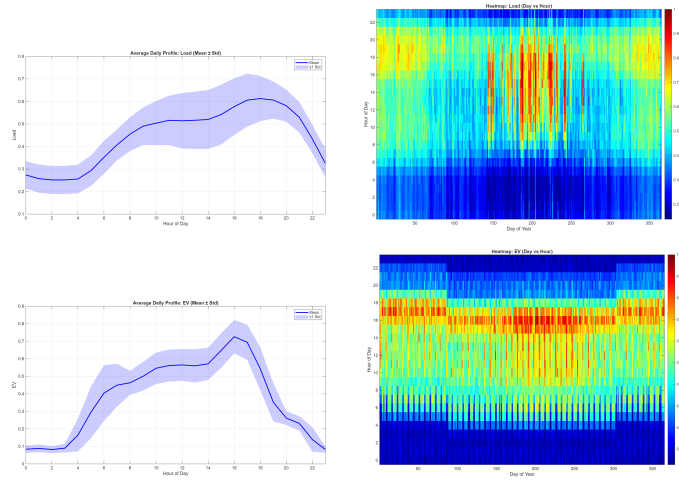

Fig. 2. Input data used in the case study (base and EV load demand profiles).

The optimal microgrid design and operation is determined by solving the proposed linear programming model under two scenarios: (i) a **base scenario** with no restrictions on grid usage for EV charging, and (ii) a **renewable-only EV charging scenario** where all EV demand must be met by local generation or storage. The grid import and export prices are related to ToU or DA market price depending on the simulation scenario. The price for selling excess energy back to the grid is set at 80% and 0% in relation to ToU or DA price depending on the scenario. The investment costs for PV, wind, and battery components are based on current market data, with PV at 700€/kW, wind at 1200€/kW, battery power at 300€/kW, and battery energy price component at 200€/kWh. The maximum grid exchange is set to 2000kW to incorporate realistic operational distribution network constraints. Although the considered microgrid test case assumes relatively low component capacity ratings, the proposed model allows easily scaling to accommodate larger component sizes and higher energy demand levels. The discount rate is set at 5% to reflect the time value of money over the project's lifetime.

The table I gives summarized overview of the optimal system configurations and the resulting LCOE for each (sub)scenario. In relation to grid only energy supply, every microgrid option that includes renewable energy sources and BEES achieves a lower LCOE compared to the grid-only scenario. The results indicate that the base scenario, which allows for grid support in EV charging, achieves a lower LCOE compared to the renewable-only scenario. This is primarily due to the reduced need for local generation and storage capacity when grid support is available. However, the renewable-only scenario increases the required capacities of PV, wind, and battery systems to meet the EV demand without grid assistance, leading to a higher LCOE.

Generally, the results show that the optimal microgrid design is highly sensitive to the assumptions regarding grid support and sellback prices, with significant implications for both the required component sizing and the overall economic

TABLE I
OPTIMAL SYSTEM CONFIGURATION AND LCOE UNDER DIFFERENT PRICING SCHEMES

		Time of use tariff					DA electricity prices				
		GRID ONLY	Base case Sellback price 0%	Base case Sellback price 80%	RES charging Sellback price 0%	RES charging Sellback price 80%	GRID ONLY	Base case Sellback price 0%	Base case Sellback price 80%	RES charging Sellback price 0%	RES charging Sellback price 80%
PV plant	[kW]	0	1793	2147	2427	2427	0	1507	1150	2427	2367
WPP plant	[kW]	0	1115	2168	1985	1985	0	1220	2652	1985	2050
BEES power	[kW]	0	696	1345	2075	2075	0	649	1731	2075	2380
BEES energy	[kWh]	0	4826	12000	12000	12000	0	3482	7759	12000	12000
LCOE	[€/MWh]	***129.41***	***66.84***	***12.33***	***91.84***	***26.83***	***107.74***	***66.10***	***24.08***	***92.05***	***36.27***

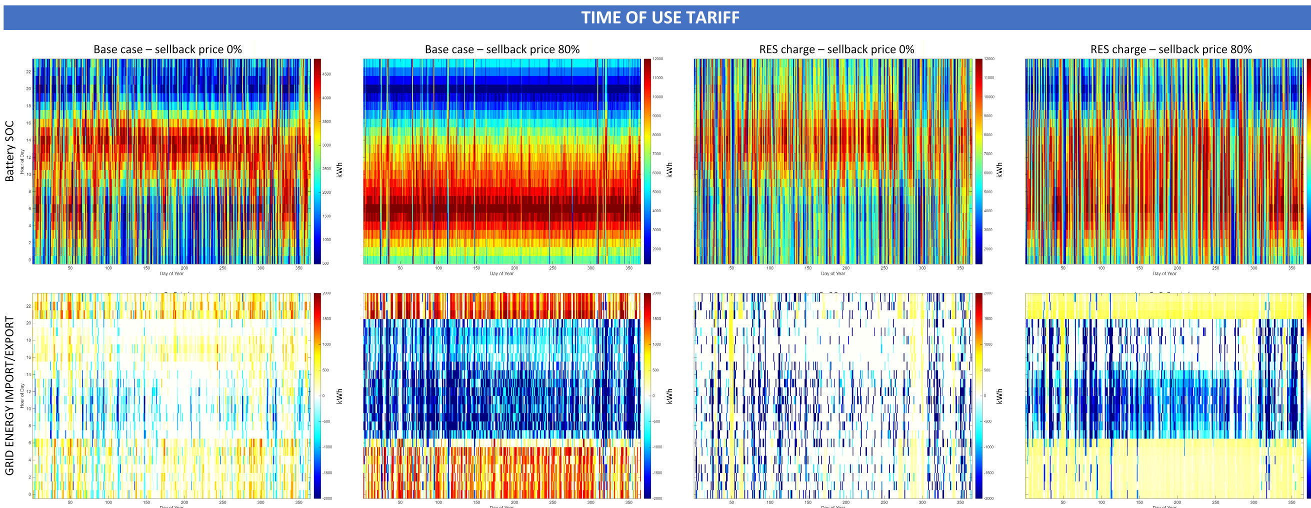

Fig. 3. Battery state of energy and grid exchange for different cases under ToU tariff scenario.

performance of the system. Figure 3 illustrates the battery state of energy and grid exchange for different cases under ToU tariff scenario. Due to space limitations, additional results for DA market prices are not shown here; however, these results lead to conclusions consistent with those presented for ToU electricity pricing.

In case of relatively high sellback price (80%), the optimal microgrid design includes more renewable capacity, larger BEES size and higher level of grid interaction despite larger capacity of BEES. In this case BEES in addition to storing excess energy from RES at periods of energy surplus and low electricty prices, also charges from the grid during low-price periods and discharges during high-price periods, capturing price spreads through energy arbitrage. Selling energy later on in a favorable moment at a relatively high sellback price leads to a significantly lower LCOE.

Conversely, when the sellback price is low (0%), the model favors a more balanced approach which relies mostly on self supply due to lower LCOE from RES in relation to the grid energy prices both in cases of ToU and dynamic DA market prices. This energy management strategy, driven by the inability to generate revenue from exporting electricity back to the grid, minimizes grid interaction but significantly increases the LCOE for both the base load and EV charging demand. The renewable-only EV charging scenario consistently requires larger investments in local generation and storage capacity, which is reflected in the higher LCOE compared to the base scenario across both pricing schemes.

These findings highlight the trade-off between economic performance and sustainability objectives in microgrid design for EV charging applications.

V. CONCLUSION

This paper presents a techno-economic optimization framework for designing and operating a grid-connected microgrid that integrates photovoltaic and wind generation with battery energy storage to supply EV charging demand. The proposed linear programming model jointly optimizes the sizing of microgrid components and their hourly dispatch over a multi-year horizon by minimizing the levelized cost of energy (LCOE). The case study demonstrates the trade-off between economic performance and sustainability objectives, showing that while allowing grid support for EV charging can reduce costs, enforcing renewable-only charging significantly increases the required local generation and storage capacity, leading to higher LCOE. Future work will explore the incorporation of uncertainty in renewable generation and demand profiles, as well as the potential benefits of demand response strategies, coordinated EV charging with vehicle-to-grid (V2G) capabilities.

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APPENDIX A
NOMENCLATURE

t	Hourly time index
$T_{\max}$	Total number of hours in the planning horizon
H_y	Hours per year
N_y	Planning horizon length
r	Annual discount rate
$y(t)$	Year index associated with hour
γ_t	Discount factor at hour
S_t	Normalized PV power
W_t	Normalized wind power
L_t	Normalized base load demand
E_t	Normalized EV-charging demand
P_{solar}	Installed PV rated power
P_{wind}	Installed wind rated power
P_{batt}	Battery power rating (charge/discharge limit)
E_{batt}	Battery energy rating
$P_{\text{solar,out}}(t)$	PV output power
$P_{\text{wind,out}}(t)$	Wind output power
$P_{\text{load}}(t)$	Base load demand
$P_{\text{EV}}(t)$	EV charging demand
$P_{\text{E,base}}$	EV charging load scaling parameter
$P_{\text{L,base}}$	Base-load scaling parameter
$P_{\text{dem}}(t)$	Total microgrid energy demand
$P_{\text{grid,buy}}(t)$	Power purchased from the grid
$P_{\text{grid,sell}}(t)$	Power sold to the grid
$P_{\text{grid}}(t)$	Net grid power ($P_{\text{grid,buy}} - P_{\text{grid,sell}}$)
$P_{\text{ch}}(t)$	Battery charging power
$P_{\text{dis}}(t)$	Battery discharging power
$P_{\text{batt}}(t)$	Net battery power ($P_{\text{ch}} - P_{\text{dis}}$)
$E(t)$	Battery stored energy (state of energy)
η	Battery round-trip efficiency
$\sqrt{\eta}$	SOC-balance efficiency split
κ_t	Available-capacity multiplier (degradation)
δ_{batt}	Lifetime capacity fade fraction
c_{buy}	Grid purchase price
c_{sell}	Grid selling price
C_s	PV CAPEX per rated power
C_w	Wind CAPEX per rated power
$C_{b,P}$	Battery CAPEX per power
$C_{b,E}$	Battery CAPEX per energy
C_{inv}	Investment cost
C_{op}	Discounted operational cost
C_{tot}	Total discounted cost
E_{tot}	Total discounted served energy
LCOE	Levelized cost of energy