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An MINLP Optimization Method to Solve the RES-Hybrid System Economic Dispatch of an Electric Vehicle Charging Station

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Abstract: Power systems' increased running costs and overuse of fossil fuels have resulted in continuing energy scarcity and momentous energy gap challenges worldwide. Renewable energy sources can meet exponential energy growth, lower reliance on fossil fuels, and mitigate global warming. An MINLP optimization method to solve the RES-hybrid system economic dispatch of electric vehicle charging stations is proposed in this paper. This technique bridges the gap between theoretical models and real-world implementation by balancing technical optimization with practical deployment constraints, making a timely and meaningful contribution. These contributions extend the practical application of MINLP in modern grid operations by aligning optimization outputs with the stochastic character of renewable energy, which is still a gap in the existing literature. The proposed economic dispatch simulation results over 24 h at an hourly resolution show that all generation units contributed proportionately to meeting EVCS demand: solar PV (51.29%), ESS (13.5%), grid (29.92%), and wind generator (8.29%). The RES-hybrid energy management systems at charging stations are designed to make the best use of solar PV power during the EVCS charging cycle. The supply–demand load profile problem dynamic in EVCS are designed to reduce reliance on grid electricity supplies while increasing renewable energy usage and reducing carbon impact.



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Keywords: renewable energy sources; RES-hybrid system; multi-integer nonlinear programming; economic dispatch; electric vehicle charging station

1. Introduction

Power systems' increased running costs and overuse of fossil fuel deposits have resulted in continuing energy scarcity and momentous energy gap challenges worldwide. The challenges of global warming, the enervation of fossil fuels, and greenhouse gas emissions have led to a search for alternative and sustainable energy sources. The increasing apprehension about the climate effects of fossil fuel usage and average costs per kWh make renewable energy sources (RESs) attractive, as presented in the energy–carbon nexus model for future transport and manufacturing industries' low-carbon products [1]. Ref. [2] reported that clean, sustainable, and renewable energy sources have become increasingly competitive in recent years, driven by technology advancements and environmental legislation. RESs like photovoltaics, wind turbines, and energy storage systems create a hybrid system (HS). These solutions can reduce downtime and increase power supply dependability while costing less than the grid power system [3]. Weather fluctuations have a significant impact on wind turbine and PV system output, hindering optimal system

utilization. Therefore, integrating renewable energy sources into hybrid systems requires a careful consideration of economic feasibility and energy management methods [4,5]. Electric vehicles (EVs) are one of the latest eco-friendly means of transportation for lowering emissions; they play a prime part in new power vehicles based on the unending advancements in battery technology [6]. The integration of dispatch generation, such as PV and wind, with an electric vehicle charging station (EVCS) can result in highly efficient EV charging; however, EV charging requirements affect the spatial and temporal distribution of electricity charges, thus promoting effective grid EVCS and EVs energy management. However, few studies employ mathematical programming to optimize RESs. A literature review and statistical analysis of photovoltaic–wind hybrid renewable systems found that, by taking into account the 550 most important papers published between 1995 and 2020 [7], particle swarm optimization (PSO) and genetic algorithm (GA) are the most commonly used optimization algorithms, while the loss of power supply probability (LPSP) and renewable fraction for the energy analysis, the energy net present cost, and the CO₂ emissions environmental analysis are the most commonly used indicators. The analysis at low-power installations demonstrates that PV systems are preferred for residential and stand-alone applications, whereas wind systems exhibit higher deployment than PV systems as power grows. Ref. [8] investigated on-grid and off-grid photovoltaic power systems that are optimized and evaluated for normal residential electricity. All the authors presented an optimization methodology that examines both numerical and mathematical modeling in their review.

Economic dispatch (ED) optimizes generators based on the optimal power flow by supplying electricity at the lowest-possible cost [9]. The integration of electric vehicle charging load into the optimization model accounts for the ED process's dynamic nature, thereby facilitating communication between energy management units, charging machines, and electric vehicles to improve the charging process. This research evaluated an optimization model for meeting grid-tied electrical demand with unconventional renewable energy. The objective function includes a quadratic equation that simulates the operation of solar PV to allow for 24-h operation under different constraints. The aim is to create an energy management system that optimizes the supply of electricity while balancing operating costs and power generation [10,11]. EMSs help to optimize the usage of hybrid systems in grids, particularly where generation and variable pricing are involved. The optimization process employs load settings and predicted pricing to sell or store energy from a battery system in a grid-tied RES. Multi-integer nonlinear programming optimization methods (MINLP) are developed from advances in computational and mathematical programming approaches that predate digital computer development. Many practical applications require design variables to follow precise physical constraints, so they cannot take random values. The design constraints are essential for ensuring the system's stability and security. A list of the mathematical modeling constraints associated with the multi-objective hybrid systems function's inputs can be found in [12].

The authors of [13], working on the EVCS energy dispatching system, provided a systematic and adaptive method for regulating energy distribution at charging stations, which benefits the electric vehicle charging process. Ref. [14] proposed an energy management plan for a big electric vehicle charging station, incorporating renewable energy sources with energy storage technology to help to optimize power dispatch and reduce charging costs. Ref. [15] investigated smart charging techniques that change charging schedules based on PV generation and EV demand, demonstrating how self-sufficiency can be increased while reducing grid electricity consumption. An analysis of EV user interactions provided significant insights into customer needs and behavior, stressing the importance of incorporating user preferences into energy management techniques for EV charging infrastructure, was

presented in [16]. Ref. [17] presented the Sooty Tern Optimization Algorithm to Solve the Multi-Objective Dynamic Economic Emission Dispatch Problem. Attia et al. [18] concluded that autonomous and grid-linked systems do not necessitate battery storage devices during further application design phases. However, the reviewed literature either ignores the available surplus electricity from the electricity supplier or uses models that are easily expressed as LP problems. A comparative alternative solution strategy, including heuristic algorithms and dynamic program design approaches, is presented in Table 1, identifying related studies preceding the classical and meta-heuristics optimization methods for energy management systems considering RESs and EVs.

Table 1. Related studies preceding the classical and meta-heuristics optimization methods for energy management systems considering RESs and EVs.

Ref.	Power System Considered and Contribution	Optimization Technique	Objective Function
[19]	Integrated electric vehicle charging stations with photovoltaic uncertainties and battery power limits.	A new stochastic scheduling optimization approach.	Maximize the mean operational profit (μ OP) under various scheduling scenarios for the PV-BESS-EVCS integrated system.
[20]	Energy demand management for optimal scheduling of electric vehicle charging and discharging.	Four algorithms (DE, PSO, WOA, and GWO) provide efficient, grid-friendly V2G strategies.	Reduce EV customers' day-to-day costs and energy demand management difficulties in smart networks.
[21]	EVCI infrastructure sizing and placement.	Modified teaching–learning-based optimization (TLBO).	Minimize the power loss index and cost, while maximizing the voltage stability and reliability index.
[22]	EVCS operation efficiency of battery energy storage systems.	Gorilla troop optimizer (GTO) algorithm.	Power loss and total voltage deviation minimization.
[23]	Fast electric vehicle charging station optimization.	Grey wolf optimization.	Minimization of land cost, power loss, and electric vehicle population.
[24]	Co-optimization of energy losses and transformer operating costs based on smart charging algorithm for plug-in electric vehicle parking lots.	Nonlinear programming (NLP).	Minimize energy loss and transformer operating cost, with voltage profile and power factor maximization.

Furthermore, the methods discussed in Table 1 are case studies for various applications that were not solved using mathematical programming approaches. MINLP is recognized as one of the most challenging classes of classical optimization techniques, owing to its capacity to handle both integer and continuous variables in nonlinear systems [25]. While often approximated through mixed-integer linear programming (MILP), real-world energy systems characterized by the intermittent behavior of RESs and nonlinear device dynamics necessitate MINLP usage for more robust and realistic optimization. For instance, one study implemented a convex MINLP model based on mixed-integer quadratic programming (MIQP) to optimize an energy system with storage, employing a heuristic within the branch-and-bound framework to support near-optimal and real-time solutions [26]. Recent studies further demonstrate the adaptability of MINLP for renewable energy management. Obaro et al. [27] modeled off-grid distributed energy systems in South Africa using MINLP to account for household electricity patterns and improve resource allocation. Alhumaid et al. [28] developed a deterministic MINLP for optimally sizing and placing energy storage in microgrids, minimizing costs while addressing supply–demand mismatches. Rodrigues Lautert et al. [29] proposed a decomposition-based MINLP framework for selecting, sizing,

and locating technologies in distributed systems, enhancing computational efficiency under multiphase power flow constraints. The primary findings are consistent with our research. Additionally, MINLP-based systems often integrate evolutionary algorithms to navigate complex multi-objective optimization landscapes, both deterministic and metaheuristic [30], along with derivative-free algorithms for bound-constrained problems [31]. This makes them foundational in modern energy optimization, particularly in applications combining mixed-integer and continuous variables under nonlinear constraints.

This section focuses on the economic viability of solar PV and the possibility of eliminating the need for batteries in grid-connected systems [32]. There is limited research on the MINLP method to solve the RES-hybrid system economic dispatch of electric vehicle charging stations. This study outlines an optimal energy management strategy for a hybrid system that maximizes RESs based on dynamic commercial daily demand profiles using the MINLP optimization technique. This paper proposes energy management for the RES-hybrid system's economic dispatch using the MINLP optimization method for an electric vehicle charging station's energy requirements. The designed MINLP optimization method for the economic dispatch of a hybrid system with an electric vehicle charging station aims to minimize investment costs while maintaining tolerable operational limits. The schematic diagram for a hybrid energy management system with an electric charging station is presented in Figure 1.

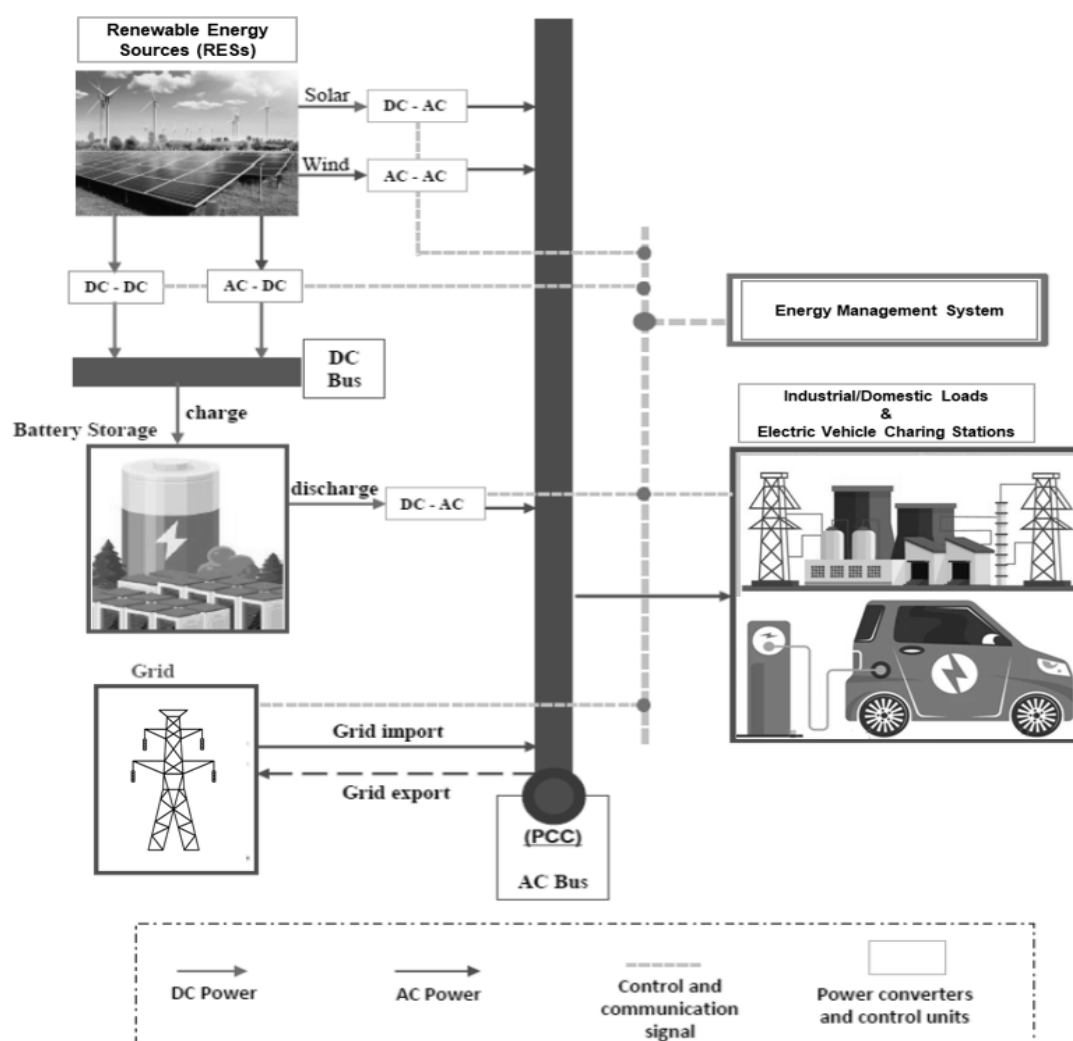


Figure 1. The schematic diagram for a hybrid energy management system with an electric charging station.

This paper's significant contribution is its MINLP energy management modeling in RES-hybrid systems for EV charging and enhancing renewable energy utilization, with objective functions defined to minimize operational expenditures while adhering to operational constraints. The practical difficulties in incorporating EV charging into economic dispatch optimization necessitate the use of EV charging dynamics to improve power system operation overall efficiency and effectiveness. Furthermore, EV consumers confront challenges such as high charging costs, lengthy charging time, and limited access to public charging infrastructure. In this paper, we present a method that uses classical algorithms to schedule EV charging and discharging activities while parking, via grid-tied RES-hybrid system integration, to lower EV customers' daily costs and tackle energy demand management difficulties in smart grids. While the MINLP structure itself is not novel, this paper's contributions are the integration, contextualization, and application of this technology to a realistic, multi-source RES system for EV charging, considering user behavior, cost dynamics, and operational restrictions. The technique bridges the gap between theoretical models and real-world implementation by balancing technical optimization with practical deployment constraints, making a timely and meaningful contribution. Furthermore, to address concerns about computational tractability for large-scale systems, a known limitation of MINLP, we added performance-aware heuristics that minimize solution time while maintaining accuracy. This pragmatic balance makes the proposed architecture better-suited to near-real-time applications. These contributions extend the practical application of MINLP in modern grid operations by aligning optimization outputs with the stochastic character of renewable energy, which is still an existing gap in the literature. This, in turn, helps to improve the entire EV user experience while addressing energy demand management challenges.

The study highlights are as follows:

- i An economic dispatch is proposed for grid-tied solar PV energy management approaches for EVCS to meet electrical demand using MINLP;
- ii The evaluation of charging station daily demand in an integrated solar PV, BESS, and grid connection while considering a nonlinear cost function algorithm for estimating PV generation power;
- iii EVCS energy demands are met while maintaining optimal grid, PV, and wind energy costs through a simulation environment to handle the supply-and-demand mismatch of a grid-tied RES-hybrid energy management system.

This paper is organized as follows. Section 2 presents related works on energy management for the hybrid system of an EVCS. Section 3 describes the MINLP optimization methodology. Section 4 presents the EMS MINLP simulation results and discussion.

2. Materials and Methods

2.1. Materials

In this paper, the RES-hybrid system is designed to consist of four major components: a grid, a solar PV, a wind turbine, and an energy storage system. The components work together adaptively to satisfy load requirements. When solar PV or wind turbine output is insufficient to fulfill load requirements, the energy storage system (ESS) serves as a backup storage solution. The best part about an RES-hybrid system is that it maximizes energy efficiency by storing excess solar PV or wind turbine energy in the ESS. The energy flow from solar PV and ESS is insufficient to meet load requirements; hence, the wind turbine is designed. The hybrid system's techno-economic feasibility is enhanced by eliminating excessive grid demand. The RES-hybrid system maximizes solar PV or wind turbine energy efficiency by storing excess energy from solar PV when ESS is insufficient to meet load requirement, hence, the design of the wind turbine is important. Eliminating excessive

grid demand improves the hybrid system's techno-economic feasibility. The absence of readily available EVCS on electrical networks delays the rapid adoption of electric vehicles as a more cost-effective mode of transportation, mostly in poorer nations. Following this difficulty, EV owners recharge their EV batteries using a home connection, resulting in significant energy system loss and a lower profitability index in the power sector [33]. Similarly, numerous EVCSs have caused distribution grid power quality difficulties, such as the system's nonlinear voltage fluctuations and power loss [34]. The inefficient and unstructured EV charging energy is linked to power issues in the distribution network [35]. These issues can be addressed by incorporating renewable resources, upgrading converter topologies [36], and adjusting charging patterns using energy management systems.

Despite the intermittent nature and high capital requirements for renewable power-generation infrastructure, there have been increases in popularity due to the environmental benefits, cost-effectiveness, and low maintenance [37]. However, using RESs for EV charging has led to system security issues and stability impacts because of their inconsistency and uncertainty. There are not enough EV charging stations in developing countries; therefore, many charge their vehicles at home, subsequently resulting in a lower viability index and system loss. These limits can be overcome by utilizing the EV charging station hybrid system energy management structure for the solar PV hybrid system of an EVCS proposed in Figure 2.

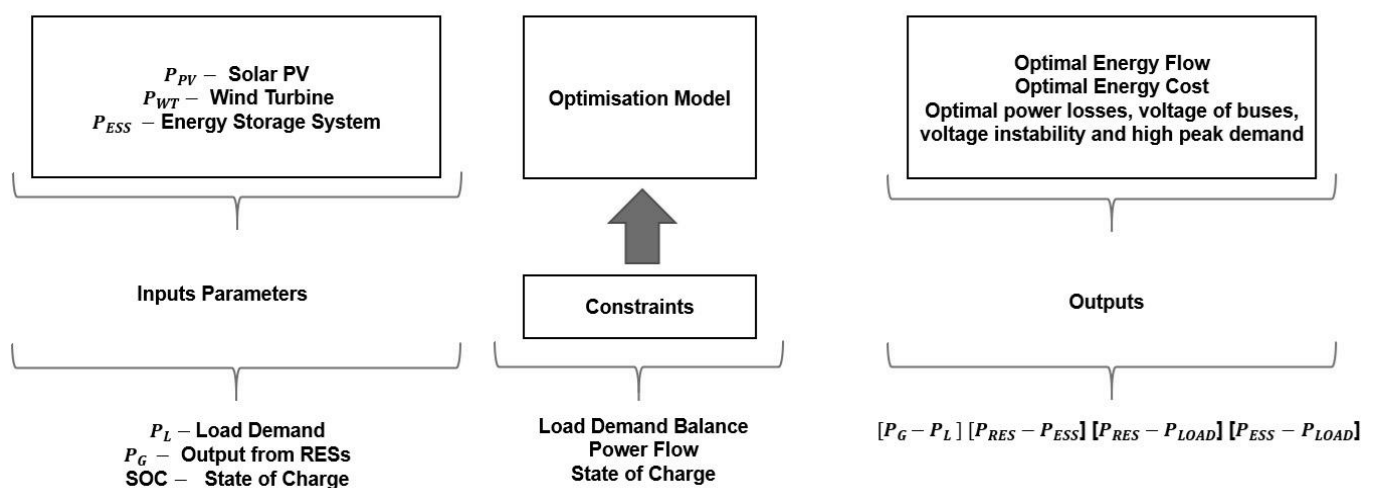


Figure 2. Energy management structure for the solar PV hybrid system of an EVCS.

2.2. Methods

This work proposes an effective way to address the limitations of the MINLP algorithm when dealing with topology constraints. The MINLP problem is decomposed into an MINLP-based ED and a nonlinear network optimization problem. Figure 3 illustrates the overall optimization approach. The following MINLP experimental approach was carried out for the paper: i. Define the problem by outlining the model parameters, including SOC limits, cost coefficients, power constraints, and variables to lessen energy expenses while satisfying demand and operating limits. The MINLP model's parameters and constraints are formulated as a user-defined algorithm problem with settings in the CPLEX optimizer; ii. Installing the required toolboxes (MATLAB R2022b 9.9 toolboxes): Optimization and Global Optimization Toolbox; iii. Formulation of the MINLP mathematical model for EMS includes defining the objective function and constraints; iv. Choosing the intlinprog optimization solver; v. Validating objective functions and analyzing the performance; vi. Implementing the EMS in a simulated environment to evaluate its performance and use MATLAB's simulation features to build realistic test cases. The inputs, constraints, and

strategies are formulated as an MINLP problem with user-defined algorithm settings and interfaced with the CPLEX optimizer. To convert this problem into an MINLP form, we linearize the nonlinear cost piecewise functions. Previous works [10,11] have simplified the ED problems into a mixed-integer nonlinear programming problem. The proposed energy management for the RES-hybrid system's economic dispatch uses the MINLP optimization method for the ECVS's energy requirements. The authors modified the methods in [38–42] and compared the optimization algorithm's performance to those works. MINLP models use mixed-integer and nonlinear programming to calculate optimal parameters such as SOC limits, cost coefficients, and power constraints. The procedure begins with establishing the objective function (such as operational expenses, fuel costs, power curtailment, and minimizing cost), defining constraints (e.g., power limitations, SOC ranges), and using appropriate solvers (e.g., branch-and-bound (B&B), outer linearization) to classify the best solution. This study's model parameter choices are clarified to improve transparency and allow reproducibility. SOC limits were set between 20 and 80%, based on manufacturer guidelines, to ensure battery longevity. Cost coefficients were derived from regional electricity pricing and studies, with renewable curtailment penalties reflecting the value of lost renewable energy sources. Power constraints, including solar PV output and battery limits, were based on realistic system specifications. Impending enhancements may involve using dynamic or probabilistic models to better capture uncertainty. The branch-and-bound algorithm solves MINLP issues efficiently by following an organized method. The integer constraints are relaxed initially, resulting in a continuous NLP formulation. If the obtained solution does not meet integer feasibility, the algorithm moves on to the branching phase, in which the problem is divided into many subproblems by fixing one or more integer variables. As the search tree grows, bounding methods are used to update the lower and upper bounds of each node, allowing for the pruning of suboptimal or infeasible branches. This iterative approach is repeated until an integer-feasible solution that meets the optimality criteria is discovered or until the bounding gap falls below a predetermined tolerance, guaranteeing convergence to the global optimum. The proposed MINLP was implemented to solve ED optimization problems for test case scenarios in the R2022b (Matlab version 9.9) environment. The proposed mathematical model is outlined in the subsections as follows.

2.2.1. Optimization Problem Formulation for Energy Management of a Solar PV-Hybrid System Economic Dispatch

The optimal linear objective function's input in a mathematical model is in Equation (1).

$$F_i Y_i = \min \sum_{i=1}^N \left[\sum_{t=1}^T c_i(t) \times x_i(t) \right] \quad (1)$$

where N = total number of RESs, F_i = objective function, i = unit number, t = time, $c_i(t)$ = unit i cost at time t , $x_i(t)$ = unit i power output at time t , Y_i = unit i fixed power output.

The nPV generation cost objective function minimization, shown in Equation (2), for m loads is

$$\begin{aligned} \min C_{PV} &= \sum_{t=1}^k \left[\sum_{i=1}^{N_s} P_{PV_i}^{pv} C_{PV_i} + P_s^t C_s^t \right], \\ \text{Subjected to } P_{PV_{min}}^t &\leq P_{PV_i}^t \leq P_{PV_{max}}^t \end{aligned} \quad (2)$$

Similarly, nWT generation cost objective function minimization, presented in Equation (3), for m loads is

$$\begin{aligned} \min C_w &= \sum_{t=1}^k \left[\sum_{m=1}^{N_w} P_{w_i}^{dm} C_{w_i} + P_s^t C_s^t \right], \\ \text{Subjected to } P_m^{min} &\leq P_m \leq P_m^{max} \end{aligned} \quad (3)$$

where C_{PV} and C_w are the solar PV and wind turbine cost, $P_{PV_i}^t$ is the PV i th output power at time t horizon, C_{PV_i} and C_{dm} are the PV i th and wind m th operating cost, P_s^t and C_s^t is

the cost of the distribution network and operation cost at time t , and P_{PVmin}^t and P_{PVmax}^t are the maximum and minimum power of the i th PV system.

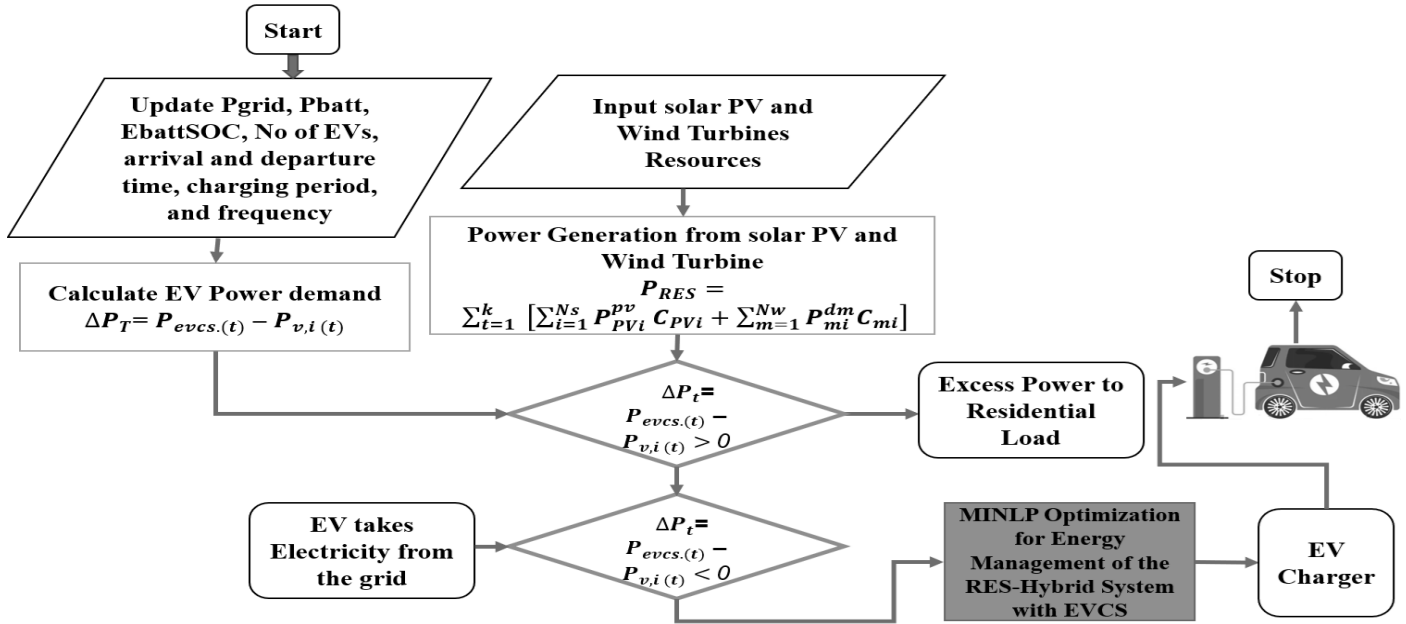


Figure 3. Flowchart for MINLP classical algorithm for energy management of the hybrid system with EVCS.

Equations (4) and (5) describe the explicit battery operating cost model while charging and discharging:

$$C_{charging} = C_{bat}^C + C_{bat}^{C,max}, \quad (4)$$

$$C_{discharging} = P_{bat}^D + P_{bat}^{D,max}, \quad (5)$$

subject to the ESS power charging or discharging constraints in Equation (6):

$$P_{ess}^{min} \leq P_{ess} \leq P_{ess}^{max} \quad (6)$$

Equations (7) and (8) provide the objective function used in Equation (1) to minimize the overall operational cost of renewable energy production while accounting for uncertainty restrictions. These real-time models are generated with intra-hour dispatch intervals, while accounting for operating and security limits using the guiding model.

$$F_i Y_i = \sum_{t=1}^{Ns} \sum_{i=1}^{Ng} C_{Gi}(P_{Gi}) + \sum_{t=1}^{Ns} \sum_{i=1}^{NPV} P_{PV_i}^t C_{PV_i} + P_s^t C_s^t + \sum_{t=1}^{Ns} \sum_{i=1}^{Ndm} P_{mi}^{dm} C_{mi} + P_s^t C_s^t \quad (7)$$

Subjected to

$$\max[P_{Gi}^{min}, P_{Gi}^{up} - R_{Gi}^{down}] \leq P_{Gi} \leq \min[P_{Gi}^{max}, P_{Gi}^{up} + R_{Gi}^{down}] V_{Dk}^{min} \leq V_{Dk}^{max} \quad (8)$$

Equation (9) is the MINLP objective function solver to compute the optimum lower bound on the inputs, derived by widening feasible sets and ignoring restrictions.

$$Z_{MINLP} = \min f(x) \leq \eta, \quad (9)$$

η is the batteries' charging and discharging efficiencies, subject to g as $0 \leq P_{bt}^C \leq P_{bt}^{C,max}$ or $0 \leq P_{bt}^D \leq P_{bt}^{D,max}$, while $f(x)$ is a cost function (minimization) or a grid function (maximization) for an ideal solution for objective function $f(x)$ in Equation (10):

$$fx \in X, x_i \in \mathbb{Z}^{1/} \text{ for all } i \in I \quad (10)$$

The expected energy storage of a PV/WT variable is constrained by the real power output of the convex function $f(x) : \mathbb{R}^n \rightarrow \mathbb{R}$, $g : \mathbb{R}^n \rightarrow \mathbb{R}^m$ of the charging or discharging of the battery, given as Equation (11):

$$E_{bt} = E_{b,t-1} + P_{bt}^C \eta_b^C \Delta t - P_{bt}^D \frac{1}{\eta_b^D} \Delta t \quad (11)$$

The constraints are given to ensure that battery energy does not exceed storage capacity, E_b^{cap} as $0 \leq E_{bt} \leq E_b^{cap} = P_{bt}^D - P_{bt}^C$ as total power. We have a convex MINLP if f and g are convex functions. If f and g are not convex, we have a nonconvex MINLP. In the adopted approach, g are convex functions but nonlinear. Dropping the integrality in convex functions results in nonlinear relaxation (removing some constraints). The ideal relaxation is the convex hull of feasible locations, while maximizing a linear function over a convex set solves the problem.

2.2.2. Constraints and Variable Limits

Having constraints $0 \leq E_{bt} \leq E_b^{cap}$ ensures that the energy in the battery does not surpass the storage capacity E_b^{cap} , where total power $P_{bt} = P_{bt}^D - P_{bt}^C$. The battery's state of charge (SOC) indicates its behavior in percentage terms and can be represented as follows. EMS allocates power proportionately between the EVCSs based on discrete EV necessities, as represented in Equation (12), making it simpler to estimate each EV charging power. Equation (13) presents the total EVCS power requisite, calculated by separating EVCS charging power demand into Equations (14) and (15).

$$P_{evcs(t)} = \left(SOC_{evcs(min)} < SOC_{ess(t)} < SOC_{evcs(max)}(t) \right) C_{evcs(t)}, \quad (12)$$

$$P_{v,i} = \frac{\left(SOC_{evcs(min)} < SOC_{ess(t)} < SOC_{evcs(max)}(t) \right) C_{evcs(t)}}{t_{di} - t - \Delta t}, \quad (13)$$

$$P_{evcs(t)-limit} = P_{v,i(t)} \times P_{max}, \quad (14)$$

$$P_{demand} = \sum_{i=1}^{T_{evcs}} P_{ss(t)}, \quad (15)$$

$P_{ess(t)}$ denotes EVCS charging power, $SOC_{evcs(max)}$ is the maximum EVCS state of charge, $SOC_{evcs(min)}$ is the minimum EVCS state of charge, $SOC_{evcs(t)}$ denotes the current charging station state of charge, $C_{evcs(t)}$ signifies battery capacity, t is the current time, T_{evcs} is dispatch horizon (24 h), t_{di} signifies the departure time, and Δt is dispatching resolution (1 h). The EMS's EV charging strategy is chosen to maximize solar energy consumption. The EMS's control approach prioritizes EV charging for solar energy utilization maximization. Following this, it considers ESS charging. Any extra electricity is dynamically distributed to supplementary loads in the system or supplied back to the grid. When the energy in the ESS is depleted (SOC less than 20%), the EMS will draw power from the grid to ensure uninterrupted functioning, using Equation (16):

$$P_{Discharge(t)} = P_{batt->L(t)} + P_{batt->Grid(t)}, \quad (16)$$

where the energy storage quantity is SOC and $P_{Charge(t)}$ is battery charging power, while $P_{Discharge(t)}$ is battery discharging power. η_{charge} and $\eta_{discharge}$ are the battery's charging and discharging efficiencies, respectively; E_{nom} is the system's nominal energy; $P_{Grid \rightarrow batt(t)}$ is the battery charge electricity imported from the grid; $P_{PV \rightarrow batt}$ is the solar PV power to charge the battery; $P_{batt \rightarrow L(t)}$ represents the battery electricity for load supply; and $P_{batt \rightarrow Grid(t)}$ represents power exports to the grid.

The model cost is the functional optimal controlled grid energy cost, where the baseline cost is the customer tariff if no optimization is applied. The imported grid energy tariff refers to the EVCS power usage and battery storage system. The surplus of PV, WT, and energy storage sold to the utility grid is registered as income.

$$\underbrace{\frac{Min}{x}}_{\frac{Max}{x}} F(x), \text{ subject to } \begin{cases} c(x) \leq 0 \\ c_{eq}(x) \\ Ax \leq b \\ A_{eq}x = b_{eq} \\ lb \leq x \leq ub \end{cases} \quad (17)$$

where $F(x)$ (Equation (17)) represents the objective function; $c(x)$ and $c_{eq}(x)$ are linear and nonlinear functions; A_{eq} and b_{eq} are the equality constraints coefficient in Equations (17) and (18); and A and B are the inequality constraint coefficients in Equations (19) and (20).

Equality constraints:

$$\begin{bmatrix} \overbrace{I_{NXN} \quad I_{NXN} \quad O_{NXN}}^{A_{eq}} \\ \overbrace{O_{NXN} \quad Y_{NXN} \quad \emptyset_{NXN}}^{A_{eq}} \end{bmatrix} X = \overbrace{\begin{matrix} P_{load}(1:N) - P_{RES}(1:N) \\ E_{batt(1)} \\ 0_{N-1} \end{matrix}}^{b_{eq}}, \quad (18)$$

Inequality constraints:

$$\begin{bmatrix} \overbrace{O_{NXN} \quad I_{NXN} \quad O_{NXN}}^A \\ \overbrace{O_{NXN} \quad -I_{NXN} \quad O_{NXN}}^A \\ \overbrace{O_{NXN} \quad O_{NXN} \quad I_{NXN}}^A \\ \overbrace{O_{NXN} \quad O_{NXN} \quad -1_{NXN}}^A \end{bmatrix} X \geq \overbrace{\begin{matrix} P_{max} \\ -P_{min} \\ E_{max} \\ -E_{max} \end{matrix}}^{b_{eq}}, \quad (19)$$

$$C_t^{bat} = \alpha^{bat} X P_t^{bat} + \beta^{bat} X P_t^{bat} + \gamma^{bat} X P_t^{bat}, \forall t \in T, \quad (20)$$

P_t^{bat} : Power supplied to (discharging) or stored in (recharging) the battery at time t;

γ^{bat} : Coefficient for pollution treatment cost;

α^{bat} : Maintenance coefficient;

β^{bat} : Value depreciation coefficient;

C_t^{RES} : RES's social cost.

Since this ESS does not emit any greenhouse gases, the value of γ^{bat} is zero. The dispatchable RES function is Equation (21), and Equation (22) is the grid cost function.

$$C_t^{MT+FC} = C_t^{MT} + C_t^{FA}, \quad (21)$$

The grid social cost function can be formulated as follows:

$$C_t^{Total} = C_t^{MT+FC} + C_t^{RES} + C_t^{grid} + C_t^{bat}, \quad (22)$$

2.2.3. EMS MINLP Classical Algorithm (Figure 3)

The proposed economic dispatch case studies are based on power generation estimates for grid systems and electric load demand. This section describes each of these mathematical models. The generation sources covered in this study can be divided into two categories based on their ability to control power generation: first, dispatchable, which can control dispatchable transmitted power, including coal, fuel cells, and tiny gas turbines; second, non-dispatchable, which lacks dispatch capability, such as solar PV. The grid is linked to the RESs via a single point as the Point of Common Coupling (PCC). Solar photovoltaic (PV) is a non-dispatchable energy source that generates electricity from sunlight; thus, the study focuses on the MINLP classical algorithm to optimize energy flow from solar PV when ESS is insufficient to meet load requirements and incorporates dispatchable wind turbine and grid in energy management strategies into grid-tied RES-hybrid systems. The steps describe the algorithm.

Step 1—Input grid settings to optimize usage of energy storage Ppv, N, EVCSload, dt, Cost, Einit, EWeight, MinMaxbattery)

N—Number of discrete steps horizon

dt—Optimization calls time [s]

Ppv—Solar PV power [W]

EVCSload—Grid load power [W]

Einit—Battery initial energy [J]

EbattV—Battery voltage [V]

Cost—Grid charge cost [\$/kWh]

EWeight—Energy storage weight

MinMaxbattery—Battery min/max

Step 2—Confirm battery/grid power differential (d) = EVCSload – Ppv

Step 3—Minimize grid energy cost from the objective optimization calls time * grid charge cost * Pgrid – Energy storage weight * Battery voltage

Step 4—Battery input/output power Optimconstr(N) = constraints. energyBalance

Step 5—Power from PV, grid, and battery Ppv + PgridV + PbattV – EVCSload = constraints. load Balance

Step 6—Battery SOC constraints

Step 7—Perform linear programming optimization

Step 8—Sub-matrices for optimization constraints

Step 9—Optimoptions(prob.optimoptions,) = Options for Linear Program

Step 10—Parsing the optimization results

2.2.4. RES-Hybrid System of an Electric Vehicle Charging Station

The growing popularity of electric vehicles requires the development of efficient charging stations that are capable of supplying acceptable charging rates. Combining on-site RES would minimize grid load while increasing charging station effectiveness. In this study, a solar PV system is combined with the grid to power an electric vehicle. Solar PV is noted for its irregular nature, which is heavily influenced by location and weather conditions. To compensate for the intermittent nature of solar PV, an energy storage system is integrated with a grid-tied RES scheme to ensure the continuous operation of a hybrid solar PV-based charging station. In general, hybrid-source-based charging stations should be inexpensive, efficient, and dependable enough to fulfill the changing needs of EV loads in a range of scenarios. This work develops and applies the MINLP strategy to optimize on-site PV energy and meet the fluctuating load of EVs while considering the ESS's rapid

response and decreasing grid stress. The recommended formulation lowers the projected operating costs.

$$\min F_{C_{total}} = \alpha_i + \beta_i P_{s,i} + c_i P_{s,i}^2 \quad (23)$$

where α_i, β_i, c_i are the cost coefficients of the generator i .

$$C_{total} = \sum_{i=1}^{N_T} \left(\sum_{g=1}^{N_g} C_g(P_{g,i}) + \sum_{r=1}^{N_r} C_r(P_{r,i}) + \sum_{v=1}^{N_v} C_{v,i}(P_{v,i}) + \sum_{m=1}^{N_m} C_{m,i}(P_{m,i}) + \sum_{ev=1}^{N_{ev}} C_{evcs,i}(P_{evcs,i}) + \gamma \right) \quad (24)$$

The variables $N_g, N_r, N_v, N_m, N_{evcs}$ represent the numbers of conventional generators, buses spinning, solar PV devices, wind turbines, and EV charging stations. The penalty function, γ , ensures a minimum dispatch renewable obligation to meet energy mix requirements. Solar PV generators have a cost function in the applied method, with P_{gi} being the generator's scheduled power output i , determining the direct cost by

$$P_{gi} = P_{v,i} + P_{evcs,i} \quad (25)$$

The MINLP flow solver considered the optimization algorithm's constraints.

2.2.5. Energy Management Strategies at an Electric Vehicle Charging Station

The EVs begin charging with the maximum charging power (15 kW) in an uncontrolled charging scheme (controller off) as they are parked at work. The method does not reflect surrounding characteristics, such as solar photovoltaic generation or electricity prices. When the target SOC is reached, the charging stops, indicating usable battery capacity full charge. If the parking period is deficient for fully charging the EV, charging is interrupted at departure. In a smart charging scheme (controller on), as used in paper [43], charging does not always begin directly upon arrival at work, nor does it continuously use the full charging power. This strategy considers the forecasted solar PV generation throughout the parking period. Energy management solutions at charging stations aim to maximize the solar PV supply usage for the EVCS charging cycle while adhering to limits such as the intended SOC and maximum charging rate. In this analysis, no residential or office building loads were examined because the primary purpose of installing a solar PV system is to meet the EV charging demand in the EVCS. Thus, only the net load from EV charging and solar PV generation is calculated. Minimizing variability in the net load will result in a flat net-load profile, increasing local generation SOC while decreasing peak loads. EMS allocates power proportionately between the EVCSs based on discrete EV necessities to estimate each of the total EVCS power requirements, calculated by separate EVCS charging powers. The dynamic mechanism optimizes the functioning of the battery, ensuring that it charges while power generation meets load demand and the storage SOC is less than 50%. The storage system will be charged until it reaches 80% of its capacity, after which the charging controller will stop charging the battery. The control strategy uses forecast and cost functions to govern the energy storage system's operation time. When RES energy generation is restricted and costly, the EMS system will verify the ESS SOC status. If the criteria are met, the controller will reconnect the ESS to the RES-hybrid system and allow discharge. Figure 4 provides an overview of the planned charging scheme. It should be emphasized that flawless PV generation estimates were utilized for the charging simulations in this study, as one of the study's goals was to determine the maximum solar PV–EV load-matching potential at workplaces that utilize charging schemes. The focus is to lessen dependency on a continuous grid electricity supply, with the primary goal of increasing renewable energy usage and lowering carbon footprint. The dynamically controlled EMS power flow prioritizes EVCS charging periods using solar PV available power to reduce operational costs by leveraging the self-consumption of

generated energy, which is more cost-effective than grid electricity when considering the long-term investment factor of solar PV infrastructure. Electric vehicles are highly efficient and can help to reduce transportation energy consumption while transitioning from fossil fuels to renewable energy. Managing renewable energy output through energy storage and dispatchable load poses a difficulty in non-dispatchable RES-hybrid system management, which leads to significant system instability [44]. Governments and utilities are interested in applying the EV charging benefits to fulfill definite grid management objectives [45]. Electric vehicle electrical systems rely upon an accurate assessment of how much energy is spent when EVs are subsequently returned to a charging station. When the possible implications of electric vehicles on the energy system are addressed, the importance of electric car driving habits is highlighted even more [46].

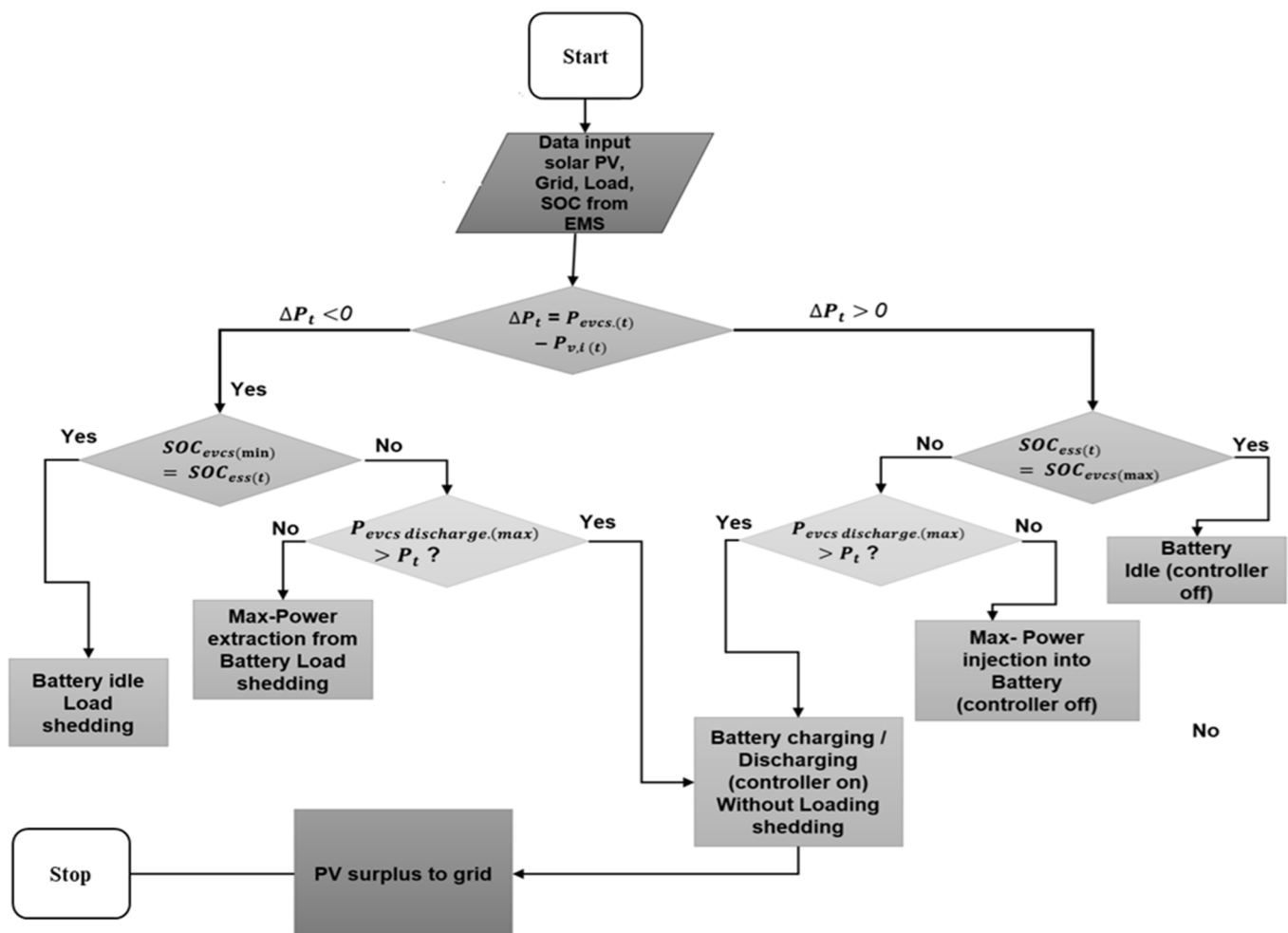


Figure 4. Electric vehicle charging station load profile-based methods.

If charging rates and timing are not limited, the system risks seeing a midnight increase in “convenience charging”. This situation is envisioned as comparable to how mobile phones are used in cars, with plugging in and charging occurring immediately upon arrival at a charging station, regardless of the time of day or impact on the grid. In this case, EVs are most likely plugged in when users arrive home and are charged to capacity. To evaluate daily EV energy usage and its influence on the grid, data from 1616 EV classes [47] were used to approximate the EV penetration rate. Table 2 displays the EV categories by class, which require an average of 15 kWh daily, depending on driving habits and energy usage.

Table 2. Parameters for charging station load model by EV consumer classes and type.

Data [47]	Electric Car	Electric SUV	Electric Van	Electric Pickup Truck
EV Class	Compact	Economy	Mid-Size Van	Light Truck
BCap, kWh	8–12	10–14	14–18	19–23
EC, kWh/km	15–25	25–40	40–55	55–60
Consumption	90	105	120	120
km for 15 kWh	1480	80	48	8

3. EMS MINLP Simulation Results and Discussion

The power output of the solar PV model based on the load demand on an hourly basis is determined by the various estimated irradiance values, which necessitates the use of an appropriate functional model. Before using the MATLAB program, data from the seasonal sun irradiance model were generated by simulation. This function calculates a solar photovoltaic (PV) system's output based on the battery's daily running costs. The FMINCON technique is used in MATLAB to handle the optimization problem of energy consumption, with the EVCS load demand profile illustrating our modeling approach, which combines building and EV station demand profiles to investigate the effects of charging on a building's daily electricity consumption and peak power demand—1000 kW in Figure 5. Figure 6 is for 2500 kW and Figure 7 is for 5000 kW during the peak period. Figures 5–7 show the battery charging during the day and the use of RES grid power at night, especially during the off-peak price period, when the SOC rises to satisfy the load needs during times of high demand.

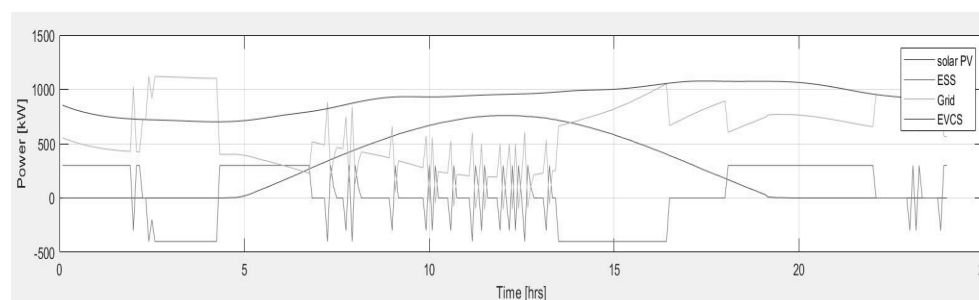


Figure 5. Case 1 of simulated power generation: The FMINCON approach is used in MATLAB for energy availability of 1000 kW to determine the EVCS load demand profile during the peak price period.

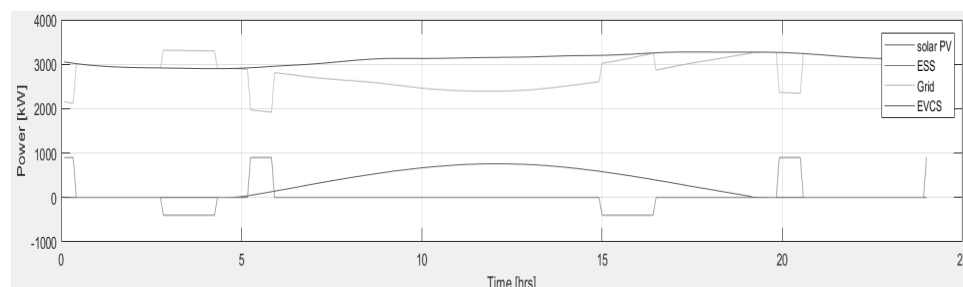


Figure 6. Case 2 of simulated power generation: The FMINCON approach is used in MATLAB for energy availability of 2500 kW to determine the EVCS load demand profile during the peak price period.

However, the grid-tied RES-hybrid system generates enough power to make up the difference during the day. During the day, the surplus energy supplied to the grid generates

a significant profit. The increase and decrease in battery energy (Figures 8–10) can be attributed to a low surplus of energy storage, that is, utility grid export, particularly during peak pricing periods. The ESS takes data from EMS optimization directives and performs energy-generation and load-balancing tasks in either off-grid or grid-connected mode.

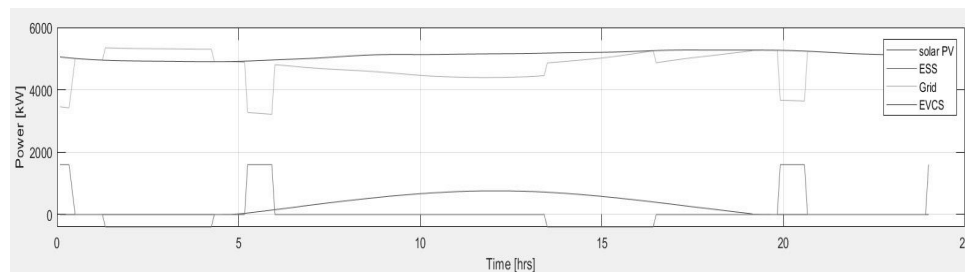


Figure 7. Case 3 of simulated power generation: The FMINCON approach is used in MATLAB for energy availability of 5000 kW to determine the EVCS load demand profile during the peak price period.

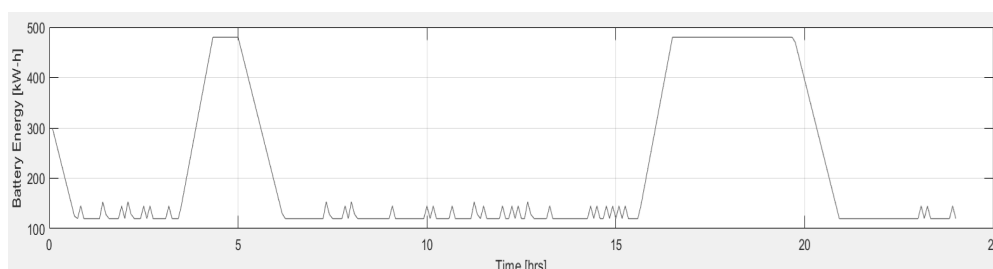


Figure 8. Case 1: Simulated energy storage system with 420 kW-hour battery capacity.

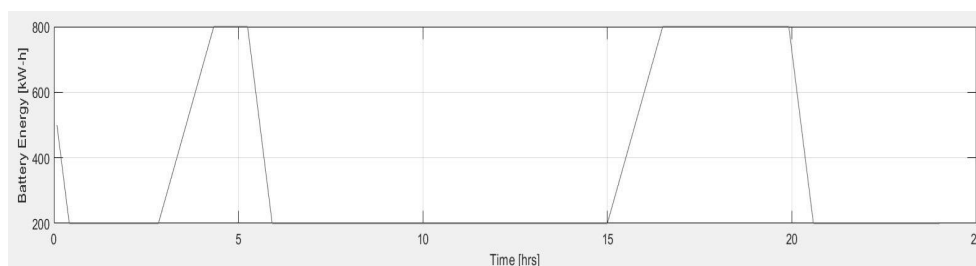


Figure 9. Case 2: Simulated energy storage system with 1000 kW-hour battery capacity.

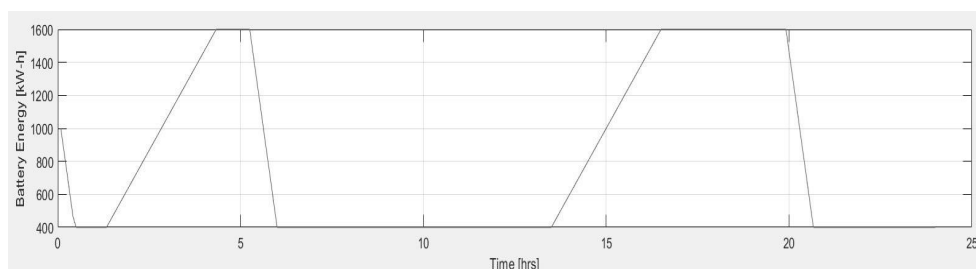


Figure 10. Case 3: Simulated energy storage system with 2000 kW-hour battery capacity.

The grid's operating costs cover 24 h, using 120 kW of solar PV power. The ESS capacity is 25,000 kWh, with a minimum discharge rate of 120 kW and a maximum charge rate of 180 kWh, both negative and positive. The battery's maximum capacity is 2000 kWh, and the SOC ranges from 20% to 80%. The grid price maintained a constant cost that started

rising from 15 h and attained the highest price at 20 h for all three cases, likely due to high peak charging by the EV customers after returning home (Figure 11).

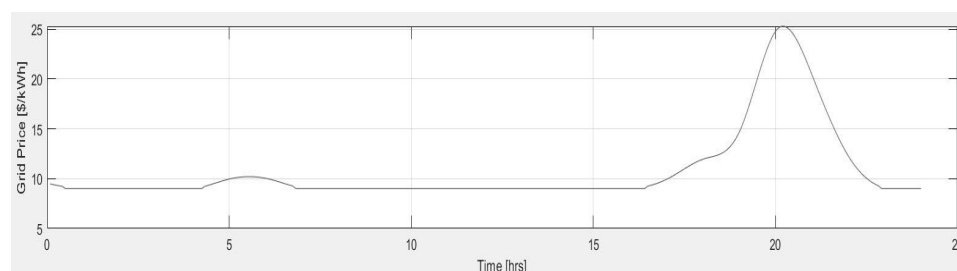


Figure 11. MINLP cumulative grid cost and usage simulation approach.

The dedicated solar PV's EMS results for EVCS demand are presented in Figure 12. When the energy demand is at its highest, between 6:00 and 19:00, the grid energy is at its lowest, and the solar PV power with battery-backed power is sufficient to meet the client's needs. Furthermore, only a fraction of the wind energy is produced during off-peak hours, and the grid system does not send any energy during the peak pricing time interval. Prioritizing RES usage due to low marginal costs is probable when solar PV generation can supply EVCS energy demand, from 06:00 to 19:00. Figure 12 shows various simulated EV arrival times and departure frequencies. The arrival time shows that EV arrivals peak between 6:00 and 19:00, showing that charging happens during the day. Bi-modal peaks occur before and after regular work hours. Plug-in hybrid electric vehicles (PHEVs) may arrive at the station with unusually low SOC since consumers drive the car in "electric only" mode before switching to gasoline. We used conventional car journey data to generate an acceptable arrival time and SOC for the simulations [48,49]. We assumed that each car enters the station with a low SOC (<20%) and exits when charged to 80% SOC. Charging to 100% SOC was not anticipated because this would extend the overall charging time at a station due to the constant-current, constant-voltage (CCCV) charging protocol, which reduces the charging rate as the battery is near full capacity [50].

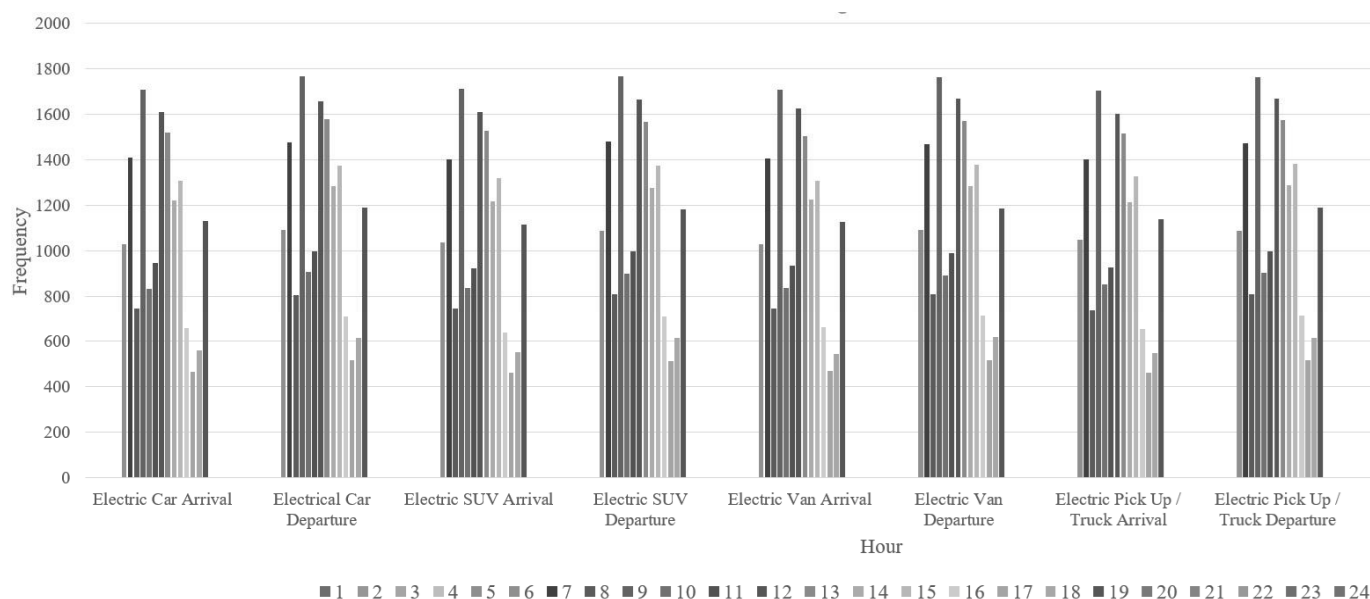


Figure 12. Simulated EV arrival and departure time frequencies.

In this case, wind turbine power is turned off, and no electricity is sent from the grid. When the marginal costs of WTs exceed the grid electricity price, power demands will come from the grid, as indicated in the EVCS loading diagram, from 0:01 to 6:00 Figure 13 illustrates grid-tied hybrid system energy management under EV charging station loads, and Figure 14 depicts EVCS loading energy management strategies for the grid-tied RES-hybrid system.

In its place, with higher electricity prices from the grid, the WTs will supply EVCS load before obtaining power from the grid. WTs will be at full capacity from 15:00 to 05:00 h.

Electric vehicle adoption is hampered by a scarcity of charging stations within the electrical grid, particularly in underdeveloped countries. Using a home connection to recharge EV batteries leads to high energy system loss and worse profitability in the power sector. Similarly, numerous EV charging stations generate distribution grid power quality issues, such as power loss and voltage fluctuations, due to the system's nonlinear behavior. Unstructured and inefficient EV charging energy is related to power difficulties in the distribution network. These difficulties can be solved by adding renewable resources and adjusting charging patterns using energy management systems. Despite its intermittent nature and high capital requirements, renewable power-generation infrastructure has increased in popularity due to its environmental benefits, low cost, and ease of maintenance. However, RES usage for EV charging has a system stability and security impact because RESs are irregular and ambiguous. Economic dispatch simulation results for 24 h at an hourly resolution show that all generation units contributed proportionately to meeting EVCS demand: solar PV (51.29%), ESS (10.5%), grid (29.92%), and wind generator (8.29%). In terms of numerical results and as a benchmark in comparison with the work in [51], the economic dispatch findings show that all generation units contributed proportionally to meeting demand: solar generator (58.33%), BESS (13.42%), diesel generator (23.92%), and wind generator (4.43%). Figure 15 presents PV curtailments over varying months in the year alongside the necessary energy injected within the grid. Table 3 presents the proposed power curtailment rate of the MINLP method as compared with other modeling methods applied to electrical energy output consumption by EVCSs in the literature.

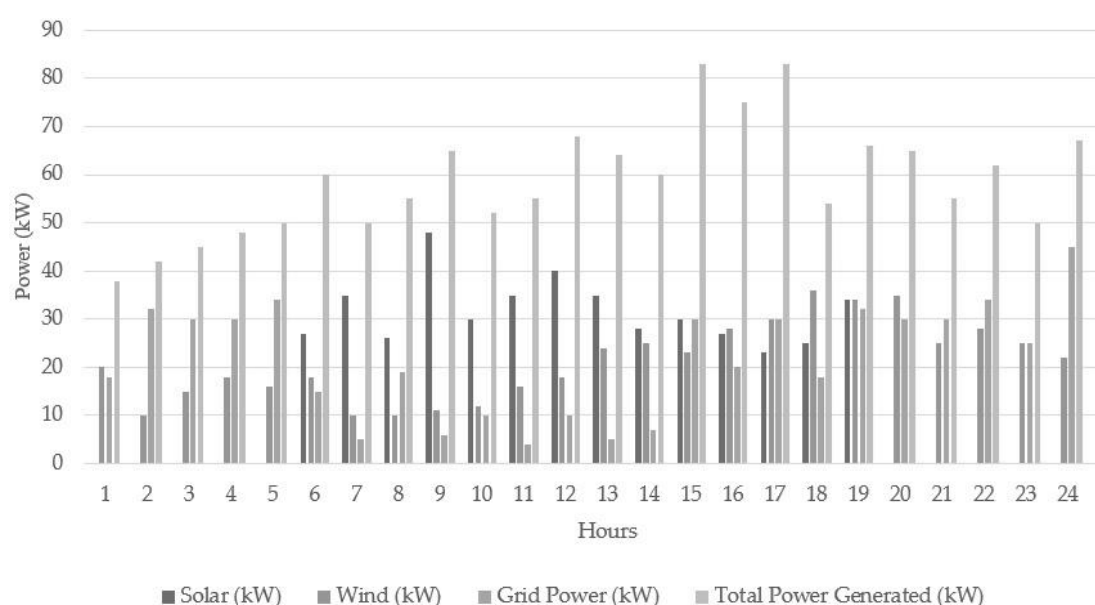


Figure 13. Grid-tied HS energy management at EV charging station loading.

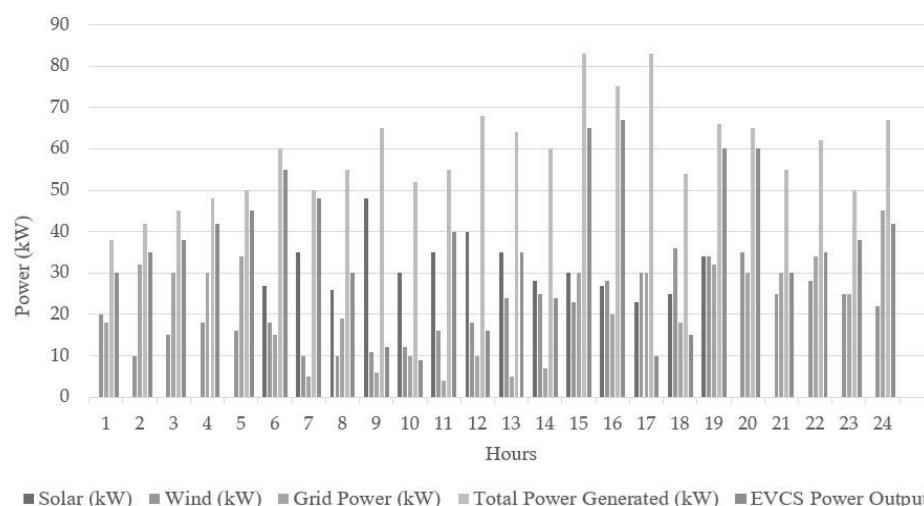


Figure 14. EVCS loading energy management strategies for grid-tied RES-hybrid system.

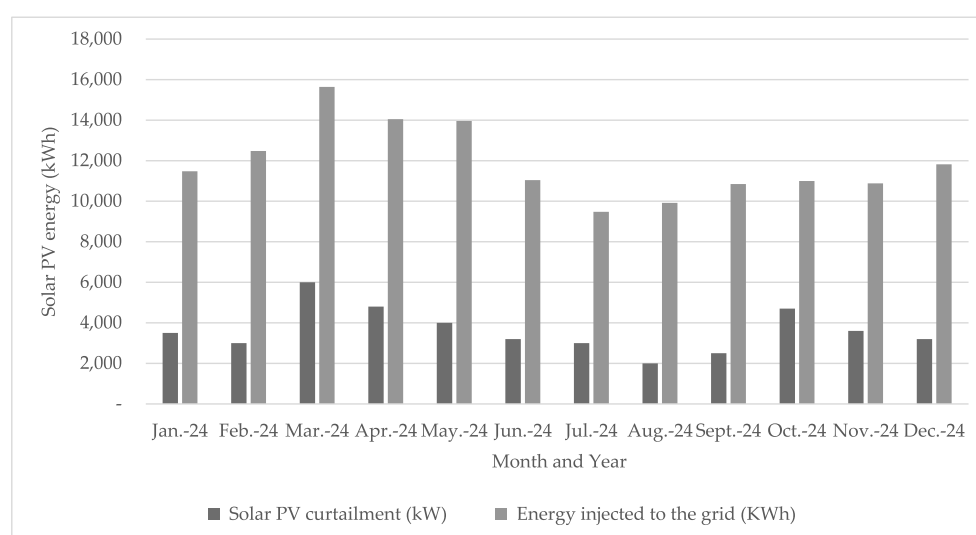


Figure 15. Solar PV curtailments over varying months in the year alongside the necessary energy injected within the grid.

Table 3. Percentage power curtailment rate of the MINLP method in comparison with the literature.

Authors	Optimization	Power Curtailment Rate (%)
Proposed work	MINLP	51.29
Dong et al., 2025 [19]	Stochastic optimization	17.83
Altaf et al., 2025 [51]	Particle swarm optimization (PSO)	58.33
Bagherzadeh et al., 2024 [52]	Salp swarm algorithm (SSA)	54.54

The grid saw 51.29% PV curtailment across several months when the net EVCS load (all generation units contributing proportionately to fulfilling EVCS demand, i.e., solar PV, ESS, grid, and wind generator) fell below the local grid's base load generation. Based on grid historical data analysis, we assumed that PV curtailment begins when solar PV power can satisfy EVCS demands. We found that curtailments were stronger between 06:00 and 19:00, due to abundant PV power coupled with relatively low grid demand around noon. The hourly PV generation surpassed 80% of the grid load, but significant energy consumption during daylight hours reduced PV generation and decreased the PV curtailment ratio. Wind turbine power is shut off, and no energy is distributed from

the grid. When the marginal costs of WTs exceed the grid energy price, the grid will meet power demands from 0:01 to 6:00 h. Because the average solar radiation was lower, the extent of PV curtailment was less visible. A power curtailment rate of 51.29% was recorded for MINLP, whereas the PSO-based strategy had an even higher rate of 58.33%. These values represent a considerable part of the available energy being reduced. This high amount of curtailment is often caused by grid capacity constraints, voltage stability limits, or a failure to absorb surplus power during low-demand periods. This emphasizes the significance of adopting more flexible grid infrastructure or storage technologies to maximize the use of generated renewable energy. The compared values show a relative difference of 33.46, 7.04, and 16.75 with the authors of [19,51], and [52]'s similar works, respectively. To evaluate the resilience of the optimization models, a sensitivity analysis was performed for renewable energy input at various levels of forecast error. The results reveal that MINLP maintains consistent curtailment levels, up to $\pm 15\%$ inaccuracy, while PSO's performance significantly deteriorates. These results show that MINLP is more resilient to prediction errors, which are common in real-world operations. Figure 16 shows detailed findings for these functions, assuming that curtailment occurs when generation surpasses a threshold. The basic profile was standardized so that the total generation amounted to a minimum of 300 kWh and a maximum of 6000 kWh. The suggested work is significant in that it compares the performance of optimization and power curtailment rates for energy consumption analysis in its study. Future research will also consider the global economic and optimum model for energy storage suggested by [17,53].

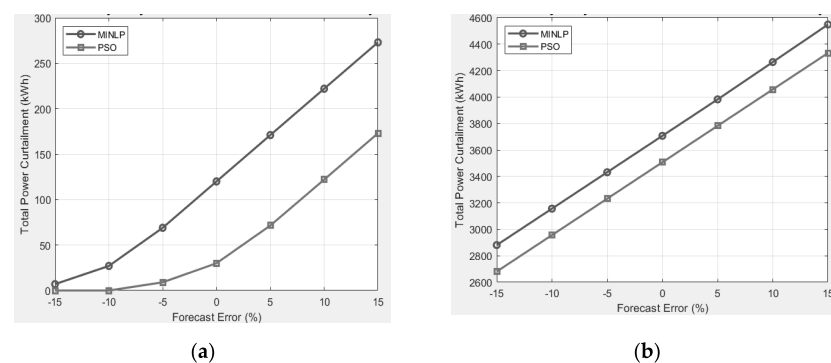


Figure 16. Sensitivity analysis curtailment levels up to $\pm 15\%$ inaccuracy of MINLP and PSO's performance under forecast variability: (a) minimum of 300 kWh, (b) maximum of 6000 kWh.

4. Conclusions

This paper proposes an economic dispatch of RES-hybrid energy management systems strategies for the EVCS problem using a convex MINLP algorithm, which is based on mixed-integer-form quadratic programming mathematical models, as well as a near-optimal solution to facilitate simulation implementation in the branch-and-bound model. Throughout the history of integer programming, the fundamental branching and cutting (B&C) has been developed to identify additional valid inequalities or cuts at the nodes of the branch-and-bound tree. An economic dispatch is proposed for grid-tied RES-hybrid energy management strategies for EVCS to meet electrical demand using MINLP. The evaluation of charging station energy demand in integrated solar PV, BESS, and grid applications considers a nonlinear cost function algorithm for estimating PV generation power. Energy management strategies are used and grid-tied renewable energy systems are tested using MATLAB-simulated weather conditions with seasonal variations to ensure optimal solar PV and grid output. Economic dispatch simulation results for 24 h with an hourly resolution, monthly variation in solar PV irradiance (kWh/m^2), and energy injected into the grid show that all generation units contributed proportionately to meeting EVCS

demand. Further research will focus on wind turbine integration with electric vehicle charging station loading to achieve self-consumption. Recent advancements in EV charging strategies focus on mitigating power quality issues such as voltage fluctuations, harmonic distortion, and load imbalance caused by uncoordinated, high-RES penetration charging. Adaptive charging algorithms and coordinated scheduling dynamically manage charging based on real-time grid data, enhancing grid stability. Integration with smart-grid systems facilitates real-time communication among EVs, chargers, and utilities, leading to better load forecasting and grid balancing. Metaheuristic algorithms have proven effective in regulating power quality across various scenarios. Vehicle-to-grid (V2G) technology is increasingly recognized for its potential to transform EVs into mobile energy storage units, supporting grid stability and enhancing energy efficiency.

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Data Availability Statement: No new data were created, and data used are referenced in the paper.

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Abbreviations

$C_{evcs,i}(P_{evcs,i})$	EVCS on-grid transmission line spinning reserve operating cost
$C_{v,i}(P_{v,i}), C_{m,i}(P_{m,i})$	PV ith and wind mth on-grid transmission line
C_{PVi}, C_{mi}	PV ith and wind mth operating cost
$C_{bat}^{C,max}, C_{bat}^{D,max}$	battery charging and discharging maximum cost
C_{bat}^C, C_{bat}^D	battery charging and discharging cost
$C_r(P_{ri})$	grid transmission line spinning reserve operating cost
C_t^{FA}	cost of operating the fuel cell at time t
C_t^{MT}	cost of operating the wind turbines at time t
C_t^{MT+FC}	total grid operating cost at time t with both wind turbines and fuel cells
$C_t^{grid}, C_t^{bat}, C_t^{RES}$	grid, battery, RES social cost
E_{bt}	battery model equation
E_{bt}^{cap}	battery storage capacity
$p_{Gi}^{min}, p_{Gi}^{max}$	minimum and maximum generated power
$p_{Gi}^{up}, R_{Gi}^{down}$	ramp-up and -down generated power
p_{PVi}^t, p_{mi}^{dm}	PV ith output and wind mth power at time t horizon
p_{bt}^C, p_{bt}^D	battery charging and discharging power
$p_{ess}^{min}, p_{ess}^{max}$	energy storage system charging or discharging power
P_{gi}	total power generation of the system
P_{ri}	real power generation of grid transmission line spinning
$P_s^t C_s^t$	cost of distribution network and operation cost at time t
$V_{Dk}^{min}, V_{Dk}^{max}$	intra-hour voltage dispatch
η	battery charging and discharging efficiencies
	spinning reserve operating cost

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