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Economic Power Dispatch of a Grid-Tied Photovoltaic-Based Energy Management System: Co-Optimization Approach

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Abstract: The requirement for the integration of power plants due to the cyclical rise in electrical energy consumption is due to the fluctuating load demand experienced with the current grid systems. This integration necessitates effectively allocating loads to the power plants for a minimum grid-tied transmission line cost, while meeting the network constraints. In this paper, we formulate an optimization problem of minimizing the total operational cost of all committed plants transmitted to the grid, while also meeting the network constraints and ensuring economic power dispatch (EPD) and energy management system co-optimization. The developed particle swarm optimization (PSO) method resolves the optimization problem using a piecewise quadratic function to describe the operational cost of the generation units, and the B coefficient approach is employed to estimate the transmission losses. Intelligent adjustments are made to the acceleration coefficients, and a brand-new algorithm is suggested for distributing the initial power values to the generation units. The developed economic power dispatch strategy successfully demonstrated an imperative cost reduction, with a connected load of 850 MW, 1263 MW, and 2630 MW of power demand, contrasted with previous PSO application cost values percentage, maximum yearly cost savings of (0.55%, 91.87), (46.55%, 3.78), and (73.86%, 89.10), respectively, and significant environmental benefits. The proposed co-optimization approach can significantly enhance the self-consumption ratio compared to the baseline method.

Keywords: economic power dispatch; photovoltaic (PV); particle swarm optimization; co-optimization; energy management system

MSC: 37N40

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1. Introduction

Renewable energy sources have led to a new era for stability enhancement and future load expansion in the power system. The regular increase in the cost of power from the grid, the environmental concerns, and the depletion of fossil fuel reserves with or without market manipulation have increased the electrical demand in recent years [1]. Photovoltaic (PV) campaigns, energy storage devices, and electric vehicles (EVs) are growing in popularity as the penetration of renewable energy resources (RESs) in distribution systems deepens [2]. The demand from the distribution networks may be met (in part) by such RESs, which can offer grid services such as voltage regulation. For the total energy management system and transmission (EMS&T) networks, it has become operationally desirable and economically sensible to incorporate RESs for energy delivery, without interfering with the distribution system's operation [3]. The power networks of many nations are designed as a networked system that heavily relies on conventional sources of generation. To adapt to changing demands, this structure needs to be improved. All nations' energy sectors now require integrated energy planning to sustainably grow [4]. As the green revolution spreads globally and RESs continue to be adopted, large interconnected and meshed electrical networks are also acting more and more as low-inertia systems. Therefore, more research should be carried out on the connections between RESs' penetration and variability, ESS size, scheduling choices, and frequency stability [5]. However, a recent study [6] demonstrated how short-term fluctuation in PV plants can vary in duration and amplitude, with the greatest perturbation reaching 60% of the plant's rated power in less than 30 s. If realistic choices on storage investment or unit scheduling in optimization algorithms are to be made, these short-term fluctuations must be considered. The updated assessment of the frequency-constrained problem, a categorization of the various techniques described in the literature, and a criticism of their numerous drawbacks are all provided in [7]. Additionally, the authors put forth a linear model that eliminates the need for external time-domain simulations by directly incorporating frequency constraints into a MILP method. However, they did not consider the impact of rapid short-term variations in RESs, along with limitations on generator ramping and the use of ESSs, on the frequency stability. Options such as using the minimum value or the maximum ramping capacity were considered, however, these can result in a nonlinear issue. The authors of [8] proposed a nonlinear model that takes frequency security restrictions and transient period dynamics into account. Their work dealt with the formulations of fluctuations in solar power balances and the proper allocation of spinning reserves from ESSs before and after contingencies, taking the generator's transient period dynamics or ramping capacity into consideration. As a result, the particle swarm optimization methods pay special attention to the frequency stability requirements and the appropriate sizing of spinning reserves, such as frequency containment reserves (FCR) and frequency restoration reserves (FRR), as presented in [7]. The sun's irradiance present at a site determines the solar panel's generation schedule. Seasons and the time of day both have an impact on solar irradiance variations [9,10]. For an accurate output value, the sun's irradiation must, therefore, be adequately modeled, simulated, and predicted using a variety of techniques.

Economic power dispatch (EPD) is a crucial and ongoing phase in a power system's operational planning. The process of allocating producing power to the grid units to economically supply the system load is described as the general economic dispatch problem [11]. In this scenario, constraints such as generation caps, power balance, etc., are crucial factors to consider. Many researchers have concentrated on the improvement in general economic dispatch problems, whereas research on dispatch considering renewables is limited [12–14]. Economic dispatch was initially implemented using equal incremental costs, and then transmission loss and penalty factors were subsequently added [15].

Particle swarm optimization (PSO), differential evolution (DE), genetic algorithms (GA), and evolutionary programming (EP) are examples of intelligent techniques that are used to solve complex dispatch problems that consider valve points, banned operation zones, and quadratic cost functions [16]. Topology, enhanced PSO, adaptive PSO, and mutation PSO are examples of quantum-behaved PSO, barebones PSO, chaotic PSO, fuzzy PSO, the PSO time-varying acceleration coefficient, opposition-based PSO, and mutation PSO. PSO hybrids include GA, evolutionary programming, artificial immune system (AIS), Tabu search (TS), ACO, simulated annealing (SA), artificial bee colony (ABC), DE, biogeography-based optimization (BBO), harmonic search (HS), Lagrange relaxation (LR), and guaranteed-convergence PSO with Gaussian mutation (GPSO-GM), among others [16,17]. PSO extensions include, among others, multi-objective, restricted, combinatorial, and discrete (binary and integer) optimization. PSO is a versatile, flexible technique that can tackle any difficult optimization problem. There are numerous definitions of flexibility. Our research defines flexibility as an algorithm's ability to automatically adjust and adapt to account for uncertainty and produce the best available outcomes. Implementation issues may have an impact on the algorithm's computational effort. Thus, selecting the appropriate programming language, libraries, and compiler is critical for optimizing the optimization performance, particularly in terms of the computational effort. Furthermore, the operating system and other computer components (such as the CPU and RAM) are critical for performing a wide range of jobs with a high computational performance. Engineers must examine numerous alternatives and choose which solutions best-match the standards.

Additionally, the engineers must identify the available resources to efficiently tackle an optimization issue. Prohibited operation zones and multiple fuel options are considered by the fuel cost function in a nonconvex issue [18,19]. The restricted working areas considered in this study correspond to restrictions on the unit's power output brought on by vibrations in a shaft-bearing or steam valve action. Therefore, to protect the unit and achieve the most cost-effective operation, Table 1 presents the outlines of the many optimization strategies.

Table 1. The many optimization strategies utilized to discover the best feasible solution to the cost reduction problem.

Objective Function	**Ref.**	**PSO Strategies for the Best Feasible Solution to the Cost Reduction Problem**
Costs of systems: annualized cost of investments, cost of replacement, cost of upkeep, and cost of load loss	[20]	Designing a combination wind–PV–fuel cell system makes use of PSO. Finding the best deal while maintaining the system's dependability for 20 years are the goals. The simulation is run with a 1 h timestep over the course of a year.
Energy pricing and overall net-present cost	[21]	PSO is used to determine the ideal size for a PV, diesel, biogas, biomass, micro-hydro, and battery for 25 years of operation. Under the given dependability requirements (anticipated energy not delivered), economic criteria (net-present costs), renewable factor, and CO_2 emission, the cost of energy is the primary parameter that needs to be minimized. Finding a hybrid system configuration that guarantees the lowest cost of energy is the goal.
Present worth of the total profit, maintenance expenditures, and capital expenses.	[22]	The PSO's goal is to determine the ideal PV module installation parameters, including the quantity of PV modules, their tilt angles, their positioning, and their distribution among the DC/AC converters. The goal of the optimization is to maximize net profit over the course of the entire operation.
Total energy cost of EMS system	[23]	Real-time EMS PSO implementation in an MG. Every three minutes, the simulation is updated. The goal is to reduce the system's overall energy cost.
Total operating costs	[24]	To reduce MG's overall operating costs, PSO was used. When optimizing, market rates and bids for power exchanges of the local grid are considered.
Fuel and OM costs and the purchase cost from the utility	[25]	EMS is based on reorganizing PSO (RegPSO) in accordance with the daily schedule. The two MG operation scenarios used in the study are grid-connected and an isolated grid. The goal is to reduce the cost of fuel, OM, and utility purchase, while increasing the revenue from selling energy to the utility.
Total operating cost and pollutant emissions.	[26]	Fuzzy self-adaptive PSO to reduce operating expenses and emissions of pollutants. The authors compare the findings with those of classic PSO and GA under various situations of MG operation to assess the performance of the suggested technique.
Energy cost of the system by saving on fuel costs	[27]	In a community in Nigeria, PSO is applied to an HRES for the supply of water and power. By reducing the cost of fuel, the optimization seeks to reduce the system's energy cost. Two operational modes—RESs with diesel engines and RESs alone—are used to conduct the investigation.
Operating costs, including the fuel and start-up costs	[28]	The introduction of EMS-based, self-adaptive, modified theta PSO aims to reduce operating expenses, including fuel and start-up costs and power exchange fees between the MG and the main grid.
Operating costs	[29]	ESS-based PSO has three goals: ESS operating cost minimization, ESS efficiency maximization, and ESS lifetime degradation minimization. Three factors: operating costs, efficiency, and lifetime degradation, are used to compare the simulations.
Capital, OM, and generation costs.	[30]	Four factors are taken into consideration as key performance indicators (KPIs) to assess the effectiveness of this method: cost, reliability, quality, and environmental impact. Hybrid PSO and pattern search are utilized to optimize the design and operation.

Table 1. *Cont.*

Objective Function	Ref.	PSO Strategies for the Best Feasible Solution to the Cost Reduction Problem
Optimal type, size, and operation of a smart grid	[31]	To overcome a master–slave objective function and determine the best type, size, and operation of a smart grid, PSO was utilized.
Capital investment and generation costs.	[32]	For determining the ideal size and operation of MG systems, the guaranteed-convergence PSO and Gaussian mutation (GPSO-GM) combination is reported. Reduced capital expenditure and generation costs are the goal. The accuracy of the results is ensured via Gaussian mutation and guaranteed convergence.
Operation costs and emissions UC	[33]	The primal-dual-interior point approach is utilized to tackle ED problems, while quantum-inspired BPSO (QBPSO) is employed to solve the UC. Finding a balance between running costs and emissions is the goal.
Fuel costs of UC and ED problems of thermal generation units	[34]	UC and ED issues with RESs in thermal generation units. To reduce the fuel expenditures of thermal units, the unit start/stop selection is carried out using a priority list (PL), and PSO calculates the ideal power flow. We contrast PL-PSO with PL-GA and DP. It is assured that PL-PSO will locate the ideal solution with the least amount of computation
Cost minimization of the UC problem of thermal-unit-integrated wind and solar power	[35]	Through GA-operated PSO, the UC of thermal-unit-integrated wind and solar power is resolved. The quick convergence of the optimization solution is ensured by the combination of GA and PSO. The suggested approach, unlike GA, the integer-coded genetic algorithm (ICGA), and the Lagrangian relaxation and genetic algorithm (LRGA), guarantees the solution of the cost minimization problem.
Energy cost, identifying a secure optimal UC schedule for thermal units with a solar power plant	[36]	Two-stage formulation of the optimization problem: UC in the first stage and OPF in the second. To choose an ON/OFF schedule for thermal equipment, the BPSO is used. The suggested method seeks to reduce energy costs and find a safe optimal UC schedule for thermal units connected to a grid-connected solar power plant.

However, no well-defined joint EMS and EPD optimization problem has yet been put forth in previous works, making it challenging to assess the overall effectiveness of their solutions. Additionally, since the joint EMS and EPD co-optimization problem typically has a larger feasible set of solutions to find, solving the network operation cost one at a time may not yield the best result. The outputs of the large generator's connection and those of the RESs in the networks are jointly optimized. A system for allocating, sizing, and analyzing RESs (solar PV generator sources) is presented. For the grid-tied PV power system to operate reliably, there must be a high penetration of intermittent RESs. These swift reserves can be provided by aggregated and coordinated loads, but they represent energy-constrained and uncertain reserves (in terms of their energy status and capability). Optimization-based strategies enable one to build a suitable trade-off between closed-loop performance and the resilience of the energy power dispatch to efficiently dispatch uncertain, energy-constrained reserves. The uncertainty linked to aggregations of RESs with energy constraints, i.e., a localized energy storage system for each connected generator, is therefore studied in this paper.

Here, we formulate an optimization problem of minimizing the total operational cost of all committed plants transmitted to the grid, while meeting network (power flow) constraints and ensuring economic power dispatch (EPD) at the transmission level. Optimization-based energy management systems are used to estimate the power flow of the grid-tied systems in MATLAB-simulated clear and cloudy weather conditions, with seasonal variations for optimal solar PV and grid output for the EPD model. The rest of the paper is organized as follows: Section 2 describes the related works on energy management systems and transmission. Section 3 presents the integration of solar PV modeling and the estimation of power output from a PV array and economic dispatch problem. In Section 4, the results and discussion are presented on the integration of solar energy into economic dispatch, and the cost optimization for various scenarios is described. Section 5 concludes the paper.

1.1. Problem Overview

The reliability issues caused by the uncertain behavior of RESs are caused by their dependability on naturally occurring phenomena, such as varying light intensity, weather conditions, and irradiance. These inadequacies make RESs uneconomical and challenging to integrate into electric grids that are rivaled by conventional hydrocarbon fuel-based generations. One of the practical methods to rise above these deficiencies is to install dispatchable-generation RESs into the electric grid, such as energy storage systems (ESSs) [37]. Integration of such RESs with higher seasonal variations is economically beneficial to use with these conventional existing power generation sources, but this increasing diversity of generation sources makes the operating strategy for these hybrid grids a challenging problem, and the cost characteristics of each RESs generator-produced power is also a nonlinear function [38]. The problem of achieving the minimum cost is the primary focus in this paper, presented as the total operating cost objective function.

Under the restrictions of the power-balancing constraint and the upper and lower operational limitations of the generators, the economic power dispatch problem is an optimization problem with the objective function of reducing the total operational cost. By ensuring that the total power generated equals the sum of the load demand plus transmission network losses, the power-balance restriction prevents overproduction. The grid-tied photovoltaic-based energy management systems problem can be mathematically stated as in Equation (1), in a power system which consists of committed units, with generation output, P_{Gi}, coupled to a single bus-bar, at a cost, C_{Gi}:

$$\varnothing_1 = \sum_{i=1}^{T} \left(\sum_{g=1}^{N_G} C_{Gi}(P_{Gi}) + \sum_{i=1}^{N_R} C_r(P_{ri}) + \sum_{v=1}^{N_V} C_V(P_{Vi})\right) + E_{batt} + \gamma, \quad (1)$$

where $C_G(P_{Gi})$ is the grid cost function, $C_r(P_{ri})$ is the grid transmission line-spinning reserve operating cost, $C_V(P_{Vi})$ are the cost functions for solar PV generators, and E_{batt} is the battery model equation.

$$C_g(P_{Gi}) = \sum_{g=1}^{NG} N_G\left(a_g P_{Gi}^2 \Delta t^2 + b_g P_{Gi} \Delta t + c_i\right), \quad (2)$$

$$C_r(P_{Gi}) = \sum_{r=1}^{NR} N_{R\rho r} P_{ri} \Delta t, \quad (3)$$

$$C_v(P_{Vi}) = \sum_{v=1}^{NV} N_V \tau_v P_{Vi} \Delta t V, \quad (4)$$

As illustrated in Equations (2)–(4), $a_i P_{Gi}^2 + b_i P_{Gi} + c_i$ implies the operating cost of solar PV and the grid, ai, bi, and ci are the unit coefficients of the power cost, and P_{Gi} is the unit output i of the real power. Note that in this paper, $\Delta t = 1$ denotes a simulated period. The second component of the total cost is the renewable component of the model indicated in (5):

$$\gamma = \sum_{i=1}^{T} \left(\alpha\left(\sum_{g=1}^{NG} N_G P_{Gi} + \sum_{v=1}^{NV} N_V P_{vi}\right) + \sum_{v=1}^{NV} N_V P_{vi}\right)^+, \quad (5)$$

where the percentage-based renewable requirement is the penalty imposed on the grid transmission line for failing to meet the customer obligation. The sign function (.)+ is equivalent to 0 in the absence of the RES fulfillment requirement. The energy regulator often gives the penalty γ as an annual amount. It is possible to convert this penalty value into a daily penalty value that reflects the daily efficient dispatch of power.

Constraints

The power-balance constraints are the total generation, $\varnothing_1$, equal to the total system power demand, P_D, plus the transmission loss, P_{Loss}:

$$P_{BALANCE} = P_D + P_{Loss}, \tag{6}$$

The power plant geographical distributions and grid-tied transmission losses are a function of its value and number of unit generation expressed as quadratic functions:

$$P_{Loss} = \sum_{i=1}^{m} \sum_{j=1}^{m} P_i B_{ij} P_j + \sum_{i=1}^{m} B_{0i} P_i + B_{00}, \tag{7}$$

The power generation of all the grid buses has maximum and minimum limits: $P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max}$, where P_{Gi}^{min}andP_{Gi}^{max} are the maximum and minimum grid bus output limits.

The power output of any generator has a maximum value dependent on the rating of the generator, with a minimum limit set by the capacity factor of the solar PV plant. The economic dispatch problem has been scheduled based on the following constraints:

Equality constraints: $\sum_{i-1}^{n} P_{Gi} = P_D$
Inequality constraints: $P_{Gimin} \leq P_{Gi} \leq P_{Gimax}$

The plants operate with equal incremental operating costs until their limits are violated. As soon as the plant reaches the limits (maximum and minimum), its output is fixed at that point and maintained constant.

1.2. Contributions

To effectively operate grid-tied solar PV power systems with high-RES penetration, this paper addresses some of the modeling challenges and formulations of power-balance variations. Here, we look at RESs' penetration and variability, the size of energy storage systems (ESSs), and correct allocation from ESSs of spinning reserves (frequency containment reserves) in the face of uncertainty, enabling lowering the power demand for ESSs.

In the multi-objective optimization problems, we maximize the reliability by minimizing the loss of grid supply (LGS) and the operational cost problems, which consist of numerous objective functions and constraints that were simultaneously realized using PSO.

In this paper, we formulate an optimization problem of minimizing the total operational cost of all committed plants transmitted to the grid, while meeting network (power flow) constraints and ensuring economic power dispatch (EPD) at the transmission level.

The developed particle swarm optimization (PSO) method resolves the optimization problem using a piecewise quadratic function to describe the operational cost of the generation units, and the B coefficient approach is employed to estimate the transmission losses.

2. Materials and Methods

2.1. Numerical Study and Simulation of Different Case Studies

The proposed dispatch case studies depend on estimations of power generation into the grid systems and the electric load demand. In this section, a detailed description of these mathematical models is presented. The generation sources discussed in this paper can be categorized into two types related to their capability of controlling power generation. First is the dispatchable type, which can control the dispatchable transmitted power. Second is the non-dispatchable type, which lacks the dispatch ability, for example, solar PV. The grid relates to the RESs via a single point, which is called the point of common coupling (PCC).

2.1.1. Non-Dispatchable Energy Sources

Solar Photovoltaic (PV)

Solar photovoltaic (PV) is a non-dispatchable energy source that harvests electric power from solar radiation. Solar power plants are viewed as lossless considering the literature review on EPD and renewable energy sources, and the climatic consequences of their power outputs are not considered [39]. Due to the resistance and reactance of the transmission lines, which are used for both the transfer of solar power and grid electrical energy, there will be significant losses. The irradiance, which in turn depends on the environmental conditions, determines solar power. In this paper, a set amount of loss is considered when transmitting grid power across the current transmission lines. The case studies are taken into consideration for various climatic circumstances (clear and cloudy conditions) because the output of solar power is climate-dependent. The cost of installation is not considered in this model because it is anticipated that public utilities will develop solar power plants. The objective of the economic power dispatch problem of the electrical grid power is to schedule the committed electrical power-generated outputs to meet the required load demand while satisfying the system equality and inequality constraints.

Model for Economic Power Delivery Coordination Using Solar PV Energy

The output power of a solar panel is mostly dependent on estimating varied irradiance values, which calls for an appropriate functional model. The MATLAB function was simulated to obtain seasonal solar irradiance model data before the function. This function estimates the output of a solar panel based on clear and cloudy days and then calculates the overall output of all solar PV systems.

The second objective function increases the level of RES energy penetration and optimal power flow, as presented in [40]. In addition to the total operating cost in (1), the maximization is shown in (8) as:

$$\varnothing_2 = \sum_{i=1}^{T} \left(\sum_{v=1}^{N_V} P_{Vi} \Delta i \right), \tag{8}$$

This solar-generated electricity is included at the point of common coupling and is seen as negative demand. The results of economic power dispatch utilizing this model were then compared. The electricity produced by PV arrays is regarded as a negative load for incorporating solar PV energy into the existing grid bus (9) and revised as the optimal power flow optimization problem, formulated to maximize the economic benefits of large-scale solar PV and hybrid energy generators in a time horizon of T intervals, and modeled to minimize the cost function of energy generation to satisfy the operating constraints for optimal power output.

Minimized as:

$$C^{RT}(PV, u) = \mathrm{F}(P_G) \sum_{k=1}^{N_G} C_i(P_{Gi}), \tag{9}$$

Constraints

The total power generated by the grid-tied solar PV is equal to the demand per hour at each load bus:

$$\sum_{g=1}^{NG} N_G P_{Gi} + \sum_{v=1}^{NV} N_V P_{Vi} = \sum_{b=1}^{NB} N_B P_{b,i} \quad \forall i, \tag{10}$$

The grid-tied bus maximum permitted ramp rate is shown in constraints (11) through (14), as:

$$P_{Gi} - P_{Gi-1} \le UG\Delta i \quad \forall i, \forall G, \tag{11}$$

$$P_{ri} - P_{ri-1} \le UR_G \Delta i \quad \forall i, \forall \tau, \tag{12}$$

$$\sum_{g=1}^{NG} N_G P_{Gi} + \sum_{v=1}^{NV} N_V P_{Vi} = \sum_{b=1}^{NB} N_B P_{b,i} \quad \forall i, \tag{13}$$

$$P_{ri-1} - P_{ri} \le DR_G \Delta i \quad \forall i, \forall \tau \tag{14}$$

Subject to the grid-tied bus and solar PV maximum capacity limitations (15) to (17):

$$P_{Gi} < min(P_{G,max} P_{Gi-1} + UR_G \Delta t) \quad \forall i. \tag{15}$$

$$P_{Gi} < max(P_{G,min} P_{Gi-1} + UR_G \Delta t) \quad \forall i. \tag{16}$$

$$P_{Vi} \leq P_{Vimax} \quad \forall i. \tag{17}$$

Subject to the spinning reserve of the grid-tied bus constrained by the generator's capacity:

$$P_{ri} \leq P_{Gmax} \quad \forall i, \forall G. \tag{18}$$

Subject to each generator's maximum spinning reserve, not greater than the grid-tied bus capacity:

$$0 \leq P_{ri} \leq SSR_{rmax} \quad \forall i. \tag{19}$$

Constraint (20) shows that the dispatch period's spinning reserve is not greater than the system's spinning reserve requirements:

$$\sum_{r=1}^{NG} N_R P_{ri} \geq SSR \quad \forall i, \tag{20}$$

In case the RESs' generators are unable to provide any power, Constraint (21) ensures that there is enough spinning reserve requirement, $SSR_{r.max}$, to guarantee that the demand can be met by the grid-tied bus:

$$\sum_{i=1}^{NG} N_G P_{Gi} + \sum_{r=1}^{NR} N_R P_{ri} \geq \sum_{b=1}^{NB} N_B P_{b,} \quad \forall i, \tag{21}$$

The power flow restrictions are represented by Constraint (22), calculated using the optimal power flow:

$$-P_{Lossmax} \leq P_{Li} \leq P_{Lossmax} \quad \forall i, \forall l, \tag{22}$$

Total generation should meet the total power demand and can be determined from the optimal power flow, as:

$$P'_D = P_D - \sum_{GiViS=1}^{n} P_{Gi} + P_{ViS,} \tag{23}$$

where P'_D is the new power demand, and $\sum_{iS=1}^{n} P_{ViS}$ is the sum of the solar PV generators.

2.1.2. Dispatchable Energy Sources

Batteries

The battery's function is to store electricity, absorb extra and fluctuating electric power, and discharge power in times of need. When it is economical or when no excess energy is obtainable, the batteries are recharged by the grid. The electric power flow cycles of a battery bank rely on the following constraints: the minimum discharge level, self-discharge rate, recharging cycles, shelf life, and recharge/discharge rate. The battery storage charge model can be formulated as outlined below.

Model of Battery Charge Storage

Unreliable renewable energy sources (RESs) are the main cause of the microgrid's peaks and gorges. The seasonal changes affect a higher percentage of microgrids if we take them into account. Dispatched energy sources, on the other hand, produce less uncertainty and fluctuation, and their societal cost is already recognized. Another key player in the power dispatch strategy is an energy storage system (ESS), which is handled in a specially optimized manner due to its limits. The main goals are to cut back on social costs and grid interactions. The cumulative societal cost equation for RESs is described as ESS performing a different role from the other microgrid components, e.g., by charging the ESS when power is virtually free (coming from the RES) or when the utility grid price is the lowest, while the charge quantity in each battery is determined by the SOC, which is measured by estimation methods [41,42]. By combining two methods, ESS can reduce societal costs, as follows: (1) profiting from the pricing differentials between peak and off-peak hours, and (2) recharging from RESs with excess energy reduces transmission. In this paper, responsive ESSs are distributed as balancing reserves and have a baseline consumption (i.e., aggregated baseline consumption of individual flexible loads in an ESS). The ESS can react to the mismatches brought on by forecast errors by regulating its controlled load over time. Any reduction (increase) in the ESS's consumption compared to the starting point is referred to as discharging (charging). Since the ESSs are responsive, they constitute a valuable resource to address demand–supply mismatches at high levels of renewable penetration. The ESS's energy-constrained properties, in contrast to those of a traditional generator, demand careful management of its state of charge. This work shows that the only factors affecting an ESS's energy evolution are the net charging orders. In addition, unlike grid-tied batteries, the system operator's level of flexibility is unknown and time-varying. In other words, the system operator's access to an ESS's flexibility can be translated into upper and lower limits on the ESS's energy state. These upper and lower boundaries depend on several stochastic factors, such as the weather and human behavior. Here, ESSs were modeled with chance constraints and were probabilistically formulated to account for these factors.

Equations (24) and (25) describe the explicit battery operating cost model while charging and discharging:

$$C_{charging} = C^{C}_{batt} + C^{C,max}_{batt}, \tag{24}$$

$$C_{discharging} = P^{D}_{batt} + P^{D,max}_{batt}, \tag{25}$$

Subject to power constraints for ESS charging or discharging: $P^{min}_{ess} \leq P_{ess} \leq P^{max}_{ess}$; when ESS is charged, $P_{ess} < 0$, while when ESS is discharged, $P_{ess} > 0$.

The local optimization function in Equation (26) for minimizing the total operating cost of renewable energy production, while accounting for uncertainty grid constraints, is given as Equation (27), and Equation (28) was adapted from the work of [43]. These models will be developed in real time, with intra-hour dispatch intervals, while accounting for operating and security limitations following the guided model.

$$\sum\nolimits_{t=1}^{Nsub} \sum\nolimits_{i=1}^{Ng} C_{Gi}(P_{Gi}) + \sum\nolimits_{t=1}^{Nsub} \sum\nolimits_{i=1}^{Nw} C_{PV}(P_{V)}), \tag{26}$$

Subject to grid power network constraints:

$$max\left[P^{min}_{Gi}, P^{T-1}_{Gi} - R^{down}_{Gi}\right] \leq P_{Gi} \leq \min\left[P^{max}_{Gi}, P^{T-1}_{Gi} + R^{up}_{Gi}\right] V^{min}_{Dk} \leq V^{max}_{Dk}. \tag{27}$$

The mathematical modeling of the MINLP solvers (Equations (28) and (29)), performed to compute the lower bound on the optimum objective function's inputs obtained by enlarging feasible sets, i.e., ignoring constraints, was guided by the work of [44].

$$z_{MINLP} = \min_{x} f(x) \leq \eta, \tag{28}$$

where η is the charging and discharging efficiencies of the batteries, subject to g as $0 \leq P^{C}_{batt} \leq P^{C,max}_{batt} u^{C}_{bt}\ 0 \leq P^{D}_{batt} \leq P^{D,max}_{batt} u^{D}_{batt}$, and (x) is an objective function or cost function (minimization), or grid function (maximization), for an optimal solution: $x \in X, x_{I} \in \mathbb{Z}^{/\mathbf{I}/}$ for all I ∈ I.

For a convex function $f(x) : \mathbb{R}^n \to \mathbb{R},\ g : \mathbb{R}^n \to \mathbb{R}^m$, smooth, sometimes convex functions applied to the expected battery energy storage of the solar PV variable are bounded by the real power output of the convex function of the charging or discharging of the battery, given as:

$$E_{batt} = E_{batt-1} + P_{batt}^{C} \eta_{batt}^{C} \Delta t - P_{batt}^{D} \frac{1}{\eta_{batt}^{D}} \Delta t. \tag{29}$$

Having constraints $0 \leq E_{batt} \leq E_{batt}^{cap}$ ensures that the energy in the battery does not exceed the storage capacity, E_{batt}^{cap}, with total power as: $P_{batt} = P_{batt}^{D} - P_{batt}^{C}$.

Proposed Optimization-Based Energy Management System

The study of the optimization-based EMS can be enriched by the developments of computational and mathematical programming methods, which predate the invention of digital computers and have revolutionized computation and numerical optimization. Design variables cannot take on random values in many practical applications because they must fulfill certain electrical or physical constraints. These limitations, also known as design constraints, are crucial for ensuring the stability and security of the system. The mathematical modeling restrictions are typical of the multi-objective function's inputs for hybrid energy systems [45].

Here, we adopted the convex MINLP, which relies on the mixed-integer quadratic program for an energy system with storage, and we found a near-optimal solution, for which a heuristic was developed in the branch-and-bound implementation of the model that facilitates online implementation [46]. The fundamental branch-and-bound approach, often known as the branch-and-cut (B&C) method, has been developed throughout the history of integer programming. This indicates that to tighten the formulation, in addition to branching, extra valid inequalities or cuts are placed at the nodes of the branch-and-bound tree. The variables to control the energy supply–demand balancing problem and power flow within different RESs in real time were motivated by this study. The aim was to investigate a broad and complex solution space with numerous objectives for utility integration, while using a guiding particle search optimization algorithm and various optimization problems. To compare its performance to other well-known optimization approaches described in the literature, the proposed PSO has been used here to solve EPD problems for several test systems that have been developed using the R2022b (MATLAB 9.9) window environment.

Economic Power Dispatch Problem

Kennedy and Eberhart introduced PSO as a multi-agent, parallel-search optimization method in 1995 [47]. PSO is based on swarm theory inspiration from the evolutionary strategies for the social behavior of fish, and bird flocking [48]. The PSO concept depends on applying different particles to find the best answer: every particle in the PSO algorithm represents a potential solution, and the optimization objective function evaluates these solutions to determine their fitness [49,50]. The number of answers doubles in the iteration until the best one is found, while more particles are imposed in each iteration, which promotes finding the best solution and cuts down on the number of optimization iterations. Particles move around in a multidimensional search space in the quest for the best solution. The particle memory (pbesti) stores the best experiences from each particle, and the best overall result from all particles is referred to as the global best particle (gbest). The following equations describe how each particle (i) adjusts its present position (xi) and velocity (vi) during flight based on its own experience and the experience of nearby particles. The economic dispatch problem aims to reduce the cost of supplying energy, subject to restrictions on the static behavior of the producing units, and assumes that the amount of power to be delivered by a given set of units is constant for a certain period. However, plant operators work to keep gearbox slopes within safe bounds to prevent reducing the life of their equipment. This restriction typically manifests as a cap on the rate at which the power output can grow or decrease. The dynamic economic dispatch is distinguished from the conventional, static economic dispatch by such ramp rate limits.

The dynamic economic dispatch cannot be solved for a single value of the load because these ramp rate limitations affect how the generators' output changes over time. Instead, it tries to reduce the cost of providing a specific demand profile. One of the primary roles of the operation and control of the power system is dynamic economic dispatch. It is a technique for allocating the outputs of the online generator to the anticipated load needs over a specific period to run an electric power system as economically as possible, while maintaining system security. Considering the limitations placed on system functioning by generator-ramping rate limits, this issue is one of dynamic optimization. The most precise version of the EPD problem is the dynamic economic dispatch, which is also the most challenging to answer due to its high dimensionality [51,52].

Particle Search Optimization Model Formulation

The PSO algorithm has two major equations. Equation (30) is the velocity equation, in which each particle in the swarm changes its velocity based on the computed values of the individual and global best solutions, as well as its current position. Individual and social acceleration factors are represented by the coefficients c_1 and c_2. They are known as trust parameters, with c_1 representing a particle's confidence and c_2 representing a particle's confidence in its neighbors. They define the stochastic influence of cognitive and social behaviors, in conjunction with the random numbers r^i_{1k} and r^i_{2k}. The formulation of the PSO, which is denoted as the stochastic vector v^i_k, is given by:

$$v^i_k = c_1 r^i_{1k}\left(\mathscr{P}^i_k - x^i_k\right) + c_2 r^i_{2k}\left(\mathscr{P}^g_k - x^i_k\right). \tag{30}$$

where r^i_{1k} and r^i_{2k} represent two uniform, real random scalar numbers between 0 and 1, updated at every iteration k, and for each solar PV generation source i in the swarm. Hence, r^i_{1k} and r^i_{2k} simply scale the magnitudes of the cognitive and transmission line powers: $c_1 r^i_{1k}(\mathscr{P}^i_k - x^i_k)$ and $c_2 r^i_{2k}\left(\mathscr{P}^g_k - x^i_k\right)$. Studying the stochastic contribution, v^i_k, in the composition of the instantaneous search domain provided in Equation (31), the cognitive vector $\mathscr{P}^i_k - x^i_k$ and transmitted powers $\mathscr{P}^g_k - x^i_k$ consist of the directions and distances from the solar generator's location, x^i_k, to the best solar generator location, $\mathscr{P}^i_k$, and the best global location, $\mathscr{P}^g_k$. The cognitive and transmitted powers can be anything from normal to parallel, with respect to each other. When the cognitive vector $\mathscr{P}^i_k - x^i_k$ and the transmitted powers $(\mathscr{P}^g_k - x^i_k)$ are not parallel, Equation (32) may be interpreted as the vector equation of a bound plane, $\mathscr{P}^i_k$, in n-dimensional space. The plane is bounded since the length of the cognitive and social vectors are independently scaled by the finite scalars $c_1 r^i_{1k}$ and $c_2 r^i_{2k}$.

The angle $\overline{\theta}$ between the cognitive vector $\mathscr{P}^i_k - x^i_k$ and the transmitted powers $(\mathscr{P}^g_k - x^i_k)$ may be determined using:

$$\overline{\theta} = \cos^{-1}\left(\frac{\left|(\mathscr{P}^i_k - x^i_k) * (\mathscr{P}^g_k - x^i_k)\right|}{\left\|(\mathscr{P}^i_k - x^i_k)\right\|\left\|(\mathscr{P}^g_k - x^i_k)\right\|}\right). \tag{31}$$

If $\overline{\theta} = 0$, the vectors $(\mathscr{P}^i_k - x^i_k)$ and $\left(\mathscr{P}^g_k - x^i_k\right)$ are parallel, and if $\overline{\theta} = 90$, the vectors $(\mathscr{P}^i_k - x^i_k)$ and $\left(\mathscr{P}^g_k - x^i_k\right)$ are perpendicular. Scaling each solar PV generator's sources independently, each component of $(\mathscr{P}^i_k - x^i_k)$ and $\left(\mathscr{P}^g_k - x^i_k\right)$ is replaced with scalar random numbers in the stochastic vector, from r^i_{1k} and r^i_{2k} to $\mathscr{R}^i_{1k}$ and $\mathscr{R}^i_{2k}$:

$$v^i_k = c_1 \mathscr{R}^i_{1k}\left(\mathscr{P}^i_k - x^i_k\right) + c_2 \mathscr{R}^i_{2k}\left(\mathscr{P}^g_k - x^i_k\right), \tag{32}$$

The $\mathscr{R}^i_{mk}$ random diagonal matrices are explicitly given as:

$$\mathscr{R}^i_{mk} = \begin{bmatrix} \mathscr{P}^i_{11k} & 0 & \cdots & 0 \\ 0 & \mathscr{P}^i_{22k} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & \cdots & \mathscr{P}^i_{nnk} \end{bmatrix}, \ \text{m} = 1, 2, \tag{33}$$

With $0 < \mathscr{P}^i_{jjk} < 1, j = 1, \ldots\ldots.., n$, a uniform random number for independently scaled solar PV generator sources.

3. Proposed Co-Optimization of EPD and EMS PSO Algorithm

For parameter selection, the optimization parameters govern the algorithm's performance when looking for the global optimum of a problem, so the choice of these parameters is an important stage in the optimization process. The following is a description of the analysis of each parameter's selection. If the number of particles is small, it can influence the PSO performance. We can reduce the number of iterations by increasing the number of particles. As a result, the algorithm can still discover the best answer. The particles are guided toward pbest and gbest by the acceleration constants c_1 and c_2. Smaller values may constrain particle movements toward a good solution. A large value, on the other hand, may cause the particles to migrate away from the solution. Particle velocity is frequently maintained within a specified range to prevent particles from leaving the search space. If Vmax is too small, particles will only explore the local best; if Vmax is too large, particles will skip over an acceptable solution. The weight of inertia balances local and global explorations. A high inertia weight results in a strong global search, whereas a low inertia weight results in a strong local search. During the optimization process, the value of the inertia weight can change. As a result, the literature recommends self-adaptive techniques that change the value of the inertia weight during the search phase. The method must not end before obtaining the global optimum, so the stopping condition is critical in PSO. To avoid wasting computer resources during execution, the method must automatically end when the optimal solution is found. As a result, the choice of stopping criterion has a significant impact on the duration of the optimization procedures. The PSO algorithm's performance is influenced by the settings and stopping criteria used. The algorithm can produce better results if appropriate parameters and stopping criteria are used, as depicted in the following sections.

3.1. EMS Classical Algorithm

Step 1—Input decision variables lower and upper bound, for battery MinMax (PgridV, PbattV, EbattV)
Step 2—Minimize the cost of electricity from the grid objective: dt*cost*PgridV—Final Weiht*EbattV(N)
Step 3—Power input/output to battery Constraints.energyBalance = Optimconstr(N)
Step 4—Power load with power from PV, grid, and battery Constraints.loadBalance = Ppv+PgridV+PbattV-Pload
Step 5—Linear program options = Optimoptions(prob.optimoptions,)
Step 6—Parse optimization results

3.2. Solar PV–Battery–Grid Algorithm Steps

Step 1—PSO Settings

set.Nparticle; set.Niteration; set.weight; set.c1; set.c2;LGS;COESS;Voltage; set.Npv_min &max; set.Nbat_minmax; set.Ngrid_minmax

Step 2—Initiate Particles

particle.position; particle.velocity; particle.best_position; particle.best_LGS;particle. best_COESS;particle.best_Mark;particle=repmat(particle,1,set.Nparticle);best_global.posi—

tion=[]; best_global.LGS=[]; best_global.COESS=[];best_global.Mark=[];log_global=repmat (best_global,1,set.Niteration);

Step 3—Initiate Condition

temp_InitiateP(:,1)=randi([set.Npv_min,set.Npv_max],set.Nparticle,1);temp_InitiateP(:,2)=randi([set.Nbat_min,set.Nbat_max],set.Nparticle,1);

temp_InitiateP(:,3)=randi([set.Ngrid_min,set.Ngrid_max],set.Nparticle,1); for n_par= 1:set.Nparticle particle(n_par).position=temp_InitiateP(n_par,:); particle(n_par).velocity=[0 0 0]; end clear n_par

Step 4—Main PSO

for n_ite=1:set.Niteration
for n_par=1:set.Nparticle
Calculate Mark; Bestparticle; Best Global; Velocity & New Position; Round Position; Limit Position

Step 5—Results

tpro=toc; fprintf('The optimum system size is:\n Npv=%d\n Nbat=%d\n Ngrid=%d\n with the LGS = %.3f%% and COESS = $%.2f\nCompute in %.2f s\n',... best_global.position, best_global.LGS*100,best_global.COESS,tpro);beep;

3.3. EPD PSO Algorithm Steps [53]

Step 1—Problem Definition

- Z=F(X) = P=PminActual+(PmaxActual-PminActual). *x
- Create a parse.m function P=ParseSolution(x,model)
- InputPmin=model.Plants.Pmin; Pmax=model.Plants.Pmax; P=Pmin+(Pmax-Pmin).*x; PZ=model.Plants.PZ; nPlant=model.nPlant; for i=1:nPlant; forj=1:numel(PZ{i})if P(i)> PZ{i}{j}(1) && P(i)<PZ{i}{j}(2)% Correction
- CreateModel for 3, 6, and 15 Units, committed generator variables; with a power demand of committed generators (particles) with uniformly random distribution, Pmin, Pmax, alpha, beta, gamma, P0, UR, DR, transmission loss, and over X (position).
- Develop CostFunction -@(x) MyCost (x, Model);
- Develop a model calculation C=alpha+beta.*P+gamma.*P.*P; PL=P*B*P'+B0*P'+B00;
- Decision Variables nVar = Model. nPlant (lower and upper bounds for 3, 6, and 15 Units, committed generator variables)

Step 2—PSO Parameters

- MaxIt—No. of iteration; nPop—Swarm Size; Constriction Coefficient—C_1 = chi*phi 1 as personal Coeff., C_2 = chi*Phi 2 as Global Coeff.; Velocity Limit

Step 3—Initialization

- BestSol.Cost = inf; for i=1; nPop, initialize position; initialize velocity;
- Evaluation of each committed generator's cost model considering the objective function value.
- Z=F(X) = P=PminActual+(PmaxActual-PminActual). *x; with or without prohibited zones
- Evaluation; Update Personal Best; Update Global Best; BestSol = Particle(1)'Best

Step 4—PSO Main Loop

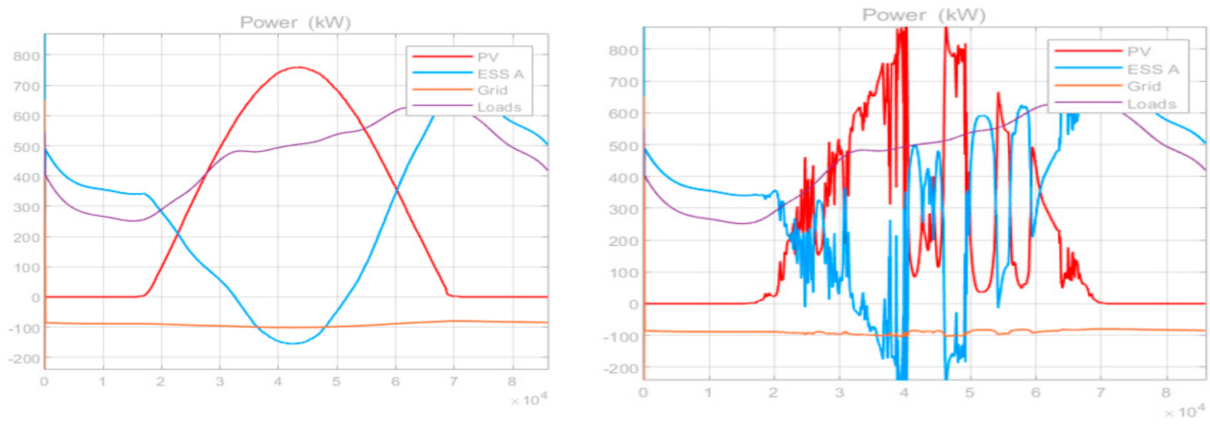
- It-1, MaxIt; for i=1: nPop, Update Velocity; Apply Velocity Limits; Update Position; Velocity Mirror Effect; Apply Position Limits; Evaluation; Update Personal Best
- Run PSO MATLAB codes by calling functions (problem definition; PSO parameters; constriction coefficients; velocity limits; initialization of particles, position, evaluation; update personal best; update global 'Best Cost')
- Results—Plot (Best Cost, x label, Y label)
- Update generators' velocities.

- Move particles to their new positions CostFunction(particle(i).Position);
- If all committed generators' present position is better than the previous best position, update the value particle(i).Cost<particle(i).Best.Cost
- Find the best-committed generator update BestCost(it)=BestSol

4. Simulation Results and Discussion

4.1. EMS Simulation Results

The operational behavior of the hybrid energy management system is the main focus of this study. A comparison with the cost function without the battery's daily operating costs was carried out. The FMINCON technique was used in the MATLAB environment to resolve the optimization problem. FMINCON optimization solver methods utilize optional input, in addition to active sets and interior points chosen from the work in [40]. The authors adapted the work from [54–56] on the grid-tied solar PV and grid patterns hybrid energy systems' operational behavior and the co-optimization approach (EPD and EMS) using the following data: Vrms = 5000, 60 Hz, with an initial power of 10 MW, in a MATLAB environment using the FMINCON algorithm. Three-phase utility points of common connection data were used (Vrms = 6600, phase angle = 0.007, initial power 10 MW). Energy storage capacity was ESS = 25,000 kWh, Pmin = 400 kW maximum discharge rate, Pmax = 400 kWh maximum charge rate, battery SOC was 20–80%, initial SOC was 50%, SOC to recharge was 11%, the SOC recharge rate was 50, and the battery capacity was 3.6 MW. Figure 1a shows the energy usage, exceeding 500 kWh during clear days in the heuristics approach simulation, and the load demand profile illustrated in Figure 1b reached a peak of 800 kWh during cloudy days in the heuristics approach simulation adopted for that period.

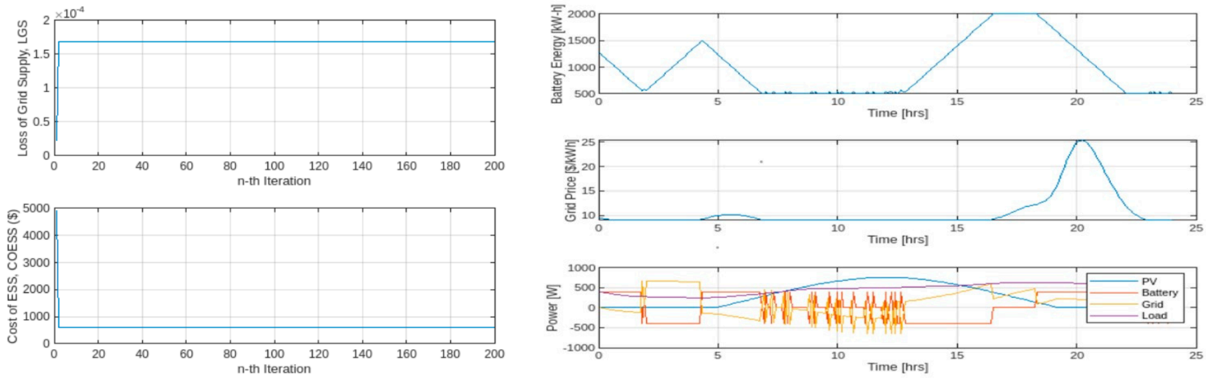


(**a**) (**b**)

Figure 1. Generated power simulation: (**a**) energy usage, exceeding 500 kWh during clear days in the heuristics approach simulation, and (**b**) a peak of 800 kWh during cloudy days in the optimization-based approach.

The ESS received data from the EMS optimization commands and then performed the appropriate energy generation and load-balancing actions in either grid-connected or off-grid mode operation. The ESS is crucial in handling demand-side management. In this simulation model, two forms of EMS were used: the heuristics technique and the linear optimization method. Equation (30) was used to compute the SOC energy restrictions of the battery limits. It should be emphasized that while SOC cannot be directly measured it can be obtained through SOC estimating and monitoring methods. The charging and discharging rate restrictions were then determined using Equations (31)–(33). When the SOC was at its maximum storage capacity, the individual solar PV power generator was run following the EMS's mode recommendations. The energy restrictions of the battery SOC were kept between 20% and 80% SOC, which is beneficial to the battery health and lifecycle. Emax, the initial battery energy, was computed with 50% SOC assumed for the ideal scenario. However, in this suggested microgrid, a lithium-ion battery with the lowest 10% SOC energy was employed, so that more saved energy could be injected into the grid-tied transmission bus when needed. The ideal cost is the cost of the grid energy once optimized, whereas the baseline cost is the price that the consumer should pay without optimization. The tariff mentions the grid energy that was imported to power the load and the battery storage system, while the surplus of solar PV and energy storage sold to the utility grid is the revenue. Figure 2 depicts the cost savings computation. The optimum system size is:

Npv = 6600
Nbat = 6600
Ngrid = 6600
LGS (loss of grid supply) = 0.017%
COESS (cost of energy storage system) = USD 594.00
Compute in 0.19 s



(**a**) (**b**)

Figure 2. Grid cost simulation: (**a**) loss of grid supply and cost of ESS, and (**b**) cumulative grid cost and grid usage for the heuristic and optimization approaches.

4.2. EPD Simulation Results

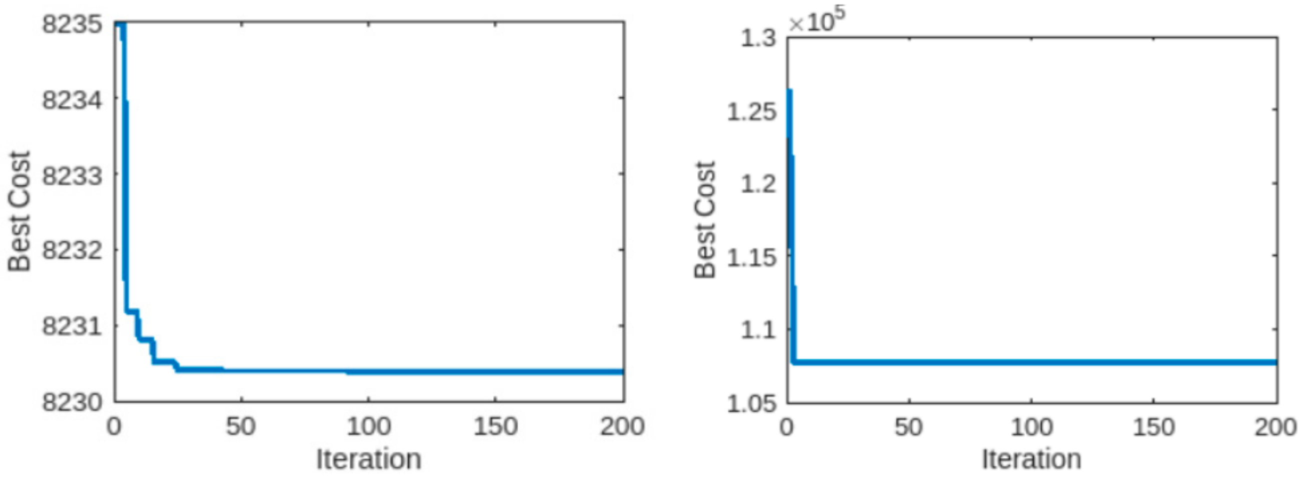
The simulation EPD covers thermal units, with data obtained from coal power plants of South Africa's energy giants (Eskom) and solar PV installations from the Solar PV Installation Company South Africa website. The total power demand was 850 MW, 1263 MW, and 2630 MW, with the chosen maximum iterations of 2 for external PSO and 100 for internal PSO. The quadratic cost functions for the cost of conventionally generated power were based on characteristics of input/output of the plant's data from the literature, while the input/output of solar PV plants were free of cost. The assumed costs were the operational costs, which are the subject of this paper. The PSO algorithm was programmed by MATLAB 2020b and operated under Intel Core i7 and Windows 10, using two unimodal functions and two multimodal functions to facilitate the original minimum problem calculation through transformation into a maximum value of 200 iterations. The effectiveness of the proposed EPD problems with different load demands and numbers of generating units was tested through cases of 3 units, 6 units, and 15 units, with and without the generation coefficient for all thermal units and without the generation coefficient for all solar PV units. The cases are described below.

4.2.1. Case 1: 3-Unit Generator System with Demand of 850 MW

This case study comprised 3-unit generators, with 850 MW load demand data taken from [51]. To identify the best solution, not many particles were required in small-scale cases, but at larger scales, the swarm's ability to accurately and quickly search the issue space increased with the number of particles. Table 2 presents the data showing the evolutionary process of the proposed EPD PSO with UR and DR (up-ramp limits and down-ramp limits) and prohibited zones of the generators. The convergence property of the suggested approach is shown in Figure 3.

Table 2. IEEE 14-bus system data: cost data and power constraints of the 3-unit system [40,49,52]. $ = USD.

			Coefficient without PV						Coefficient with PV		
Unit	**Pmin (MW)**	**Pmax (MW)**	***ai*** **($/MW^{2}h)**	***bi*** **($/MWh)**	***ci*** **($/MW)**	**Unit**	**Pmin (MW)**	**Pmax (MW)**	***ai*** **($/MW^{2}h)**	***bi*** **($/MWh)**	***ci*** **($/MW)**
Unit 1	100	600	561	7.92	0.0016	Unit 1	100	600	561	7.92	0.0016
Unit 2	100	400	310	7.85	0.0019	PV 1	20	100	0	0	0
Unit 3	50	200	78	7.97	0.0048	PV 3	50	200	78	7.97	0.0048



(**a**) (**b**)

Figure 3. 3-Unit EPD simulation for the minimum cost (best cost): (**a**) convergence of the minimum cost (best cost) for 3 thermal units, and (**b**) second-run convergence of the minimum cost (best cost) for 2 thermal and 1 solar PV units.

4.2.2. Case 2: 6-Unit Generator System with Demand of 1263 MW

The next case study comprised 6-unit generators, with 1263 MW load demand data and loss coefficients taken from [57]. The thermal units have 26 buses and 46 transmission lines of a 6 × 100 population [58]. Table 3 presents the data showing the evolutionary process of the proposed EPD PSO, with UR and DR (up-ramp limits and down-ramp limits) and prohibited zones of the generators as the main part of the algorithm for limiting the model, and with the main cost function part as the parse solution for unit commitment. The fitness value was 99.0 for each independently run function to eliminate randomness in each algorithm. Figure 4 presents the sample of the prohibited zones of the generating plants for the unit's number. Figure 5 shows the 6-unit EPD simulation for the minimum cost (best cost).

Table 3. IEEE 14-bus system data: cost data and power constraints of the 6-unit system [49–51]. $ = USD.

	Coefficient without Solar PV						Coefficient with Solar PV				
Unit	**Pmin (MW)**	**Pmax (MW)**	***ai*** **($/MW^{2}h)**	***bi*** **($/MWh)**	***ci*** **($/MW)**	**Unit**	**Pmin (MW)**	**Pmax (MW)**	***ai*** **($/MW^{2}h)**	***bi*** **($/MWh)**	***ci*** **($/MW)**
Unit 1	100	500	240	7.00	0.0070	Unit 1	100	500	240	7.00	0.0070
Unit 2	50	200	200	10.0	0.0095	PV 1	20	200	0	0	0
Unit 3	80	300	220	8.5	0.0090	PV 3	80	300	0	0	0
Unit 3	50	150	200	11.0	0.0090	PV 3	50	150	0	0	0
Unit 3	50	200	220	10.5	0.0080	PV 3	50	200	0	0	0
Unit 3	50	120	190	12.0	0.0075	PV 3	50	120	190	12.0	0.0075

```
model.Plants.PZ{1}={[210 240],[350 380]};
model.Plants.PZ{2}={[90 110],[140 160]};
model.Plants.PZ{3}={[150 170],[210 240]};
```

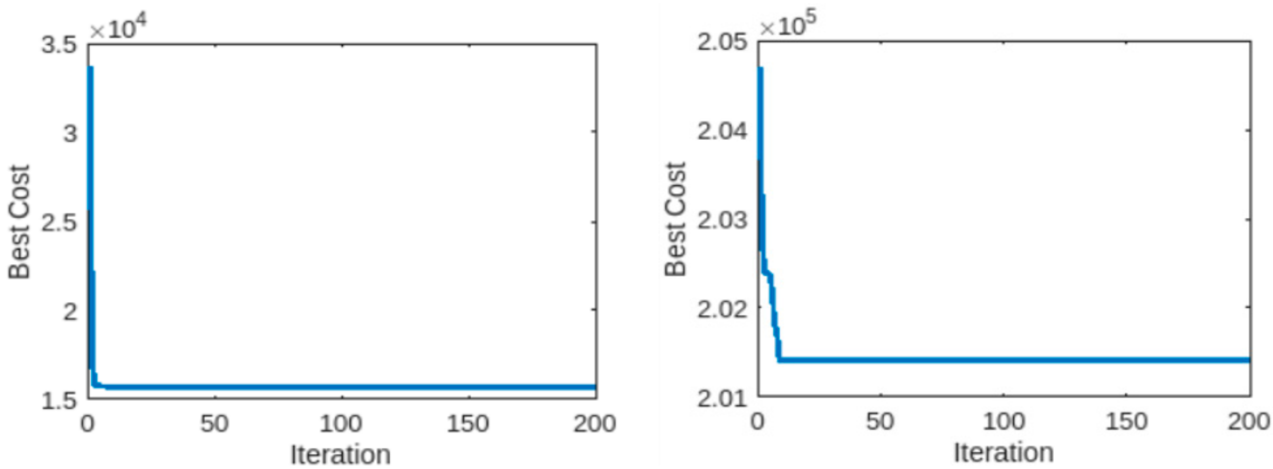
```
model.Plants.PZ{1}={[210 240],[350 380]};
model.Plants.PZ{2}={[90 110],[140 160]};
model.Plants.PZ{3}={[150 170],[210 240]};
model.Plants.PZ{4}={[80 90],[110 120]};
model.Plants.PZ{5}={[90 110],[140 150]};
model.Plants.PZ{6}={[75 85],[100 105]};
```

(**a**)

```
model.Plants.PZ{1}={[210 240],[350 380]};
model.Plants.PZ{2}={[210 240],[350 380]};
model.Plants.PZ{3}={[90 110],[140 160]};
model.Plants.PZ{4}={[80 90],[110 120]};
model.Plants.PZ{5}={[210 240],[350 380]};
model.Plants.PZ{6}={[210 240],[350 380]};
model.Plants.PZ{7}={[210 240],[350 380]};
model.Plants.PZ{8}={[150 170],[210 240]};
model.Plants.PZ{9}={[080 090],[110 120]};
model.Plants.PZ{10}={[080 090],[110 120]};
model.Plants.PZ{11}={[065 075],[060 80]};
model.Plants.PZ{12}={[065 075],[060 75]};
model.Plants.PZ{13}={[065 075],[060 75]};
model.Plants.PZ{14}={[030 055],[040 50]};
model.Plants.PZ{15}={[030 055],[040 50]};
```

(**b**)

Figure 4. Prohibited zones of the generating plants: (**a**) 3 and 6 thermal units and (**b**) 7 thermal and 8 solar PV units.



(**a**) (**b**)

Figure 5. 6-Unit EPD simulation for the minimum cost (best cost): (**a**) convergence of the minimum cost (best cost) for 6 thermal units, and (**b**) second-run convergence of the minimum cost (best cost) for 2 thermal and 4 solar PV units.

4.2.3. Case 3: 15-Unit Generator System with Demand of 2630 MW

The 15-unit generator system has a demand of 2630 MW and input/output characteristics as shown in Table 4, with a 15 × 100 population. The data show the evolutionary process of the proposed EPD PSO, with UR and DR (up-ramp limits and down-ramp limits), and Figure 6 shows the 15 × 15 prohibited zones of the generators.

Table 4. IEEE 14-bus system data: cost data and power constraints of the 15-unit system [56–58]. $ = USD.

Coefficient without PV						Coefficient with PV					
Unit	**Pmin (MW)**	**Pmax (MW)**	***ai*** **($/MW^{2}h)**	***bi*** **($/MWh)**	***ci*** **($/MW)**	**Unit**	**Pmin (MW)**	**Pmax (MW)**	***ai*** **($/MW^{2}h)**	***bi*** **($/MWh)**	***ci*** **($/MW)**
Unit 1	150	455	671	10.10	0.0003	Unit 1	150	455	671	10.10	0.0003
Unit 2	150	455	574	10.20	0.0001	Unit 2	150	455	574	10.20	0.0001
Unit 3	20	130	374	8.80	0.0011	PV 1	20	130	0	0	0
Unit 4	20	130	374	8.80	0.0011	PV 2	20	130	0	0	0
Unit 5	150	470	461	10.40	0.0002	Unit 3	150	470	461	10.40	0.0002
Unit 6	135	460	630	10.10	0.0003	Unit 4	135	460	630	10.10	0.0003
Unit 7	135	465	548	9.80	0.0003	Unit 5	135	465	548	9.80	0.0003
Unit 8	60	300	227	11.20	0.0003	Unit 6	60	300	227	11.20	0.0003
Unit 9	25	162	173	11.20	0.0008	PV 3	25	162	0	0	0
Unit 10	25	160	175	10.70	0.0012	PV 4	25	160	0	0	0
Unit 11	20	80	186	10.20	0.0035	PV 5	20	80	0	0	0
Unit 12	20	80	230	9.90	0.0055	PV 6	20	80	0	0	0
Unit 13	25	85	225	13.10	0.0003	PV 7	25	85	0	0	0
Unit 14	15	55	309	12.10	0.0019	PV 8	15	55	0	0	0
Unit 15	15	55	323	12.40	0.0044	Unit 7	15	55	323	12.40	0.0044

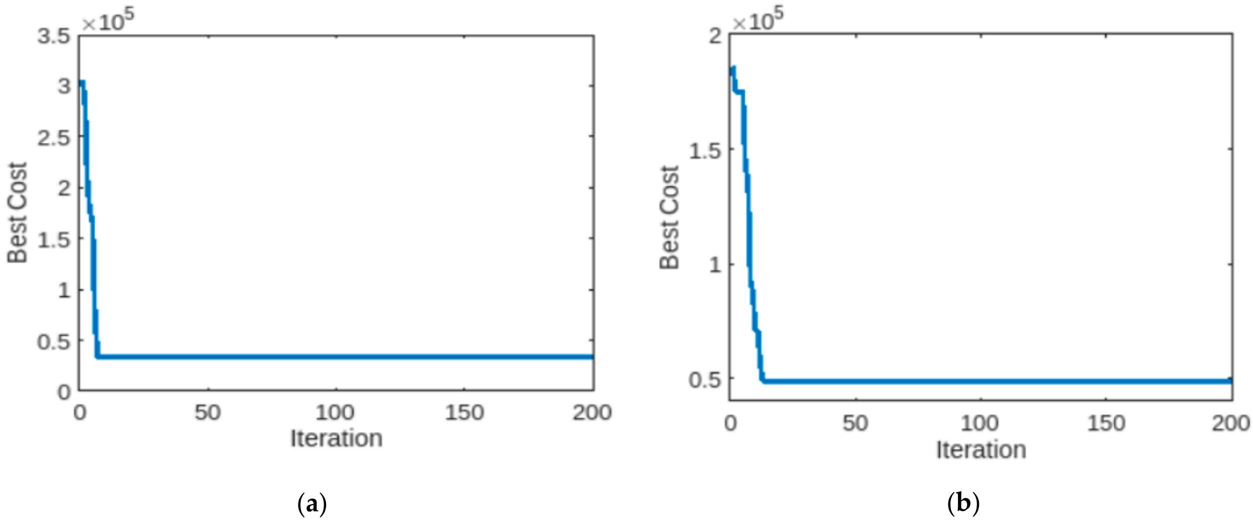


Figure 6. 15-Unit EPD simulation for the minimum cost (best cost): (**a**) convergence of the minimum cost (best cost) for 15 thermal units, and (**b**) second-run convergence of the minimum cost (best cost) for 7 thermal and 8 solar PV units.

Figure 4 displays the suggested approach's convergence property for a 15-unit EPD simulation for the minimum cost (best cost). It is expected that the best plant selection is at the discretion of the grid operators to ensure the scheduling of the right plants.

In modest circumstances, the PSO algorithm's performance is influenced by the settings and the stopping criteria used. The algorithm can produce better results if appropriate parameters and stopping criteria are used [59,60], and this has led to a noticeable disparity in the results. The maximum results according to the suggested technique and previous results are listed in Table 5; however, we did not need many particles to find the optimum answer on a small scale, but at medium and large scales, the number of particles increased the speed and accuracy of the swarm's search of the problem space. To design the best scale of RESs' capacity, we introduced a new particle swarm optimization (PSO) technique. Operating energy costs, as well as transmission line losses (TLLs), have been defined as objective functions for optimal solar PV generator allocation and sizing. The optimization approach employs multi-objective particle swarm optimization with different scenarios for optimal operation under various operating situations. This study makes a novel contribution by employing a new PSO algorithm for finding the optimal size while accounting for time variations. Simulated grid-tied, photovoltaic-based energy management systems were presented. Optimization-based energy management systems were used to estimate the power flow of the grid-tied systems in MATLAB-simulated clear and cloudy weather conditions, with seasonal variations for optimal solar PV and grid output for the EPD model. The findings obtained utilizing the newly proposed optimization program demonstrate a high potential for the deployment of solar PV energy sources in terms of lowering energy and TLL costs and enhancing the system operational conditions.

Table 5. IEEE 14-bus thermal units, with 26 buses' and 46 transmission lines' system data [57]. $ = USD.

Best Cost (million $) (Iterations)					
Unit	**PSO Plants Model**	**Best Cost**	**% Best Cost/Day**	**Compared Best Cost**	**% Compared Best Cost/Day**
3 Units	3 Thermal	8230.38	0.055	8234.07 [61] 8194.35 [62] 8242 [63]	0.04 −0.43 0.14
	2 Thermal and 1 PV	95,283.67	91.87		
6 Units	6 Thermal	15701.8	46.55	15,447 [58,64] 15,450.00 [61] 15,465.83 [65]	−0.01 −0.01 −0.01
	2 Thermal and 4 PV	201,411.1	3.784		
15 Units	15 Thermal	33,330.2	89.10	33,049 [57,66] 32,708 [64] 32,858.00 [62]	−0.008 −0.015 −0.014
	7 Thermal and 8 PV	48,653.8	73.86		

5. Conclusions

This study focused on the grid-tied solar PV-battery system's daily operation costs for an optimization problem of minimizing the total operational cost of all committed plants transmitted to the grid, while meeting network (power flow) constraints and ensuring economic power dispatch (EPD) at the transmission level. In this paper, a co-optimization approach was developed, and the FMINCON technique was used in the MATLAB environment to resolve the performance of the hybrid EMS and support the power balance. The system was implemented under the conditions of rising self-consumption strategies. The approach included a baseline method with consideration of the operational cost, the battery SOC charge, the recharge rate, and the PSO algorithm for EPD. Based on the outcomes of the simulation, the following conclusions can be drawn: the results indicated that the proposed EMS optimization was successful in lowering the grid-connected system's daily running costs and in increasing the self-consumption of RE sources.

The developed economic search optimization PSO successfully demonstrated an imperative cost reduction of the maximum yearly cost savings and a significant cost–benefit ratio. The proposed co-optimization approach can significantly enhance the self-consumption ratio compared to the baseline method. Future work will cover the integration of wind turbines and electric vehicle charge station placement to further significantly enhance the self-consumption ratio compared to the baseline method.

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