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Multi-Area Interconnected Virtual Power Plant Scheduling: Multi-Objective Profit Maximization and Emission Minimization with Multi-Time-Scale Optimization

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Abstract

A virtual power plant (VPP) serves as a promising solution by aggregating distributed energy resources (DERs) and fulfilling the prosumer's requirements for power availability, quality, and reliability. This study presents the optimized scheduling of an interconnected VPP within a multi-area framework, with tie-line connections and various renewable resources. The scheduling process begins with a day-ahead (hourly) interval, then advances to an hour-ahead interval (intra-hour and real-time), specifically using 15-minute and 5-minute time steps for the proposed VPP in the multi-area setting. The problem features two primary objective functions: net profit (to be maximized) and emissions (to be minimized). Given the involvement of renewables in the energy portfolio and the inherent complexity of the problem, the suggested multi-area VPP is evaluated using an advanced nature-inspired metaheuristic algorithm. Additionally, the formulation is extended to a multi-objective framework, with various scheduling approaches implemented to simultaneously lower emissions and enhance overall profit margins by boosting cumulative system profits. Moreover, an extensive numerical assessment across different optimization horizons demonstrates fast convergence and low computational time in achieving the optimal solution.

Keywords Virtual power plant, Multi-area framework, Renewable energy communities, Energy management and planning, Sustainable development, Integrated energy systems

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Introduction

Incorporating renewables into the energy mix can lead to instability in the electricity supply, causing voltage and frequency fluctuations and disturbances. Effective management and control are essential to assess renewable penetration levels before their integration into the utility grid. A virtual power plant (VPP) functions as a unified entity that integrates multiple distributed energy resources (DERs) located at different sites, along with controllable and flexible loads. These components can be coordinated collectively via cloud-based software to deliver grid-supporting services. Shifting from a centralized to a decentralized system demands substantial planning, coordination, and—crucially—historical data combined with resource availability to establish a DER network. This is typically overseen and managed by a dedicated VPP operator or an independent system operator (ISO) [1]. In this study, the ISO denotes the VPP operator, who bears full responsibility for controlling and supervising the virtual power plant structure (distinct from a transmission system operator). The ISO/VPP operator is responsible for all power scheduling and dispatch activities. Transitioning to a decentralized architecture necessitates extensive planning, coordination, and optimal resource placement to fully exploit

DER capabilities under the management of an independent system operator (ISO). The ISO acts as a resource aggregator, gathering demand-side and decentralized energy resources while executing efficient control measures. VPP technology allows the ISO to integrate available sources and unify them for superior, optimized scheduling. Furthermore, VPPs alleviate grid overload by optimizing power consumption, particularly during abrupt climate-driven changes that primarily impact solar and wind output.

Conventional large-scale coal- or gas-fired generation systems demand significant upgrades, incurring extra costs and requiring considerable manpower. A VPP offers a viable alternative by aggregating flexible DERs—regardless of scale—and balancing supply and demand progressively based on their capacity allocations [2]. Owing to the intermittent nature of renewables and their dependence on weather conditions, this innovative energy approach combines renewable sources with remotely operable energy storage systems that require minimal human intervention and behave similarly to traditional power plants. The shift toward a renewable-based ecosystem becomes feasible because the VPP network primarily consists of non-conventional sources, supplemented by storage, and is interconnected through advanced communication technologies that deliver real-time data. Upon data acquisition, the algorithm forecasts energy needs for the upcoming day or hour—termed day-ahead (DA) and hour-ahead (HA) scheduling. Subsequently, it evaluates predicted demand and optimizes scheduling and dispatch via the interconnected resources. The VPP facilitates enhanced aggregation of participating sources, rendering them visible for efficient energy delivery while minimizing costs, increasing profits, and flexibly reducing carbon emissions.

VPP technology supports operational control and effective management through demand response (DR), delivering flexibility across retail and wholesale markets and transactive market frameworks [3]. By offering diverse tariff options, electricity consumers can select the most appropriate structure based on their usage patterns—such as critical peak pricing (CPP), time-of-use (TOU), and real-time (RT) pricing—along with operator-provided participation incentives. A narrow definition fails to capture the extensive services offered by VPPs, including broad programs such as DER aggregation, demand-side management, flexible demand response, and behind-the-meter (BTM) applications, among others. Critically, demand flexibility from residential and commercial sectors can substantially lower peak demand, a major contributor to grid instability.

The evolution of consumers (sole electricity users) into prosumers (who both consume and supply surplus energy for grid services) stems from individual electricity generation at residential, commercial, or industrial scales (captive generation), albeit small in each case. Aggregating these sources and treating them collectively as a single entity promotes the VPP concept. Moreover, the progression to prosumage—integrating prosumer, consumer, and storage roles—holds transformative potential for grid operations, benefiting utility operators, small-scale DER owners, and policymakers alike. This unified and efficient DER aggregation transcends geographical boundaries and remains unaffected by political constraints. Given the ongoing fluctuations in demand and supply, real-time data empowers the VPP operator to make prompt decisions.

A VPP represents a highly effective technological innovation that enables real-time management of renewable energy operations. It also allows participants to generate additional revenue through participation in ancillary services while promoting greater community awareness of sustainable practices. In addition to enhancing profit margins, it contributes to reducing the carbon footprint by increasing the proportion of renewables in the energy mix and fostering an environmentally conscious society. Beyond incorporating energy storage systems as spinning reserves, the VPP system proposed in this study comprises a diverse array of sources, including solar PV, wind as DERs, combined heat and power (CHP) units, fuel cells, and electric vehicles (EVs) that can serve as potential reserves. EVs are incorporated into the examined multi-area-based VPP (MAREAVPP) network due to their accelerating adoption rates, with projections indicating that EV numbers will continue to rise significantly in the coming years, matching or surpassing those of internal combustion engine (ICE)-powered vehicles [4]. This trend provides utility operators with an opportunity to efficiently manage these mobile energy sources (MES) by drawing on their stored energy during peak demand periods and offering incentives to owners for contributing to grid services. The integration and management of EVs are not merely beneficial but increasingly essential, as they present a complex challenge for utilities and could potentially disrupt grid performance

and stability if left unmanaged. Specifically, their unpredictable patterns of connection and disconnection—i.e., unregulated mobility—create difficulties for grid operators, underscoring the need for VPP-based coordination and management of EVs. By 2050, integrating VPPs into grid operations can prevent 44–59 million metric tons of CO₂ emissions and deliver various climate benefits by increasing reliance on renewables and reducing dependence on fossil-fuel-based power plants [5]. Active involvement in a VPP lowers energy costs for participants while providing broader support to the utility grid and the community at large.

The literature related to the present topic is outlined below. Basu *et al.* [6] introduced multi-operator markets within a VPP framework to boost profit margins. They accounted for renewable energy uncertainty alongside demand-side management to achieve optimal power flow. Multiple operators, including the VPP, are interconnected via tie lines, incorporating solar PV, wind, small hydro, bioenergy, and plug-in electric vehicles. The primary objective function—net profit, defined as revenue minus cost—was optimized using the bottlenose dolphin optimizer (BDO), hierarchical PSO, and grey wolf optimization. Akkas and Cam [7] conducted optimal scheduling and bidding for a VPP comprising PV, wind, CHP, and battery storage in a day-ahead timeframe. The mixed-integer nonlinear programming (MINLP) problem was solved using GAMS. Three risk-based cases were evaluated, with results indicating that the second case offered the most favorable outcomes for VPP participants in terms of optimal scheduling and bidding. Zheng *et al.* [8] proposed a VPP model enabling resource coordination and control through peer-to-peer (P2P) decentralized trading. The model's advantages were evaluated based on maximizing social welfare. The authors highlighted the effectiveness of the Shapley method for ensuring fairness in VPP cooperation and the combined benefits across multiple VPPs. Finally, benefit distribution for each VPP was compared between centralized trading and the proposed P2P transaction approach.

Rouzbahani *et al.* [9] delivered a comprehensive review of operational scheduling in VPPs, arguing for multiple focus areas including commonly used scheduling techniques, techno-economic assessments for optimal scheduling, and uncertainty management. The authors stressed that learning-based methods represent a comprehensive solution, offering benefits such as scalability, feature extraction, and generalization through the integration of deep and reinforcement learning (DRL). Krishna *et al.* [10] developed a decision tree algorithm (DTA) to forecast load demand, utility prices, and renewable power generation. Their approach was compared with artificial neural networks (ANNs) and autoregressive integrated moving-average (ARIMA) models, demonstrating the DT method's superior accuracy and reduced computational time. The authors employed metrics—including root mean square error, mean square error, mean absolute error, and R-squared—to evaluate forecasting performance for variables such as utility prices, load, and solar/wind power. Azimi and Hooshmand [11] presented an energy management system (EMS) governed by an industrial virtual power plant (IVPP). The core goal was to maximize revenue by minimizing power interruptions in industrial facilities and ensuring grid reliability during peak loads. Incorporating electric vehicles during idle parking periods significantly increased the IVPP's storage capacity. Three simulation scenarios were conducted: only distributed energy sources (DES), demand response program (DRP), and DES combined with EV inclusion under DRP. Ultimately, the authors concluded that the proposed method reduces operational costs by leveraging electric vehicles as an effective storage resource.

Xue *et al.* [12] introduced an emergency frequency control approach designed to maintain frequency deviations within acceptable bounds. On the demand side, a VPP is expected to decrease power usage by aggregating controllable DERs. To address the model, particle swarm optimization (PSO) is applied in conjunction with parallelized electrochemical transient simulation, enhancing solution capabilities and enabling potential use in online decision-making processes. Upon receiving instructions from the VPP operator, the control center identifies and activates specific DER devices that meet the required criteria. The research concludes by demonstrating a control strategy that successfully keeps frequency within limits. Liu [13] proposed an assessment method to quantify VPPs' regulatory capacity. The DERs integrated into the VPP formation include EVs, air conditioners, storage devices, water heaters, and various other controllable assets. Three scenarios are examined, with variations in temperature ranges aligned to user comfort levels. The analysis incorporates time delays during emergency regulation, as well as users' physical attributes and behavioral patterns. Falsafi *et al.* [14] developed a stochastic framework that accounts for high wind power variability to schedule energy and reserves within the power system. The primary objectives involve minimizing costs and emissions while incorporating

demand response (DR), with the problem extended to a multi-objective setting. The authors found that integrating demand-side participation (DSP) into scheduling reduces total costs and emissions, particularly through participation in incentive-based DR programs. Wind energy and DR scheduling are intensified when emission reduction is prioritized over cost considerations. Several cases are evaluated: cases 1 and 2 focus on optimal cost, cases 3 and 4 emphasize emissions, and cases 5 and 6 apply multi-objective optimization. Li et al. [15] explored multiple scenarios by scaling up the number of EVs significantly, with the final scenario featuring a control strategy that includes 50 slow-charging and 100 fast-charging EVs participating in DR, tested on the IEEE 33-bus system. The authors emphasized that achieving effective peak shaving on the power grid requires increasing EV participation in the VPP, given 8-hour regulation durations for slow charging and 1.5 hours for fast charging. However, this study did not extend the analysis to a multi-area VPP framework.

Given that the majority of reviewed studies in the literature focus on optimal VPP scheduling within single-interval frameworks and explore only limited reserve options, the following research gaps have been identified in the VPP domain. First, most VPP developments rely heavily on renewables in the energy mix, excluding any conventional power sources. Second, the presence of numerous renewable sources introduces intermittency due to the unpredictable nature of resources such as solar and wind. To mitigate this, cogeneration units can be incorporated into the network, along with fuel cell units, which are also classified as renewable sources. Additionally, optimal scheduling is predominantly conducted on a day-ahead basis, which remains appropriate when conventional resources are involved but necessitates more advanced strategies to accommodate renewables. A significant gap in VPP optimal scheduling is its restriction to single-area networks, presenting substantial opportunities to investigate VPP systems in multi-area contexts.

Furthermore, effectively addressing the proposed approach requires an advanced optimization tool with multifaceted capabilities that surpass those of conventional methods, overcoming common limitations such as local stagnation, elevated computational time, and premature convergence.

Drawing on identified research gaps in the existing literature, this paper provides further insights into an optimized scheduling model and the energy management system (EMS) of a VPP in a multi-area context. The key contributions, encompassing multiple cases within a multi-objective framework, are outlined as follows:

- (1) A collection of flexible resources is aggregated to combine diverse DERs, with the predominant portion of power sourced from renewables, supplemented by a cogeneration unit. Storage provisions are integrated into the system to enhance reliability by harnessing reserve potential through energy storage systems (ESSs) as spinning reserves and EVs as flexible reserves.
- (2) The system's performance is initially evaluated under a single-objective scheduling approach, which is subsequently expanded to a multi-objective context, specifically a multi-area VPP (MAREAVPP).
- (3) Optimal scheduling for the proposed MAREAVPP commences with day-ahead scheduling (DAS) over a 24-hour optimization interval, followed by intra-hour scheduling (IHS) over a 15-minute interval. The scheduling is further refined to a 5-minute timescale for the proposed real-time scheduling (RTS).
- (4) The formulated problem is optimized using an advanced technique, namely the Mountain Gazelle Optimizer (MGO), which simultaneously increases system profit and minimizes generated emissions.
- (5) Moreover, the overall profit of the MAREAVPP system is enhanced through dynamic scheduling strategies that accompany emission reductions and are supported by a Pareto-based method to identify the optimal trade-off.

Materials and Methods

The virtual power plant (VPP) concept is still in its early stages, and the present study aligns with a foundational conceptual framework for VPPs. Accordingly, a detailed analysis is conducted, and the value of the proposed methodology is thoroughly examined to pave the way for new research directions. The identified research gaps are addressed meaningfully, leading to the development of a novel approach to evaluating the performance and effectiveness of a VPP, particularly in a multi-area setting.

The proposed methodology features a multi-area (MAREA)-based VPP that integrates a carefully selected mix of resources, predominantly non-conventional ones—namely renewable energy sources and cogeneration units such as combined heat and power (CHP)—along with readily available storage options that can be deployed immediately during peak demand periods or emergencies. The primary motivation for incorporating this feature stems from the enhanced capabilities and advantages of interconnected systems, as illustrated in **Figure 1**, which offer higher profitability and improved reliability compared to single-area configurations. Such integrated combinations, especially optimized scheduling within multi-area VPP networks, have not been thoroughly investigated in prior work. In particular, there remains considerable potential to explore MAREA-based power systems from a VPP perspective, utilizing a variety of scheduling strategies.

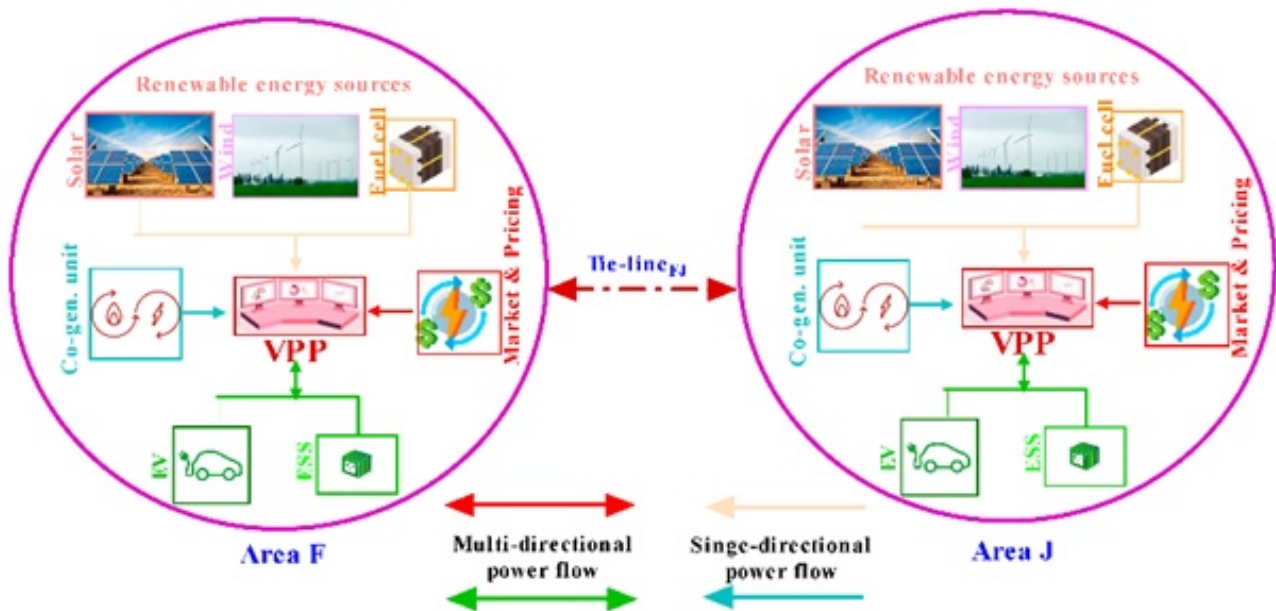


Figure 1. The primary motivation for incorporating the feature stems from the enhanced capabilities and advantages of interconnected systems.

Problem formulation

Net Profit (NP)

In the proposed MAREAVPP, the objectives are divided into two main components, with the primary focus placed on maximizing net profit. The formulation for net profit (NP) is expressed in **Eq.1**, with the meanings of the symbols provided below.

$$NP = \text{maximization} \sum_{m=1}^M \sum_{s=1}^{N_s} \pi_s \times \sum_{t=1}^{24} \left\{ - \sum_{p=1}^{N_p} (CF_{chp} + c_{hou}) (p_{em} \times c_{ph} + c_{se}) + \sum_{p=1}^{N_p} \{ (c_{ph} + p_{hou}) - c_{ens} \} + \sum_{p=1}^{N_p} (c_{ph} - c_{se}) \right\} \quad (1)$$

Where the following apply:

M is the number of areas.

s and p represent sets of scenarios and plants, respectively. t denotes time intervals, ranging from 1 to 24 for day-ahead scheduling (DAS), 1 to 96 for intra-hour scheduling (IHS), and 1 to 288 for the proposed real-time scheduling (RTS).

c_{ph} and c_{se} are the tariffs for purchasing and selling power from the grid.

π_s are the probabilities of scenarios.

p_{em} is the price associated with the energy market, and c_{ens} is the cost of energy not served.

CF_{chp} and c_{hou} represent the cost functions for CHP and heat-only units (HOU).

p_{hou} is the price of HOU.

Emission (EM)

The secondary objective is formulated in Eq. 2 to minimize emissions. Emissions reductions are evaluated at both the day-ahead (DA) and hour-ahead (HA) intervals to assess the effectiveness of the proposed MAREAVPP system.

$$EM = \text{minimization} \sum_{m=1}^M \sum_{s=1}^{N_s} \pi_s \times \sum_{t=1}^{24} \left\{ \sum_{p=1}^{N_p} (e_{chp} + e_{hou}) + (e_{ph} + e_{se}) + \sum_{p=1}^{N_p} (c_{ph} - c_{se}) \right\} \quad (2)$$

Where the following apply:

e_{ph} and e_{se} denote emissions from the grid (purchased and sold power, respectively).

e_{chp} and e_{hou} represent emissions generated by CHP and HOU, respectively.

Emissions are treated as a key objective, with efforts focused on reducing them through the inclusion of cogeneration units. Various emission types are considered and elaborated in the textual explanations supporting Eqs. 3-5. The primary justification for this emphasis lies in the presence of cogeneration units in the MAREAVPP configuration, which makes emission reduction a critical priority. Total emissions from CHP, heat-only units, and grid power transactions (purchasing and selling) are quantified using Eqs. 3-5. Although VPPs aim to maximize benefits for all participants and prioritize renewables, the intermittent and variable nature of these sources necessitates adding storage capacity and reliable cogeneration resources to ensure power availability even during periods without solar irradiation or wind generation. Carbon emissions pose a particularly serious threat and must be minimized to support ecosystem sustainability. In addition to CO₂, other pollutants, such as sulfur dioxide (SO₂) and nitrogen oxides (NO_x), contribute to adverse health effects in humans and animals. The emissions of NO_x, CO₂, and SO₂ are specifically accounted for—without detailing their full impacts—because they act as indirect greenhouse gases that contribute to global warming. These gases have relatively short atmospheric lifetimes, complicating precise quantification of their effects, yet their presence remains harmful: elevated NO_x levels can exacerbate respiratory conditions, while SO₂ can aggravate cardiovascular issues. The combined impact of these pollutants is similar, with prolonged exposure increasing the risk of lung infections. CO₂ exposure can lead to elevated blood carbon dioxide levels, irregular breathing, and general discomfort. Therefore, increasing the proportion of non-conventional sources and reducing dependence on fossil-based generation not only benefits human and animal health but also supports planetary well-being, aligning with the Sustainable Development Goals (SDGs) and nationally determined contributions (NDCs). The overarching goal is to mitigate environmental contamination from various pollutants, even at marginal levels, in line with the dominant sources of carbon emissions. Emissions are quantified in kilograms (kg), with values specified where applicable. The underlying rationale is to lessen

the environmental impact of pollutants that contribute to degradation, even modestly, while addressing the primary contributors to carbon emissions.

$$e_{chp} = (NO_x^{chp} + SO_2^{chp} + CO_2^{chp}) \times P_{t,p}^{chp} \quad (3)$$

$$e_{hou} = (NO_x^{hou} + SO_2^{hou} + CO_2^{hou}) \times H_{t,p}^{hou} \quad (4)$$

$$e_{ph} + e_{se} = (NO_x^{ph+se} + SO_2^{ph+se} + CO_2^{ph+se}) \times \max\{-P_{t,p}^{ph+se}, 0\} \quad (5)$$

Where the following apply:

NO_x, SO₂, and CO₂ refer to nitrous oxide, sulfur dioxide, and carbon dioxide emissions associated with the cogeneration unit.

Resources included in MAREAVPP

The modeling of the proposed VPP network is elaborated in the following sub-sections, which provide a concise overview of the associated resources. These encompass a variety of non-conventional sources combined with reserves to bolster the overall performance of the VPP [16].

Solar power

The key factors influencing the extraction of maximum power from solar modules are outlined below. The corresponding expressions for calculating solar power output are presented in Eqs. 6-8, with the underlying data derived from Chen and Xu [17]. Solar generation is regarded as one of the most significant non-conventional energy resources (NCERs).

$$p_{s,t,p}^{pv}(sor_{s,t}) = N_p^{pv} \times FF \times V_{s,t} \times I_{s,t} \quad (6)$$

$$V_{s,t} = V_{oc} - K_v \times T_{Cs,t} \quad (7)$$

$$I_{s,t} = sor_{s,t} \times [I_{SC} + K_i \times (T_{Cs,t} - 25)] \quad (8)$$

Where the following apply:

$ppvs_{,,}$ represents the power extracted from the PV array, and $sors_{,t}$ denotes solar radiation.

FF is the Fill Factor, and N_{pvp} is the rated power from the solar module.

VOC and I_{sc} indicate open-circuit voltage and short-circuit current, respectively.

K_i and K_V refer to the temperature coefficients for current and voltage.

TC_s , is the solar cell temperature.

Wind

Power generation from wind turbines is a vital component of renewable energy production and is widely recognized as a clean, environmentally friendly resource. The relevant data are obtained from Chen and Xu [17], while the modeling approach is adapted from Sadeghi et al. [18], with the formulation provided in Eq. 9.

$$p_{wind}^i = \begin{cases} p_{rated} \frac{V_t^b - V^b}{V^e - V^b} & V^b \leq V_t < V^e \\ p_{rated} & V^e \leq V_t \leq V^s \\ 0 & V_t \leq V^b, V_t > V^s \end{cases} \quad (9)$$

Where the following apply:

p_{wind} is the output power generated, P_{rated} denotes the rated power, and V_{bt} represents the wind speed.

V_b and V_s are the cut-in speed and cut-out speed, respectively, while V_e indicates the nominal (rated) speed.

Fuel cell

Fuel cells (FCs) are incorporated into the system configuration to increase the proportion of renewable energy resources (RERs). Various types of fuel cells exist, corresponding to different electrolyzer technologies, including alkaline water electrolyzer (AWE), anion exchange membrane (AEM), solid oxide electrolyzer cell (SOEC), polymer electrolyte membrane fuel cells (PEMFCs), phosphoric acid fuel cells (PAFCs), and reversible fuel cells (RFCs), among others. Each type is selected and applied based on its suitability for the specific application.

In the current system setup, PEMFCs are employed owing to their broad operating temperature range, extended reliable operation hours, and relatively long lifespan compared to alternatives. Notably, they exhibit a high power-to-volume ratio, which supports efficient performance. The model for the FC is adapted from Wu et al. [19], with the expressions as follows:

When $PLR_i < 0.05$:

$$p_{fc_eff}^i = 2.2716; r_{fi}^i = 6.6816 \quad (10)$$

When $PLR_i \geq 0.05$:

$$p_{fc_eff}^i = 0.9033PLR_i^5 - 2.9996PLR_i^4 + 3.6503PLR_i^3 - 2.0704PLR_i^2 + 0.4623PLR_i^1 + 0.37$$

(11)

$$r_{fl}^i = 1.0785PLR_i^4 - 1.9739PLR_i^3 + 1.5005PLR_i^2 - 0.2817PLR_i^1 + 0.6838 \quad (12)$$

Where the following apply:

p_{ifc_eff} is the FC's efficiency at the i th interval.

r_{ifl} is the heat-to-electricity ratio of the FC at the i th interval.

PLR denotes the part load ratio.

The power output of the unit is constrained not to exceed the defined limits, as specified in [Eq. 13](#).

$$\Delta P_{fl_down} \cdot T \leq P_{fl}^i - P_{fl}^{i-1} \leq \Delta P_{fl_up} \cdot T \quad (13)$$

Where the following apply:

$\Delta P_{fl_up} \cdot T$ is the up-ramp limit, and ΔP_{fl_down} is the down-ramp limit for fuel cells.

P_{ifl} is the power produced by FCs at the i th interval.

P_{i-1fl} is the power produced by FCs at the previous interval.

CHP unit

Combined heat and power (CHP) units are included to improve overall system efficiency, functioning as cogeneration units, as discussed in Hadayeghparast et al. [20]. The formulations for Type (i) are given in [Eqs. 14-16](#), while the output power constraints are expressed in [Eqs. 17 and 18](#).

$$P_{t,p}^{chp} - P_{p,A}^{chp} - \frac{P_{p,A}^{chp} - P_{p,B}^{chp}}{H_{p,A}^{chp} - H_{p,B}^{chp}} (H_{t,p}^{chp} - H_{p,A}^{chp}) \leq 0 \quad (14)$$

$$P_{t,p}^{chp} - P_{p,B}^{chp} - \frac{P_{p,B}^{chp} - P_{p,C}^{chp}}{H_{p,B}^{chp} - H_{p,C}^{chp}} (H_{t,p}^{chp} - H_{p,B}^{chp}) \geq -(1 - V_{t,p}^{chp}) \quad (15)$$

$$P_{t,p}^{chp} - P_{p,C}^{chp} - \frac{P_{p,C}^{chp} - P_{p,D}^{chp}}{H_{p,C}^{chp} - H_{p,D}^{chp}} (H_{t,p}^{chp} - H_{p,C}^{chp}) \geq -(1 - V_{t,p}^{chp}) \quad (16)$$

$$0 \leq P_{t,p}^{chp} \leq P_{p,A}^{chp} \times V_{t,p}^{chp} \quad (17)$$

$$0 \leq H_{t,p}^{chp} \leq H_{p,B}^{chp} \times V_{t,p}^{chp} \quad (18)$$

Where the following apply:

P_{chpt} , is the electric power output of the CHP unit.

V_{chpt} , indicates the commitment status of the CHP unit.

The formulations for Type (ii) are presented in Eqs. 19–22, with output power limitations in Eqs. 23 and 24. The operational status of the cogeneration unit is determined using Eq. 25, where the operating region is either Type I ($Y1=1, Y2=0$) or Type II ($Y1=0, Y2=1$). The terms $Y1$, and $Y2$, designate the operational sections for the CHP unit, with the feasible operating regions (FORs) illustrated in Figure 2.

$$P_{t,p}^{chp} - P_{p,B}^{chp} - \frac{P_{p,B}^{chp} - P_{p,C}^{chp}}{H_{p,B}^{chp} - H_{p,C}^{chp}} (H_{t,p}^{chp} - H_{p,B}^{chp}) \leq 0 \quad (19)$$

$$P_{t,p}^{chp} - P_{p,C}^{chp} - \frac{P_{p,C}^{chp} - P_{p,D}^{chp}}{H_{p,C}^{chp} - H_{p,D}^{chp}} (H_{t,p}^{chp} - H_{p,C}^{chp}) \leq 0 \quad (20)$$

$$P_{t,p}^{chp} - P_{p,E}^{chp} - \frac{P_{p,E}^{chp} - P_{p,F}^{chp}}{H_{p,E}^{chp} - H_{p,F}^{chp}} (H_{t,p}^{chp} - H_{p,E}^{chp}) \geq -(1 - Y_{1,t}) \quad (21)$$

$$P_{t,p}^{chp} - P_{p,D}^{chp} - \frac{P_{p,D}^{chp} - P_{p,E}^{chp}}{H_{p,D}^{chp} - H_{p,E}^{chp}} (H_{t,p}^{chp} - H_{p,D}^{chp}) \geq -(1 - Y_{2,t}) \quad (22)$$

$$0 \leq P_{t,p}^{chp} \leq P_{p,A}^{chp} \times V_{t,p}^{chp} \quad (23)$$

$$0 \leq H_{t,p}^{chp} \leq H_{p,C}^{chp} \times V_{t,p}^{chp} \quad (24)$$

$$Y_{1,t} + Y_{2,t} = V_{t,p}^{chp} \quad (25)$$

$$H_{t,p}^{chp} - H_{p,E}^{chp} \leq (1 - Y_{1,t}) \quad (26)$$

$$H_{t,p}^{chp} - H_{p,E}^{chp} \leq (1 - Y_{2,t}) \quad (27)$$

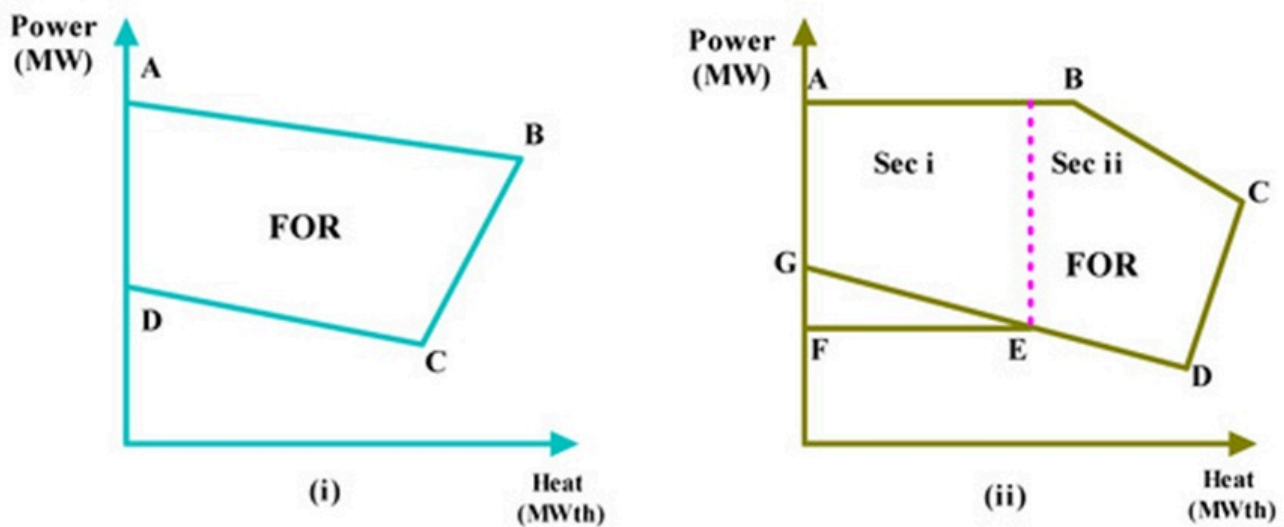


Figure 2. Type (i) and Type (ii) regions of operation for the cogeneration unit.

The cost function (CF) is defined in (28), which consists of the start-up and shutdown costs given in Eq. 29, along with the corresponding status variables from Eqs. 30 and 31.

$$CF_{t,p}^{chp}(P_{t,p}^{chp}, H_{t,p}^{chp}) = a \times (P_{t,p}^{chp})^2 + b \times P_{t,p}^{chp} + c + d \times (H_{t,p}^{chp}) + e \times H_{t,p}^{chp} + f \times (P_{t,p}^{chp}, H_{t,p}^{chp}) \quad (28)$$

Where the following apply:

CF_{chpt} is the cost function.

$$p_{chp}^i = CF_{t,p}^{chp} + C_p^{stup} \times STUP_{t,p}^{chp} + C_p^{stud} \times STUD_{t,p}^{chp} \quad (29)$$

$$STUP_{t,p}^{chp} = V_{t,p}^{chp} \times (1 - V_{t-1,p}^{chp}) \quad (30)$$

$$STUD_{t,p}^{chp} = (1 - V_{t,p}^{chp}) \times V_{t-1,p}^{chp} \quad (31)$$

Where the following apply:

C_{stup} and C_{stud} represent the costs associated with start-up and shutdown.

$STUP_{chpt}$ and $STUD_{chpt}$ denote the status indicators for start-up and shutdown.

Reserve provision

In this study, the two-area system is linked via tie-lines, incorporating various reserve options. Specifically, electric vehicles (EVs) are utilized as flexible reserves, while energy storage systems (ESS) serve as spinning reserves. These resources provide additional support within the MAREAVPP framework, enabling the VPP operator to address power shortages caused by non-conventional sources. Consequently, the inclusion of multiple storage alternatives enhances the system's overall dynamism and reliability.

Flexible reserve

By integrating EVs into the reserve provision, EV owners can earn attractive incentives through participation in VPP services. Meanwhile, the operator gains a mobile reserve option to deploy when the grid cannot meet demand on its own, thereby helping alleviate congestion. The relevant expressions are presented in the equations below.

$$P_{EV}^i = \sum_t \sum_e h(\lambda_{price}^{w,t} P_{EV,eh}^{e,t} + C_{EV,dis}^{w,t} P_{EV,dch}^{e,t}) \quad (32)$$

$$C_{EV,dch}^{w,t} = F_{EV,dch} \lambda_{price}^{w,t} \quad (33)$$

Where the following apply:

$P_{e,h}$, and $P_{e,tEV,dch}$ represent the charging and discharging power of EVs.

λ_w , is the electricity price, and C_w, V_{dis} denotes the cost associated with EVs.

The constraints are outlined in **Eqs. 34–36**, with the EV charging and discharging rates specified in **Eqs. 37 and 38**. Readers are referred to our prior work [21] for additional details.

$$E_{EV_max}^e \leq E_{EV}^{e,t} \leq E_{EV_max}^e \quad (34)$$

$$E_{EV_min}^e = F_{EV_min}^e E_{EV_batcap}^e \quad (35)$$

$$E_{EV_max}^e = F_{EV_max}^e E_{EV_batcap}^e \quad (36)$$

Where the following apply:

E_{EV_min} and E_{EV_max} indicate the minimum and maximum energy stored in the EV.

F_{EV_min} and F_{EV_max} represent the minimum and maximum energy storage factors for the EV.

E_{EV_batcap} is the battery capacity of the EV.

$$0 \leq (\eta_{EV, ch}^e P_{EV, ch}^{e,t}) \leq u_{EV, ch}^{e,t} P_{EV, ch, max}^e \quad (37)$$

$$0 \leq \left(\frac{1}{\eta_{EV, dch}^e} P_{EV, dch}^e \right) \leq u_{EV, dch}^{e,t} P_{EV, dch, max}^e \quad (38)$$

Where the following apply:

$\eta_{EV, h}$ and $\eta_{EV, dch}$ are the charging and discharging efficiencies of the EV.

$P_{e, maxEV, ch}$ and $P_{e, maxEV, dch}$ denote the maximum charging and discharging power of the EV.

Spinning reserve

ESS is incorporated into the problem formulation specifically as spinning reserves, offering advantages for an effective operational structure. Within the MAREAVPP framework, they help preserve system flexibility. Their modeling is described in the equations that follow.

$$P_{ESS}^i = \sum_t \sum_s h C_{S, deg}^s (P_{S, ch}^{s,t} + P_{S, dch}^{s,t}) \quad (39)$$

Where the following apply:

$C_{S, deg}$ is the degradation cost of the ESS.

$(P_{S, h} + P_{S, dch})$ represent the charging and discharging power of the ESSs.

The state of charge (SoC) for ESS is calculated according to [Eq. 40](#).

$$E_S^{s,t} = E_S^{s,t-1} + \left[\left(\eta_{S,ch} P_{S,ch}^{s,t} \right) - \left(\frac{1}{\eta_{S,dch}} P_{S,dch}^{s,t} \right) \right] \quad (40)$$

The constraints related to ESS degradation are given in [Eqs. 41–43](#).

$$E_{ESS_min}^e \leq E_{ESS}^{e,t} \leq E_{ESS_max}^e \quad (41)$$

$$E_{ESS_min}^e = F_{ESS_min}^{e,t} E_{ESS_batcap}^e \quad (42)$$

$$E_{ESS_max}^e = F_{ESS_max}^{e,t} E_{ESS_batcap}^e \quad (43)$$

Where the following apply:

E_{ESS_min} and E_{ESS_max} indicate the minimum and maximum energy stored in the ESS.

F_{e_max} and $F_{e,tESS_min}$ represent the minimum and maximum energy storage factors for the ESS.

E_{ESS_cap} is the capacity of the ESS.

The charging and discharging rates of the ESS are governed by [Eqs. 44 and 45](#). For each time interval, only charging or discharging (not both) is allowed, as specified in [Eq. 45](#).

$$0 \leq \left(\eta_{ESS,ch}^e P_{ESS,ch}^{s,t} \right) \leq u_{ESS,ch}^{s,t} P_{ESS,ch,max}^e \quad (44)$$

$$0 \leq \left(\frac{1}{\eta_{ESS,dch}^e} P_{ESS,dch}^{s,t} \right) \leq u_{ESS,dch}^{s,t} P_{ESS,dch,max}^e \quad (45)$$

Where the following apply:

$\eta_{ESS,h}$ and $\eta_{ESS,dch}$ are the charging and discharging efficiencies of the ESSs.

$P_{eESS,h,max}$ and $P_{sESS,dch,max}$ denote the maximum charging and discharging rates of the ESSs.

$$u_{ESS,ch}^{s,t} + u_{ESS,dch}^{s,t} \leq 1 \quad (46)$$

Tie-line constraint

Power transfer is maintained such that it does not exceed the maximum allowable limit, as expressed in Eq. 47:

$$-P_{TFJ,t}^{\max m} \leq P_{TFJ,t} \leq P_{TFJ,t}^{\max m} \quad (47)$$

$$\begin{cases} -P_{TFJ,t}^{\max m} = \max \sum_{t=1}^T -P_{TFJ,t}^* \\ P_{TFJ,t}^{\max m} = \max \sum_{t=1}^T P_{TFJ,t}^* \end{cases} \quad (48)$$

Where the following apply:

P_{TFJ} , is the tie-line power flow from area F to area J at time t.

The tie-line capacity is maintained within $\pm 25\%$ of the nominal values under loading conditions [21]. As stated in Eq. 48, the tie-line is constrained by the maximum permissible power exchange across the multi-area system, as specified in Li et al. [22].

Power balance

The power balance equation for the MAREAVPP is formulated in Eq. 49.

$$P_{s,t,p}^{equiv} = P_{TFJ} + P_{chp}^i + P_{fl}^i + P_{wind}^i + P_{p_pv}^i + P_{EV}^i + P_{ESS}^i - P_{el_load}^i \quad (49)$$

Where the following apply:

$PTFJ$ represents the power exchange between the multi-area regions.

P_{chp} is the output power from the CHP unit, and P_{fl} is the power generated by the fuel cell.

P_{wind} denotes the power output from the wind turbine, and P_{p_pv} is the power obtained from solar PV.

P_{EV} indicates the available power from EVs, and P_{ESS} represents the available power from ESS.

P_{el_load} corresponds to the load demand.

Methodological framework

Figure 3 illustrates the detailed methodology employed to derive high-quality outcomes from the formulated objective function. The assessment of objectives 1 and 2 is accomplished through the application of the MAREA mechanism. A thorough description of the proposed approach is provided, aiming to offer readers an in-depth understanding. This encompasses an extensive discussion of the optimization technique used to address the problem formulation. Given that

this represents a relatively novel method, this study includes a comprehensive explanation, and the Discussion section also provides accessible insights into the MAREAVPP approach for a broad research audience.

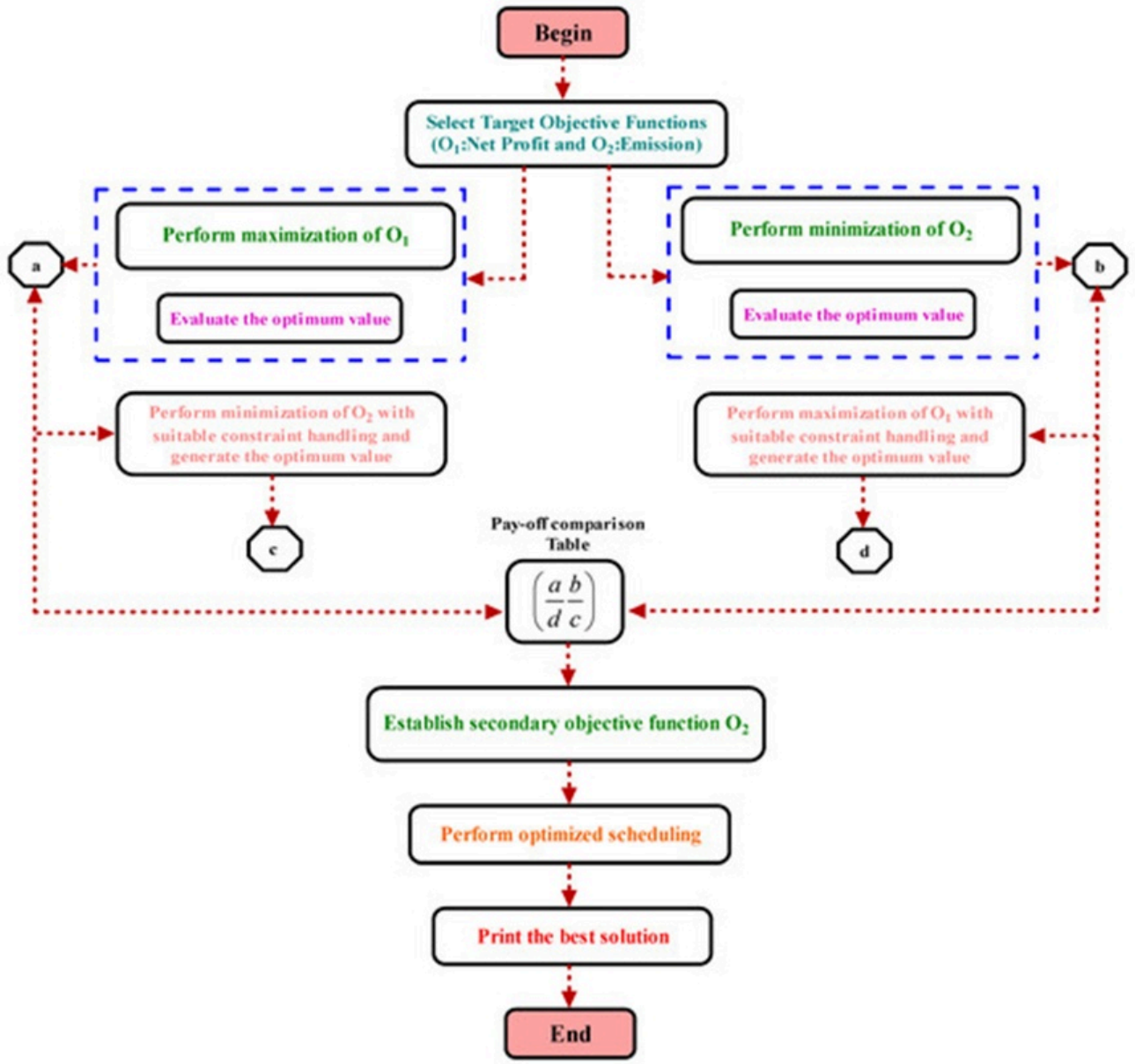


Figure 3. Multi-objective scheduling approach.

The objectives are initially determined by the type of VPP, with the primary goal of this research being to maximize profitability using a commercial virtual power plant (CVPP). In addition to improving profitability, a secondary objective focuses on emissions reduction, labeled as O1 and O2 in **Figure 3**. The evaluation process prioritizes maximizing O1 while minimizing O2. The resulting optimal values are presented and analyzed in Cases 1 and 2 under a single scheduling strategy. As the method involves multiple objectives, a separate multi-objective scheduling is conducted in Case 3. Here, both net profit (NP) and emissions (EM) are optimized concurrently, and the most effective global optimal solutions are reported as pay-off comparisons. These provide valuable guidance to the VPP operator for decision-making and facilitate power scheduling tailored to the needs of participating stakeholders.

The study considers a two-area system in which Areas F and J are connected via a tie line, as depicted in **Figure 4**. Given the problem's multi-objective nature, achieving optimal scheduling within the proposed MAREAVPP network is challenging. Accordingly, a multi-objective approach is adopted, combined with a Pareto-based estimation technique, to identify the most suitable solution at any specific time. Both objectives are structured within the multi-area context, taking into account economic and environmental perspectives. The aim is to assess the economic viability of the VPP in a MAREAVPP setup by capitalizing on financial gains while simultaneously reducing emissions.

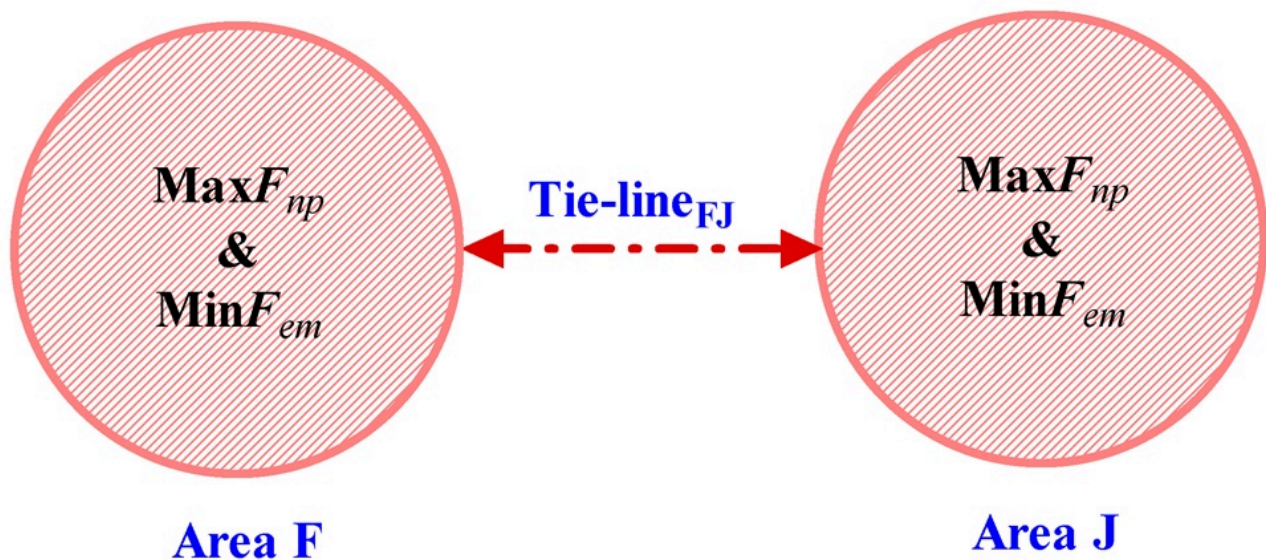


Figure 4. Problem-solving approach for a multi-objective problem.

Consistent with single-objective scheduling, multi-objective scheduling is executed using three distinct advanced strategies.

Optimization method

Optimization techniques serve as tools for refining a specified objective to meet specific needs. They fall into evolutionary or swarm-based categories, encompassing a wide range of methods known collectively as metaheuristic algorithms. These soft computing approaches draw inspiration from nature and are mathematically modeled on the behaviors of specific species as they adapt and survive in challenging environments by overcoming obstacles. Unlike exact methods, metaheuristics simplify the optimization process by reducing mathematical complexity, making them applicable to diverse problems and enabling the achievement of intended results. Notably, solutions derived from nature-inspired soft computing methods may reach the global or near-optimum, a limitation of metaheuristics, though their computational speed is highly advantageous. In contrast, exact methods guarantee optimal solutions but typically require longer computation times and struggle with nonlinear problems due to their discrete nature, thereby increasing complexity.

Numerous well-known optimization algorithms exist, such as PSO, ABC, GA, GWO [23], ALO, and others, which have been applied to solve various engineering problems, particularly in power systems. However, a common drawback of many of these is their tendency to become trapped in local optima, leading to premature convergence. Moreover, computation time increases with problem complexity, which varies depending on the problem's nature and nonlinearities. Finally, maintaining a proper balance between exploration and exploitation becomes difficult as iterations advance, due to reliance on local best solutions, leading to stagnation in local regions and preventing the attainment of the near-global optimum. To overcome these limitations and effectively tackle the current VPP problem—considering its nonlinear formulation—a recently introduced nature-inspired metaheuristic, the Mountain Gazelle-based technique, is adopted. This

approach effectively achieves the target objectives by substantially mitigating the aforementioned issues across various scheduling strategies.

In this study, the recently introduced metaheuristic, Mountain Gazelle Optimization (MGO), is employed owing to its strong performance and the variety of mechanisms incorporated into its optimization procedure. This species, a type of gazelle, is indigenous to the Arabian Peninsula and exhibits highly territorial behavior [24]. Mountain gazelles (MG) can reach speeds of up to 80 km/h, enabling them to cover considerable distances. They typically migrate over ranges of up to 120 km in pursuit of food and more favorable living conditions [25]. MG populations are organized into three main social groups: solitary adult males, groups of young males, and mother-offspring herds. Conflicts among individuals are generally low in intensity and primarily arise when competing for territory or access to females. The optimization algorithm is structured around four key behavioral aspects of MG life: solitary males in the herd (M1), maternity herds (M2), bachelor male herds (M3), and the migration phase (M4). The most promising candidate solution is modeled as a healthy adult MG, while the poorest solution corresponds to aged or weakened individuals [26]. Thanks to these four distinct mechanisms, intermediate solutions situated between the best and worst progressively move toward the most promising regions, thereby achieving an effective balance between exploration and exploitation.

The mathematical expressions of this technique are outlined in the following equations.

Solitary males in territory (M1)

The initial phase models the behavior of adult gazelles that have reached maturity and are strong enough to establish and defend individual territories. Young males in the group strive to claim territory, compete for females, and assist adult males in protecting the herd and its surroundings. This adult male's territorial behavior is represented by Eq. 50.

$$TSM = male_{mg} - \left| (rand_{i1}) \times cof_{ym} - (rand_{i2}) \times X(t) \right| \times E \times cof_{rand} \quad (50)$$

Where the following apply:

$male_{mg}$ is the position vector representing the best solution.

$rand_{i1}$ and $rand_{i2}$ are random integers, each taking the value 1 or 2.

cof_{ym} is the young male coefficient vector, computed via Eq. 51, while E is determined by Eq. 52.

cof_{rand} is a coefficient vector updated iteratively throughout the process.

The young male coefficient vector is calculated according to Eq. 51.

$$cof_{ym} = X_{rand} \times [r_1] + M_{avg} \times [r_2], \quad rand = \left\{ \left\lceil \frac{K}{3} \right\rceil \dots K \right\} \quad (51)$$

Where the following apply:

X_{rand} is a randomly generated solution within the interval defined by $rand$.

M_{avg} is the average position of the search agents (mountain gazelles).

r_1 and r_2 are random numbers uniformly distributed between 0 and 1.

K denotes the total number of search agents.

$$E = K_1(D) \times \exp \left(2 - Iter \times \left(\frac{2}{MaxIter} \right) \right) \quad (52)$$

Where the following apply:

K_1 is a random number.

$\exp$ denotes the exponential function, and $Iter$ represents the current iteration number.

$MaxIter$ is the maximum number of iterations.

$$cof_j = \begin{cases} (a + 1) + r_3, \\ a \times N_2(D), \\ r_4(D), \\ N_3(D) \times N_4(D)^2 \times \cos((r_4 \times 2) \times N_3(D)) \end{cases} \quad (53)$$

Where the following apply:

$\cos$ denotes the cosine function.

cof_j represents the vector variation.

The parameter a is computed using [Eq. 54](#).

$$a = -1 + Iter \times \left(\frac{-1}{MaxIter} \right) \quad (54)$$

Maternity herds (M2)

This phase is significant because maternity herds are responsible for producing robust male offspring. Their behavior is mathematically described by [Eq.55](#).

$$MatHer = (cof_{ym} + cof_{1,r}) + (r_{i3} \times male_{mg} - r_{i4} \times X_{rand}) \times cof_{1,r} \quad (55)$$

Where the following apply:

r_{i3} and r_{i4} are an integer (1 or 2) and a random number, respectively.

$male_{mg}$ is the best solution identified in the current iteration.

X_{rand} is the position vector of a randomly selected gazelle.

Bachelor male herds (M3)

In the third phase, gazelles establish territorial claims based on their maturity and compete for females. Younger males engage in contests with others to gain control of territory, as formulated in Eq. 56.

$$MaleHer_Bach = (X(t) - D) + (r_{i5} \times male_{mg} - r_{i6} \times cof_{ym}) \times cof_r \quad (56)$$

Where the following apply:

(t) is the position vector of the gazelle at time t .

r_{i5} and r_{i6} are randomly chosen integers (1 or 2).

cof_{ym} represents the influence of young males from the herd.

cof_r is a randomly selected vector.

$$D = (|X(t)| + |male_{mg}|) \times (2 \times r_6 - 1) \quad (57)$$

Where the following apply:

(t) is the current position of the male gazelle in the present iteration.

$male_{mg}$ is the position of the best solution (adult male).

r_6 is a random number between 0 and 1.

Migration phase (M4)

To ensure access to essential resources and sustain their habitat, MG continuously search for food sources and are prepared to migrate to neighboring areas. They possess remarkable speed and jumping ability, modeled by Eq. 58.

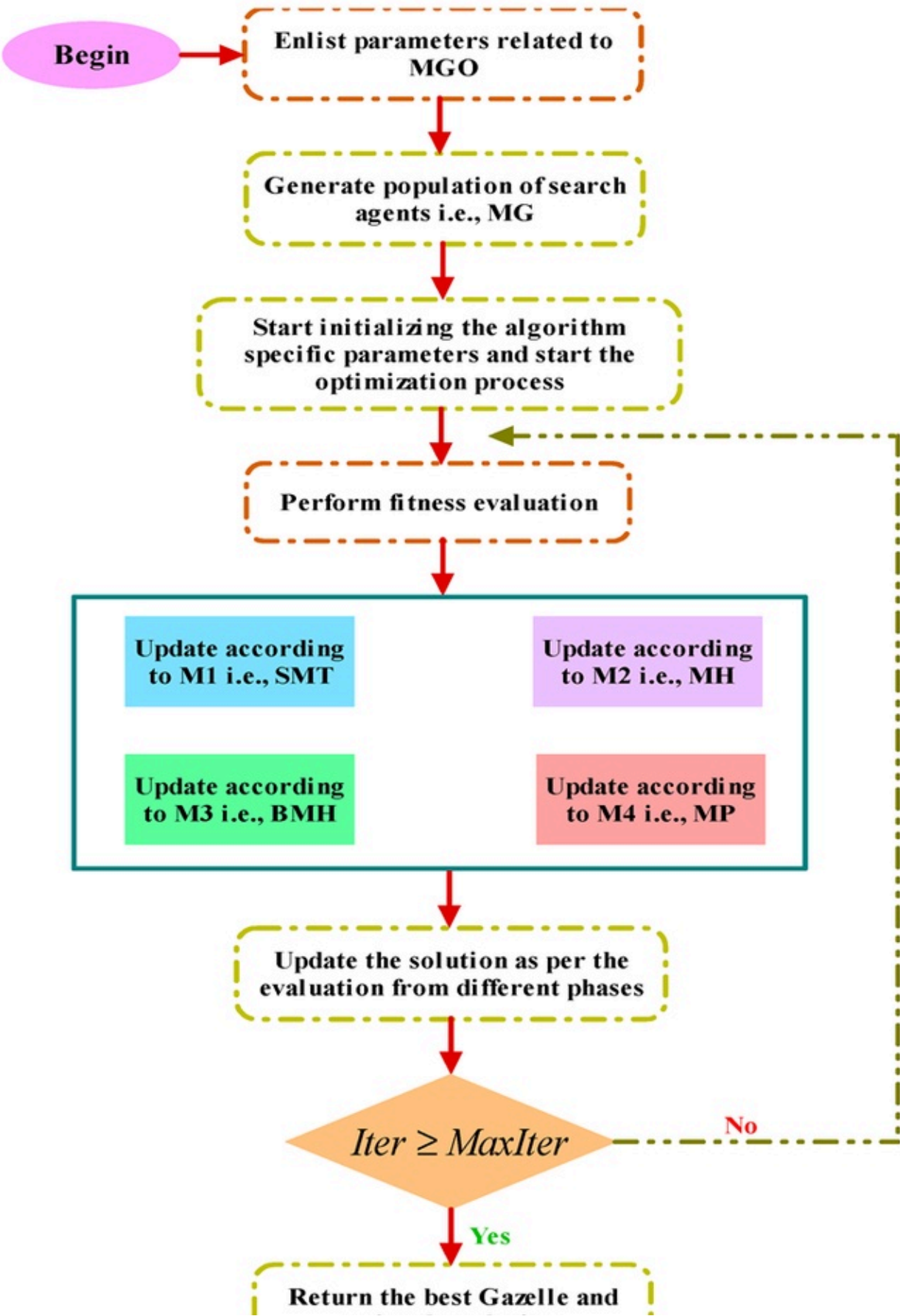
$$MP = (upb - lwb) \times r_7 + lwb \quad (58)$$

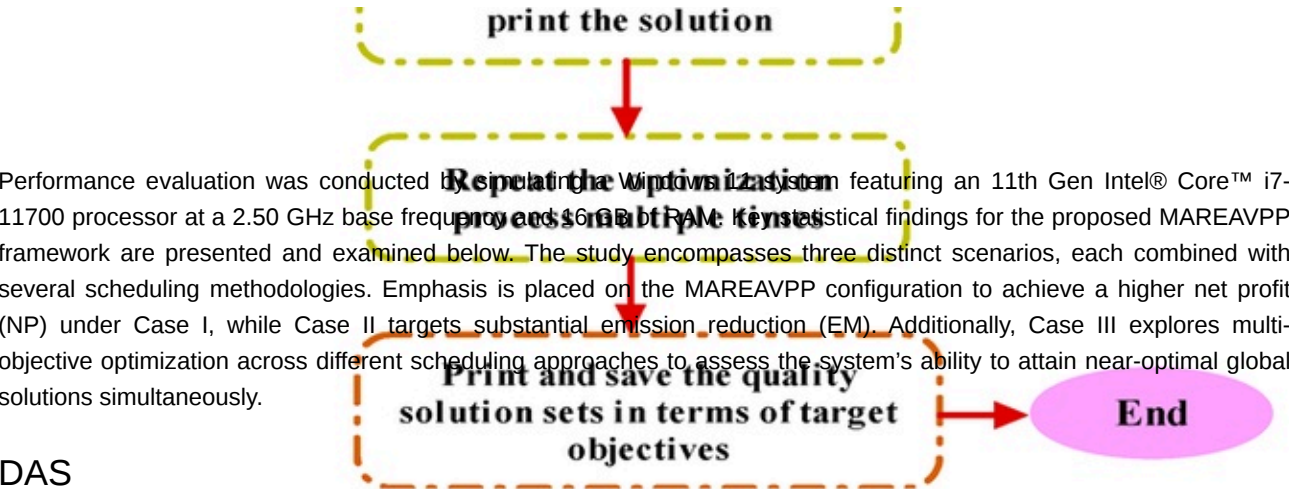
Where the following apply:

upb and lwb are the upper and lower bounds, respectively.

r_7 are random integers selected between 0 and 1.

All four mechanisms are applied across the entire population of MGs to generate new candidate solutions and perform updates. Each set of newly produced solutions constitutes one iteration. At the end of each iteration, the fittest individuals (best solutions) are retained, while the weakest are discarded. The complete optimization procedure leading to the desired solution is illustrated in the flowchart shown in Figure 5.





The chosen optimization time step for the proposed method is initially set to 1 hour, segmenting the full scheduling horizon into 24 hourly slots, a commonly used approach termed day-ahead scheduling (DAS). The resulting power balance behavior of the MAREAVPP in the DAS framework appears in Figures 6 and 7.

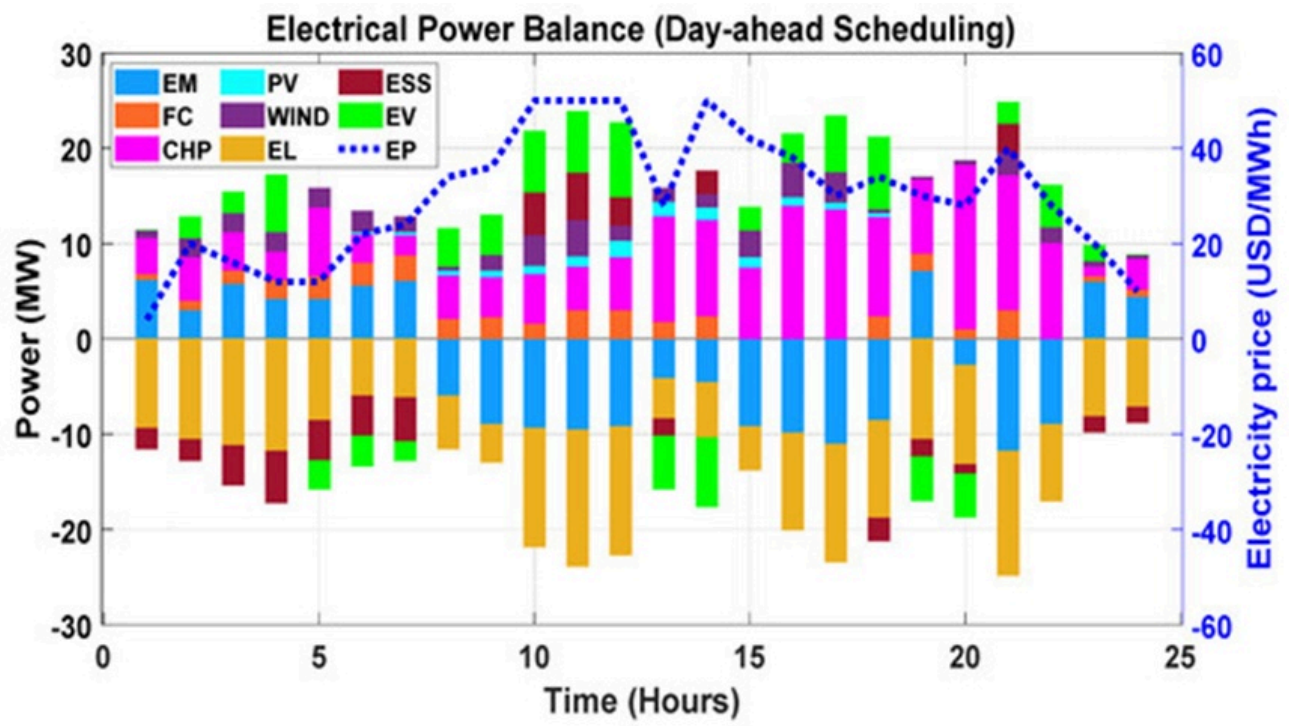


Figure 6. Power balancing for Case I (DAS).

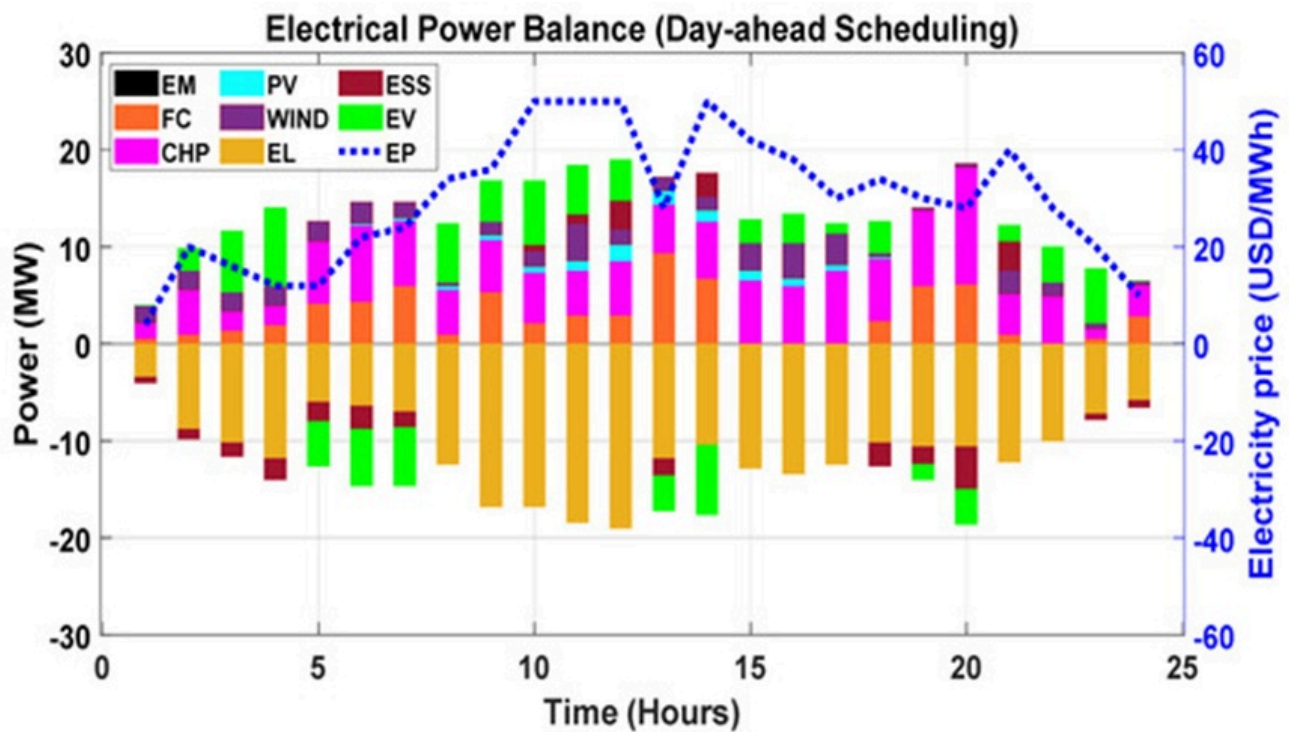


Figure 7. Power balancing for Case II (DAS).

Proposed IHS

The preceding evaluation is specific to the DAS timescale and has been extended to intra-hour scheduling (IHS), where the optimization granularity is tightened to 15-minute intervals. Consequently, the scheduling horizon is partitioned into 96 time slots rather than the 24 used in DAS. Corresponding power balance diagrams for the MAREAVPP during IHS are shown in [Figures 8 and 9](#) for Cases I and II, respectively.

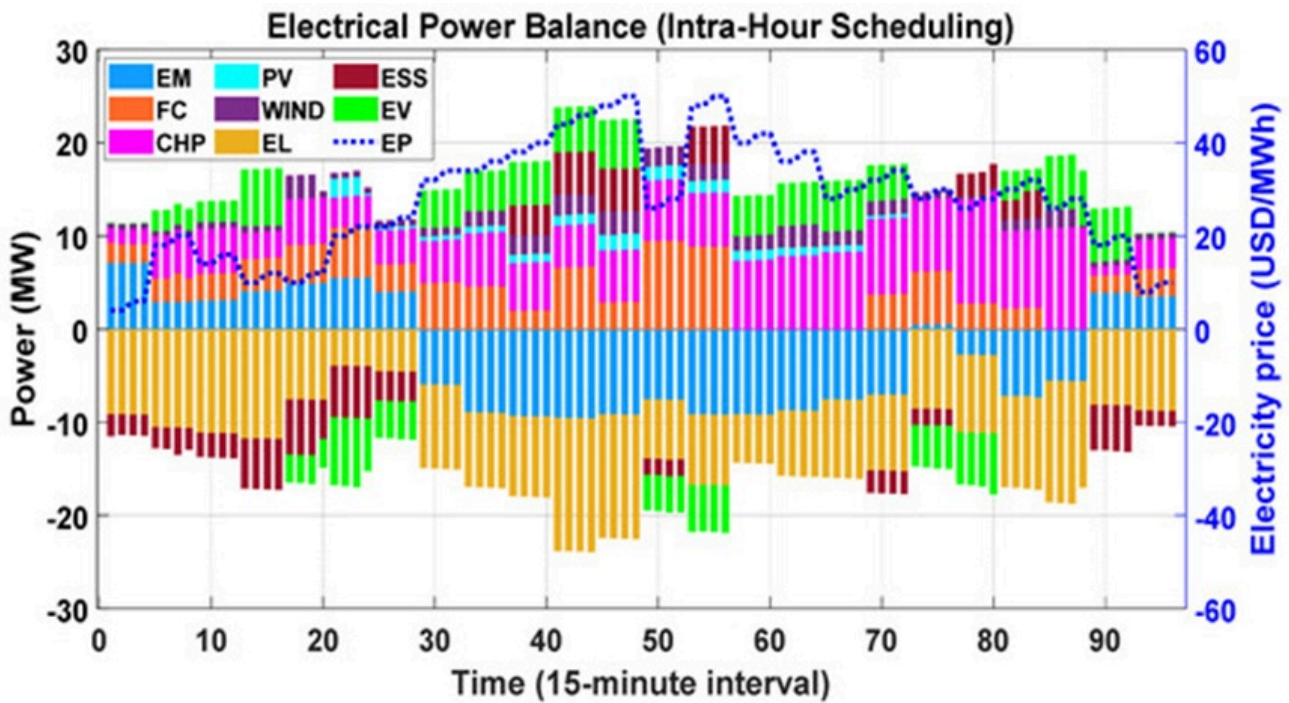


Figure 8. Power balancing for Case I (IHS).

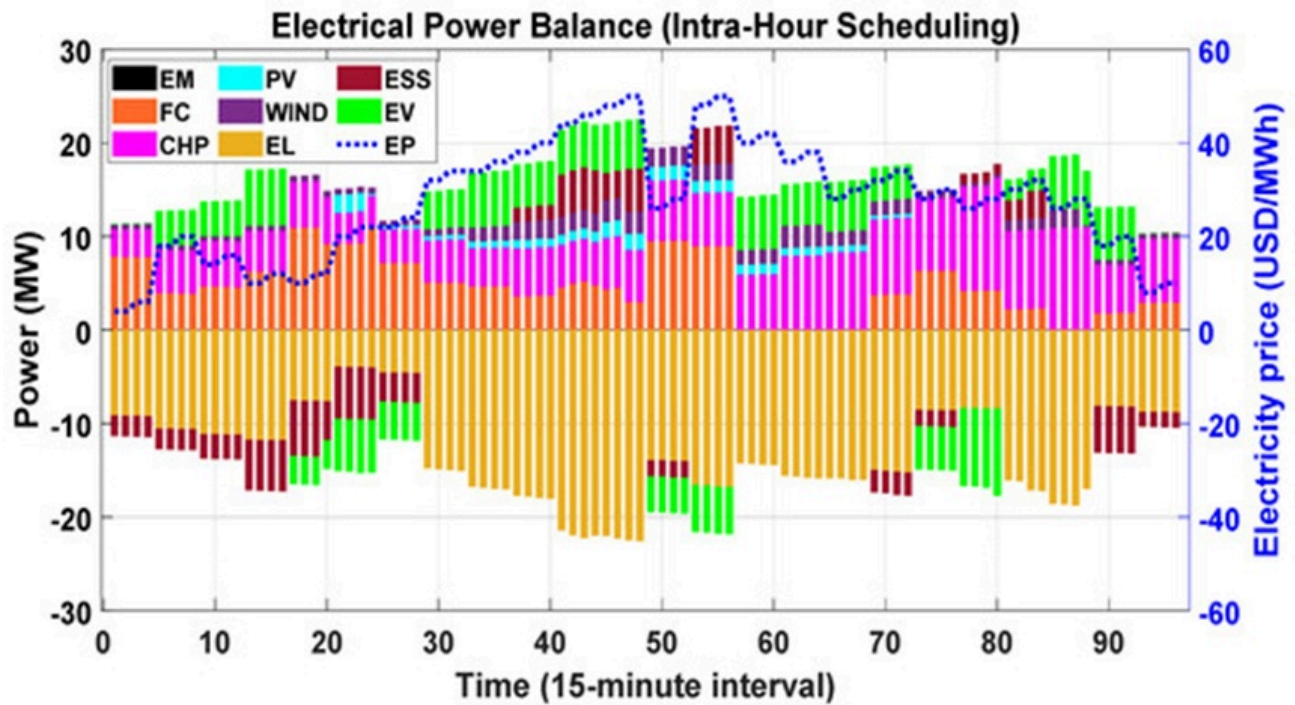


Figure 9. Power balancing for Case II (IHS).

Proposed RTS

Consistent with the progression from DAS to IHS, a finer resolution is achieved by adopting a 5-minute optimization interval to investigate real-time scheduling (RTS) performance, yielding 288 discrete intervals for greater temporal precision. Power balance outcomes for the MAREAVPP under RTS are displayed in [Figures 10 and 11](#). Furthermore, incorporating renewable generation sources into the virtual power plant structure significantly enhances overall system agility, yielding superior final performance metrics compared to those under DAS.

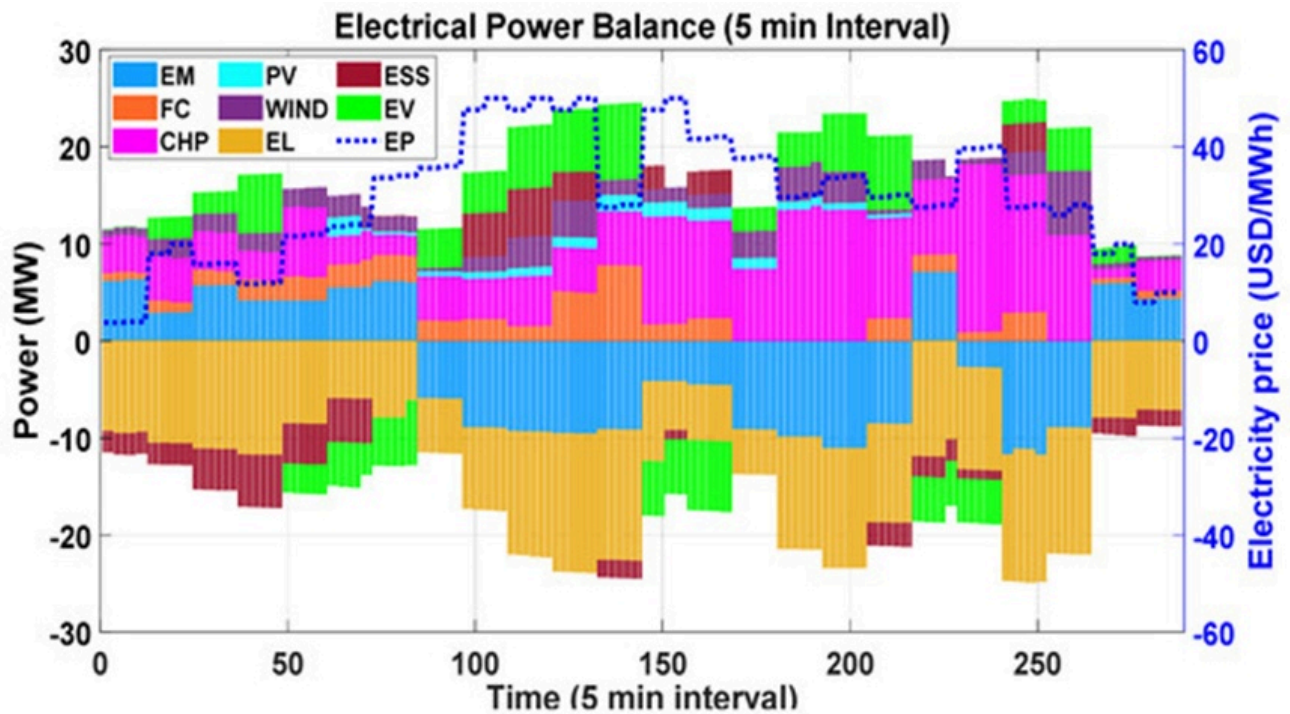


Figure 10. Power balancing for Case I (RTS).

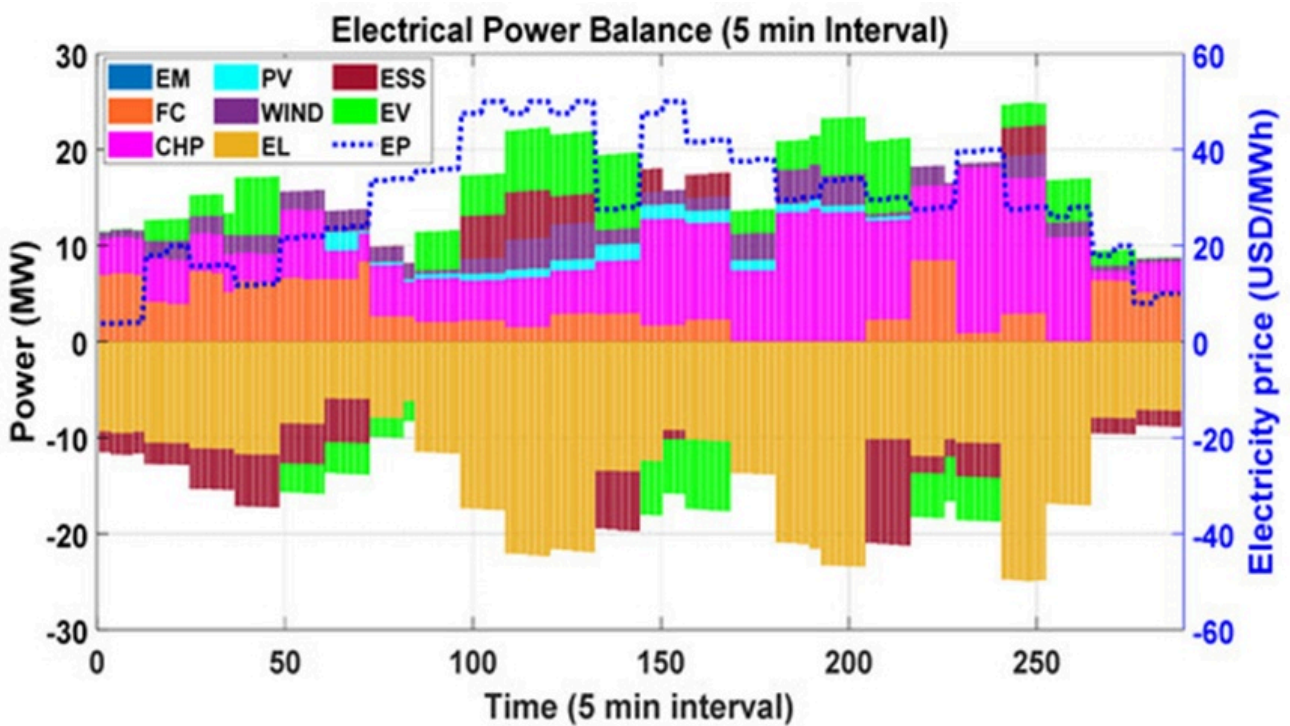


Figure 11. Power balancing for Case II (RTS).

In essence, the power balance is illustrated across two primary scenarios: one designed to maximize financial gain (net profit) through active participation in the energy market, and another focused on quantifying and minimizing environmental emissions. The analysis systematically applies a range of scheduling techniques, commencing with day-ahead scheduling (DAS) at 1-hour (24-interval) resolution. This is followed by intra-hour scheduling achieved through

successive refinement steps at 15-minute and subsequently 5-minute intervals. A comparative assessment of system behavior under these multiple scheduling resolutions concludes the section.

Here is a substantially reworded version with fresh phrasing throughout, while strictly preserving the original structure, all numerical values, table/figure references, acronyms, currencies, percentages, and placing all reference numbers inside brackets as instructed.

Numerical results

A series of test cases was conducted on the developed MAREAVPP model, using different combinations of renewable generation to satisfy load requirements. Validation relied on an enhanced metaheuristic solver. Solution sets exhibit progressive quality gains across iterations. The accompanying convergence plots appear robust, and execution efficiency rises noticeably when shorter optimization intervals are adopted. Case I is dedicated to maximizing financial return, whereas Case II prioritizes minimizing environmental emissions via multi-goal optimization (MGO).

Case I

A large portion of earlier research has limited evaluations to daily (24-hour) horizons, omitting any sub-hourly adjustments. That conventional setup is replicated here as a reference point for assessing the new system. The numerical outcomes from PSO and MPO are shown in [Table 1](#), with peak profits of USD 58,978.3 for PSO and USD 59,351.88 for MPO. The data in [Table 1](#) highlight MPO's stronger runtime behavior and a resulting 0.64% uplift in attainable profit. The pair PSO and marine predator optimization (MPO) was intentionally selected to balance classic, widely accepted solvers against more contemporary ones when judging overall system effectiveness.

Table 1. Assessment of Case I with different algorithms considering DAS [\[21\]](#).

Output metric	PSO	MPO
Highest profit (USD)	58,978.3	59,351.88
Lowest profit (USD)	45,226.52	45,620.52
Average profit (USD)	52,102.41	52,486.2
Computational time (s)	122.41	92.96

Next, the sophisticated MGO solver is deployed for both DAS and the higher-resolution schedules, and the comprehensive findings are compiled in [Table 2](#). The central aim of examining temporal granularities is to verify whether real-time resolution yields results that are clearly superior to those from coarser resolutions. Extension of the study to the proposed IHS and RTS configurations reveals consistent gains, thereby validating the method tailored for Case I ([Table 2](#)). Application of MGO produces a clear 1.1% profit increase in the proposed IHS scenario and a 1.27% increase in the proposed RTS scenario relative to the PSO baseline.

Table 2. Assessment of Case I with multiple scheduling from MGO.

Performance metric	DAS (proposed)	IHS (proposed)	RTS
Highest profit (USD)	59,592.32	59,628.98	59,726.68
Lowest profit (USD)	47,547.28	47,698.96	47,878.86
Average profit (USD)	53,569.8	53,663.97	53,802.77
Computation time (s)	140.46	162.97	189.35

The evolution of the objective function under the examined scheduling policies is shown in **Figure 12**. The proposed IHS settles at a top net profit of USD 59,628.98; the proposed RTS advances further to USD 59,726.68. By comparison, the DAS case stabilizes at USD 59,592.32, falling short of the finer-grained strategies.

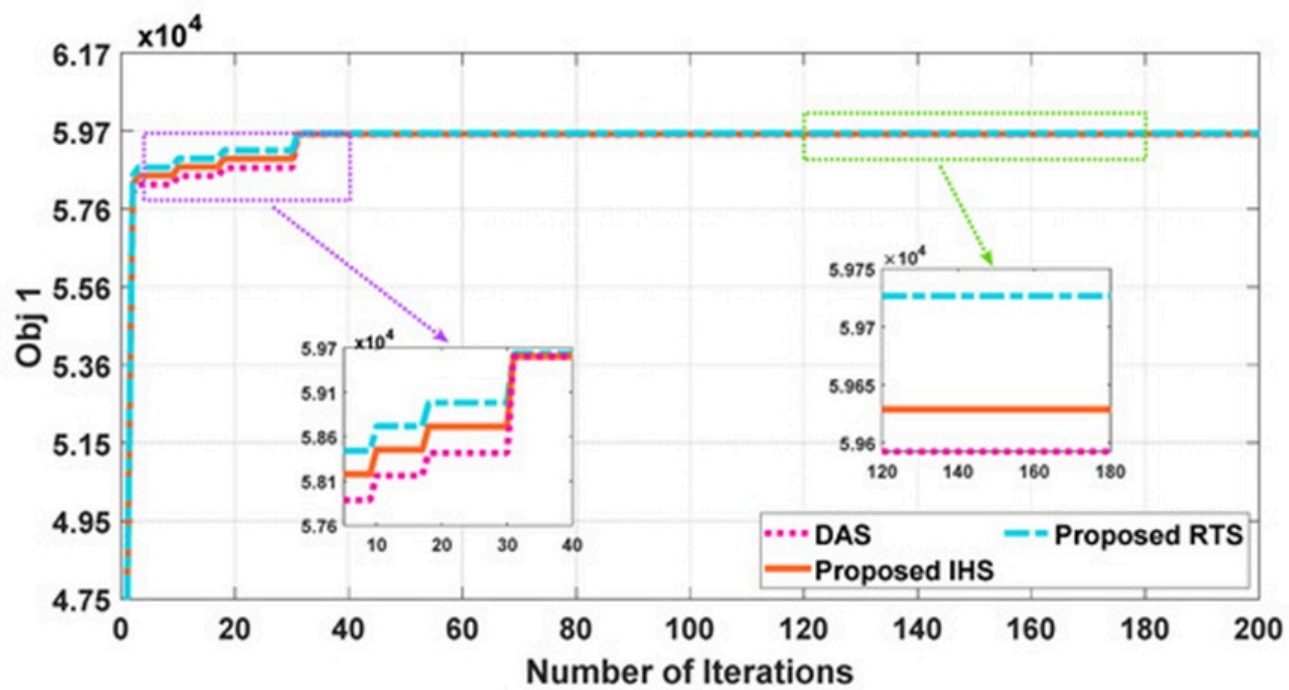


Figure 12. Convergence curve obtained from multiple scheduling for Case I.

Case II

Building on the profit-focused work of Case I, Case II shifts attention to cutting emissions. The initial phase considers only DAS and compares PSO against MPO; corresponding emission quantities are listed in **Table 3**. MPO registers roughly a 1.9% lower emission footprint than PSO, marking a worthwhile though limited advance.

Table 3. Assessment of Case II with different algorithms considering DAS [21].

Metric	PSO	MPO
Minimum emission (kg)	52,700.94	51,700.73
Maximum emission (kg)	64,384.63	63,352.37
Average emission (kg)	58,542.79	57,526.55
Computational time (s)	121.49	107.64

Subsequent tests incorporate the MGO framework and extend coverage to intra-hour resolutions. According to **Table 4**, the lowest emission level—47,580.21 kg—is recorded under the proposed RTS, outperforming both DAS and IHS. A detailed comparison indicates a 7.74% reduction in emissions for the proposed IHS versus the PSO benchmark, while the proposed RTS achieves an impressive 9.72% reduction, representing a highly meaningful improvement. Associated convergence trajectories appear in **Figure 13**.

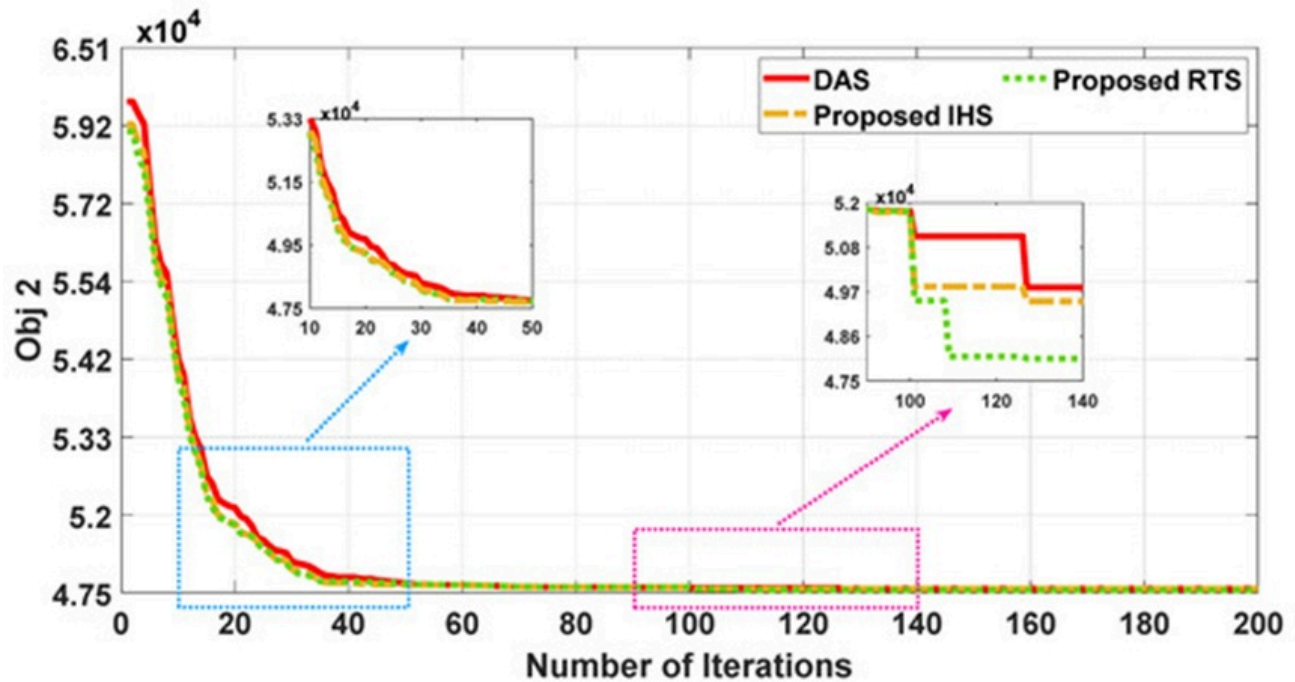


Figure 13. Convergence curve obtained from multiple scheduling for Case II.

Table 4. Assessment of Case II with multiple scheduling from MGO.

Metric	DAS	Proposed IHS	Proposed RTS
Minimum emission (kg)	51,432.42	48,622.34	47,580.21
Maximum emission (kg)	63,062.31	60,152.42	59,228.81
Average emission (kg)	57,247.37	54,387.38	53,404.51
Computational time (s)	135.26	161.32	189.15

Case III

Case III addresses simultaneous optimization of conflicting goals. Results for the DAS horizon, evaluated with PSO and MPO, are tabulated in **Table 5** under objectives O1 and O2.

Table 5. Results of different algorithms considering DAS [21].

Objective function	PSO	MPO	PSO	MPO
	NP (USD)	NP (USD)	NP (USD)	EM (Kg)
Maximum profit	58,978.3	59,351.88	111,784.36	110,561.51
Minimum emission	29,202.86	29,633.49	52,700.94	51,700.73

Results covering the full spectrum of scheduling resolutions for the MAREAVPP appear in **Table 6**. The proposed RTS emerges as the clear leader, offering the best compromise by delivering the highest net profit while minimizing emissions among all tested strategies.

Table 6. Results of multiple scheduling for Case III from MGO.

Objective function	Net profit (USD) – DAS	Net profit (USD) – proposed IHS	Net profit (USD) – proposed RTS	Emissions (Kg) – DAS	Emissions (Kg) – proposed IHS	Emissions (Kg) – proposed RTS
Maximum profit (MaxFprofit)	59,592.32	59,628.98	59,726.68	110,519.48	107,551.18	106,837.46
Minimum emissions (MinFemission)	29,612.31	29,853.46	29,890.24	51,432.42	48,622.34	47,580.21

With the proposed RTS, net profit peaks at USD 59,726.68—exceeding all other resolutions—while emissions bottom out at 47,580.21 kg, below levels seen in DAS and the proposed IHS. Multi-resolution convergence patterns for Case III are displayed in [Figure 14](#). To offer the independent system operator (ISO) flexibility in navigating trade-offs among competing targets, the Pareto-optimal front derived from the proposed RTS is shown in [Figure 15](#).

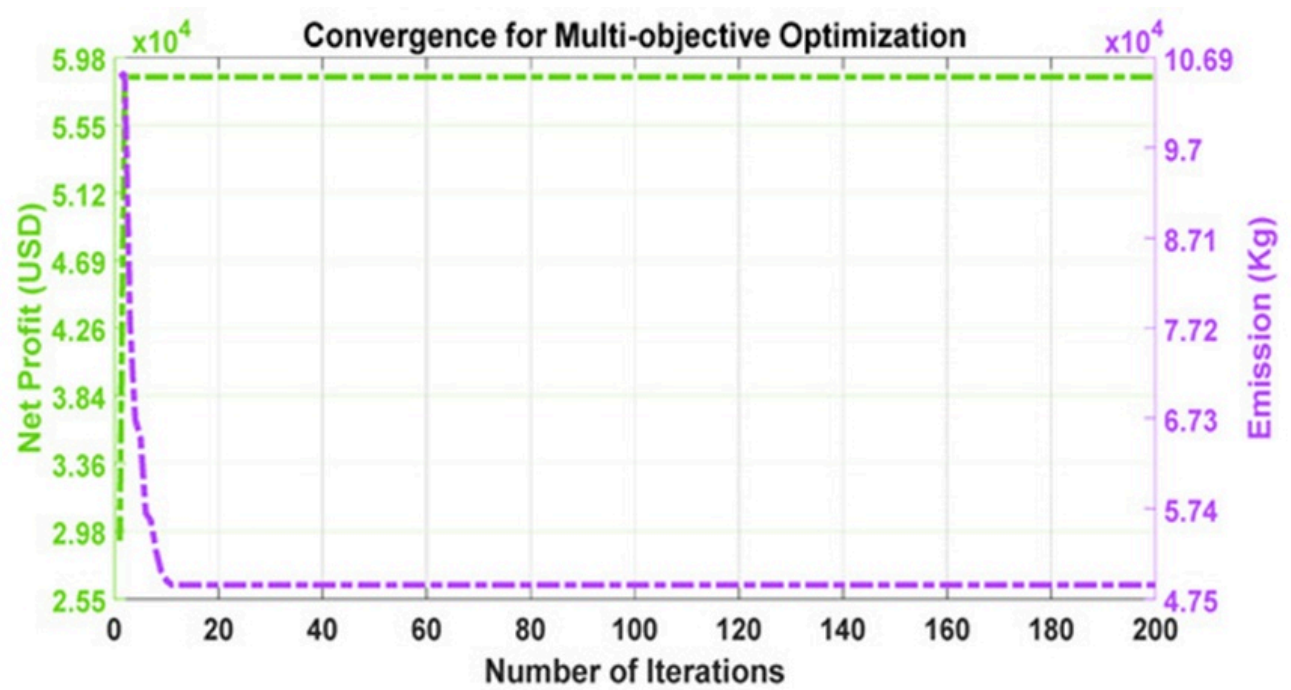


Figure 14. Convergence curve obtained from RTS for Case III.

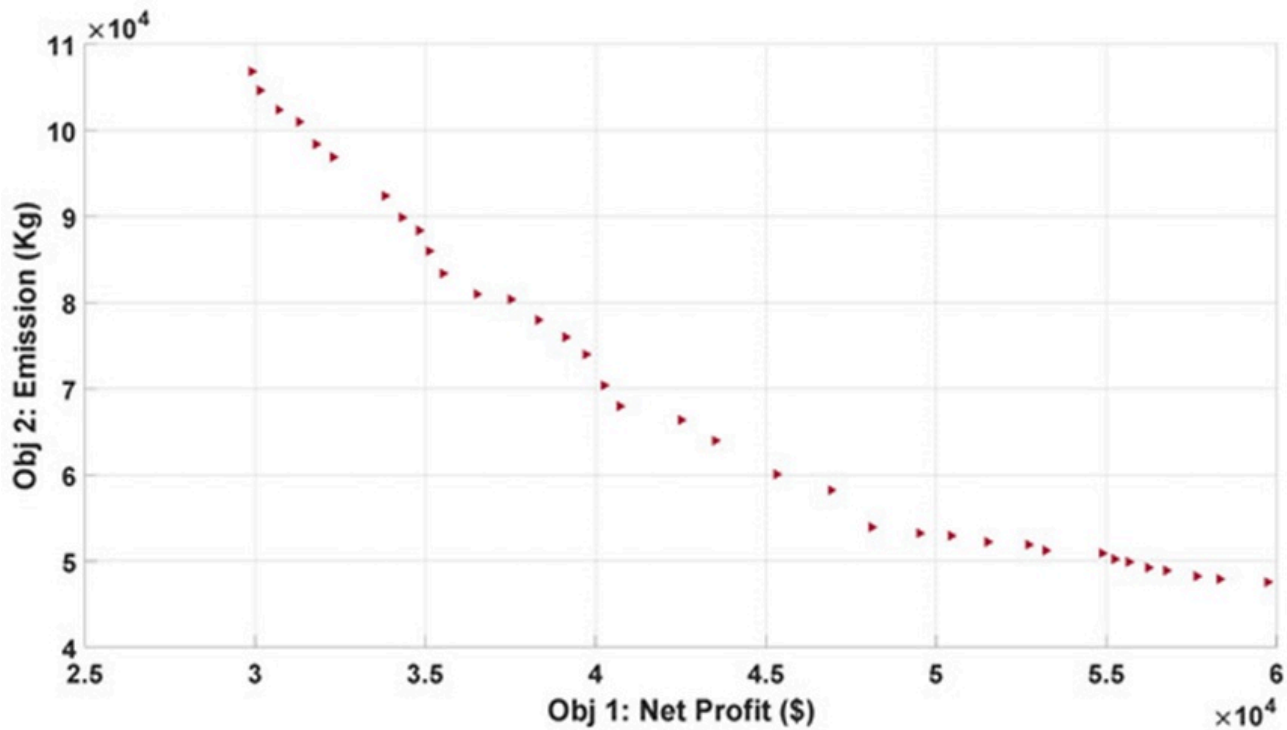


Figure 15. Pareto optimal solution obtained from (RTS) for Case III.

Diverse operating scenarios were simulated for the proposed VPP architecture, leveraging assorted renewable inputs to cover demand. The employed bio-inspired optimizer was used for validation, and solution quality improved iteration by iteration. Displayed convergence profiles remain strong, and runtime performance is favorable compared to competing algorithms.

The effective operation of the selected MGO solver is essential to unlocking the full potential of the MAREAVPP concept. Rapid convergence to high-quality solutions constitutes one of the principal goals of the present research. The processing durations needed to obtain the reported outcomes are documented in [Tables 1 and 2](#); these figures illustrate how MGO behavior adjusts in response to the changing optimization step sizes across the different scheduling approaches.

This section highlights key inferences from research on Virtual Power Plants (VPPs), with a particular focus on multi-area system configurations.

First, an optimization framework is proposed for the effective scheduling of a Multi-Area Renewable Energy Aggregated VPP (MAREAVPP) that integrates diverse renewable energy sources with a cogeneration unit. Additionally, two conflicting objectives are defined that simultaneously address both economic and environmental considerations.

Given the inherent complexities of the MAREAVPP, an advanced Multi-Goal Optimizer (MGO) is used to efficiently solve the problem, achieving an appropriate trade-off between exploration and exploitation. Furthermore, for illustrative purposes, the scheduling process is optimized across several strategies within the proposed MAREAVPP framework. System performance is further enhanced through interconnection via a tie-line.

The primary contributions of this study are presented below in chronological order to provide the reader with clear, straightforward insights:

- Due to the integration of renewable sources, intermittency represents a major challenge. To mitigate this unpredictability, energy storage systems are incorporated into the network, thereby improving the overall reliability of the proposed system.
- The proposed framework is coordinated and operated by a VPP acting as an Internet of Energy Hub (IEH), where aggregation occurs through software rather than physical hardware. Optimal scheduling is

typically performed on a day-ahead basis for simplicity. However, given the presence of multiple renewables, three distinct scheduling approaches are examined: day-ahead scheduling (DAS), intra-hour scheduling (IHS), and real-time scheduling (RTS). These multiple strategies help maintain balance across the multi-area MAREAVPP system, thereby enhancing system dependability. · Constraints on tie-line capacity are duly incorporated and satisfied, leading to overall improvements in net profit (NP) and reductions in emission levels (EM). · An advanced nature-inspired metaheuristic algorithm is applied to achieve the desired objectives within a reduced number of epochs and minimal computational time, delivering high-quality solution sets. The analysis demonstrates that the chosen MGO exhibits strong performance in terms of optimization accuracy and convergence behavior. · Ultimately, the net profit of the entire system increases substantially, accompanied by a significant decrease in emissions, aligning with both economic and environmental goals.

Incorporating renewables into any energy system introduces uncertainty arising from their intermittent and variable nature. This factor is critical when evaluating system performance. To address this, supplementary resources are integrated into the configuration in this study to meet power demand during periods when solar and wind generation fall short, given inherent uncertainties.

Furthermore, the operator employs three distinct tools—DAS, IHS, and RTS—to forecast uncertainties in both generation and load, thereby improving accuracy through shorter optimization intervals. This work introduces the concept of a multi-area structure to manage uncertainty more effectively, as interconnected systems offer greater efficiency and reliability. This approach serves as a promising solution.

Scenario generation and reduction techniques are applied to align supply with retailer demand, providing the VPP operator with greater flexibility to balance power needs thanks to the diversity of resources available across both areas. Surplus power in one area can be utilized by another—an important benefit of the MAREAVPP configuration.

Various types of fuel cells are available depending on application requirements. In this study, Proton Exchange Membrane Fuel Cells (PEMFCs) are selected owing to their broad operating temperature range and extended reliable operation hours relative to alternatives. The adopted model is tailored specifically to the case examined here.

VPPs play a vital role in shifting from the existing centralized power architecture toward a more advanced, decentralized, and integrated framework—a key step in advancing toward a renewable and sustainable energy future. The establishment of large-scale VPPs or community-level VPPs fosters cleaner energy adoption and smart-grid development, delivering value and advantages to prosumers, utility operators, and all relevant stakeholders.

Accordingly, the framework developed in this work integrates multiple scheduling strategies. It assesses the economic viability of multi-area VPP networks using advanced soft-computing methods in a highly effective manner. It not only boosts the system's overall net profit but also reduces emissions collectively. Hour-ahead and real-time scheduling intervals are explored to counteract the unpredictability of wind and solar power by addressing the problem across different optimization time scales.

The analysis confirms the effectiveness of the proposed approach, as validated through a variety of scheduling-based implementations. The results indicate that the MAREAVPP methodology is well-suited for this purpose. The selected algorithm is thoroughly discussed, along with the relevant supporting equations. To relate the proposed framework to practical scenarios, an intra-hour scheduling strategy is implemented, involving detailed extrapolations to evaluate MAREAVPP performance under IHS and RTS conditions.

Moreover, the optimization problem is formulated in a multi-area context to maximize the profit objective—one of the most essential features that render Virtual Power Plants economically viable.

The two zones are modeled as independently capable yet interconnected entities, enabling greater profit through efficient resource allocation and aggregation. For simplicity, the resources considered in both zones are identical, with no

additional correlations assumed. Nevertheless, the potential of MAREAVPP extends beyond this scope; it can be expanded to three- or four-area systems by adjusting the number and types of resources to meet power demand requirements.

Conclusion

The growing penetration of renewable energy sources in the energy sector underscores the necessity for a robust energy management platform capable of replicating the functionalities of traditional conventional power plants. The most promising solution, generating significant interest across the research community and the broader energy sector, is the adoption of Virtual Power Plants (VPPs). These systems enable effective power scheduling through sophisticated, software-driven technologies.

While VPP implementations have traditionally been limited to single-area configurations, this study introduces and optimizes the scheduling of a multi-area renewable energy aggregated Virtual Power Plant (MAREAVPP). To fully harness the capabilities of VPPs, multiple areas are interconnected via tie lines, enabling a comprehensive evaluation of their technical performance and economic viability. The framework incorporates a diverse set of renewable energy resources alongside a cogeneration (CHP) unit. By linking multiple VPPs through tie-line connections, this work demonstrates improvements in net profit and reductions in total emissions, achieved through the integration of CHP units within the problem formulation.

Furthermore, this research investigates several scheduling strategies applied to the developed MAREAVPP system. These include day-ahead scheduling (DAS) and the proposed hour-ahead approaches—namely, intra-hour scheduling (IHS) and real-time scheduling (RTS). These strategies leverage multiple reserve options, specifically Electric Vehicles (EV) and Energy Storage Systems (ESS). Scheduling is performed across varying optimization intervals, with time resolutions adjusted according to DAS, IHS, and the proposed RTS frameworks.

Initially, the proposed method is formulated as a single-objective optimization problem that maximizes the VPP system's profit margin, with a secondary focus on emission reduction. Subsequently, the approach is extended into a multi-objective formulation, enabling simultaneous execution of multiple scheduling strategies. By employing a nature-inspired Multi-Goal Optimizer (MGO) technique, the method achieves both increased net profit and substantial reductions in emissions. The proposed technique exhibits excellent convergence characteristics, reduced average computational time, and effectiveness with a low number of iterations.

The results confirm the appropriateness of the developed optimal scheduling strategy for MAREAVPP, particularly given the need for real-time adaptability in systems with high shares of renewables, which are characterized by variability and uncertainty.

In summary, the methodology presented in this study opens promising new directions for future research in the field of Virtual Power Plants. Moreover, the proposed framework holds strong potential for further enhancement by incorporating additional constraints, leading to problem reformulation and the application of hybrid optimization techniques in subsequent investigations.

Abbreviations

VPP: Virtual Power Plant.

DERs: Distributed Energy Resources.

ISO: Independent System Operator.

DA: Day-ahead.

HA: Hour-ahead.

DR: Demand Response.

RT: Real-Time.

BTM: Behind the Meter.

CHP: Combined Heat and Power.

MAREAVPP: Multi-area based Virtual Power Plant.

EVs: Electric Vehicles.

P2P: Peer to Peer.

PSO: Particle Swarm Optimization.

DSP: Demand Side Participation.

EMS: Energy Management System.

ESSs: Energy Storage Systems.

MGO: Mountain Gazelle Optimizer.

DAS: Day-ahead Scheduling.

IHS: Intra-Hour Scheduling.

RTS: Real Time Scheduling.

NP: Net Profit.

EM: Emission.

NCERs: Non-Conventional Energy Resources.

FC: Fuel cells.

CVPP: Commercial Virtual Power Plant.

MPO: Marine Predator Optimization.

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Conflict of interest

None

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Ethics statement

None

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