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Efficient Resource Allocation in Virtual Power Plant for Real-Time Energy Market Framework.

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Abstract. The increasing evolution of the global energy landscape has made the adoption of distributed energy resources (DERs) and the emergence of virtual power plants (VPPs) crucial for the development of sustainable and efficient energy systems. This paper delves into the critical aspect of efficient DER coordination within VPPs, especially tailored to real-time market framework. The enhanced pelican optimization algorithm (enhanced POA), which is used in this paper, enhances the VPP's capacity to adjust to rapidly shifting energy demands and market dynamics. This effort attempts to build a complete framework that ensures economic feasibility while maximising efficiency by utilising the combined potential of diverse DERs, including storage systems and renewable energy sources.
The paper compares the proposed resource allocation technique with other evolutionary algorithms and evaluate its performance in several case studies using thorough simulation and analysis. With a 8% decrease in energy expenses when compared to other algorithms, the results offer insightful information about optimizing VPP operations and provide a route toward a more adaptable, sustainable, and robust energy management system.

Keywords. Energy management, energy market, renewable energy resources, virtual power plant**.**

1. Introduction

In an era marked by a profound shift towards sustainable energy solutions, VPPs have appeared as a transformative force in the global energy landscape. This paradigm evolution reflects a departure from the traditional, centralized models of power generation, caused by an increasing integration of RERs and a growing demand for real-time adaptability within energy markets.

The urgency of transitioning towards cleaner energy alternatives has propelled VPPs to the forefront of innovative solutions[1]. As society pivots towards renewable sources such as wind and solar, the energy infrastructure is marked with inherent challenges of variability and intermittency. In this context, VPPs present a dynamic approach, aggregating diverse energy sources into a unified, intelligent network. This amalgamation positions VPPs as a key player in reshaping the dynamics of energy generation, distribution, and consumption.
The operational intricacies of VPPs are magnified when confronted with the dynamic nature of real-time energy markets. Unlike traditional power grids, real-time operations demand a level of adaptability and responsiveness that transcends conventional capabilities. The ability to instantaneously adjust to demand fluctuations, respond to pricing variations, and optimize resource allocation in real-time is crucial for ensuring both viability and sustainability of VPPs.

Resource allocation at core of VPP optimization, encapsulates the strategic distribution of energy resources to meet demand while navigating the complexities of market dynamics. It is a delicate orchestration, requiring a meticulous balance between harnessing the potential of renewable energy sources, managing energy storage, and aligning with the flow of market conditions.

Persistent challenges like complexity and scalability persist within the optimization techniques, demanding ceaseless refinement to ensure their efficacy in navigating the intricate demands of evolving energy paradigm. After careful literature review, it became evident that algorithms designed to address stochastic challenges exhibit limitations such as low precision and a tendency to converge swiftly to the local optima. Motivated by this insight, this paper employs collaborative foraging of the enhanced POA to optimize resource allocation within the real-time energy market framework. The aim is to introduce an energy management strategy for the optimal operation of various components within a Virtual Power Plant (VPP), including wind turbines (WT), micro turbines (MT), photovoltaics (PV), fuel cells (FC), batteries (BESS), and interactions with the external grid. As a result, this paper's contributions are centred on the algorithm's effective resource allocation by:

- Seeing to a balanced approach to exploration and exploitation of the solution space.

- Efficient adaptation to dynamic grid conditions.
- Mitigation of premature convergence and improved robustness in handling uncertainties.

To validate the effectiveness of the algorithm, case studies are evaluated, and the algorithm compared to others to establish strength and weaknesses, evaluate performance, and showcase how the algorithm mimics or directly relate to real-world use. The rest of the paper is outlined as follows: section 2 covers related work, section 3 details the problem formulation and the optimization procedure, section covers the case studies, results and analysis, and section 5 concludes this work.

2. Literature Survey

A VPP combines energy sources into a unified, controllable entity. The combination of energy sources creates a more adaptable, responsive, and economically practical energy system that can contribute to a sustainable and robust power infrastructure. However, there are aspects that needs addressing before this aim can be achieved. This section delves into some of the work that has been undertaken. By examining literature, the idea is to gain comprehensive understanding and contribute to the collective conception in the domain of VPP.

Examining the complex domain of resource availability and feasibility is one of the aspects that needs attention. The VPP must have a full comprehension of the features and difficulties presented by different energy sources [2]. Renewable energy sources are inherently unpredictable and volatile. Advanced forecasting models are essential in addressing this issue of volatility since they can find patterns in energy output and help VPP improve its operations on a dynamic basis. In [3], wang et al, suggests a model for forecasting photovoltaic power with precise intervals, utilizing a combination of frequency-domain decomposition and a composite deep learning model. Compared to other models, the results showed superior effectiveness. On average, there was a 15% prediction enhancement in both prediction accuracy and stability compared to other models. Also in [4], a convolutional neural network is introduced to capture correlations among multiple energy sources. The outcome shows that the proposed framework surpasses alternative models in terms of accuracy. The proposed method showed reductions of 0.134, 0.229 and 0.271 in error for solar PV, solar thermal, and wind power, respectively.
It is noticeably clear from the references that, using predictive analysis, the VPP can forecast variations in resource accessibility and change its approach instantaneously, guaranteeing dependable and effective energy production.

Another important aspect is the optimization for efficient resource allocation. This aspect is the pivotal point of this paper – to utilize an optimization algorithm which best allocate the resources efficiently to meet demand. The VPP utilizes forecasting models to accurately predict renewable resources availability, and market prices, providing a foundation for decision making. This decision-making stage is the work of the optimizer. It plays a crucial role in dynamically and intelligently managing the allocation of resources to maximize efficiency and achieve predefined objectives. Table I shows selected literature that has been conducted on resource allocation optimization with various algorithms. Another aspect of consideration is the inclusion of energy storage in the VPP. Energy storage emerges as a key component in enhancing resource efficiency. Batteries, fuel cells and other storage technologies enable the VPP to store surplus energy during peak production periods and discharge it when renewable sources face low production [12]. This not only mitigate the impact of variability but also contributes to grid stability by providing a buffer for fluctuations in supply and demand. As technology continues to evolve, exploring innovative storage solutions becomes integral to the VPPs resilience and adaptability in the face of changing resource dynamics. The impact of large scale battery energy storage systems (BESS) on a low inertia power grid's ability to maintain a stable and desired frequency level is numerically assessed by Zuo et al [13]. It compares the effectiveness of grid-forming and grid-following control modes in further details. Large BESSs installations can significantly improve the system's frequency stability and desired level, as demonstrated empirically through simulations.

Table I. – Selected Literature on Resources Optimization

Ref	Objective	Algorithm	Relevance
[5]	Optimal scheduling	HHO	Energy management
[6]	Power management	BOA	Voltage control
[7]	Carbon-neutral economic scheduling	MILP	Meeting climate target
[8]	Carbon emission reduction	SCV-PSO	Clean energy
[9]	Profit maximization	RO	VPP viability
[10]	Optimal scheduling	PSO	Power system flexibility
[11]	Emission reduction	BWO	Clean energy

3. Problem Formulation and Optimization

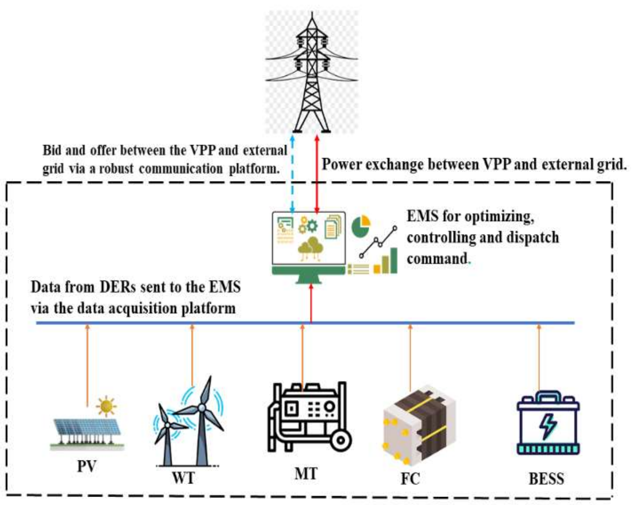

Fig.1 Proposed VPP topology

In this section, the objective function and the constraints are discussed. The VPP topology as shown in Fig.1 consists of photovoltaic (PV) panels, wind turbines (WT), micro turbine (MT), fuel cells (FC), and BESS.

A. Objective Function

The overall operational expenses encompass the fuel and operational costs associated with the energy sources, and the expenditures linked with power transactions between the VPP and the external grid, as well as costs related to the initiation and cessation of operations. The problem is formulated as below:

$$\boldsymbol{Min(OF)} = \sum_{N}^{T} \boldsymbol{Exp}$$

$$= [(\boldsymbol{P_{EG}} + \boldsymbol{Q_{EG}}) + (\boldsymbol{P_{FC}} * \boldsymbol{O_{FC}} * \boldsymbol{Q_{FC}}) + (\boldsymbol{P_{PV}} * \boldsymbol{O_{PV}} * \boldsymbol{Q_{PV}}) + (\boldsymbol{P_{WT}} * \boldsymbol{O_{WT}}(\boldsymbol{P_{WT}} * \boldsymbol{O_{WT}} * \boldsymbol{Q_{MT}}) + \sum_{K}^{X}(\boldsymbol{O_K} * \boldsymbol{W_{BESS}} * \boldsymbol{Q_{BESS}}) + \sum_{M}^{N}[\boldsymbol{S_{GM}}(\boldsymbol{U_X} - \boldsymbol{U_Y}) \quad (\mathbf{1})$$

Where $\boldsymbol{P_{EG}}$ and $\boldsymbol{Q_{EG}}$ are the power purchased from and sold to the external grid, as well as the utility's bid at a particular moment respectively.

$\boldsymbol{Q_{FC}}$, $\boldsymbol{Q_{PV}}$, $\boldsymbol{Q_{WT}}$, $\boldsymbol{Q_{MT}}$, $\boldsymbol{Q_{BESS}}$ are the bids of FC, PV, WT, MT, and BESS.
$\boldsymbol{O_{FC}}$, $\boldsymbol{O_{PV}}$, $\boldsymbol{O_{WT}}$, $\boldsymbol{O_{MT}}$, $\boldsymbol{O_K}$ are the states of FC, PV, WT, MT, and BESS respectively.
$\boldsymbol{P_{FC}}$, $\boldsymbol{P_{PV}}$, $\boldsymbol{P_{WT}}$, $\boldsymbol{P_{MT}}$, $\boldsymbol{W_{BESS}}$ are the power outputs from FC, PV, WT, MT, and BESS respectively.

B. Constraints

1) Power Balance. The power balance constraints ensure that the total power consumed or generated is the same as the power supplied. In this paper, the balance constraints is given by:

$$(\boldsymbol{P_{EG}} + \boldsymbol{P_{MT}} + \boldsymbol{P_{PV}} + \boldsymbol{P_{WT}} + \boldsymbol{P_{FC}} + \boldsymbol{W_{BESS,DISCHARGE}}) = (\boldsymbol{P_{DEMAND}} + \boldsymbol{W_{BESS,CHARGE}}) \quad (2)$$

Where $\boldsymbol{P_{DEMAND}}$, $\boldsymbol{W_{BESS,CHARGE}}$, $\boldsymbol{W_{BESS,DISCHARGE}}$ are the power demand, the power discharge from the BESS, and the discharged power from the BESS respectively.

2) Power Output. Power output constraints is the requirement placed on the amount of power the energy sources can generate. Mathematically, it is given as:

$$\boldsymbol{P_{MIN}} \leq \boldsymbol{P_{OUTPUT}} \leq \boldsymbol{P_{MAX}} \quad (3)$$

3) Transmission Loss. Power exchange between the VPP and the external grid will experience losses. These losses are caused by factors such as resistance in lines, distance of transmission etc. For this paper, it is assumed that transmission loss is negligible, and that power exchange experiences no dissipation.

C. Uncertainties.

Uncertainties in the optimization process are the variable factors that can impact the outcome of the results. In this paper, the uncertainties are generated from the wind and solar generations due to their variable nature. To mitigate adverse impacts on the optimization results, probabilistic methods are employed make accurate predictions of the solar and wind generations.

1) Wind Generation Modelling. Wind generation modelling explains how turbines behave and produce energy under different conditions. A Weibull distribution is used to model the uncertainty of wind generation [14].

$$\boldsymbol{F(v)} = \left(\frac{i}{j}\right)\left(\frac{v}{j}\right) \mathbf{exp}\, \boldsymbol{i} - \mathbf{1}\ .\mathbf{exp}\ [-\left(\frac{v}{j}\right)] \quad (4)$$

The probability distribution function (PDF) of wind speed is represented by F(v), the degree of divergence of the observed distribution is expressed by I and the position of the PDF's maximum is indicated by j. It's also critical to remember that the wind speed needs to stay within the turbine's permitted bounds. The cut-in and cut-out speeds determine the WT's operating range, and it is given by the equation below.

$$\boldsymbol{V_{CUT-IN}} \leq \boldsymbol{V_{WT}} \leq \boldsymbol{V_{CUT-OUT}} \quad (5)$$

The rates at which the WT starts producing and stops producing to protect itself from damage are denoted by the variables $\boldsymbol{V_{CUT-IN}}$ and $\boldsymbol{V_{CUT-OUT}}$.

2) Solar Generation Modelling. The number of installed panels $\boldsymbol{N_O}$, their maximum output, $\boldsymbol{Max.rating_{PANELS}}$, efficiency, ɳ, and solar intensity (Irradiation) all affect the PV's power output. Mathematically, it is given by.

$$\boldsymbol{P_{PV}} = \boldsymbol{N_O} \times \boldsymbol{Max.rating_{PANELS}} \times \eta \times \boldsymbol{Irradiation} \quad (\mathbf{6})$$

Solar irradiance is also stochastic. Hence, the modelling of the solar irradiance in this work follows a Rayleigh distribution.

$$\boldsymbol{F(S)} = \left(\frac{\boldsymbol{S_{IR}}}{\boldsymbol{C^2}}\right) \mathbf{exp}\left(-\frac{\boldsymbol{S_{IR}^2}}{\boldsymbol{2C^2}}\right) \quad (7)$$

Where $\boldsymbol{S_{IR}}$ is the solar irradiance data and $\boldsymbol{C}$ is the characteristic variable that establishes the solar irradiance fluctuation.

D. Optimization Process

Living in big groups, pelicans are sociable animals. With their extraordinary fishing skills, these massive birds manage to capture both frogs and turtles. Their hunting methods, which are an interesting process that improves their skill, served as the main inspiration for the development of the Pelican optimization algorithm.
The prey is generated at random throughout the investigating stage, as opposed to relying on their best alternative. The pelican then navigates in the direction of the prey using the equation below [15].

$$\boldsymbol{X_{m,n}} = \begin{cases} \boldsymbol{X_{m,n}} + \boldsymbol{rand} * (\boldsymbol{P_n} - \boldsymbol{I.X_{m,n}}), & \boldsymbol{F_b} < \boldsymbol{F_c} \\ \boldsymbol{X_{m,n}} + \boldsymbol{rand} * (\boldsymbol{X_{m,n}} - \boldsymbol{P_n}), & \boldsymbol{else} \end{cases} \quad (\mathbf{8})$$

$\boldsymbol{X_{m,n}}$ is the current state as per the initial stage of the m^th solution and the n^th dimension. $\boldsymbol{P_n}$ is the pelican's posture relative to its random prey. $\boldsymbol{I}$ is a parameter that is chosen at random to explore space.

During the utilization phase, pelicans expand their wings to lift prey and deposit it in their neck pouch when the fish reach the water's surface. When the pelicans use this tactic, they have greater success in catching fish in the targeted location. The incorporation of pelican behaviour enhances the birds' ability to be exploited by facilitating their migration into more fruitful hunting sites. Pelicans' hunting behaviour can be quantitatively replicated using the equation below:

$$\boldsymbol{X_{m,n} = X_{m,n} + Rand * \left(1 - \frac{Iter_C}{Iter_{max}}\right) * (2 * (Rand - 1) * X_{m,n}} \tag{9}$$

$\boldsymbol{X_{m,n}}$ is the updated stance in accordance with the second stage of the m[th] solution and the n[th] dimension. $\boldsymbol{Rand}$ is a constant with a value of 0.2. $\boldsymbol{Iter_C}$ is the current iteration and the maximum iteration is denoted by $\boldsymbol{Iter_{max}}$. According to [16], premature convergence and inadequate local search capability are two of the issues that still need to be fixed in the basic pelican optimization algorithm (POA). As a result, an enhanced POA is put up to resolve the challenges of the basic POA model.

The two key modifications are to increase both the inclination toward exploration and exploitation. A superior solution and rapid optimization of performance are the objectives. Losing POA variety over time and quickly sliding into the local optima zone were problems that were solved with the development of the Levy flying technique [16]. Often, optimization algorithms use this technique. The algorithm's high step probability causes a large rise in randomness. The exploitation phase of the basic POA introduces the Levy flight in the following manner:

$$X_{i,new} = X_{best} + \omega . R . \left(1 - \frac{t}{T}\right) . (2.rand - 1) . X_{best} . Levy(D)) \tag{10}$$

$$\boldsymbol{Levy(D) = 0.01 . \left(\frac{c \, x \, \sigma}{|d|^{\frac{1}{\beta}}} \right)} \tag{11}$$

Where D is the problem's dimension, and the Levy is the Levy function. β is a constant equal to 1.5, and c and d are random values between 0 and 1.

4. Data, Results and Discussions

The test set-up is sourced from [17], which comprises of the ratings, bid, start-up / shut-down expenses of the distributed energy resources and the utility are given in Table II.

Table II – Ratings and bids of DERs and Utility

Generator	Max. Power (kW)	Min. Power (kW)	Start-up/Shut-down cost (Euro / kWh)	Bid (Euro)
Utility	30	-30	-	-
PV	25	0	0	2.584
WT	15	0	0	1.073
FC	30	3	1.65	0.294
MT	30	6	0.96	0.457
BESS	30	-30	0	0.38

The load demand data, anticipated generation from wind turbines and photovoltaics are also illustrated in Fig.2 and Fig.3 respectively. This information helps the VPP to make informed decisions regarding energy production, distribution, and management, ultimately contributing to a more reliable and effective operation of the VPP.

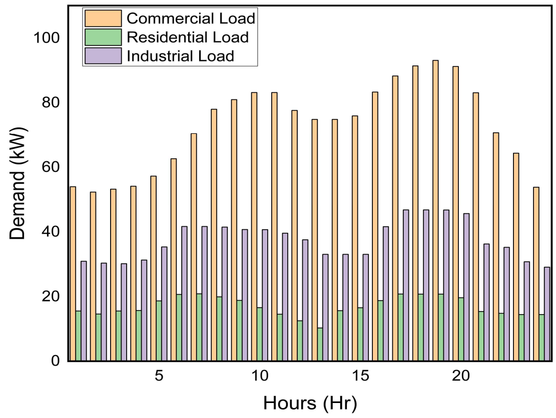

Fig.2. Load demand

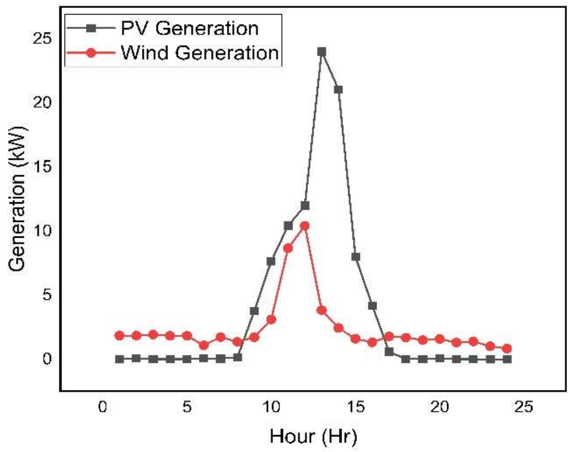

Fig.3. Anticipated wind and solar generations

In the real-time market, dynamic pricing of energy purchasing costs refers to a pricing strategy in which the price of buying electricity varies according to current supply and demand situations. Unlike fixed pricing models, dynamic pricing allows electricity prices to vary throughout the day, aligning more closely with the real-time conditions of the electricity market. With dynamic pricing, power prices can fluctuate throughout the day rather than remaining constant. This allows electricity rates to accurately reflect the current state of the supply and demand, facilitating efficient resource allocation and market equilibrium. The pricing rating determines the VPP's bidding strategy with the external grid. The VPP decides when and how much energy to buy or sell to the grid strategically based on the pricing rating. For instance, in order to maximize revenue, the VPP will decide its electricity export to the grid and instead prioritize selling electricity to the grid during peak pricing periods. The hourly real-time market prices data is sourced from [18] and illustrated in Fig. 4.

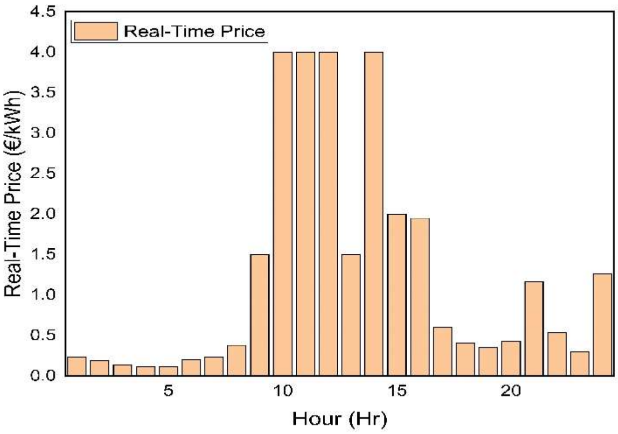

Fig. 4. Real-time pricing

To enhance the study's comprehension, three distinct cases are accessed.

In case 1, it is assumed that all units produce power, with the DERs exchanging power with the utility depending on the demand and dynamic pricing set by the utility. In Fig.5, the optimal scheduling using the enhanced POA is presented. The success of the optimal decision is attributed to the enhanced POA. The algorithm stands out due to its adaptability to dynamic scenarios, and efficient exploration-exploitation presented by the Levy flying technique.

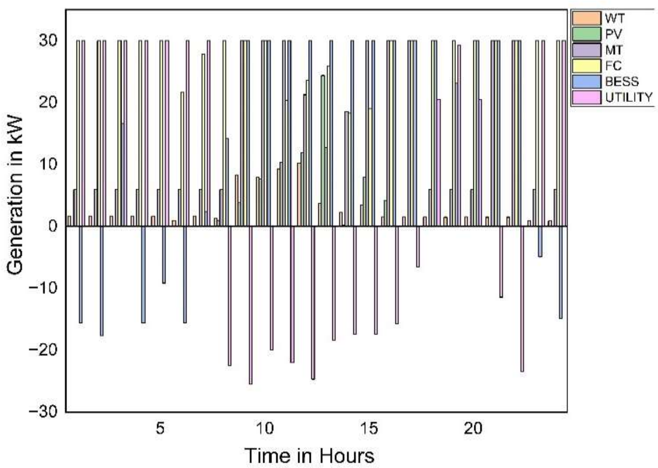

Fig. 5. Optimal scheduling for case 1

The cost of generation (objective function in section 3A) for case 1 is presented in Table III. It presents a compelling narrative of the VPP cost operations in optimally scheduling the energy sources, showcasing the superiority of the enhanced POA over other algorithms [18].

Table III – Cost of generation for case 1

Algorithm	Ideal Solution, €	Worst Solution, €	Average, €
AMPSO-L	274.43	274.73	274.08
CPSO-L	274.74	281.11	277.93
CPSO-T	275.04	286.54	280.79
GA	277.74	304.58	290.43
PSO	277.32	303.37	290.35
enhanced POA	**249.3793**	**254.5783**	**251.9788**

In case 2, the FC and BESS are assumed to be in the OFF mode in this configuration. Fig. 6 displays the results of the simulation for this situation and shows the optimal resource schedule made possible by the enhanced POA. All power generation units operate within their specified limits, enduring a continuous supply of energy to the grid for 24 hours. During the hours spanning 9am to 9pm, both the MT and WT operate at their maximum power generation capacities. Given that the bid from these generators is more economical compared to that of the PV, the VPP, with the aid of the enhanced POA optimally utilizes MT and WT to meet the load requirements. Consequently, power is procured from the grid during the initial 8 hours and last 9 hours, coinciding with periods of comparatively lower market prices. This strategic approach allows the VPP to effectively balance cost considerations while ensuring a consistent and reliable power supply throughout the 24-hour period.

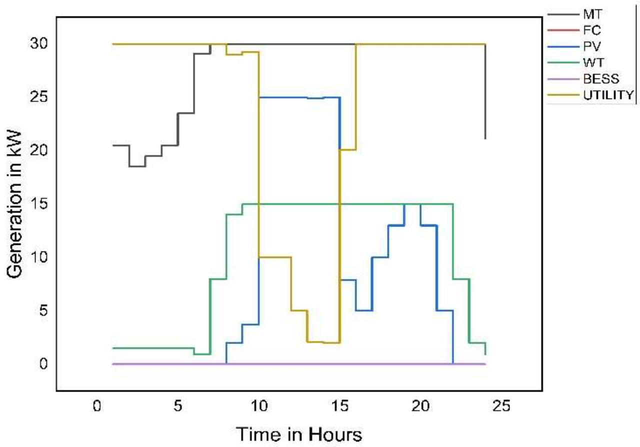

Fig. 6 Optimal scheduling for case 2

In case study three, it is assumed that while the other generators are running, PV is in the off mode. Fig. 7, which illustrates the generators' optimal scheduling using the enhanced POA, provides specific scheduling information. Analogous to the first situation, the optimal power dispatch attained by enhanced POA is shown along with contrasts with other algorithms. The systematic priority of the FC for optimal power generation throughout a whole 24-hour period by the suggested algorithm is noteworthy.

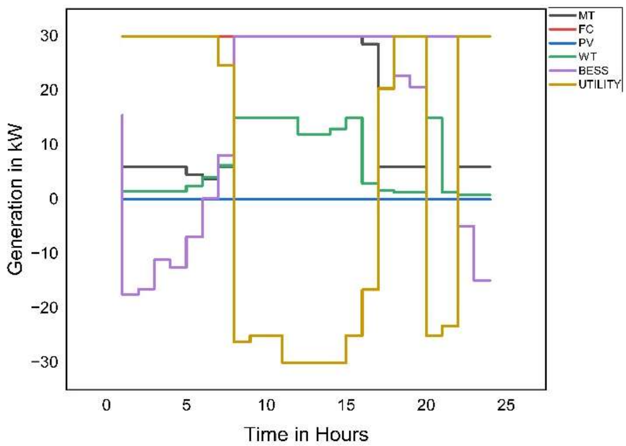

Fig.7 Optimal scheduling for case 3

Table IV illustrates case 3's cost of generation. One reason for enhanced POA's success in producing better results is that it has unique features that improve its optimizing skills. Enhanced POA strikes the perfect balance between focusing on solutions that appear promising and broadening the search space for possible solutions. Compared to other algorithms, VPP performs better financially and is more cost-effective because it increases operational efficiency and ensures that power generated meets demand while taking into account the most economical combination of resources. This leads to lower costs associated with power generation and procurement.

Table IV- Cost of generation for case 3

Algorithm	Ideal solution, €	Worst Solution, €	Average, €
AMPS-L	89.97	90.04	90.00
CPSO-L	90.48	100.87	95.68
CPSO-T	90.55	102.10	96.33
GA	90.33	127.76	109.05
PSO	90.76	112.86	101.8
enhanced POA (proposed)	**82.4613**	**84.5649**	**83.5131**

5. Conclusion

The methodology for allocating DERs in a VPP efficiently to satisfy load demand within the scope of the real-time energy market was provided in this paper. One promising path toward effective and responsive energy management was the integration of several DERs within the VPP. This paper's optimization procedure made use of the enhanced pelican optimization algorithm. The simulation results obtained with the proposed algorithm were compared to those obtained with alternative optimization techniques. The findings showed that the proposed algorithm reduced the energy cost by 7% and 8%, respectively, when compared to variants of particle swarm and genetic algorithm.

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