Virtual Power Plant Profit Maximization in Day Ahead Market using Different Evolutionary Optimization Techniques

2022 4th International Conference on Energy, Power and Environment (ICEPE) | 978-1-6654-7124-4/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICEPE55035.2022.9797939

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***Abstract*—Virtual Power Plant (VPP) is a cloud-based software-controlled distributed power plant that aggregates heterogeneous distributed generation units into a single operating profile to participate in the energy trading with the wholesale energy market. The concept of VPP is mainly employed to deal with the uncertain nature of RESs. This paper discourses an electricity trading scheme involving VPP, consisting of a photo-voltaic (PV), wind turbine, and a micro-turbine (MT) unit in addition to load. The VPP participates in the Day-Ahead Market (DAM) with an objective of profit maximization. The generation scheduling is performed using different evolutionary optimization techniques to maximize the profit of VPP and its participants. Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Manta Ray Foraging optimizer (MRFO) and RUNge Kutta Optimizer (RUN) are the four algorithms being considered and compared in this study. The results show a comparative study in terms of maximum profit of VPP and execution time of optimization techniques. The optimal result is obtained consistently by MRFO.**

***Index Terms*—Virtual Power Plant (VPP), Day Ahead Market, Energy Trading, Renewable Energy Sources, Evolutionary Algorithms**

I. Introduction

In this era of the 21^{st} century, the level of penetration of Distributed Energy Resources (DER) into the main grid has become very high. The capacity of the wind power generation has been increased from 220 GW to 733 GW and for solar it has increased from 73 GW to 713 GW [1] from 2011 to 2020. However, the problem arises because of the intermittency of the DERs like wind, solar, etc. Virtual Power Plants (VPP) are set up by aggregating a large number of DERs with traditional units or flexible loads so that they behave like a single entity and exhibit more robust and predictable characteristics [2]. DER can not replace the capacity of the conventional energy units because without active management and participation, it cannot perform system supporting activities . VPP is deployed to avoid problems like over-capacity issues, efficiency reduction which in turn enhance visibility and controllability of the DERs [3]. Besides working as an aggregator, VPP participates in the trading of electricity with the main energy market. The main idea of the smart grid is to deliver power from generators to end users using digital technology to improve reliability and transparency. This reduces cost not only from the generation end but also from the consumer end [3]. This concept of making the grid smart will be more efficient if VPP is deployed. According to the FENIX project, the VPP combines the volume of several DER by creating a single entity and feeding the network with an aggregated DER output. Being a single profile, VPP can participate to make contracts with the wholesale market and serve system operators. Two types of VPP are there: Technical VPP (TVPP) is more into technical management of the system by examining balancing and ancillary services and Commercial VPP (CVPP) is more into participation in energy market and maximization of profits. The operator of TVPP needs to consider the detailed information i.e. Real-Time (RT) influence of local network on the portfolio of DER. Enabling small capacity DERs to take part in the electricity market is one of the important roles of VPP [4].

The aim of VPP's introduction into the electricity market is to get better results in the electricity market in terms of revenue. A solar power plant (SPP) and a wind power plant (WPP), are aggregated along with a conventional gas power plant (CPP) to act as a single profile in the electricity market. The VPP profit is modeled as a mixed-integer linear programming model (MILP) and the aim is to maximize it [5]. The forecasted power output for WPP and SPP is considered to be known. These power plants are scheduled according to the forecast and CPP comes into the consideration to compensate for the mismatch that happens due to the uncertainty of DERs . In [6], a stochastic programming method is deployed for self-scheduling of the VPP. Similarly, in [7], the profit of multiple microgrids is maximized which are participating in energy trading.

A three-stage model of VPP to take part in the bidding process of the wholesale market is introduced in [8]. Here VPP behaves as a price-taker, not a price-maker as it does not affect the market price. In the first stage, VPP enters the DAM, and all the units in VPP should send the forecasted power output data to the VPP control center. Based on the forecasted value in the DAM, VPP schedules and forecasts the bidding output of each unit in Real-Time Market (RTM) based on forecasted price. In general, the DAM opens a day before the actual trading day for 3 hours. The Day-Ahead (DA) bidding output of each unit is obtained which has less mismatch than the previous ones. In [9], a robust optimization approach is used to cope up with the fluctuating market price.

In [10], the objective function is the VPP profit. As this is a maximization problem, an Artificial Bee Colony (ABC) algorithm is applied to optimize it. The parameters associated are DAM bidding output and RT forecasted output. In [11], Particle Swarm Optimization (PSO) technique is implemented to maximize the revenue function. Different optimization techniques are discussed in [12].

In this paper, a rigid load profile is considered, and the generation is taken as flexible. VPP consists of a solar energy unit, a wind energy unit, and a MT unit in this case study. This paper deals with proper scheduling between RESs and the MT to have the maximum profit from the VPP and reduce the cost of electricity generation. An optimization problem is modeled by building a revenue function and maximizing it. PSO, ABC, Manta-Ray algorithm, and Runge Kutta method – optimization techniques are implemented for solving the problem. Results obtained through these techniques are compared.

This paper has following sections, section II, discusses the optimization algorithms in brief. In section III, the problem formulation is explained. Results for profit maximization of VPP are discussed in section IV. In section V, conclusions have been derived. In this paper four different algorithms have been applied and the obtained results are compared.

II. Evolutionary Optimization Techniques

The firm-level research on VPP scheduling leads to an optimization problem having multiple parameters. This paper compares four different optimization techniques to solve this non-linear problem. An algorithm is developed, consisting of VPP and wholesale market to optimize the bidding strategy assuring no unit is overloaded.

A. Particle Swarm Optimization (PSO)

PSO is a population-based stochastic technique that mimics bird flocking, fish schooling and swarming theory in particular. A basic variant of the PSO algorithm consists of a swarm i.e. population of solutions in the feasible region. Each solution is considered as a particle, which flies through the search space with a particular velocity. The path of the particle depends upon its inertia, the local best, and the global best position [13]. Updation of the solution is performed as eq (1) and (2).

$$v_{i+1} = \omega \cdot v_i + c_1 \cdot r_1(p_b - x_i) + c_2 \cdot r_2 \cdot (g_b - x_i) \quad (1)$$

$$x_{i+1} = x_i + v_{i+1} \quad (2)$$

where v_i and x_i are particle velocity and position in i^{th} iteration respectively. ω, c_1, c_2 are inertia weight, weight associated to local and global best respectively. r_1,r_2 are two random values between [0,1].

B. Artificial Bee Colony Algorithm (ABC)

ABC is a population-based meta-heuristic technique inspired by the collective behavior bees. A colony of bees consists of three types of bees: employed, onlooker and scouts. At first, the employed bees explore and give details regarding the food stock to the onlookers. Then the same number of onlookers waiting in the dancing area, decide and explore the food sources. The task of the scouts is to discover a new food source [14]. ABC uses the eq (3) to update food position:

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \quad , \quad k \neq i \quad (3)$$

where i is index of employed bees whose food source is to be updated and k is a random index and $j \in \{1, 2...D\}$, where D is the extent of problem.

C. Manta Ray Foraging Optimization (MRFO)

In [15], a new meta-heuristic algorithm named as Manta Ray Foraging Optimizer (MRFO) is proposed. MRFO imitates the foraging behavior of manta rays. The foraging operators introduced in this method are: chain foraging, cyclone foraging and somersault foraging. The acceptability of the solution is decided based on the concentration of plankton (food). At first, manta rays line up head-to-tail to form a foraging chain. Now the manta rays move towards the best solution and also towards the solution in front of it, except the first manta ray. In cyclone foraging, they spirally move towards the food. Individuals, except the first, follow the one in front of it and also traverses spirally towards the food. To improve the exploration, they search for new solutions far from the current best. In somersault foraging, the food sources are observed as a pivot and individuals swim to and fro around it and come up with a new solution.

D. Runge Kutta Optimizer (RUN)

In [16], a new swarm-based optimizer with stochastic components named Runge Kutta optimizer (RUN) is briefly discussed. RUN uses the basic concept of Runge Kutta (RK) technique along with population-based evolution of swarms. This algorithm uses the concept of slope calculation which has been proposed in the RK method. A search mechanism which finds its basics in RK method is used in the RUN algorithm. The exploitation or exploration phase in the search process is decided by the condition $rand < 0.5$, where rand is a random number.

if $rand < 0.5$, the exploration phase starts which is given as eq (4):

$$x_{n+1} = (x_c + r \cdot SF \cdot g \cdot x_c) + SF \cdot SM + \mu \cdot randn(x_m - x_c) \quad (4)$$

else, the exploitation phase starts which is given as eq (5):

$$x_{n+1} = (x_m + r \cdot SF \cdot g \cdot x_m) + SF \cdot SM + \mu \cdot randn \cdot (x_{r1} - x_{r2}) \quad (5)$$

where g is random number in [0,2], r is integer, having value of 1 or -1, μ is a random number and SF is an adaptive factor. A special operation Enhanced Solution Quality (ESQ) is utilised to avoid being stuck in a local optima as shown in eq (6) and (7):

if $rand < 0.5$
if $w < 1$

$$x_{new2} = x_{new1} + r \cdot w \cdot |(x_{new1} - x_{avg}) + randn| \quad (6)$$

else

$$x_{new2} = (x_{new1} - x_{avg}) + r \cdot w \cdot |(u \cdot x_{new1} - x_{avg}) + randn| \quad (7)$$

where c is a random number in [0,5], random number w decreases with the iteration, r is an integer, which can have values of 1, 0 or 1 and, u is a parameter to increase the diversity.

III. Problem Formulation

In this research work, the bidding strategy of VPP does not affect the market price. The basic objective of the bidding model is maximization of VPP's profit by trading energy in wholesale market. The VPP is configured by aggregating a SPP and WPP as RESs and an MT plant as conventional unit as shown in Fig.1.

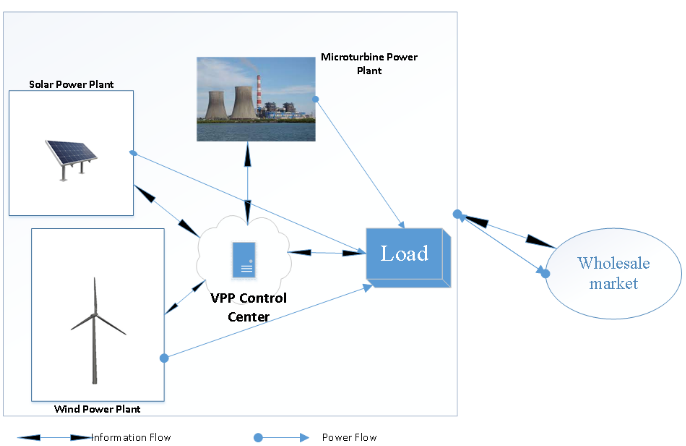

Fig. 1. VPP Configuration

A. Objective Function

The formulation of objective function representing VPP's profit, is performed in this section. The loss due to line flow is neglected i.e., assumed to be 0, as the physical distance between the generating units and the loads is taken as small. The profit function is developed by summing all the earnings of each unit and then subtracting the cost of generation and trading from it is as follows:

$$max \sum_{h=1}^{24} (E_{w,h}^{DAM} + E_{pv,h}^{DAM} + E_{mt,h}^{DAM}) - (V_h^{DAM} + V_{mt,h}^{DAM}) \quad (8)$$

where $E_{w,h}^{DAM}$, $E_{pv,h}^{DAM}$ and $E_{mt,h}^{DAM}$ is the forecast bidding earnings of wind, solar and mictroturbine plant in DAM at h^{th} hour respectively. V_h^{DAM} is the trading cost of DAM and $V_{mt,h}^{DAM}$ is the MT plant cost in DAM.

In eq (8):

- The cost of generation from the SPP is assumed to be zero, and only earning component is considered. The forecasted earning of SPP in DAM is derived as follows:

$$E_{w,h}^{DAM} = B_{w,h}^{DA} \cdot \Omega_h^{DA} + B_{w,h}^{RT} \cdot \Omega_h^{RT} \quad (9)$$

In eq (9), $B_{w,h}^{DA}$ and $B_{w,h}^{RT}$ is the WPP bidding output in DAM and forecasted bidding output in RTM respectively. And Ω_h^{DA} and Ω_h^{RT} are the forcasted price of DAM and RTM respectively.

- The cost of generation of the WPP is also assumed to be zero and only earning of WPP is considered in the profit function. The forecasted earning of WPP in DAM is as follows:

$$E_{pv,h}^{DAM} = B_{pv,h}^{DA} \cdot \Omega_h^{DA} + B_{pv,h}^{RT} \cdot \Omega_h^{RT} \quad (10)$$

In eq (10), $B_{pv,h}^{DA}$ and $B_{pv,h}^{RT}$ is the SPP bidding output in DAM and forecasted bidding output in RTM respectively.

- For MT both the forecasted earning and output cost in DAM are taken into account. The forecasted earning of MT in DAM is as follows:

$$E_{mt,h}^{DAM} = B_{mt,h}^{DA} \cdot \Omega_h^{DA} \quad (11)$$

In eq(11), $B_{mt,h}^{DA}$ is the MT bidding output in DAM.

- In case of a shortage or surplus of power in the VPP, it has to trade with the wholesale electricity market to annul the load - generation imbalance. The mismatch between the load and generation is derived as:

$$B_h^{MARKET} = L_h^{DAM} - (B_{w,h}^{DA} + B_{w,h}^{RT} + B_{pv,h}^{DA} + B_{pv,h}^{RT} + B_{mt,h}^{DA}) \quad (12)$$

eq (12) shows, if B_h^{MARKET} is positive, the generation of VPP units does not meet the demand of the loads associated with it i.e. VPP has to buy electricity from the external market. And negative B_h^{MARKET} indicates that there is a surplus amount of generation in VPP and extra power is to be sold to the external market.

- The parameter B_h^{MARKET} consists of the DA and RT component of trading power between the VPP and the wholesale market.

$$B_h^{market} = B_{DA,h}^{market} + B_{RT,h}^{market} \quad (13)$$

In eq (13), $B_{DA,h}^{MARKET}$ and $B_{RT,h}^{MARKET}$ are the trading power of VPP and wholesale market in the DAM and RTM, respectively.

- The VPP will incur costs due to energy trade with the external wholesale market. The forecasted trading cost in the DAM at h^{th} hour is derived in eq (14):

$$V_h^{DAM} = B_{DA,h}^{market} \cdot \Omega_h^{DA} + B_{RT,h}^{market} \cdot \Omega_h^{RT} \quad (14)$$

- $V_{mt,h}^{DAM}$ indicates MT's operational cost at h^{th} hour. The output cost of MT in DAM comprises of four components: MT running cost, MT starting / stopping cost, environmental penalty on MT and MT base cost under operating condition. The MT operational cost is derived as:

$$V_{mt,h}^{DAM} = (\delta_h - \delta_{h-1}) \cdot C_{start/stop} + C_{dc} \cdot (B_{mt,h}^{DA} - B_{mt}^{min}) + \delta_h \cdot C_{base} + B_{mt,h}^{DA} \sum_{i=1} \beta_i \cdot Z_i \tag{15}$$

In eq (15), δ_h is the MT status co-efficient at h^{th} hour, $C_{start/stop}$ is the MT starting / stopping cost, C_{dc} is MT dynamic cost coefficient, B_{mt}^{min} is MT minimal power output, C_{base} is MT fixed cost. The value of δ_h is 1 when MT is in ON condition and 0 when MT is in OFF condition. β_i and Z_i are the environmental penalty factors of the MT. The environmental penalty and technical parameters of the MT are presented in Tables I and II respectively.

TABLE I
TECHNICAL PARAMETERS OF MT

B_{mt}^{max}	B_{mt}^{min}	C_{dc}	$C_{start/shut}$	C_{base}	B_{mt}^{ramp}
5.67MW	2.5MW	6.31\$/MW	30\$	30\$	3MW/H

TABLE II
ENVIRONMENTAL PENALTY OF MT

Pollutant	NO_x	CO_2	CO	SO_2
Emission(β_i)(kg/MWh)	0.6188	184.0829	0.1702	0.000928
Environmental Value(E_i)(\$/kg)	1	0.002875	0.125	0.75
Penalty(p_i)(\$/kg)	0.25	0.0125	0.02	0.125

B. Constraints

The constraints of the bidding output parameters of each unit are given as follows:

$$0 \leq B_{w,h}^{DA} + B_{w,h}^{RT} \leq B_{WPP}^{DA} \tag{16}$$

$$0 \leq B_{pv,h}^{DA} + B_{pv,h}^{RT} \leq B_{SPP}^{DA} \tag{17}$$

$$B_{mt,h}^{DA} \leq B_{mt}^{max} \tag{18}$$

$$B_{mt,h+1}^{DA} - B_{mt,h}^{DA} \leq B_{mt}^{ramp} \tag{19}$$

- eq (16) and (17) limit the bidding output powers of WPP and SPP to less than the DAM forecasting output respectively.
- eq (18) ensures that MT's output can not be greater than the maximum output.
- eq (19) ensures the MT can neither ramp up nor ramp down beyond the ramp limit.

IV. RESULTS

In order to analyze the dispatch of each unit of VPP in DAM, the bidding output parameters of each unit in DAM are discussed in this paper. A comparison between the forecasted price of the DAM and RTM is done in Fig. 2. It can be seen that the energy price values are almost same for the first 10 hours but an unavoidable variation comes after 10^{th} hour for the remaining part of the day. The VPP system being considered in this study, has to schedule the RESs properly so that it can achieve maximum profit by participating in the wholesale energy market. Fig. 3. and Fig. 4 shows the maximum DA forecasting output data of WPP and SPP which are taken from Nordpool. Fig. 5. represents the load profile of the VPP.

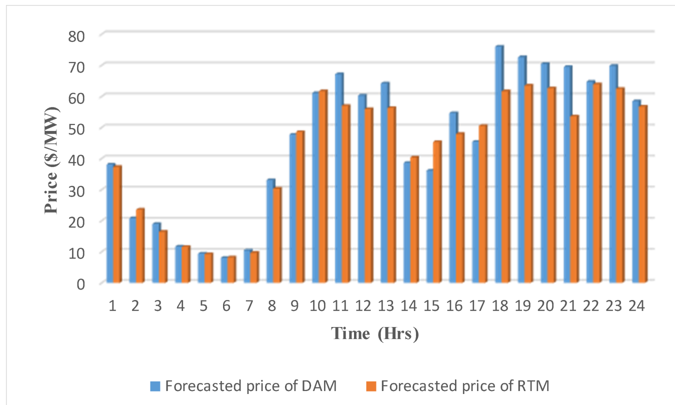

Fig. 2. Forecasted Price Details of DAM and RTM

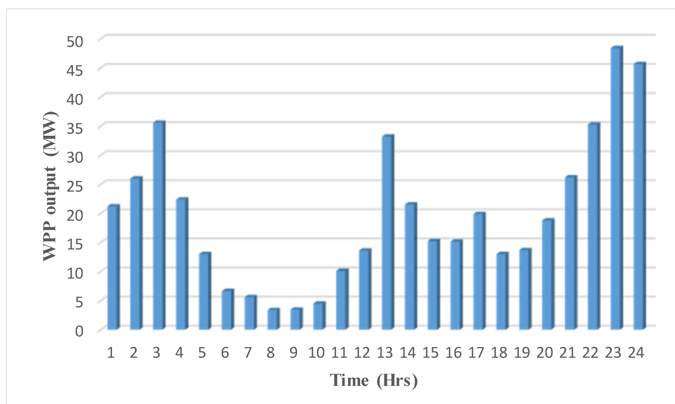

Fig. 3. Output of WPP in VPP

In this paper, the maximization problem is solved using four different optimization algorithms: PSO, ABC, MRFO, RUN. Each algorithm is executed 40 times. A comparison between the best objective function values and the average values is shown in Fig. 6. The scheduled bidding output of each unit in VPP corresponding to their respective best objective function values is shown in Fig. 7, 8, 9 and 10 respectively. In PSO and ABC algorithm there is a peak at 24^{th} hour for the WPP

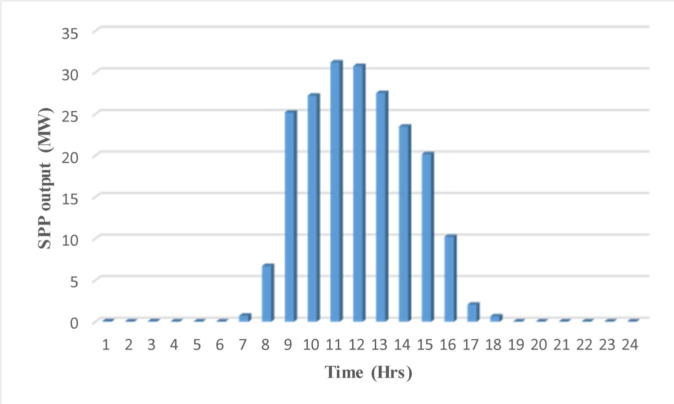

Fig. 4. Output of SPP in VPP

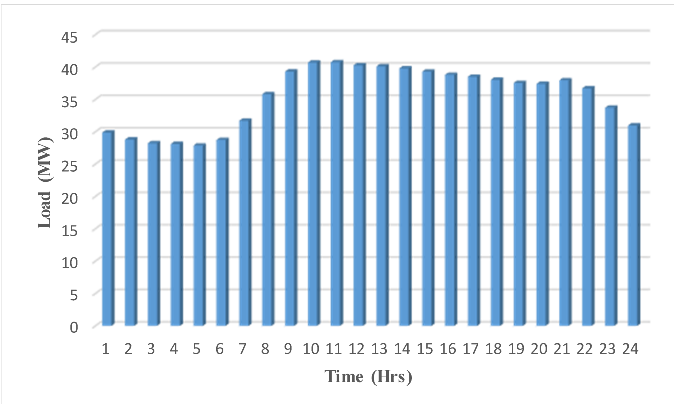

Fig. 5. Load Curve of The VPP

bidding output in DAM. But in MRFO and RUN algorithm there is a peak at the 23^{rd} hour for the WPP output in DAM. For all methods it can be observed that the MT output in DAM is staying almost minimum for all hours. The comparison of the execution time for each algorithm is shown in Fig.11.

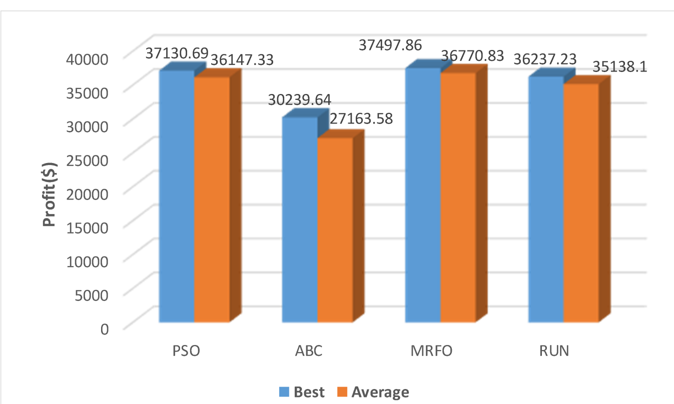

Fig. 6. Optimal and Average Profits

A comparison of standard deviation between different algorithms is presented in Fig. 12.

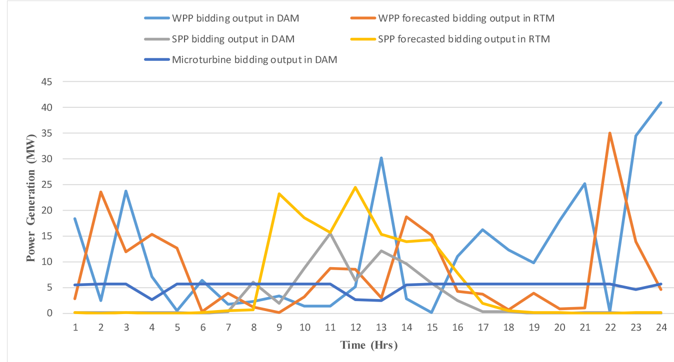

Fig. 7. Bidding Output Achieved Using PSO

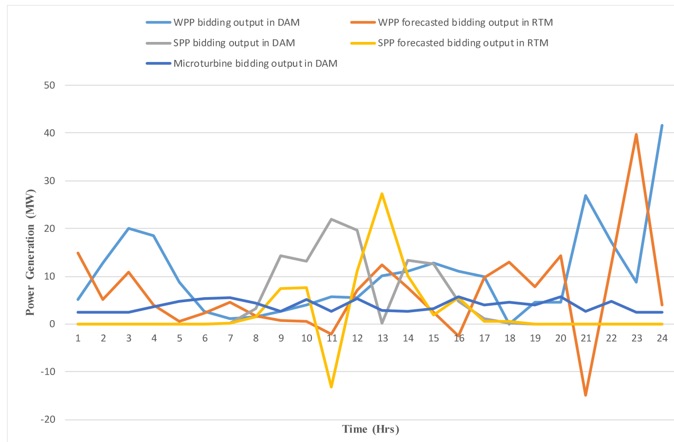

Fig. 8. Bidding Output Achieved Using ABC

It is evident from Fig. 11 that the ABC algorithm takes about 15 seconds to give result, which is the fastest of all the algorithms used. Anyway, Fig. 6. shows the profit value obtained using MRFO is \$37497.86, which is the highest profit value obtained by any optimization technique.

V. Conclusion

A study on a VPP profile participating in the DAM is analyzed in this research work. The objective of the research is to maximize the profit of the VPP by properly scheduling

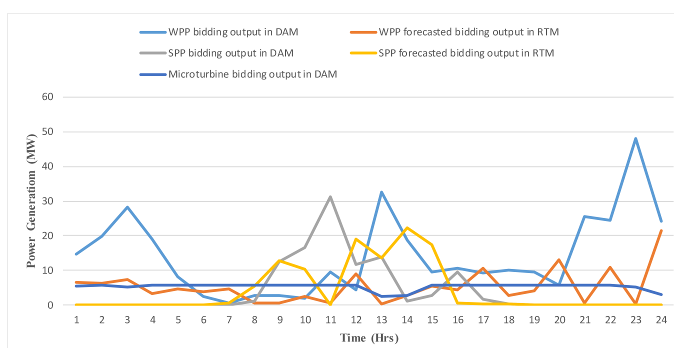

Fig. 9. Bidding Output Achieved Using MRFO

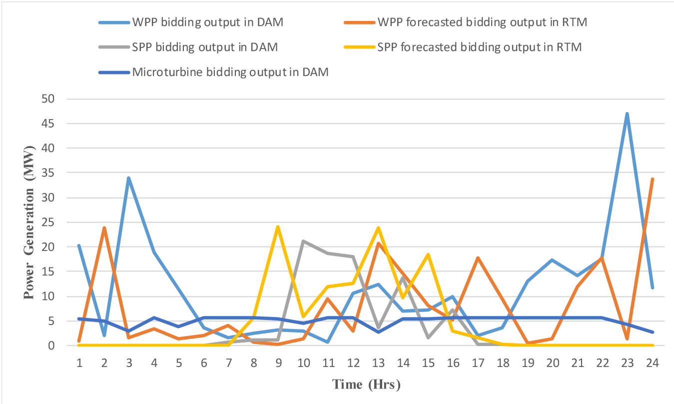

Fig. 10. Bidding Output Achieved Using RUN

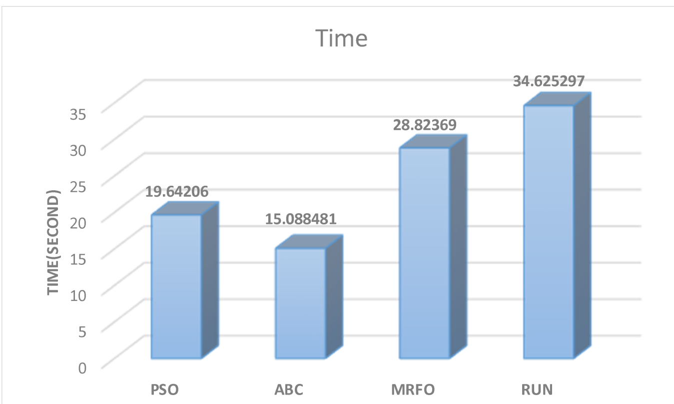

Fig. 11. Comparison of The Execution Times of Each Algorithm

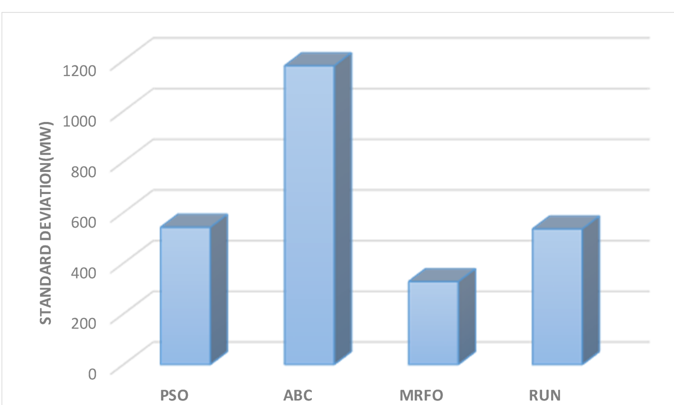

Fig. 12. Comparison of The Standard Deviations

the RESs and MT. PSO, ABC, MRFO and RUN optimization techniques have been implemented to maximize the profit and a comparative study is performed. In terms of execution time, ABC is taking lesser time due to less computational burden. However, MRFO is able to obtain the optimal result in terms of profit value. The standard deviation is also minimum for the MRFO technique.

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