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Optimal power scheduling of microgrid considering renewable sources and demand response management

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Abstract
Generation planning in the power system has been a complex and challenging multi-objective optimization problem. Numerous methodologies have been developed and applied to solve this problem. Still, researchers look forward to further improved methods that can further enhance the outcomes for this problem. This article suggests a hybrid FPA-PPSO scheme that combines the flower pollination algorithm (FPA) and phasor particle swarm optimization (PPSO) algorithm to solve this problem. The suggested FPA-PPSO scheme includes a high search efficiency, balanced local and global search capabilities, etc. which can help in more efficient planning of the generation in a microgrid. To analyze the supremacy of the suggested FPA-PPSO scheme over FPA and PPSO methods, a comparative study using twenty-three benchmark functions is presented. From the analysis conducted from the Friedman test, the suggested method gets a rank of 1.59 which is better compared to PPSO and FPA which get ranks of 2.61 and 3.04 for the twenty-three benchmark functions. Further, the suggested method is tested using four test cases to show its effectiveness in solving the scheduling problem of a microgrid considering renewable energy sources, energy storage systems, and demand response management. The obtained results conclude that the suggested methods show promising performance in planning the generating unit. Using the DRM scheme further helps to efficiently schedule the generation as the utilities save up to $ 25545 more when DRM planning is considered.

Keywords Dynamic economic emission dispatch problem (DEED) · Flower pollination algorithm (FPA) · Phasor particle swarm optimization (PPSO) · Renewable energy sources (RES) · Demand response management (DRM)

1 Introduction

1.1 Motivation and purpose

The rapid growth of the economy in this modern world of highly capitalized society led to environmental concerns for which renewable energy resources are a hot issue in the power system [1]. The generation of energy with more reliability, flexibility, less cost of generation, and fewer environmental effects can be achieved by the use of renewable energy sources (RESs) [2]. The power generated by these sources has an advantage in remote places where the supply of grid power is a difficult task. However, microgrids with small-scale power generation and distribution have various challenges in the efficient power system operation [3]. One of the major challenges which is encountered is the unpredictable nature of power generated by the RESs. RESs such as solar, wind, etc. are weather dependent and thus the power delivered from them is unpredictable [4]. Therefore, to match the demand and supply, it becomes an important task to schedule the other generating sources optimally.

The scheduling problem in the power system is well-known among researchers and is commonly known as the economic dispatch (ED) problem. The objective of the ED problem is to minimize the cost of power generation and emission rates along with the fulfillment of power demand

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considering various constraints of the system [5]. Owing to the objectives and constraints encountered in solving, the ED problem is considered to as a complex, multi-objective optimization problem [6–9]. Traditional optimization methods such as Newton method [10], gradient method [11], lambda-iteration method [10], etc. fail to provide an efficient and reliable solution for such complex optimization problems. Therefore, researchers have looked at meta-heuristic optimization methods as an alternative method to solve ED problems.

Meta-heuristic optimization methods are iterative methods that use random search techniques to obtain a solution for an optimization problem by minimizing or maximizing a given objective function. Although these optimization methods have shown supremacy over the traditional optimization scheme, some serious issues are still present. The majority of these approaches have one flaw: they are sensitive to user-defined parameters. Another disadvantage is that meta-heuristic algorithms may not always achieve the global optimum, instead converging to a local optimum. Finally, these methods have a high processing complexity, which increases the time it takes to solve an optimization problem. [12]. To address these drawbacks of meta-heuristic optimization methods, researchers aim to develop new and efficient optimization schemes to solve optimization problems for further improved results. Some of the recently developed methods developed and applied to solve different optimization problems include single candidate optimizer [13], player unknown's battlegrounds ranking-based optimization [14], artificial hummingbird algorithm (AHA) [15], prairie dog optimization algorithm [16], etc. In the case of the ED problem, the recently developed methodologies are discussed in the following section.

1.2 Literature review

Many researchers have done tremendous work in the field of generation planning. In [17], the authors suggested the use of the leader white shark optimization algorithm to solve the economic load dispatch (ELD) problem. In [18] and [19], the authors investigated the performance of enhanced social network search and two-archive Harris hawk optimization respectively to solve the ELD problem. The authors in [20] and [21], used many-objective marine predators algorithm and multi-agent system respectively to solve multi-objective ED problem. In [22], a reduced gradient method is used to solve the ED problem for a microgrid considering RESs. In [23], a genetic algorithm is used to solve the ED problem for an integrated microgrid. In [24], the dynamic model of the microgrid having uncertain factors such as power fluctuations of renewable energy and load fluctuations is solved. In [25], a hybrid flower pollination algorithm for solving ED problems with a time-varying fuzzy selection mechanism is presented. In [26], a dynamic emission economic dispatch (DEED) problem is solved for an integrated microgrid. In [27], a modified harmony search algorithm is used for the combined economic emission dispatch (CEED) problem of microgrids. In [28], the semi-definite programming approach is used to solve the ED problems for energy storage systems in microgrids. In [29], an improved quantum particle swarm optimization is used to solve the ED problem for a microgrid. In [30], a coronavirus herd immunity algorithm is developed to solve the DEED problem in the presence of RESs for a microgrid. In [4], a bottlenose dolphin optimization (BDO) algorithm is developed to solve DELD and DEED problems in the presence of RESs for a microgrid. In [31], authors developed a search and rescue optimization algorithm to solve ELD and CEED problems. In [32], the authors investigate different off-grid RES options available and determine the most economical one the most economical for remote locations.

In the process of designing an efficient optimization scheme, hybrid optimization methods have gained a lot of attention among researchers. Hybrid optimization methods are formulated by combining two or more optimization methods with the specific goals to improve the exploration and exploitation capabilities [33]. This makes them more efficient and stable in providing a global optimal result compared to traditional optimization methods. In the past few years, many hybrid optimization techniques have been investigated and presented in different literature. Some of these hybrid optimizations include a hybrid genetic algorithm (GA) and particle swarm optimization (PSO), GA-PSO [34], a hybrid differential evolution (DE), chaos sequences and sequential quadratic programming (SQP), DEC-SQP [35], a hybrid PSO and bacterial foraging algorithm (BFA), PSO-BFA [36], a hybrid bat algorithm (BA) and firefly algorithm (FA), BA-FA [37], etc. In the field of generation planning, in [38], a genetic algorithm and mixed-integer linear programming are used to optimize the unit commitment and ED problem in microgrids. In [39], a multi-objective spotted hyena and emperor penguin optimizer is used for solving basic ED problems and microgrid power dispatch problems. In [40], the authors introduced an aggrandized class topper optimization to solve the ELD and CEED problems. In [41], the authors investigated the performance of quantum class topper optimization to solve the CEED problem. In [3], the authors investigated the planning of an interconnected microgrid using an interactive class topper optimization.

Optimization of resources in a microgrid is also possible by optimizing the load profile of a microgrid [3]. For this purpose, demand response management (DRM) and demand-side management (DSM) schemes have been introduced in microgrids for optimizing the load demand profile. Generally, the load profile optimization is performed using different approaches which are load shedding, peak clipping, strategic load conservation, strategic load building, valley filling, flexible load shape, etc. [42]. DSM and DRM schemes not only benefit the customers but also benefit the utilities by reducing utility bills, generation costs, emissions, peak loads, etc. Many works have been presented to incorporate these schemes into microgrids. In [42], a heuristic-based evolutionary algorithm has been used to optimize the load profile for a microgrid. In [26], authors solved a DEED problem considering wind power uncertainties, and energy storage systems. In [43], the authors used a robust optimization approach with a bidding strategy to optimize the cost of a microgrid along with the optimization of the load profile using demand response programming. In [44], a genetic algorithm is used to solve DSM and ED problems for a microgrid. In [45], particle swarm optimization is used to optimize the cost for DSM in a smart grid. In [46], an artificial fish swarm algorithm is used for scheduling generation and storage in a microgrid considering DSM. In [47], an optimal generation scheduling for a hydrothermal system with DSM is presented. In [48], authors solve a day-ahead scheduling ED problem considering combined heat and power units and uncertainty in the load demand response using co-evolutionary PSO. The authors in [49] investigated the performance of the modified differential evolution (DE) algorithm by scheduling CHP units considering RESs and electric vehicles.

1.3 Contribution and paper organization

With the advancement in the field of renewable generation and rising concern towards environmental problems, optimal planning of the generating units has gained interest among researchers in recent years. Although this problem is not new and various optimization schemes have already been applied to obtain efficient results, the researcher investigates new methods for better and improved results. In this regard, this study investigates a hybrid optimization method developed by combining the existing flower pollination scheme (FPA) and phasor particle swarm optimization (PPSO). The developed hybrid FPA-PPSO method solves the problem of low search efficiency faced by the FPA scheme. The integration of the PPSO scheme helps to improve the efficiency of the optimizer to solve large variable optimization problems. For the validation of supremacy with respect to FPA and PPSO, the suggested FPA-PPSO scheme is tested with twenty-three benchmark functions for its exploration and exploitation capabilities. Next, the performance of the suggested FPA-PPSO scheme is investigated with four test cases for the scheduling problem. The results obtained from the investigation confirm the supremacy of the suggested FPA-PPSO scheme in exploring and exploiting the search space for an optimal solution.

To conclude the main objectives and contribution of this study:

- A hybrid FPA-PPSO method is developed to overcome the drawbacks of the FPA optimization scheme.
- For the validation of the supremacy of the suggested FPA-PPSO scheme with respect to existing FPA, and PPSO schemes, a comparative analysis is presented using twenty-three benchmark functions.
- The suggested optimization method is applied to the scheduling problem in a microgrid along with the integration of renewable energy sources to show its supremacy in solving complex optimization problems.
- The impact of demand response management on generation planning when renewable energy sources are considered and when eliminated is studied.

The rest of the article is arranged as follows. Section 2 presents a discussion of the problem formulation and mathematical modeling of the optimization problem. Section 3 presents a discussion on the motivation, mathematical modeling, and validation of the suggested FPA-PPSO scheme. Section 4 shows the simulation results and discussions. Finally, section 5 presents the conclusion and works that can be taken up in the near future.

2 Problem formulation

2.1 Overview of isolated microgrid

A dynamic ED problem for an isolated microgrid is formulated using thermal generators, diesel generators, wind generation, solar generation, and energy storage devices. A layout of this system is shown in the Fig. 1. The model of each generating unit is briefly described in the following section.

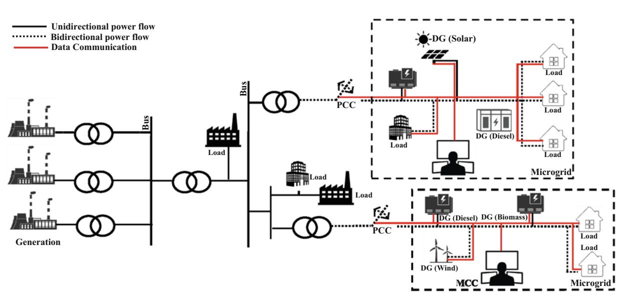

Fig. 1 Layout of the microgrid system

2.1.1 Thermal generator

For typical thermal generators, the fuel cost and emissions associated with generating units are mathematically described as:

$$C_T = \sum_{t=1}^{24}\sum_{T=1}^{n}(a_T + b_T P_{T,t} + c_T P_{T,t}^2), \tag{1}$$

$$E_T = \sum_{t=1}^{24}\sum_{T=1}^{n}(\alpha_T + \beta_T P_{T,t} + \gamma_T P_{T,t}^2), \tag{2}$$

where C_T denotes the generation cost, a_T, b_T, c_T shows the fuel coefficients of the T^{th} generating unit, and $P_{T,t}$ shows the generated power by the T^{th} generating unit at t^{th} time interval, E_T denotes the total emission, α_T, β_T, γ_T shows the emission coefficients of the T^{th} generating unit.

Taking total fuel cost and emissions into account formulates a multi-objective DEED problem. By factoring in weights, this multi-objective DEED problem is reduced to a single objective. This single objective problem can be phrased as follows:

$$F_T = \omega_1 \times C_T + \omega_2 \times E_T, \tag{3}$$

where F_T denotes the objective function, ω_1 and ω_2 are the weights. Here, the weight ω_1 can take values from [0, 1], whereas, ω_2 = 1 - ω_1. The two weight used helps to regulate the contribution of the respective objective, C_T and E_T, in the final objective function (F_T). If ω_1 is set to 1, then ω_2 becomes 0 and the objective function (F_T) will optimize the generating units such that only the fuel cost is minimized. For equal contribution of both the objectives in the objective function, generally ω_1 is set to 0.5, which makes ω_2 also 0.5 [50]. With this consideration the generating units are optimized such that a tradeoff is maintained while both fuel cost and emission are minimized.

2.1.2 Diesel generator

Diesel generators are widely used at airports, power stations, and manufacturing plants. They are suitable for long operations and generally work with less fuel consumption and emission rates. The total fuel cost associated with the diesel generators while generating $P_{D,t}$ units of power is mathematically represented as follows:

$$C_D = \sum_{t=1}^{24}\sum_{D=1}^{n}(a_D + b_D P_{D,t} + c_D P_{D,t}^2), \tag{4}$$

where C_D denotes cost of generation, a_D, b_D, c_D shows the cost coefficients of the D^{th} diesel unit.

Further, the total emission associated with the diesel generators while generating $P_{D,t}$ units of power is mathematically represented as follows:

$$E_D = \sum_{t=1}^{24}\sum_{D=1}^{n}(\alpha_D + \beta_D P_{D,t} + \gamma_D P_{D,t}^2), \tag{5}$$

where E_D is the total emission, α_D, β_D, γ_D are emission coefficients of the D^{th} generating unit.

A multi-objective DEED issue, similar to that of conventional generators, is constructed by taking total fuel cost and emissions into account. By taking weights into account, this problem is reduced to a single aim. This single objective problem can be phrased as follows:

$$F_D = \omega_3 \times C_D + \omega_4 \times E_D \tag{6}$$

where F_D is the total cost to be minimized, ω_3 and ω_4 are the weights. Here, the weight used works in the similar way as the weights used for (3). For equal contribution of both the objectives, ω_3 is set to 0.5, then ω_4 also becomes 0.5.

2.1.3 Wind-power generation

The total cost associated with the power generation from the wind farms is represented as follows:

$$F_w = \sum_{t=1}^{24} P_w^t \times \left(\frac{r}{1-(1+r)^{-N}} \times I_p + G_e\right), \tag{7}$$

where F_w is the total cost, P_w^t is the power output from the wind farm at t^{th} time instant, I_p is the ratio of investment cost to unit established power, G^e is the operational and maintenance cost, r is the interest scale and N is the investment duration.

By considering the parameters I_p, G_e, r and N as 1400$\$/kw$, 0.016$\$/kw$, 0.09 and 20, (7) can be written as [51]:

$$F_w = \sum_{t=1}^{24}(153.381 \times P_w^t). \tag{8}$$

The power P_w^t obtained from a wind farm considering uncertainty is computed as follows [52]:

$$P_w^t = \begin{cases} 0, & \text{if } WS^t < S_{ci}; \\ P_n \times \left(\dfrac{WS^t - S_{ci}}{S_r - S_{ci}}\right), & \text{if } S_{ci} < WS^t < S_{cr}; \\ P_n, & \text{if } S_{cr} < WS^t < S_{co}; \\ 0, & \text{if } WS^t > WS_{co}; \end{cases} \tag{9}$$

where P_n is the nominal power of wind turbine; WS^t is the speed of wind at t^{th} instant; S_{ci} denotes the cut-in speed, S_{cr} shows the rated speed and S_{co} shows the cut-out speed.

2.1.4 Solar-power generation

The total cost associated with a solar farms generating P_s units of power is represented as follows:

$$F_s = P_s^t \times \left(\frac{r}{1-(1+r)^{-N}} \times I_p + G_e \right), \tag{10}$$

where F_s is the total cost, P_s^t is the power output from the solar farm at t^{th} time instant,

By considering the ratio for investment cost as 5000 $\$/kw$, the operational and maintenance cost as 0.016 $\$/kw$, interest scale 0.09 and investment duration as 20 years as presented in [51], (10) can be written as:

$$F_s = \sum_{t=1}^{24} (547.7483 \times P_s^t). \tag{11}$$

The power P_s^t obtained from a solar farm considering uncertainty is computed as follows [53]:

$$P_s^t = \frac{S_R^t}{S_R^0} \times \left(P_s^m + \mu \times \left(T^t + S_R^t \times \frac{N_T - 20}{800} - T_s \right) \right), \tag{12}$$

where the total irradiance is represented by S_R^t; irradiance value under standard conditions is represented by S_R^0; rated power under standard conditions is shown as P_s^m; temperature and module temperature is shown as T^t and T_s respectively; N_T and μ represents the normal cell operating temperature and temperature power coefficient respectively.

2.1.5 Energy storage system (ESS)

ESS improves the reliability of the power system network by dealing with the unpredictability generated by the inclusion of renewable energy sources. ESS units, including NaS, Li-Ion, and Lead-Acid batteries, serve as backup power sources. The ESS state of charge (SoC) and state of discharge (SoD) are determined by the power of diesel, RES, and load demand. If $P_D + P_s + P_w > P_{den}$, the ESS is charging, as described mathematically below:

$$P_b^t = P_b^{t-1} + (P_G^t - P_L^t)\eta_b, \tag{13}$$

where P_b^t is the energy available at t^{th}, P_b^{t-1} is the energy available at $(t-1)^{th}$ time instant, P_G^t is the generated energy by diesel and RES together at t^{th}, P_L^t is load demand at t^{th} and η_b is the efficiency of energy conversion.

Whereas, if $P_D + P_s + P_w < P_{den}$, the ESS is in the state of discharging which is mathematically expressed as follows:

$$P_b^t = P_b^{t-1} - (P_G^t - P_L^t)\eta_b, \tag{14}$$

The cost associated with the ESS is computed as [54]:

$$F_b = \frac{1}{365} \left\{ \left[\frac{r(1+R)^Q}{(1+R)^Q - 1} \times F_C \times C_E \right] + (C_E - M_C) \right\}, \tag{15}$$

where F_b represents the day-ahead cost, r, Q, F_C, M_C and C_E represents the interest rate, lifetime, fixed cost, maintenance cost and size of storage device.

2.2 Objective function

Using the diesel, solar, wind and ESS, the objective function of the microgrid is formulated as follows:

$$min(C_f) = min(F_T + F_D + F_s + F_w + F_b), \tag{16}$$

where C_f is the objective which has to be minimized.

2.3 Constraints

While optimizing the generating units, it is important that all the generation and power constraints are satisfied. The constraints considered in this study are discussed in this section.

2.3.1 Load balance

It is important that the total power demand is equal to the total power generation. This is mathematically expressed as follows:

$$\sum_{t=1}^{24} P_T^t + \sum_{t=1}^{24} P_D^t + \sum_{t=1}^{24} P_w^t + \sum_{t=1}^{24} P_s^t + \sum_{t=1}^{24} P_b^t = \sum_{t=1}^{24} P_{dem}^t, \tag{17}$$

where P_{dem}^t is the total demand at t^{th} time instant.

2.3.2 Generator limits

It is necessary that all the generating units are operated within prescribed operating limits. This is mathematically represented as follows:

$$P_T^{min} \le P_T \le P_T^{max}; \tag{18}$$

$$P_w^{min} \le P_w \le P_w^{max}; \tag{19}$$

$$P_D^{min} \le P_D \le P_D^{max}; \tag{20}$$

$$P_s^{min} \le P_s \le P_s^{max}; \tag{21}$$

$$P_b^{min} \le P_b \le P_b^{max}; \tag{22}$$

where P_T^{min}, P_w^{min}, P_D^{min}, P_s^{min}, and P_b^{min} represents the minimum generation limits for thermal generators, wind farms, diesel generators, solar farms, and ESS repeatedly. Whereas, P_T^{max}, P_w^{max}, P_D^{max}, P_s^{max}, and P_b^{max} are the maximum generation limits.

2.4 Demand response program

In a microgrid, load profile management helps the utilities to maximize their profits. Therefore, to optimize the load profile, in this article, a demand response program (DRP) scheme is considered. DRP scheme is generally based on energy pricing where prices are varied according to the load demand. Furthermore, to improve the load profile, shiftable loads are moved from high-price peaks to low-price off-peak hours. This helps to reduce the cost of operating the microgrid. The mathematical model for the DRM technique, provided in [43], is as follows:

$$D_L^t = (1 - D_R^t) \times L_B^t + L_s^t, \tag{23}$$

where t time period, D_L^t, D_R^t, L_B^t, and L_s^t represents the load demand considering DRP, base load percentage which participates in DRP, base load without considering DRP and shiftable load respectively.

2.4.1 Constraints

As in a DRM approach, the loads are only shifted from the peak periods to off peak periods, the total load demand remains unchanged. Mathematically, this can be expressed as follows:

$$\sum_{t=1}^{T} L_s^t = \sum_{t=1}^{T} D_R^t \times L_B^t, \tag{24}$$

Further, it is important that the increment and decrement of the load should follow some criterion values which are given as follows:

$$L_{inc}^t \le inc^t \times L_B^t; \tag{25}$$

$$D_R^t \le D_R^{max}; \tag{26}$$

$$inc^t \le inc^{max}, \tag{27}$$

where L_{inc}^t is the incremented load, inc^t represents the incremented load percentage, D_R^{max} represents the maximum loads participates in DRP and inc^{max} shows the maximum load that will be incremented.

3 Hybrid FPA-PPSO technique

3.1 Overview of FPA technique

The flower pollination algorithm (FPA), presented in [55], is a technique that is inspired by the pollination process of flowering plants. In FPA, pollens (search agents) are pollinated (updated) using either local pollination or global pollination. Local pollination is generally referred to as abiotic or self-pollination which does not require any pollinators. The mathematical model for local pollination as per [55], is represented as follows:

$$P_i^{t+1} = P_i^t + \epsilon^t \left(P_j^t - P_k^t \right), \tag{28}$$

where P_i^{t+1} is the updated pollen or solution vector at $(t+1)^{th}$ instant P_i^t is the pollen or solution vector at t^{th} instant, P_j^t and P_k^t are pollen from flowers j and k at t^{th} instant and ϵ^t is a constant value between 0 and 1 at t^{th} instant.

In the case of global pollination which is generally referred to as a biotic or cross-pollination process, a pollen carrier is required. The mathematical model for global pollination as per [55], is represented as follows:

$$P_i^{t+1} = P_i^t + L_f \left(P_g^t - P_i^t \right), \tag{29}$$

where P_g^t is the best solution found among all solutions at t^{th} instant and L_f is the strength of pollination, which is essentially a step size and is computed using a Levy distribution function which is given as:

$$L_f = \frac{\lambda \Gamma(\lambda) sin\left(\frac{\Pi \lambda}{2}\right)}{\Pi} \frac{1}{s^{1+\lambda}}, (s > 0), \tag{30}$$

where $\Gamma(\lambda)$ represents a standard gamma function and s represents the size of the steps.

Pollens can pollinate using either of the methods. To switch between the local pollination and global pollination, a switch probability (S_P) is used. If S_P^r is less than S_P, then agents are updated using the local pollination rule. Whereas, if S_P^r is greater than S_P, then agents are updated using the global pollination rule. S_P^r is a switch probability function which generally represents a random number between 0 and 1.

3.2 Overview of PPSO technique

Particle Swarm Optimization (PSO), presented in [56], is a popular and most commonly used optimization method. PSO has been used to solve a variety of optimization problems related to different fields. In the past few decades, many modified and improved versions of PSO have been developed which are claimed to have a better performance than the basic PSO technique. One such method is a Phasor Particle Swarm Optimization (PPSO) presented in [57]. The PPSO method uses a diverse strategy which not only helps in improving the convergence ability but also increases the optimization efficiency. In PPSO, each particle (search agent) is equipped with a scalar phasor angle (θ) and a magnitude ($\mathbf{X}$) which are together presented as $\mathbf{X}\angle\theta$. In order to update the particles, both the magnitude and phasor angles of each particle are updated in each iteration. This is mathematically represented as follows:

$$V^t = p(\theta^t) \times (P^b - X^t) + g(\theta^t) \times (G^b - X^t), \tag{31}$$

$$P^{t+1} = P^t + V^t, \tag{32}$$

where the global and position best particle is represented by G^b and P^b respectively; the magnitude of the present and updated particle position is presented by P^t and P^{t+1} respectively; To evaluate $p(\theta^t)$ and $g(\theta^t)$ following mathematical models are used.

$$p(\theta^t) = |cos(\theta^t)|^{2\times sin(\theta^t)}, \tag{33}$$

$$g(\theta^t) = |sin(\theta^t)|^{2\times cos(\theta^t)}, \tag{34}$$

The phasor angles for each particle, in every iteration are updated as follow:

$$\theta^{t+1} = \theta^t + |cos(\theta^t) + sin(\theta^t)| \times 2 \times \pi, \tag{35}$$

3.3 Proposed hybrid FPA-PPSO algorithm

As discussed in the previous section 1, for any optimization scheme to efficiently explore the search space for an optimal solution, it is important that the optimizer is equipped with good exploration and exploitation capabilities. In the case of the FPA optimization scheme, the optimizer explores the search space when global pollination is performed. Whereas, in the case of local or self-pollination, the optimizer exploits the search space. To switch between the exploration and exploitation stages, a switch probability is used as discussed in Sect. 3.1. This mentioned strategy may help the optimizer to solve numerous optimization problems, but still, some loopholes that may result in its poor searching efficiency exist. Firstly, at a given time interval the optimizer can either perform exploration or exploitation with a randomized switching probability. With such a strategy, there may be a chance that only exploration or exploitation of the search space is carried out. As a result, there are high chance that the optimizer may miss out on the optimal solution, resulting in poor searching efficiency. Secondly, during the local search, there is unavailability of a self-guide which again may lead the optimizer to stick to a local optimal solution and result in a low searching efficiency [58].

To overcome these drawbacks, in this study, a hybrid FPA-PPSO is suggested which combines the FPA optimizer with the PPSO scheme to overall improve the searching ability of the suggested hybrid optimizer. Owing to the popularity of the PSO scheme in the field of optimization, for the development of the suggested hybrid method, PSO is selected. Further, among the different variants of the PSO scheme, the PPSO scheme is selected. PPSO scheme includes the concept of phasor angles which is used for all control variables. This makes the PPSO scheme a self-adaptive nonparametric meta-heuristic optimization scheme which is quite simple in implementation. Further, in case the problem dimensions are increased, the optimization efficiency of the PPSO scheme is better compared to other optimization algorithms [59].

In order to implement the suggested technique, the two optimization methods, FPA and PPSO, are cascaded with each other. In the suggested method, the suggested algorithm is split into two stages. In the first stage, the search agents follow the updating rule of local and global pollination from the FP algorithm. After obtaining the updated solutions from the first stage, i.e., the updated agents are used in the second stage. In the second stage, the updated agents follow the position and phase update rule from the PPSO technique. Further, the agents are tested with the boundary conditions. Then they are feedback for the first stage. This process is repeated until the termination condition is satisfied. Further to explain the workflow, Figs. 2 and 3 presents the pseudo-code and flow chart for the hybridization process of the FPA and PPSO algorithms respectively.

3.3.1 Time complexity analysis

The time complexity of the suggested FPA-PPSO algorithm depends on the population size of search agents, the maximum number of iterations (T), and the assessment cost of the objective function (C). Further, the population of search agents comprises population size (P), dimension of the problem (D), and phasor angles (A). Based on these parameters, during the initializing stage, the time complexity of the FPA-PPSO is given by $O(P \times D \times A)$. During the assessment stage of the objective function, the time complexity is given as $O(P \times C \times T)$. The assessment of objective function is done twice, once in the case of the FPA scheme and second in the case of PPSO. With this, the total time complexity for this stage is $2 \times O(P \times C \times T)$. For updating the position of search agents, for the FPA scheme, the time complexity is given by $O(P \times D \times T)$. Whereas, in the case of the PPSO scheme it is given by $O(P \times D \times A \times T)$. Combining all the cases, the time complexity for FPA-PPSO is given as $O(P \times D \times A + 2 \times P \times C \times T + P \times D \times T + P \times D \times A \times T)$. The time complexity in the case of FPA and PPSO is given as $O(P \times D + P \times C \times T + P \times D \times T)$ and $O(P \times D \times A + P \times C \times T + P \times D \times A \times T)$ respectively. From this analysis, it is clear that the time required to solve any optimization problem is more of FPA-PPSO and is generally of the order $FPA < PPSO < FPA - PPSO$.

Fig. 2 Pseudo code

Input: **Initialize a random population of search agent within the search space. These agents virtually represent the power allocated to each generating units and search space is the operating limits. Also define** θ **between** $(0,2\pi)$ **for each search agents and parameters** s, λ, t_{max}

Begin algorithm

while$(t < t_{max})$

Run FPA algorithm

Evaluate the fitness (fuel cost) of each search agent using Eq. (16).

Define the current best solution P_g^t.

Update S_P^r

if $(S_P^r < S_P)$

Update the agents using the local pollination concept represented by Eq. (28).

else if $(S_P^r > S_P)$

Update the agents using the global pollination concept represented by Eq. (29).

end if

Evaluate each search agents and check if all agents are within the boundary conditions.

Run PPSO algorithm

Evaluate the fitness of each updated search agent using Eq. (16).

Define the current best solutions P^b **and** G^b.

Update each agent using Eq. (33) and Eq. (34).

Update theta using Eq. (35).

Evaluate each search agents and check if all agents are within the boundary conditions.

$t = t + 1$

end while

Output

Return: **Optimal power allocations for the generating units and fuel cost.**

3.3.2 Validation using benchmark functions

This section examines twenty-three benchmark functions in order to test the exploration, exploitation, and convergence capabilities of the suggested FPA-PPSO technique. Among these twenty three benchmark functions presented in [50], functions F_1-F_7 are the uni-modal benchmark functions. Uni-modal functions have only one local optimum (global optimal point), which makes it easier to evaluate the exploitation capabilities of any optimization strategy. Whereas, functions, F_8-F_{13} and F_{14}-F_{23}, comprise multi-modal and fixed dimension multi-modal functions. Multi-modal functions have several local optima but a single global optimal point which makes them useful for exploration analysis.

To evaluate the performance of the suggested FPA-PPSO technique, all twenty-three functions are simulated using the LabVIEW©2015 platform which is installed on an Intel (R) core (TM) i7, 2:0GHz processor, 64 bit computer. Each function is simulated 30 times with a population size of 50 and iteration counts of 500. The results obtained post 30 simulation runs are utilized to calculate key parameters: average value, standard deviation, and computing time. Table 1 shows the results for the suggested method and PSO, FPA, and PPSO used for a comparative study. By analyzing the average value obtained for the functions, it is observed that the suggested FPA-PPSO shows superior performance. In some cases, the method shows an identical performance in comparison to PSO, FPA, and PPSO. Considering the deviation values, it can be concluded that the suggested optimizer can converge close to the optimal solution. As a result, we might conclude that it is more stable. Finally, the hybridization of the FPA and PPSO is observed to affect the run time performance the FPA-PPSO scheme. For all circumstances, the suggested technique has the longest run time. Lastly, by analyzing the convergence plots present for functions F_1, F_6, F_{10}, F_{13}, F_{18} and F_{23} in Fig. 4, one may conclude that the suggest FPA-PPSO approach has a faster convergence rate with respect to PPSO and FPA simulated under same conditions.

To further analyze the results obtained for the benchmark functions and show the supremacy of the suggested FPA-PPSO, in this study, the Wilcoxon test and Friedman test are also conducted. The results for the two tests are presented in Table 2. From analyzing the Friedman test, it is observed that the suggested FPA-PPSO has a mean rank of 1.59 which is the smallest in comparison to the other methods PSO, PPSO, and FPA used for comparison. In the case of the Wilcoxon rank test, the suggested algorithm shows a significant difference in the results obtained for most of the functions as the obtained p-value is less than 0.05. Whereas, in some of the cases it shows a similar

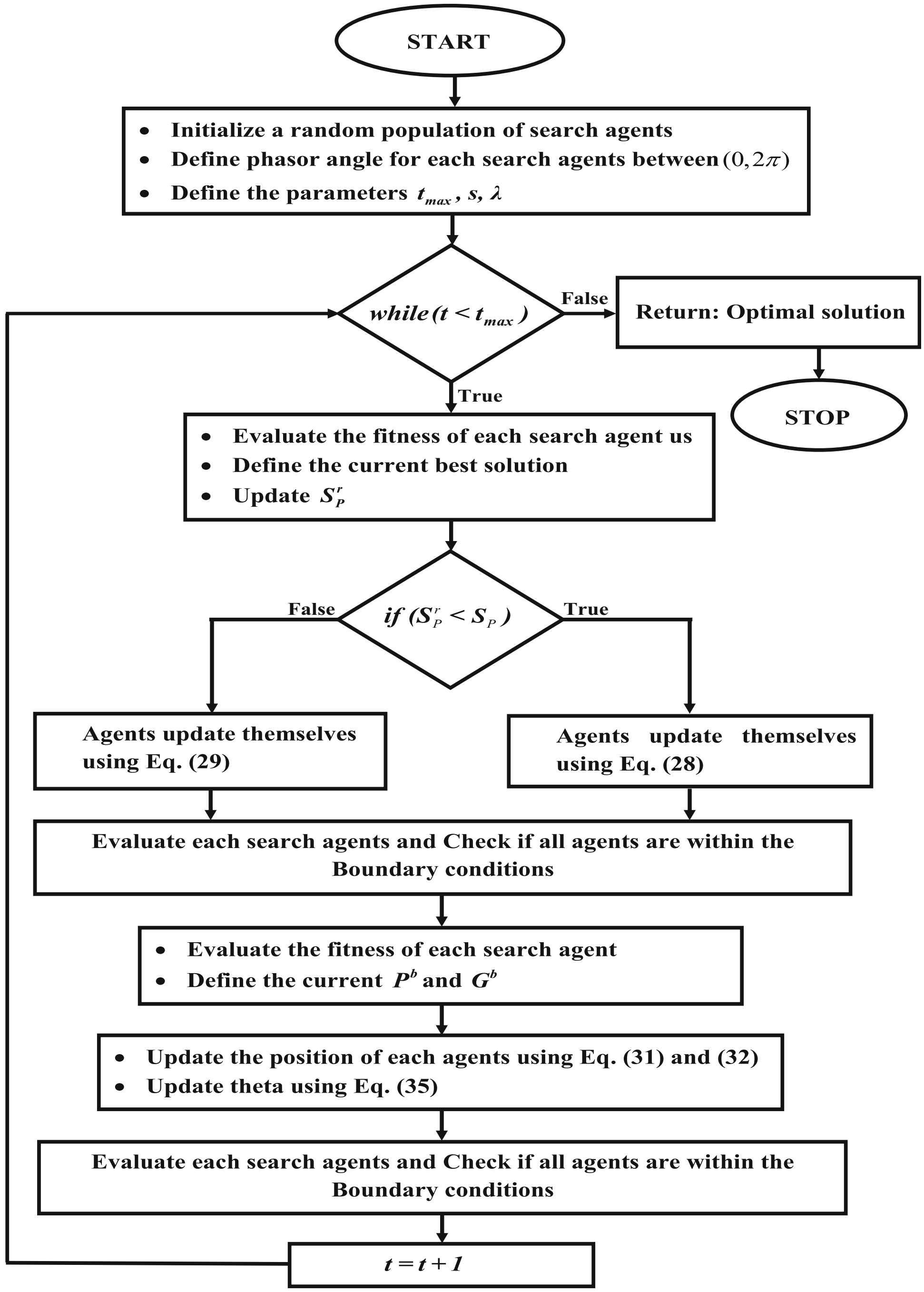

Fig. 3 Flowchart for hybrid FPA-PPSO

behavior and has a p-value greater than 0.05. From these two tests, it can be concluded that the suggested FPA-PSSO performs better than the existing PSO, PPSO, and FPA schemes.

From the analysis with the benchmark functions, it is observed that the suggested FPA-PPSO scheme has some advantages and disadvantages over the FPA & PPSO schemes. These advantages and disadvantages are listed below:

– From the analysis with the uni-modal function it is found that for almost all the functions the suggested FPA-PPSO scheme provides improved results. This confirms that the suggested has better exploitation capabilities with respect to FPA and PPSO.
– From the analysis with the multi-model function it is observed that the suggested method has improved exploration capabilities with respect to FPA and PPSO which help it to provide improved results.

Table 1 Comparative results analysis for benchmark functions using PSO, PPSO, FPA and FPA-PPSO schemes

Method	PSO			PPSO			FPA			FPA-PPSO		
BF	Average	Deviation	Time	Average	Deviation	Time	Average	Deviation	Time	Average	Deviation	Time
F_1	0.000136	0.000202	**3.56**	1.237E-22	9.16E-23	4.71	0.019362	0.015973	3.77	**3.95E-122**	**6.83E-122**	7.82
F_2	0.042144	0.045421	**3.72**	1.846E-12	2.99E-13	5.16	0.669356	0.285141	4.11	**3.00E-65**	**3.18E-65**	8.31
F_3	70.12562	22.11924	**3.99**	1.208E-20	1.02E-20	5.75	0.007454	0.009744	4.68	**5.78E-111**	**1.00E-110**	8.88
F_4	1.086481	0.317039	**4.23**	2.837E-11	1.61E-11	6.12	25.77333	4.249736	5.54	**1.105E-21**	**1.91E-21**	9.29
F_5	96.71832	60.11559	**4.78**	2.870E+01	0.007081	6.65	23.2983	4.940419	6.10	**6.013**	**7.951**	9.91
F_6	0.000102	8.28E-05	**5.21**	2.545E-22	3.93E-22	7.97	0.20181	0.339907	6.78	**5.14E-33**	**6.41E-33**	10.47
F_7	0.122854	0.044957	**5.89**	1.139E-03	0.000284	8.36	3.319087	0.549097	7.55	**3.9971E-05**	**1.62E-05**	10.99
F_8	−4841.29	1152.814	**86.26**	− 9.469E+03	978.46	112.71	− 7120.16	1261.15	99.11	**− 3861.29**	**576.56**	160.58
F_9	46.70423	11.62938	**86.75**	3.546E+01	16.151	113.69	22.561	19.156	102.16	**16.591**	**7.451**	161.35
F_{10}	0.276015	0.50901	**87.52**	1.184E-15	2.05E-15	113.99	9.12361	2.61605	102.75	**0**	**0**	161.89
F_{11}	0.009215	0.007724	**88.11**	**0**	**0**	114.36	0.671899	0.487123	103.24	0.255724	0.443	162.56
F_{12}	0.006917	0.026301	**89.03**	**- 6.732E-01**	**1.66E-01**	114.82	3.651653	3.252136	103.98	− 0.25721	0.255	162.97
F_{13}	0.00675	0.008907	**90.71**	1.350E-32	0.00E+00	115.65	17.33197	4.641035	104.57	**1.34978E-32**	**0**	163.56
F_{14}	3.627168	2.560828	**16.64**	3.277E+00	1.047702	29.16	**0.998004**	**0**	22.96	**0.998004**	**0**	42.3
F_{15}	0.000577	0.000222	**17.46**	3.221E-02	0.052634	31.32	0.000752	0.000372	23.5	**0.0009697**	**2.033E-05**	43.14
F_{16}	**− 1.03163**	6.25E-16	**17.98**	− 5.729E-01	0.429824	31.81	− 1.03136	**0**	25.12	− 1.03136	**0**	43.86
F_{17}	**0.397887**	**0**	**18.52**	6.182E-01	0.201742	32.45	**0.397887**	6.8E-17	26.57	**0.397887**	1.36E-17	44.34
F_{18}	**3**	1.33E-15	**19.1**	4.907E+01	12.72001	35.12	**3**	**0**	28.03	**3**	**0**	44.97
F_{19}	− 3.86278	2.58E-15	**19.87**	− 2.947E+00	0.606562	36.69	**− 3.87943**	5.44E-16	30.11	− 3.5941	**2.56E-16**	45.56
F_{20}	− 3.26634	**0.060516**	**20.57**	− 2.163E+00	0.172855	38.15	**− 3.28249**	0.068774	31.91	− 3.24279	0.06520	45.98
F_{21}	− 6.8651	3.019644	**22.48**	− 8.469E+00	2.917022	39.06	− 4.27961	1.383014	32.69	**− 10.1532**	**0**	46.26
F_{22}	− 8.45653	3.087094	**23.31**	− 5.286E+00	4.389415	40.16	− 6.09455	3.915841	33.13	**− 10.4029**	**0**	46.75
F_{23}	− 9.95291	1.782786	**24.66**	− 5.426E+00	4.425494	41.65	− 5.38322	4.462785	36.59	**− 10.5364**	**0**	46.99

Best results indicate in bold

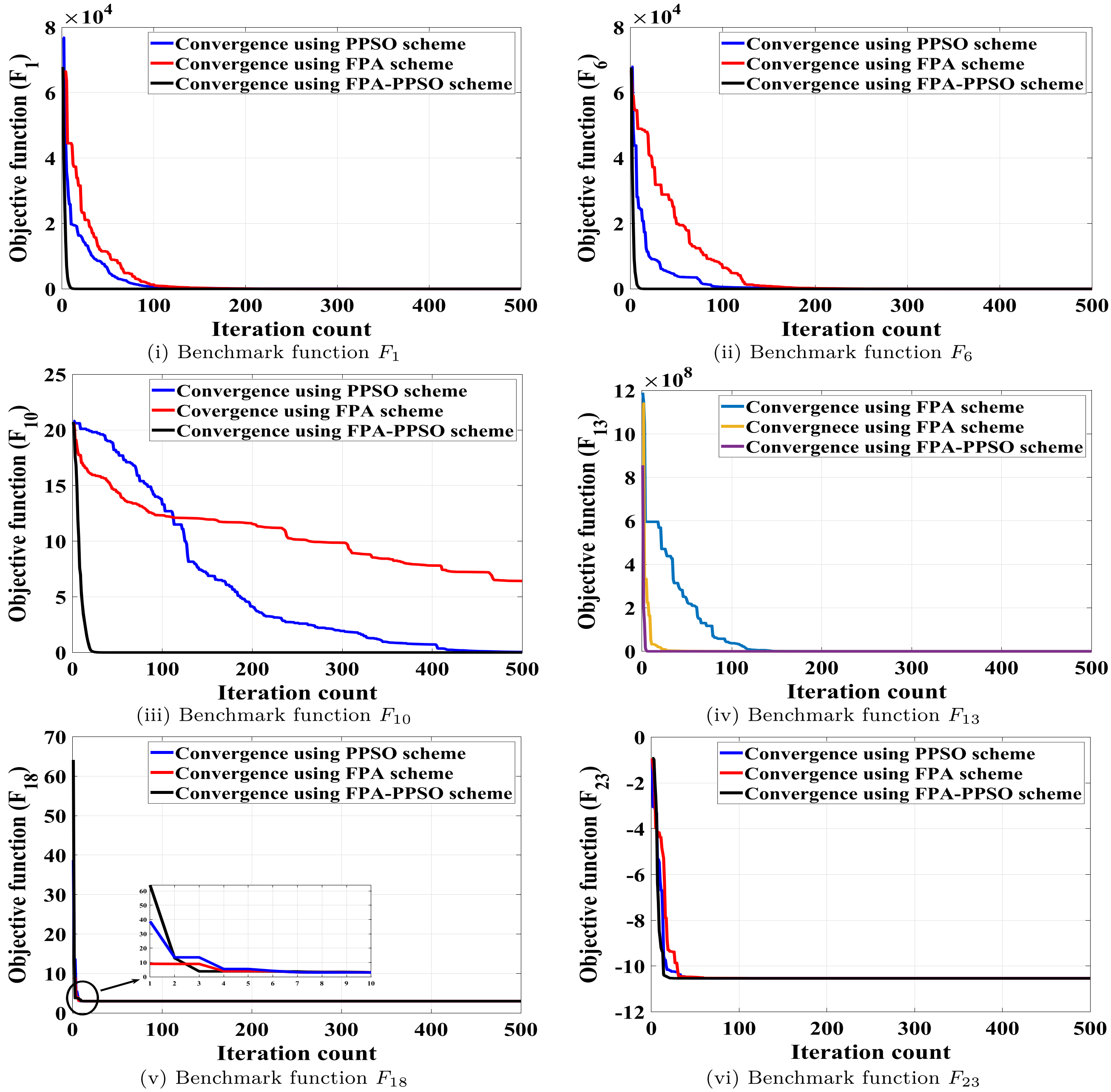

Fig. 4 Convergence behavior for benchmark functions F_1, F_6, F_{10}, F_{13}, F_{18} and F_{23}

– From the time complexity analysis and the computational time presented, the computational requirement of the suggested scheme is increased with respect to the existing FPA and PPSO schemes.
– From the convergence plots it observed that the rate of convergence of the objective function with respect to the iteration counts is enhanced. This can compensate for the increased execution time if the population size and iteration count are optimally set.

4 Simulation and results

To evaluate the performance of the suggested hybrid FPA-PPSO technique to solve the scheduling problem, four different test cases have been considered in this study. All the test cases are simulated five times using the LabVIEW©2015 platform which is installed on an Intel (R) core (TM) i7, 2:0GHz processor, 64 bit computer. The population size and iteration counts are set as 100 and 500 respectively. The results obtained are then used to compute statistical parameters such as best value, worst value,

Table 2 Wilcoxson and Friedman rank test results for benchmark functions using PSO, PPSO, FPA and FPA-PPSO schemes

Methods	PSO		PPSO		FPA		FPA-PPSO	
Parameter	p-value	Rank	p-value	Rank	p-value	Rank	p-value	Rank
F_1	0.036078	3	0.021481	2	0.0090746	4	–	1
F_2	0.001398	3	0.030114	2	0.01094813	4	–	1
F_3	0.019416	4	0.00677	2	0.01726412	3	–	1
F_4	0.020701	3	0.006786	2	0.02777374	4	–	1
F_5	0.059961	4	0.049222	2	0.02022949	2	–	2
F_6	0.010623	3	0.042838	2	0.02926749	4	–	1
F_7	0.016411	3	0.021124	2	0.02937839	4	–	1
F_8	0.961749	3.5	0.691532	1	0.8115022	3.5	–	2
F_9	0.443971	3	0.325931	3	0.21165431	3	–	1
F_{10}	0.077932	3	0.064887	2	0.21300019	4	–	1
F_{11}	0.067831	2	0.604887	1	0.222182	4	–	3
F_{12}	0.951572	2	0.658813	1	0.00873817	4	–	3
F_{13}	0.018456	3	1	2	0.22552089	4	–	1
F_{14}	0.070875	4	0.306314	3	1	1.5	–	1.5
F_{15}	0.867867	1	0.054649	4	0.90736122	3	–	2
F_{16}	0.999869	3	0.599823	4	1	1.5	–	1.5
F_{17}	1	1	0.539948	4	1	2.5	–	2.5
F_{18}	1	3	0.248306	4	1	1.5	–	1.5
F_{19}	0.295671	2.5	0.369646	4	0.29576447	1	–	2.5
F_{20}	0.995208	1.5	0.797706	4	0.99404078	1.5	–	3
F_{21}	0.69976	4	0.791422	2	0.59620917	3	–	1
F_{22}	0.776739	2	0.572315	4	0.6263637	3	–	1
F_{23}	0.894502	2	0.576534	3	0.573522	4	–	1
Mean Rank	-	2.76	-	2.61	-	3.04	–	1.59

average value, and standard deviation. The results are also compared with the results obtained using some other existing techniques to show the supremacy of the suggested scheme. For a fair comparison, the results for the existing method are also obtained under the same environmental conditions i.e. with a population size of 100 and an iteration count of 500. Further, the objectives and other system specifications considered for the three test cases have been presented briefly in the following section.

4.1 Test case - I

To assess the performance of the suggested FPA-PPSO strategy in solving the scheduling problem, a large system with forty generating units supplying a demand of 10500 MW is considered. While solving this test system the objective function considered is (3) considering t = 1. Further, the fuel and emission coefficients for generating units were obtained from [60]. Post five simulation runs the obtained best power distribution across the generating units which is presented in Table 3. Whereas, Table 4 reports the computed statistical parameters. Table 4 also displays the results for existing methods such as modified ABC with disruptive logistic map (MABC/D/Log) [50], modified ABC with disruptive cat map (MABC/D/C) [50], pareto differential evolution (PDE) [50], non-dominating sorting genetic algorithm II (NSGA−II) [50], Strength Pareto evolutionary algorithm (SPEA−2) [50], FPA [50], Kho-kho optimization (KKO) [50], quasi-oppositional teaching learning based optimization (QOTLBO) [61], PSO-gravitational search algorithm (PSOGSA) [61], optimization without penalty-based optimization by morphological filter algorithm (OWP-based OMF) [61].

From the analysis presented in Table 4, it is found the suggested FPA-PPSO provides the minimum fuel cost. The average and deviation values indicate that the suggested FPA-PPSO has good accuracy and stability compared to the existing PSO, PPSO and FPA scheme. Further, a comparison of the generation cost (C_T) and emission rate (E_T) is also included. From the result, it is found that the suggested optimizer maintains a tradeoff between the two objectives. In the case of minimizing generation cost, the KKO scheme provides the minimum result. Whereas, the emission cost is minimum for the suggested FPA-PPSO scheme. In the case of the computation time, the suggested optimizer has the largest computation time. Finally, Fig. 5 shows the convergence of the objective function based on iteration count.

Table 3 Scheduling of generating units for test case I

Unit	Power (MW)	Unit	Power (MW)
P1	113.959	P21	437.727
P2	114	P22	437.022
P3	119.758	P23	436.799
P4	177.852	P24	438.033
P5	96.9861	P25	436.548
P6	128.506	P26	437.922
P7	299.635	P27	24.1173
P8	297.509	P28	24.237
P9	297.195	P29	24.4608
P10	131.219	P30	97
P11	306.922	P31	173.582
P12	306.868	P32	174.557
P13	433.594	P33	175.062
P14	408.207	P34	200
P15	411.999	P35	199.983
P16	411.062	P36	200
P17	452.293	P37	103.866
P18	450.987	P38	102.731
P19	436.952	P39	103.753
P20	437.413	P40	439.683
Fuel Cost ($/hr)	128965	Emission Cost (tons/hr)	178038
Total Cost ($/hr)		153501.5	

Table 4 Comparative analysis for Test Case I

Algorithm	Best* ($/hr)	Worst ($/hr)	Average ($/hr)	Deviation	C_T ($/hr)	E_T (tons/hr)	Time (*sec*)
PDE [50]	168750	–	–	–	125730	211770	–
NSGA-II [50]	168390	–	–	–	125830	210950	–
SPEA-2 [50]	168455	–	–	–	125810	211100	–
MABC/D/C [50]	190525.6	–	–	–	124490.9	256560.3	–
MABC/D/Log [50]	190525.8	–	–	–	124491.2	256560.3	–
KKO [50]	164732	–	–		**123034**	206430	–
QOTLBO [61]	165825.7	-	–	–	125161	206490.4	–
PSOGSA [61]	153651.3	–	–	–	128710.9	178591.7	–
OWP-based OMF [61]	153576.6	–	–	–	128596.0	178557.2	**0.078**
PSO [56]	153717	153786	153725	83.19	128713	178703	10.14
PPSO [57]	153659	153702	153678	47.23	128749	178570	25.11
FPA [55]	153677	153764	153714	63.15	128803	178551	12.96
FPA-PPSO	**153501.5**	**153582.1**	**153543.3**	**40.39**	128965	**178038**	33.76

Best results indicate in bold

* Kindly note that the best value are computed based on the C_T and E_T using the objective (3)

4.2 Test case II

For the next test case, a basic microgrid model with three conventional thermal generating unit systems along with a solar and wind farm has been considered. The fuel coefficients and emission coefficients along with the dynamic load profile are taken from [8]. The suggested hybrid FPA-PPSO is tested considering two different objectives i.e. DELD and DEED. The solar and wind uncertainties are not considered for this test case. The dynamic power output from the wind and solar farm is taken from [8].

Considering the DELD objective, FPA-PPSO is simulated under two case scenarios (i) without considering RES and (ii) considering the RES. The behavior of generating units and the obtained best fuel cost for these two test scenarios are presented in Table 5. For a comparative study, a statistical analysis of the results obtained using the suggested method and other existing methods such as grey wolf optimization (GWO), whale optimization algorithm (WAO), symbiotic organism search (SOS) algorithm, PSO, PPSO, etc. are presented in Table 6. It is observed from Table 6 that the suggested method optimizes the generating units more efficiently as the obtained cost function is minimum. Further, from the comparison of the average value and standard deviation, it can be concluded that the suggested method provides a more promising and stable result in comparison to the existing FPA and PPSO techniques. Further, to study the convergence rate and behavior of the objective function, Fig. 7 is presented. By observing Fig. 7, it can be concluded that FPA-PPSO has a faster convergence rate compared to FPA and PPSO.

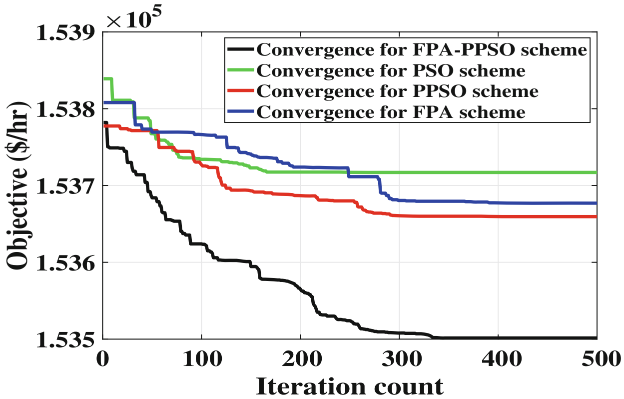

Fig. 5 Convergence for FPA-PPSO for test case I

Further, considering the DEED objective, FPA-PPSO is also simulated for two case scenarios (i) without considering RES and (ii) considering RES. For these two cases, the power distribution among the generating units along with the best-obtained fuel cost is presented in Table 5. To

Table 5 Behavior of generating units for test case II under the two case scenarios

Objectives	DELD						DEED					
Sources	Without RES			With RES			Without RES			With RES		
Units	P_T^1	P_T^2	P_T^3	P_T^1	P_T^2	P_T^3	P_T^1	P_T^2	P_T^3	P_T^1	P_T^2	P_T^1
H_1	37.5211	45.4687	57.0101	37.2583	44.9087	56.133	50	40	50	48.2999	40.0001	50
H_2	40.8139	48.2363	60.9498	38.0463	45.8669	57.5868	60	40	50	51.4951	40.0045	50.0004
H_3	42.534	49.6393	62.8267	39.3672	47.0607	59.302	63.1882	41.8117	50.0001	55.73	40	50
H_4	44.2339	50.9827	64.7835	38.6049	46.3938	58.3413	64.8169	45.1828	50.0003	53.34	40	50
H_5	45.8769	52.4311	66.692	43.4043	50.4471	63.9287	66.3135	48.6865	50	64.19	43.59	50
H_6	47.5748	53.7988	68.6264	45.8452	52.4895	66.7253	67.3892	51.1313	51.4796	66.3114	48.7476	50.001
H_7	49.1848	55.2664	70.5489	42.1822	49.4164	62.4714	68.0992	52.7741	54.1267	62.9671	41.1028	50
H_8	50.9115	56.6183	72.4702	37.0584	44.3778	55.8238	68.8075	54.4046	56.7879	47.26	40	50
H_9	61.0583	64.9904	83.9513	46.0145	52.5564	66.7991	73.0538	64.2148	72.7313	66.419	48.9498	50.0012
H_{10}	67.6734	70.5671	91.7595	48.5147	54.6534	69.6118	75.8786	70.7862	83.3352	67.7741	52.0298	52.9762
H_{11}	71.2077	73.2703	95.5219	64.3093	67.6865	87.7942	77.318	74.0496	88.6324	74.4591	67.4253	77.9057
H_{12}	74.6026	76.0886	99.3088	66.9853	69.9006	90.8141	78.7461	77.3602	93.8937	75.5851	70.0246	82.0904
H_{13}	71.0479	73.3461	95.606	55.5061	60.4412	77.7627	77.3222	74.0119	88.6659	70.7436	58.8971	64.0693
H_{14}	64.3887	67.7546	87.8567	51.8687	57.4474	73.5238	74.4702	67.5386	77.9911	69.2237	55.312	58.3043
H_{15}	57.6334	62.221	80.1457	51.4584	57.1172	73.0844	71.638	60.9622	67.3999	69.047	54.954	57.659
H_{16}	50.8284	56.6979	72.4738	44.5694	51.2946	65.1261	68.8041	54.4287	56.7673	65.132	45.8574	50.0006
H_{17}	47.5397	53.806	68.6543	43.1845	50.2019	63.6036	67.3796	51.0749	51.5456	63.9864	43.003	50.0006
H_{18}	52.6128	57.9972	74.39	51.1515	56.8908	72.7776	69.5076	56.063	59.4295	68.9148	54.6679	57.2373
H_{19}	57.6387	62.2032	80.1581	57.4042	62.0287	79.8171	71.6497	60.9518	67.3985	71.5659	60.7143	66.9698
H_{20}	71.0918	73.3303	95.5779	70.9701	73.3219	95.538	77.3234	74.0294	88.6472	77.287	73.9844	88.5587
H_{21}	66.0851	69.1807	89.7343	66.0369	69.1414	89.6717	75.195	69.1589	80.6462	75.1833	69.0746	80.5921
H_{22}	54.2796	59.3891	76.3312	54.1267	59.3486	76.2146	70.2235	57.7044	62.0721	70.1853	57.5705	61.9342
H_{23}	44.164	51.0657	64.7703	43.8154	50.7457	64.3689	64.765	45.235	50	64.4413	44.4886	50
H_{24}	39.1372	46.8756	58.9872	38.917	46.7005	58.8025	55	40	50	54.42	40	50
Cost ($)	176165.8			299893.4			202871.3			325349.2		

Table 6 Comparative analysis of the results for test case II considering DELD objective

Techniques	Without RES					With RES			
	Best ($)	Worst ($)	Average ($)	Deviation	Best ($)	Worst ($)	Average ($)	Deviation	Time (sec)
PSO [8]	176177.9175	–	–	–	299919.4357	–	–	–	–
DE [8]	176169.0719	–	–	–	299916.0487	–	–	–	–
SOS [8]	176168.04244	–	–	–	299906.3846	–	–	–	–
GWO [8]	176167.827	–	–	–	399896.6562	–	–	–	–
WOA [8]	176166.5662	–	–	–	299895.531	–	–	–	–
BDO [4]	176166	–	–	–	299895.1	–	–	–	–
FPA [8]	176172	176187	176175	10.8167	299900	299908	299904	11.9304	**135.19**
PPSO [8]	176168	176178	176172	5.1316	299897	299905	299899	5.2915	144.74
FPA-PPSO	**176165.7**	**176168.8**	**176166.5**	**4.16333**	**299893.4**	**299903**	**299898.1**	**4.04145**	189.16

Best results indicate in bold

Table 7 Comparative analysis of the results for test case II considering DEED objective

Techniques	Without RES					With RES			
	Best ($)	Worst ($)	Average ($)	Deviation	Best ($)	Worst ($)	Average ($)	Deviation	Time (sec)
PSO [8]	202886.6496	–	–	–	325377.3173	–	–	–	–
DE [8]	202884.8852	–	–	–	325371.3072	–	–	–	–
SOS [8]	202882.0837	–	–	–	325369.7976	–	–	–	–
GWO [8]	202882.6042	–	–	–	325368.4448	–	–	–	–
WOA [8]	202881.7751	–	–	–	325364.4919	–	–	–	–
BDO [4]	202874.7	–	–	–	325351.6	–	–	–	–
FPA [8]	202881.5	202895	202891	9.602	325366	325402	325384	28.155	**139.42**
PPSO [8]	202880	202893	202887	6.957	325359	325400	325376	27.124	147.63
FPA-PPSO	**202871.3**	**202891**	**202884**	**5.504**	**325349.2**	**325392**	**325356**	**20.2662**	195.06

Best results indicate in bold

show the effectiveness of the suggested FPA-PPSO in solving this problem, a comparative study using statistical data obtained using the suggested method and other existing methods such as PSO, PPSO, etc. have been presented in Table 7. From the comparative study presented in Table 7, it is observed that the suggested FPA-PPSO not only provides the best fuel cost but also the results obtained are more stable compared to the existing FPA and PPSO. Next, to analyze the convergence behavior of the objective function, Fig. 7 is presented. It is observed from Fig. 7, that FPA-PPSO has a faster convergence rate than FPA and PPSO.

4.3 Test case III

For the third test case, a conventional thermal generator, three diesel generators, a solar farm, a wind farm, and ESS units have been considered. The fuel and emission coefficients along with ESS capacity are presented in Table 8. Whereas, the dynamic load profile is considered to be the same as that used for the second test case. Further, an uncertainty model for solar generation and wind generation as presented in [52, 53] has been considered in this study.

The optimal power allocations for the generating units along with the total fuel cost are presented in Table 10. For a comparative analysis and to show the effectiveness of the suggested FPA-PPSO method to solve this problem, results with the existing optimization techniques have also been presented. The techniques used for this comparative study are PSO, GWO, PPSO, and FPA. All the comparative results are presented in Table 9. From Table 9, it is observed that the suggested method provides the best fuel cost. Further, by observing the average value and standard deviation, it can be concluded that the suggested method can provide effective results with minimum deviation. Hence, the method is more stable. Further, to analyze the convergence rate and behavior of objective function with time (iteration counts), Fig. 7 is presented. It is observed

Table 8 Generating units cost and emission coefficients data for test case III [8, 62]

Units	G_{min} (MW)	G_{max} (MW)	a_i $(\$/MW^2h)$	b_i $(\$/MWh)$	c_i $(\$/h)$	α_i (Kg/MW^2h)	β_i (Kg/MWh)	γ_i $(\$/h)$	η_b
T_1	37	190	0.021	20.4	600	0.012	−0.555	30	-
D_1	0	1.5	0.00024	0.21	15.3	0.000105	−0.01355	0.6	-
D_2	0	1	0.000425	0.3	14.88	8.00E-05	−0.006	0.45	–
D_3	0	1	0.000315	0.306	9	0.00012	−0.00555	0.3	–
ESS	0	300	–	250	–	–	–	–	90%

Table 9 Comparative analysis of the results for test case III

Technique	Best ($)	Worst ($)	Average ($)	Deviation ($)	Time (sec)
PSO [56]	140568	140575	140573	4.04145	**162.26**
GWO [63]	140600	140610	140604	5.2915	178.26
FPA [55]	140569	140582	140574	6.80686	168.14
PPSO [57]	140559	140569	140563	5.2915	176.36
FPA-PPSO	**140543**	**140562**	**140554**	**3.84886**	210.11

Best results indicate in bold

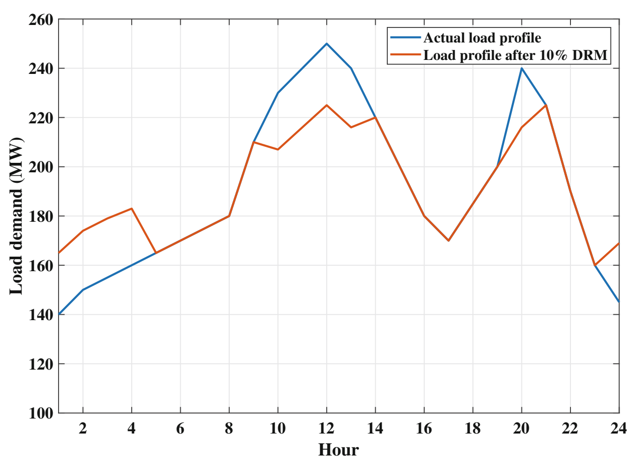

Fig. 6 Load profile with and without DRM

from Fig. 7 that the suggested method has a good convergence rate as compared to other methods such as PSO, GWO, PPSO, and FPA used for comparison.

4.4 Test case IV

This test case is an extension of Test Case III and presents a study on the effect of DRM on the generation side. To implement a DRM scheme, like [47, 64], 10 percent of the loads from peak locations of 4, 5, 6, and 7 h are shifted to the off-peak location of 8, and 9, 10, and 11 h. The advantage of DRM is that the peak load of the load demands is reduced in comparison to the actual day-ahead load demand. The generating units are then optimized using the new optimized load profile. The generating units and other parameters such as load profile, ESS units, etc. are considered similar to that used in test case III.

The optimal power allocation to the generating units and the optimal fuel cost are presented in Table 12. Further, the impact of DRM on the generation side can be observed from Fig. 6. From Table 10 and 12, it is observed that the total fuel cost after considering DRM is reduced by $ 25545. The load distribution among the generating units is improved which also reduces the stress on the ESS units. ESS units feed 166.5731 MW of power which is less than 274.6371 MW in the case when DRM is not considered. Further, load profile optimization also improves the power delivery as the overall load shedding is reduced from 30.51923 MW to 18.51923 MW.

Next, to show the impact of the suggested FPA-PPSO scheme in solving this problem, a comparative study has been presented. For this comparison, PSO, FPA, GWO, and PPSO have been considered. All the comparative results are presented in Table 11. It is observed from Table 11 that the overall performance of the suggested FPA-PPSO is better compared to the existing methods used for the comparative study. The suggested method provides the best fuel cost with good stability as the average value and standard deviations are minimum. Further, Fig. 7 is presented to show the behavior of the objective function obtained using different methods. It is observed from Fig. 7 that suggested FPA-PPSO converges faster than PPSO, PSO, GWO, and FPA.

Table 10 Behavior of generating units for Test case III

Hours	P_T	P_D^1	P_D^2	P_D^3	P_W	P_S	P_B	Load sheading	Load demand	ESS Behavior
H_1	136.564	1.36983	0.556201	0.391	1.11917	0	0	0	140	300
H_2	146.042	1.14466	0.819128	0.479697	1.51417	0	0	0	150	300
H_3	150.072	1.49647	0.857349	0.993506	1.58	0	0	0	155	300
H_4	155.443	1.14815	0.962832	0.875715	1.58	0	0	0	160	300
H_5	161.286	1.32897	0.181593	0.524215	1.58	0.101816	0	0	165	300
H_6	165.827	1.00561	0.800061	0.55603	1.58	0.232417	0	0	170	300
H_7	169.655	1.47783	0.877018	0.9327	1.58	0.477168	0	0	175	300
H_8	174.393	1.49821	0.936305	0.96	1.58	0.633548	0	0	180	300
H_9	190	1.5	1	1	1.2245	0.757286	13.0664	1.45182	210	286.934
H_{10}	190	1.5	1	1	1.01383	0.870068	31.1545	3.46161	230	255.779
H_{11}	190	1.5	1	1	0.658333	1.01464	40.3443	4.4827	240	215.435
H_{12}	190	1.5	1	1	0.5135	0.959335	49.5244	5.50272	250	165.91
H_{13}	190	1.5	1	1	0.9085	0.811376	40.3021	4.47801	240	125.608
H_{14}	190	1.5	1	1	0.9875	0.665094	22.3627	2.48474	220	103.246
H_{15}	190	1.5	1	1	1.106	0.589812	4.32377	0.480419	200	98.9218
H_{16}	190	1.5	1	1	0.895333	0.265628	0	0	180	112.117
H_{17}	190	1.5	1	1	0.6715	0.223167	0	0	170	134.072
H_{18}	190	1.5	1	1	0.8295	0.162946	0	0	185	142.615
H_{19}	190	1.5	1	1	1.04017	0.068275	4.8524	0.539156	200	137.763
H_{20}	190	1.5	1	1	0.724167	0	41.1983	4.57758	240	96.5644
H_{21}	190	1.5	1	1	0.895333	0	27.5442	3.06047	225	69.0202
H_{22}	190	1.5	1	1	1.027	0	0	0	190	73.0945
H_{23}	190	1.5	1	1	0.948	0	0	0	160	104.098
H_{24}	190	1.5	1	1	0.842667	0	0	0	145	148.506

Table 11 Comparative analysis of the results for test case IV

Technique	Best ($)	Worst ($)	Average ($)	Deviation ($)	Time (sec)
PSO [56]	115039	115062	115050	11.5036	**163.61**
GWO [63]	115017	115039	115025	11.9304	181.01
FPA [55]	115021	115029	115025	4	170.96
PPSO [57]	115005	115035	115023	15.695	178.09
FPA-PPSO	**114988**	**115011**	**115002**	**2.50555**	211.96

Best results indicate in bold

4.5 Analysis on the performance of FPA-PPSO scheme

From the results presented in Tables 4, 6, 7, 9 and 11 for the four test cases, it is observed that the suggested FPA-PPSO obtains the best-optimized result. The objective function is optimized to provide the minimum cost. This confirms that the suggested method shows a superior performance in comparison to the other methods used for comparisons. Based on the average and deviation values obtained for test cases, it is observed that the suggested optimizer produces a value that is close to the best values obtained. This observation confirms that the suggested methods show more accuracy and stability when compared to other methods used for the comparisons. A similar conclusion is already drawn from the analysis with the benchmark functions. Hence, from the analysis, it can be concluded that the suggested method is superior in terms of efficiency, accuracy, and stability in comparison to the methods used for comparative study.

To further investigate and confirm the supremacy of the suggested optimizer, the Wilcoxson and Friedman test is conducted for the results obtained for the four test cases.

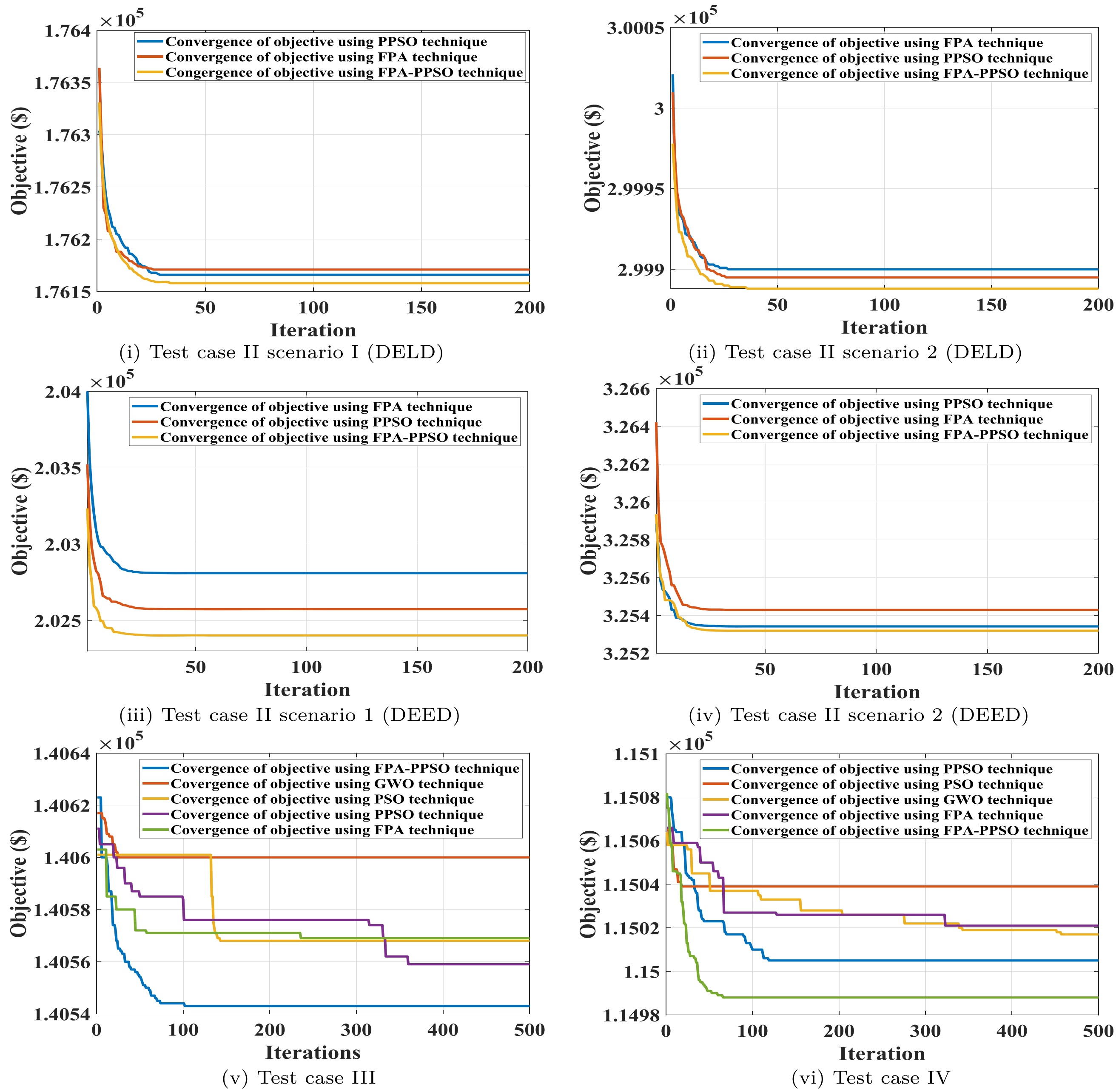

Fig. 7 Convergence behavior of objective function for test case II, III & IV

The results for the two tests are presented in Table 13 along with the result obtained for PSO, PPSO, and FPA. By observing the results for the Friedman test, it is observed that the suggested FPA-PPSO scheme gets a mean rank of 1. Whereas, the PPSO gets a rank of 2.25 followed by FPA with a rank of 3.125, and PSO with a rank of 3.625. As the rank obtained by FPA-PPSO is the smallest, it is regarded as the winner. In the case of the Wilcoxson test, it is observed that in all the cases, the suggested FPA-PPSO scheme gets a score less than the significant level of 0.05. This confirms that the suggested method is more efficient than PPSO, PSO, and FPA.

5 Conclusions and future research

This article presents a hybrid version of the flower pollination algorithm and phasor particle swarm optimization technique i.e. FPA-PPSO scheme to solve complex optimization problems. The supremacy of the suggested optimizer with respect to existing FPA and PPSO schemes is

Table 12 Behavior of generating units for test case IV

Hours	P_T	P_D^1	P_D^2	P_D^3	P_W	P_S	P_B	Load sheading	Load demand	ESS Behavior
H_1	161.819	0.587504	0.759304	0.714897	1.11917	0	0	0	165	300
H_2	169.734	1.34698	0.691374	0.713819	1.51417	0	0	0	174	300
H_3	174.889	1.4286	0.780776	0.321528	1.58	0	0	0	179	300
H_4	178.652	1.26445	0.691205	0.812426	1.58	0	0	0	183	300
H_5	160.08	1.43638	0.999171	0.8035	1.58	0.101816	0	0	165	300
H_6	165.082	1.25732	0.861442	0.986761	1.58	0.232417	0	0	170	300
H_7	169.748	1.48608	0.737791	0.971172	1.58	0.477168	0	0	175	300
H_8	174.487	1.49709	0.943193	0.868	1.58	0.633548	0	0	180	300
H_9	190	1.5	1	1	1.2245	0.757286	13.0664	1.45182	210	286.934
H_{10}	190	1.5	1	1	1.01383	0.870068	10.4545	1.16161	207	276.479
H_{11}	190	1.5	1	1	0.658333	1.01464	18.7443	2.0827	216	257.735
H_{12}	190	1.5	1	1	0.5135	0.959335	27.0244	3.00272	225	230.71
H_{13}	190	1.5	1	1	0.9085	0.811376	18.7021	2.07801	216	212.008
H_{14}	190	1.5	1	1	0.9875	0.665094	22.3627	2.48474	220	189.646
H_{15}	190	1.5	1	1	1.106	0.589812	4.32377	0.480419	200	185.322
H_{16}	190	1.5	1	1	0.895333	0.265628	0	0	180	198.517
H_{17}	190	1.5	1	1	0.6715	0.223167	0	0	170	220.472
H_{18}	190	1.5	1	1	0.8295	0.162946	0	0	185	229.015
H_{19}	190	1.5	1	1	1.04017	0.068275	4.8524	0.539156	200	224.163
H_{20}	190	1.5	1	1	0.724167	0	19.5983	2.17758	216	204.564
H_{21}	190	1.5	1	1	0.895333	0	27.5442	3.06047	225	177.02
H_{22}	190	1.5	1	1	1.027	0	0	0	190	181.095
H_{23}	190	1.5	1	1	0.948	0	0	0	160	212.098
H_{24}	190	1.5	1	1	0.842667	0	0	0	169	234.906

Table 13 Wilcoxson and Friedman rank test results for test case I, II, III and IV

Method	FPA-PPSO		PPSO		FPA		PSO	
Parameter	Rank	p-value	Rank	p-value	Rank	p-value	Rank	p-value
Test Case 1	1	–	2.75	0.00587	2.5	0.00141	3.75	0.0081
Test Case II	1	–	2.25	0.00407	4	0.00596	2.75	0.0006
Test Case III	1	–	2	0.00617	3	0.00559	4	0.0072
Test Case IV	1	–	2	0.00789	3	0.00951	4	0.0041
Mean Rank	1	–	2.25	-	3.125	-	3.625	–

validated using twenty-three benchmark functions. Based on the results obtained it is found that the suggested methods show a better performance with respect to FPA, PPSO, and PSO methods. Next, the suggested FPA-PPSO method is applied to solve the generation scheduling problem of a microgrid, including renewable generating sources and energy storage systems. The suggested method is tested using three cases which include different parametric conditions. Further, an additional test case is also considered which presents a study on the impact of demand response management on the generation side. It is observed that DRM improves the overall generation cost and reduces load shedding. The comparative study presented for the test cases proves that the suggested FPA-PPSO method has good stability and the probability of obtaining an optimal solution is high. The results also show that the suggested method provides a superior result with respect to some well-known existing methods such as PSO, FPA, PPSO, WOA, GWO, DE, etc.

To conclude, the result obtained confirms that the suggested FPA-PPSO scheme shows superior performance in comparison to the existing optimization scheme. Additionally, it is also observed that by the use of a demand management scheme, the scheduling problem can be efficiently solved. In the near future, the works that can be taken up to further enhance the contributions of this study include:

– Testing and analyzing the performance of the suggested optimizer in scheduling the generating units by considering more practical constraints such as transmission losses, valve point effect, ramp rate limits, prohibited operating zones, etc. encountered in the real world which were not included in this study.
– Development and implementation of a more rigorous demand management scheme which can further help in scheduling the load profile and generating units.
– Population size and iteration counts used in the suggested FPA-PPSO method can be made adaptive to improve the computational time to solve the optimization problems as in most of the cases the suggested optimizer convergence at a faster rate.
– Lastly, based on the performance shown by the suggested FPA-PPSO scheme, it can be applied to solve other offline optimization problems.

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Declarations

Conflict of interest The authors declare no potential Conflict of interest.

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