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Akanksha Sharma, Sanjay Kumar Jain, Navdeep Kaur

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Hybrid multi-objective optimisation for ancillary service procurement in renewable energy integrated deregulated environment

Akanksha Sharma*

Lovely Professional University,
Phagwara, Punjab, India
Email: akanksha.30944@lpu.co.in

*Corresponding author

Sanjay Kumar Jain

Thapar Institute of Engineering and Technology,
Patiala, Punjab, India
Email: skjain@thapar.edu

Navdeep Kaur

Lovely Professional University,
Phagwara, Punjab, India
Email: navdeep.29714@lpu.co.in

Abstract: In this manuscript, the reactive power control ancillary services are procured in a thermal-wind-solar deregulated system with renewable energy generation uncertainties. This procurement is devised as a dynamic bi-objective optimisation problem to find the optimum switching schedule of the shunt capacitor for cost and voltage fluctuations minimisation. The capacitors participate in offering ancillary services, and their switching decisions, constrained by their operational lifespan, are influenced by marginal pricing. A particle swarm and electric field hybrid optimisation (PSEFHO) algorithm is presented in this paper utilising Pareto-based approach and non-dominance sorting. The convergence of algorithm is assessed using statistical performance measures. The effectiveness of developed algorithm is verified using IEEE 118-bus and IEEE 300-bus test system. Moreover, an analysis is undertaken to accommodate seasonal variations in solar irradiance.

Keywords: ancillary service; deregulated system; dynamic framework; multi-objective optimisation; renewable power generation.

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Biographical notes: Akanksha Sharma is working an Assistant Professor in Lovely Professional University, Phagwara, Punjab, India. She has received her PhD from the Thapar Institute of Engineering and Technology, Patiala, Punjab, India in 2022. Her research areas include power system optimisation, deregulation, renewable energy, and electricity markets. She was awarded University Gold Medal for securing the highest CGPA in Master of Engineering program in 2016. She was also awarded DST INSPIRE fellowship by the Government of India for her PhD research work.

Sanjay Kumar Jain is currently a Professor in the Electrical and Instrumentation Engineering Department, Thapar Institute of Engineering and Technology, Patiala. He obtained his PhD in 2001 from Indian Institute of Technology, Roorkee. He has about twenty years of teaching experience. His current area of research interest includes power system operation and control, power system optimisation and distribution systems.

Navdeep Kaur is currently an Associate Professor in the Lovely Professional University, Phagwara, Punjab, India. She obtained her PhD from the Thapar Institute of Engineering and Technology, Patiala. She has about 15 years of teaching experience. Her current area of research interest includes power system optimisation and renewable energy systems.

1 Introduction

The environmental concerns and depleting fossil fuels resulted in the substantial incorporation of renewable energy sources (RES), which are often variable and subject to intermittency, into the grid. However, such uncertain behaviour of RES greatly impacts the system security and necessitates ancillary services procurement suitably in a deregulated setup. The reactive power control ancillary service (RPCAS) plays a pivotal role in managing and optimising reactive power flow to ensure voltage stability and augment the reliability of the power system. In a deregulated environment, the system operator procures these services from market participants, ensuring proper remuneration to them (Anaya and Pollitt, 2020).

The increasing integration of RES presents a grid challenge owing to their intermittent and uncertain nature. The effect of these uncertainties was analysed statistically for varying load (Ciupageanu et al., 2019). These uncertainties were accounted in the study of optimal power flow (Biswas et al., 2017). Wind power capability to provide enhanced AS was investigated with wind integration (Hansen et al., 2016). The variability and uncertainty of wind and solar RES were accounted for real-time dispatch over scheduling interval (Reddy et al., 2015), optimal dispatch with load demand (Ebeed et al., 2020). Mamdani method for fuzzification is utilised to effectively adapt the fluctuating ambient conditions and varying loads in hybrid power system (Sharma et al., 2023). The techno-economic viability of a PV and wind power plant was assessed through the utilisation of the RETScreen software (Aljendy et al., 2021).

The location marginal price (LMP) for reactive power, characterised as the minimum expense required to fulfill the additional reactive power (VAr) demand, was employed to facilitate VAr pricing (Jay and Swarup, 2021). The marginal price was used in VAr

dispatch for optimising the reactive power cost (Malakar et al., 2016), cost allocation of active and reactive power (Ketabi et al., 2010), and the marginal pricing of VAr in an electricity market (Bhattacharyya and Karmakar, 2019). The influence of different factors on marginal price was studied in the deregulated environment (Dai et al., 2000).

In contemporary times, heuristic evolutionary algorithms, drawing inspiration from natural processes, are increasingly employed to address practical optimisation challenges because of being problem independent, easy to implement, and capable of escaping local minima. Among various heuristic techniques namely particle swarm optimisation (PSO) (Wang et al., 2020), artificial bee colony (Ettappan et al., 2020), Jaya algorithm (Movahhed-Ghodsinya, 2023), grey wolf optimiser (Jamal et al., 2020), fuzzy-PSO integrated with the firefly algorithm (Gilvaei et al., 2020), have been used to solve VAr dispatch problems. A hybrid improved teaching-learning algorithm and double differential evolutionary algorithm (Ghasemi et al., 2014) were utilised for VAr dispatch to yield faster convergence to the optimal solutions. A modified hybrid algorithm was implemented for VAr dispatch with RES integration for enhancing voltage stability and reduction in power losses (Khan et al., 2020). A reactive power dispatch problem was solved by enhanced coyote optimisation involving RES (Abaza et al., 2021). An improved differential evolution algorithm was applied for active-VAr dispatch considering wind and solar generation (Awad et al., 2019). An artificial electric field algorithm is used for VAr AS procurement considering wind generation (Sharma and Jain, 2021).

The literature reviewed predominantly emphasises either single-objective optimisation in static scenarios for VAr dispatch or tends to overlook the integration of diverse RES. Furthermore, these investigations typically centre around smaller-scale test systems. A multi-objective dynamic optimal dispatch model is presented (Li et al., 2019), however it does not include the impact of demand response to address uncertainty in RES. In light of the preceding literature, it becomes apparent that there has been a notable gap in research concerning the development of an efficient market model for acquiring ancillary services within dynamic multi-objective frameworks, especially for large-scale test systems incorporating various RES and accommodating fluctuating load conditions. Consequently, this paper addresses the challenge of procuring RPCAS in a dynamic context within a competitive system that integrates RES. Additionally, the model's performance is assessed by utilising practical solar irradiation data from Tucson, Arizona, to account for seasonal variations.

The hybridisation of different algorithms has been investigated for achieving a balance between exploration and exploitation capabilities. As the PSO has excellent exploitation capability (Mirjalili and Hashim, 2010), and AEFA has good exploration capability, less computational complexity, and fast convergence towards the global optimal solution (Anita and Kumar, 2020). A particle swarm and electric field hybrid optimisation (PSEFHO) algorithm involving social thinking aspect of PSO while integrating the acceleration of AEFA for velocity updation, is developed in this manuscript. It uses sparse matrices realisation of Newton power flow to reduce the computational effort in terms of memory requirement and run time. The efficacy of developed PSEFHO is evaluated in comparison to other algorithms and is substantiated by statistical measures.

2 Model formulation

A forward market-based multi-objective dynamic optimisation model is developed for procuring RPCAS in wind and solar integrated deregulated system. The optimisation problem is solved using PSEFHO algorithm to simultaneously minimise cost and voltage fluctuations. The total cost consists several active and reactive cost components associated with supply.

2.1 Cost associated with production of power by generators

The cost characteristic of real as well as reactive power from u^{th} thermal unit is expressed by (Malakar et al., 2016; Ketabi et al., 2010):

$$C_{gpu}^t(P_{gu}) = a_u P_{gu}^2 + b_u P_{gu} + c_u \quad (1)$$

$$C_{gqu}^t(Q_{gu}) = a'_u Q_{gu}^2 + b'_u Q_{gu} + c'_u \quad (2)$$

where a, b, c and a', b', c' are coefficients of real and reactive power of thermal plant, respectively.

The cost characteristic of power generation from wind plants is characterised by linear cost equation as (Malakar et al., 2016):

$$C_{gpw}^t(P_{gw}) = h_w P_{gw} \quad (3)$$

$$C_{gqw}^t(Q_{gw}) = h'_w Q_{gw} \quad (4)$$

where h_w and h'_w ($h'_w = h_w \cdot \sin\theta$) are the cost coefficients of P and Q power, P_{gw} and Q_{gw} are the scheduled powers for wind unit w .

Similarly, the cost characteristic of active power from solar unit also follows linear cost function, expressed as (Biswas et al., 2017):

$$C_{gps}^t(P_{gs}) = h_s P_{gs} \quad (5)$$

where h_s and P_{gs} is the active power cost coefficient and scheduled active power of s^{th} solar unit, respectively.

2.2 Opportunity cost

The VAR pricing should be structured in a way that allows for the recovery of lost opportunity of active power production thereby facilitating the generation of additional reactive power, and are defined as:

$$C_{opu}^t(Q_{gu}) = \sum_{u=1}^{N_u} \left[C_{gpu}(\bar{S}_u) - C_{gpu} \left(\sqrt{\bar{S}_u^2 - Q_{gu}^2} \right) \right] \cdot R_p \quad (6)$$

$$C_{opw}^t(Q_{gw}) = \sum_{w=1}^{N_w} \left[C_{gpw}(\bar{S}_w) - C_{gpw} \left(\sqrt{\bar{S}_w^2 - Q_{gw}^2} \right) \right] \cdot R_p \quad (7)$$

where $\bar{S}$ represent the maximum apparent power of units, R_p denotes the effectiveness rate of VAR (Ketabi et al., 2010).

2.3 Imbalance penalties on RES generation

The uncertainty in output of wind and solar are accounted via imbalance penalties as overestimating (reserve) and underestimating (penalty) costs. The cost functions for reserve and penalty associated with RES are expressed by (Biswas et al., 2017):

$$\begin{aligned} C_{Rw}^t(P_{gw} - P_{gw}^{\text{al}}) &= \xi_{Rw}(P_{gw} - P_{gw}^{\text{al}}) \\ &= \xi_{Rw} * f_w(P_{gw}^{\text{al}} < P_{gw}) * [P_{gw} - E(P_{gw}^{\text{al}} < P_{gw})] \end{aligned} \quad (8)$$

$$\begin{aligned} C_{Pw}^t(P_{gw}^{\text{al}} - P_{gw}) &= \xi_{Pw}(P_{gw}^{\text{al}} - P_{gw}) \\ &= \xi_{Pw} * f_w(P_{gw}^{\text{al}} > P_{gw}) * [E(P_{gw}^{\text{al}} > P_{gw}) - P_{gw}] \end{aligned} \quad (9)$$

$$\begin{aligned} C_{Rs}^t(P_{gs} - P_{gs}^{\text{al}}) &= \xi_{Rs}(P_{gs} - P_{gs}^{\text{al}}) \\ &= \xi_{Rs} * f_s(P_{gs}^{\text{al}} < P_{gs}) * [P_{gs} - E(P_{gs}^{\text{al}} < P_{gs})] \end{aligned} \quad (10)$$

$$\begin{aligned} C_{Ps}^t(P_{gs}^{\text{al}} - P_{gs}) &= \xi_{Ps}(P_{gs}^{\text{al}} - P_{gs}) \\ &= \xi_{Ps} * f_s(P_{gs}^{\text{al}} > P_{gs}) * [E(P_{gs}^{\text{al}} > P_{gs}) - P_{gs}] \end{aligned} \quad (11)$$

where ξ_R and ξ_P are the reserve and penalty cost coefficient of units, respectively; P_{gw}^{al} and P_{gs}^{al} are the actual available power of wind and solar units, respectively.

2.3.1 Intermittent wind and solar power

Here, Weibull and Log-normal probability distribution functions are employed to predict the profiles of wind speed (v) and solar irradiation (I) which are defined as (Biswas et al., 2017; Sharma and Jain, 2021):

$$f_v(v) = \frac{\beta}{\gamma} \left(\frac{v}{\gamma} \right)^{\beta-1} \exp \left[- \left(\frac{v}{\gamma} \right)^{\beta} \right], \quad (0 < v < \infty) \quad (12)$$

$$f_I(I) = \frac{1}{I\sigma\sqrt{2\pi}} \exp \left[\frac{-(\ln(I) - \mu)^2}{2\sigma^2} \right], \quad (I > 0) \quad (13)$$

The power production from a wind turbine is contingent upon the prevailing wind speed and can be characterised as:

$$p_w = \begin{cases} 0, & \text{for } v < v_{in} \text{ and } v > v_{ot} \\ P_{Rt} \left(\frac{v - v_{in}}{v_{rt} - v_{in}} \right), & \text{for } v_{in} \leq v \leq v_{rt} \\ P_{Rt}, & \text{for } v_{rt} < v \leq v_{ot} \end{cases} \quad (14)$$

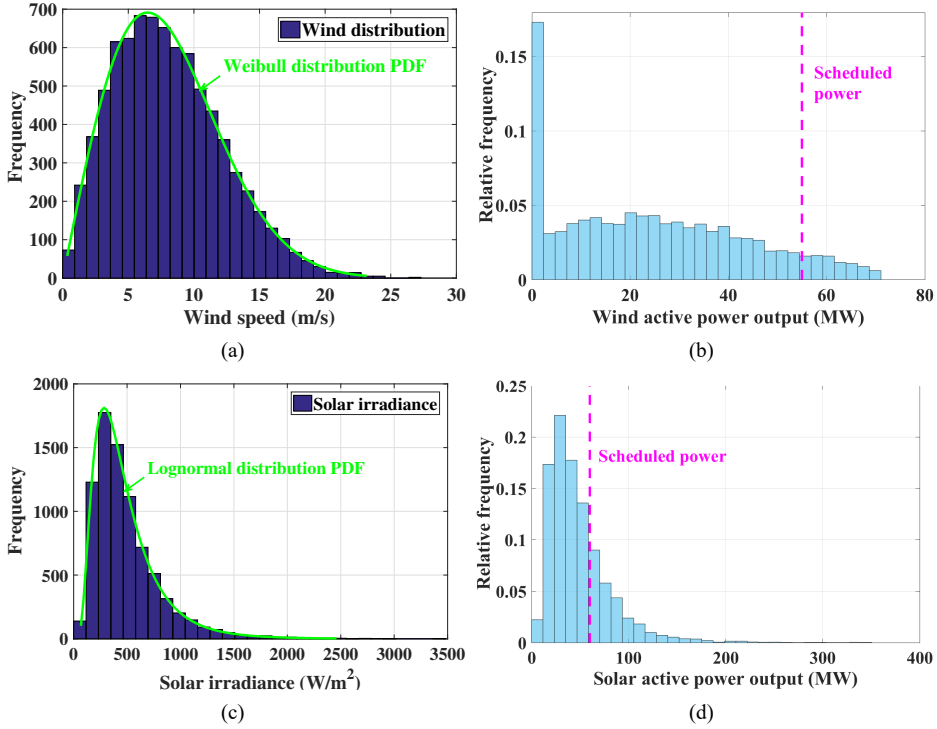
where P_{Rt} represent the rated power output of the wind unit, v_{rt} , v_{ot} , and v_{in} are rated speed, cut-out speed, and cut-in speed of wind unit, respectively and their values considered in this work are 3, 16, and 25.

The power output from solar photo voltaic (PV) depends on solar irradiation and is described as (Biswas et al., 2017):

$$p_s = \begin{cases} P_S \left(\frac{I^2}{I_{sd} R_c} \right), & \text{for } 0 < I < R_c \\ P_S \left(\frac{I}{I_{sd}} \right), & \text{for } I \geq R_c \end{cases} \quad (15)$$

where P_S correspond to the rated power output, I_{sd} signifies the standard solar irradiance, and R_c denotes certain irradiance point.

Figure 1 (a) Weibull PDF (b) Active power distribution for wind (c) Lognormal PDF (d) Active power distribution for solar PV (see online version for colours)



2.3.2 Computation of imbalance penalties for RES power uncertainty

The distribution of wind speed and solar irradiance is depicted in Figures 1(a) and 1(c), respectively. Similarly, Figures 1(b) and 1(d) display the active power output. The over and underestimating cost of wind generation (Biswas et al., 2017) is calculated using equations (16) and (17), respectively, as:

$$C_{Rw}^t(P_{gw} - P_{gw}^{\text{al}}) = \xi_{Rw}(P_{gw} - P_{gw}^{\text{al}}) = \xi_{Rw} \sum_{n=1}^{N_-} [P_{gw} - P_{wn-}] \times f_{wn-} \quad (16)$$

$$C_{Pw}^t(P_{gw}^{\text{al}} - P_{gw}) = \xi_{Pw}(P_{gw}^{\text{al}} - P_{gw}) = \xi_{Pw} \sum_{n=1}^{N_+} [P_{wn+} - P_{gw}] \times f_{wn+} \quad (17)$$

Here, N_+ and N_- represent the discrete segments situated on the right and left sides of the anticipated power P_{gw} . P_{wn-} indicates the actual output generation, which falls below P_{gw} and is positioned to its left. P_{wn+} is available power exceeding P_{gw} . f_{wn-} and f_{wn+} describe the relative frequencies of occurrences for P_{wn-} and P_{wn+} . Similarly, the over and under-estimation cost of solar generation is calculated by:

$$C_{Rs}^t(P_{gs} - P_{gs}^{al}) = \xi_{Rs}(P_{gs} - P_{gs}^{al}) = \xi_{Rs} \sum_{n=1}^{N_-} [P_{gs} - P_{sn-}] \times f_{sn-} \quad (18)$$

$$C_{Ps}^t(P_{gs}^{al} - P_{gs}) = \xi_{Ps}(P_{gs}^{al} - P_{gs}) = \xi_{Ps} \sum_{n=1}^{N_+} [P_{sn+} - P_{gs}] \times f_{sn+} \quad (19)$$

2.4 Cost of supplying reactive power from shunt capacitor

The VAR providers should be compensated to account for both the investment and supply costs, as these costs are defined as:

2.4.1 Depreciation cost

Throughout the entire operational lifespan of shunt capacitors, there exists a restriction on the number of switching actions permitted. The cost associated with each switching event is defined as the depreciation cost relative to the initial investment IC , expressed as (Malakar et al., 2016):

$$C_{dsh} = \frac{Q_c * IC}{\text{operating hours}} \$/\text{MVA}r\text{h} \quad (20)$$

where Q_c signifies the capacity of capacitor.

2.4.2 Cost of providing VAR

The shunt capacitor's are providing reactive power and they must be compensated based on their generation output Q_{sh} (Immaraju et al., 2021) which is considered to be contingent upon LMP of the bus (Sharma and Jain, 2023). The cost of reactive supply from capacitor is:

$$C_{vsh}^t(Q_{sh}) = LMP \times Q_{sh} \quad (21)$$

In the initial interval, the reactive supply for the shunt capacitor is determined by its rated capacity. Subsequently, the output is determined by fluctuations in the marginal prices. Shunt capacitor's output is evaluated as:

$$Q_{sh}^t = Q_{sh}^{t-1} \pm \Delta Q_{sh} \quad (22)$$

2.5 Objective functions and constraints

The proposed bi-objective optimisation involves minimisation of cost f_1 and voltage fluctuations f_2 , expressed by:

2.5.1 Minimisation of total cost

The aim is to optimise the total cost which incorporates all above defined cost and is expressed as equation (23) at the top of next page.

$$\begin{aligned}
 \text{Minimise, } f_1 = & \sum_{t=1}^{N_T} \left[\sum_{u=1}^{N_u} [C_{gpu}^t(P_{gu}) + C_{gqu}^t(Q_{gu})] \right. \\
 & + \sum_{w=1}^{N_w} [C_{gpw}^t(P_{gw}) + C_{gqw}^t(Q_{gw})] \\
 & + \sum_{w=1}^{N_w} [C_{Rw}^t(P_{gw} - P_{gw}^{al}) + C_{Pw}^t(P_{gw}^{al} - P_{gw})] \\
 & + \sum_{s=1}^{N_s} C_{gps}^t(P_{gs}) \\
 & + \sum_{s=1}^{N_s} [C_{Rs}^t(P_{gs} - P_{gs}^{al}) + C_{Ps}^t(P_{gs}^{al} - P_{gs})] \\
 & + \sum_{u=1}^{N_u} C_{opu}^t(Q_{gu}) + \sum_{w=1}^{N_w} C_{opw}^t(Q_{gw}) + \sum_{sh=1}^{N_{sh}} C_{vsh}^t(Q_{sh}) \left. \right] \\
 & + \sum_{sh=1}^{N_{sh}} C_{dsh} \cdot n
 \end{aligned} \tag{23}$$

2.5.2 Minimisation of voltage deviation

The aim of minimising voltage deviation is crucial for ensuring the system's security and upholding service quality. This is quantified by assessing the voltage fluctuations across all load buses from standard 1.0 p.u value, as follows (Sharma and Jain, 2023; Eze et al., 2023):

$$\text{Minimise, } f_2 = \sum_{p=1}^{N_{pq}} (V_p - 1)^2 \tag{24}$$

where N_{pq} represents the total load buses.

The multi-objective optimisation presented above is constrained by the subsequent equality and inequality constraints (Sharma and Jain, 2021).

2.5.2.1 Power balance constraint

The power balance at each bus is given by:

$$\begin{aligned}
 P_{gj}^t - P_{dj}^t &= V_j^t \sum_{k=1}^{N_b} V_k^t (G_{jk} \cos(\delta_j^t - \delta_k^t) + B_{jk} \sin(\delta_j^t - \delta_k^t)) \\
 Q_{gj}^t - Q_{dj}^t &= V_j^t \sum_{k=1}^{N_b} V_k^t (G_{jk} \sin(\delta_j^t - \delta_k^t) - B_{jk} \cos(\delta_j^t - \delta_k^t))
 \end{aligned} \tag{25}$$

2.5.2.2 Power generation constraint

The power outputs from thermal, RES units and shunt capacitors are curbed by their maximum and minimum power generation limits given by:

$$\begin{aligned}
 P_{gu}^{\min} &\leq P_{gu}^t \leq P_{gu}^{\max}, \quad u = 1, 2, \dots, N_u \\
 Q_{gu}^{\min} &\leq Q_{gu}^t \leq Q_{gu}^{\max} \\
 P_{gw}^{\min} &\leq P_{gw}^t \leq P_R, \quad w = 1, 2, \dots, N_w \\
 Q_{gw}^{\min} &\leq Q_{gw}^t \leq Q_R \\
 P_{gs}^{\min} &\leq P_{gs}^t \leq P_S, \quad s = 1, 2, \dots, N_s \\
 Q_{sh}^{\min} &\leq Q_{sh}^t \leq Q_{sh}^{\max}, \quad sh = 1, 2, \dots, N_{sh}
 \end{aligned} \tag{26}$$

2.5.2.3 Switching constraint

To extend the operational lifespan of shunt capacitors, a limit is imposed on the number of switching operations, as specified by:

$$\begin{aligned}
 n &\leq n^{mx} \\
 n &= \sum_{t=2}^{N_T} |Q_{sh}^t - Q_{sh}^{t-1}|
 \end{aligned} \tag{27}$$

where n denotes the number of switchings in a day for capacitor and n^{mx} is maximum allowable change which is kept fixed in this work ($n^{mx} = 4$) (Malakar et al., 2016).

2.5.2.4 Doubly fed induction generator reactive capability limits

This limit of induction generator is given by:

$$Q_g \geq -\frac{V_T^2}{\omega_s(L_s + L_m)} - \frac{L_m V_T}{L_s + L_m} \sqrt{I_{\max}^2 - \left[\frac{P_{st}(L_s + L_m)}{V_T L_m} \right]^2} \tag{28}$$

$$Q_g \leq -\frac{V_T^2}{\omega_s(L_s + L_m)} + \frac{L_m V_T}{L_s + L_m} \sqrt{I_{\max}^2 - \left[\frac{P_{st}(L_s + L_m)}{V_T L_m} \right]^2} \tag{29}$$

2.5.2.5 Security constraint

The constraints pertaining to load bus voltages and line flows are articulated as follows:

$$\begin{aligned}
 V_p^{\min} &\leq V_p^t \leq V_p^{\max}, \quad p = 1, 2, \dots, N_{pq} \\
 S_{jk}^t &\leq S_{jk}^{\max}
 \end{aligned} \tag{30}$$

3 Outline of hybrid algorithm

The developed PSEFHO algorithm involves the exploitation and social thinking capability (x_{Gb}) of PSO (Kennedy and Eberhart, 1995) and retains the exploration capability of AEFA (Anita and Kumar, 2020) for faster convergence. This algorithm follows a Pareto-based approach, incorporating the principle of non-dominance. Initially, a population is randomly generated, and sorting is performed using the non-dominance concept, followed by the assignment of ranks to each solution. An external archive is utilised which initialises in the starting and is updated in succeeding iterations in accordance with dominance between new and existing particles in archive. Therefore, when comparing two solutions with different ranks, we choose the one with the lower rank. In cases where two solutions share the same rank, preference is given to the solution placed in a less crowded region. This selection process is managed by a crowding operator to attain a uniform Pareto front. A true multi-objective optimisation gives multiple non-dominated solutions, which are stored as $\mathbf{X}_{Gbest}$. Since all solutions within ($\mathbf{X}_{Gbest}$) possess equal quality, a non-dominated solution is chosen at random, as follows:

$$(X_{Gb}) = \text{rand}(\mathbf{X}_{Gbest}) \quad (31)$$

Here, particles are attracted to the global best solution based on their acceleration values. A poor particle moves more rapidly toward the direction of the global best solution, enhancing exploitation. Conversely, a good particle explores the search space around its current position, maintaining exploration capability. This combination allows the hybrid algorithm to achieve a balance between exploitation and exploration, resulting in improved capabilities to find better solutions. (X_{Gb}) is employed to assist the particle in capitalising the global best. Consequently, the velocity of agent k undergoes an update, as referenced in

$$V_k^{i+1} = [\omega \times \text{rand}() \times V_k^i] + [a_k^i \times \text{rand}() \times (X_{Gb} - X_k^i)] \quad (32)$$

In this algorithm, the following mutation operators are used for maintaining diversity and reducing local minima trapping. In the sign mutation, the particle's position gets modified as (Sharma and Jain, 2021):

$$\begin{aligned} V_k'^{i+1} &= \Psi_k^i V_k^{i+1}, \quad k \in [1, N_a] \\ \Psi_k^{i+1} &= \begin{cases} -1, & \text{rand} < P_s \\ 1, & \text{elsewise} \end{cases} \\ X_k^{i+1} &= X_k^i + V_k'^{i+1} \end{aligned} \quad (33)$$

Using reordering mutation, the particle position becomes:

$$\begin{aligned} V_k'^{i+1} &= \text{sign_mutation}(V_k^{i+1}) \\ V_k''^{i+1} &= \text{reorder_mutation}(V_k'^{i+1}) \\ X_k^{i+1} &= X_k^i + V_k''^{i+1} \end{aligned} \quad (34)$$

The X_k solution is considered to be the non-dominant value among X_k and X_k^{new} .

$$X_k = \text{nondominated}(X_k, X_k^{new}) \quad (35)$$

4 Study results

The PSEFHO algorithm is employed to perform a multi-objective dynamic optimisation, which aims to simultaneously minimise the cost and voltage fluctuations for the procurement of RPCAS. The selection of the optimal solution was made using a fuzzy decision-maker approach as described in Sharma and Jain (2021). A performance analysis is conducted using the IEEE 118-bus and IEEE 300-bus test systems, comparing the outcomes produced by PSEFHO against those obtained through multi-objective gravitational search algorithm (MOGSA), multi-objective particle swarm optimisation (MOPSO), and multi-objective AEFA (MOAEFA) based on objectives and performance metrics such as distance (convergence), and spread. The comparison was based on various performance metrics, including objectives, convergence (distance), and spread. The distance metric quantifies the extent of convergence toward Pareto optimal solutions (Deb et al., 2002). A lesser value of this metric signifies improved convergence. Whereas, spread metric measures the diversity along with uniformity based on the spread values (Zhang and Li, 2020). A lesser spread metric's value signifies a uniform and desirable distribution of Pareto optimal solutions. The parameters of PSEFHO algorithm are: population size, external archive size, coulomb constant, alpha, starting and final inertial coefficient as 100, 100, 500, 30, 0.9, and 0.4; respectively.

This problem encompasses a combination of continuous and discrete control variables, specifically, the scheduled active power output of thermal, RES units, as well as the power produced by shunt capacitors. The scheduling is performed over a 24-hour period, with intervals of one hour each. The performance is analysed for different seasons at Tucson, Arizona (Wilcox and Andreas, 2020) differing by solar irradiations with upper and lower bounds as shown in Figure 2.

- Case A: Solar irradiation in January (Winters).
- Case B: Solar irradiation in April (Spring).
- Case C: Solar irradiation in June (Summers).

The reactive and active demands are considered to fluctuate randomly within a range of 75% to 125% around their respective base values, i.e., 1,438.00 MVar and 4,242.00 MW, respectively (Power System Test Case Archive, 2018). It comprises ten thermal generators; six wind units and three solar PV units. These PV units are considered to provide only active power, i.e., $q = 0$. It is presumed that all solar PV face same solar irradiation at the same interval, but the output generation of each unit is contingent on its individual capacity. Two shunt capacitors are assumed of 25 MVar rating to provide RPCAS in increments of 1 MVar, following marginal price considerations. It is presumed that marginal prices and their fluctuations are similar on the buses at which capacitors are placed.

The outcomes obtained from executed algorithms are presented in Table 1. The proposed PSEFHO optimises the objectives more efficiently as compared with other algorithms and yielded cost and voltage deviation as \$4,492,715.32 and 1.3499 p.u. The reactive power output of the shunt capacitors with respect to change in marginal prices is presented in Figure 3. The figure depicts that the capacitor's output is changing only 4 times in 24 intervals following the change in LMP, thus satisfying the switching limit constraint. The load bus voltages for different hours are shown in Figure 4 which are maintained within the specified limits.

Figure 2 Upper and lower bounds of solar irradiance for, (a) case A (b) case B (c) case C (see online version for colours)

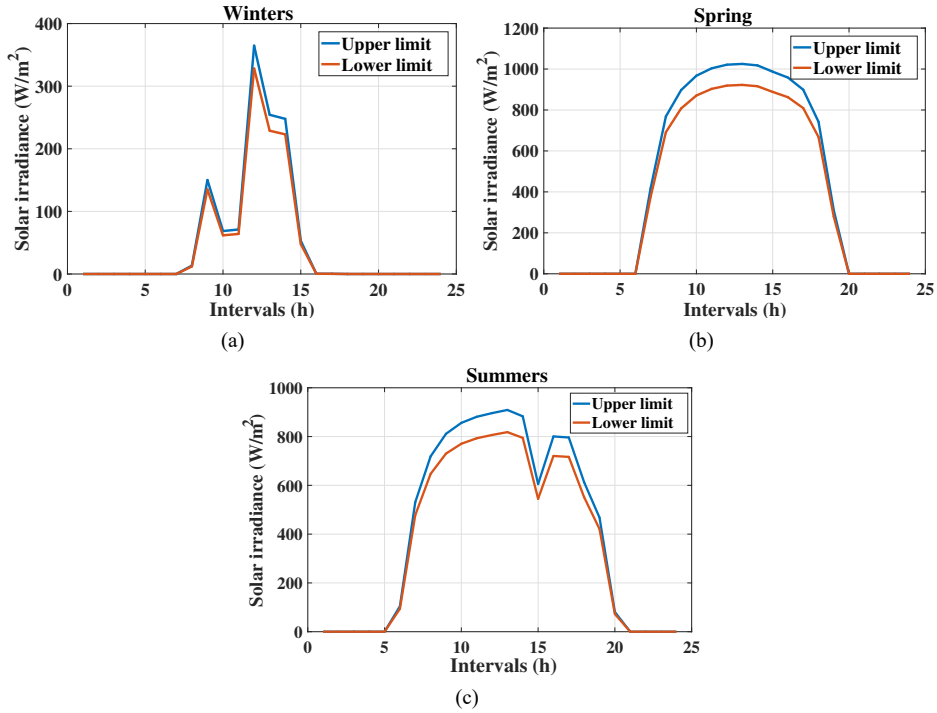
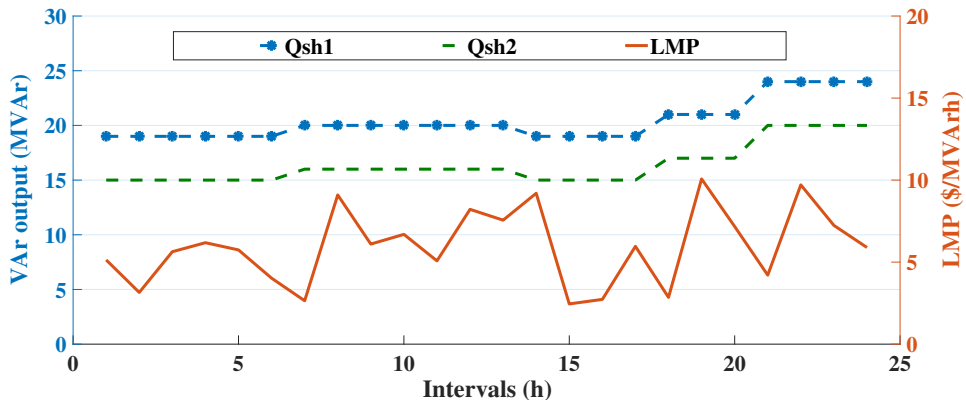


Figure 3 Reactive power from shunt capacitor relative to marginal price for IEEE 118-bus system (see online version for colours)



The Pareto fronts generated by all implemented algorithms are shown in Figure 5. The PSEFHO algorithm produces Pareto solutions that closely approximate the reference Pareto front, indicating its effectiveness (Deb et al., 2002). Further, the performance metrics namely convergence and spread are also evaluated and are summarised in Table 2. PSEFHO outperforms other algorithms, achieving the lowest values for both the distance (0.0027) and spread (0.8918) metrics. Therefore, the Pareto front produced

by PSEFHO is not only closest to the reference Pareto optimal front but also maintains better convergence and has a diversified set of solutions.

Figure 4 Voltage variation at PQ buses over time for IEEE 118-bus system (see online version for colours)

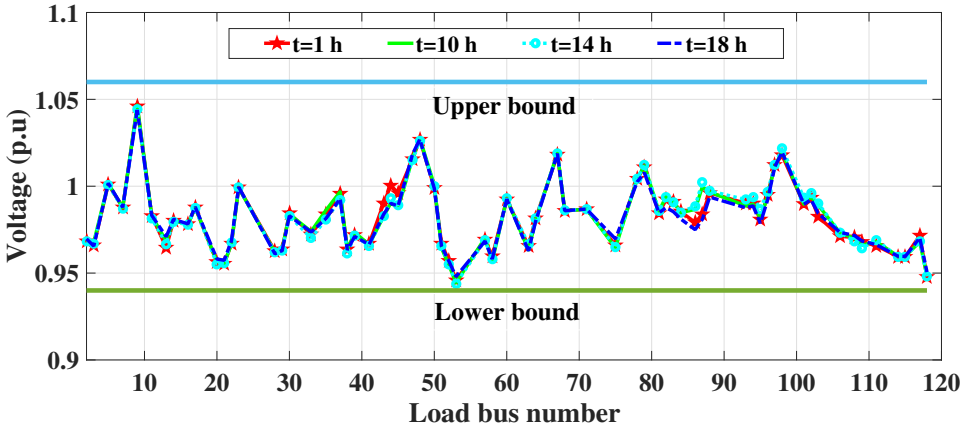
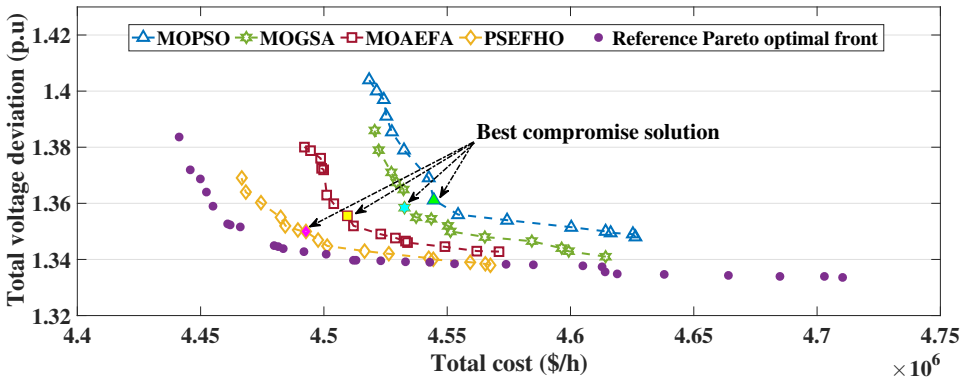


Figure 5 Pareto optimal fronts yielded by executed algorithms for IEEE 118-bus system (see online version for colours)



The case studies are carried out for VAR procurement in different seasons. The objective values, as achieved by the PSEFHO algorithm under various studies, are outlined in Table 3. Notably, the total cost incurred in case A amounts to \$4,566,287.87, which exceeds the costs observed in the other cases. This increased cost is due to increased thermal generation cost as solar PV is not producing enough real power owing to less solar irradiation in Winters. Whereas, minimum total cost is obtained in Case B due to high solar irradiance in Spring season. The lowest voltage deviation is also observed in case B, i.e., 1.3485 p.u can be attributed to the higher VAR production.

4.1 IEEE 300-bus test system

The efficacy of the developed algorithm is investigated for a large IEEE 300-bus test system. The active and VAR base load for this test system are 23,525.85

MW and 7,846.77 MVar, respectively. In this case, the demands are considered to fluctuate randomly within a range of 90% to 110% around their respective base values considering available maximum generation limits of the thermal units (Power System Test Case Archive, 2018; Zimmerman et al., 2011). It comprises forty thermal generators; 12 wind units of 220 MW each with buses locations 76, 88, 125, 128, 156, 164, 199, 221, 222, 253, 259, and 262; and five solar PV arrays of 60 MW at buses 80, 256, 258, 295, and 296. Thirty-nine scheduled real power and ten shunt capacitor outputs are treated as control variables. As a consequence, this test system is investigated with a higher population size of 200 after careful experimentation. Four capacitors of 60 MVar rating to provide RPCAS in increments of 1 MVar, following marginal price considerations.

Table 1 Objectives comparison for executed algorithms in IEEE 118-bus system

	<i>MOPSO</i>	<i>MOGSA</i>	<i>MOAEFA</i>	<i>PSEFHO</i>
Active thermal generation cost	2,951,719.99	2,969,280.44	2,932,601.34	2,952,546.70
Reactive thermal generation cost	934,061.24	947,745.54	936,339.52	924,651.24
Active wind generation cost	456,432.21	408,977.07	439,233.17	425,118.29
Reactive wind generation cost	130,717.45	134,957.54	129,933.87	119,413.17
Active solar generation cost	49,127.15	48,977.32	49,128.18	49,014.97
Imbalance penalty cost, wind	6,696.95	6,692.32	7,125.77	6,660.18
Imbalance penalty cost, solar	2,137.42	2,147.41	2,148.24	2,157.51
Lost opportunity cost, thermal	5,810.73	5,732.65	5,688.81	5,793.40
Lost opportunity cost, wind	2,088.96	2,081.78	2,059.54	1,984.19
VAr supply cost	5,722.81	6,008.28	5,267.56	5,294.60
Depreciation cost	81.07	81.07	81.07	81.07
Total cost	4,544,595.98	4,532,681.42	4,509,607.07	4,492,715.32
Total voltage deviation	1.3612	1.3584	1.3556	1.3499

Notes: Cost in \$ and total voltage deviation in p.u.

Table 2 Performance metric values for both test systems

<i>Algorithm</i>	<i>Metrics</i>	<i>IEEE 118-bus system</i>			<i>IEEE 300-bus system</i>		
		<i>Best value</i>	<i>Average value</i>	<i>Worst value</i>	<i>Best value</i>	<i>Average value</i>	<i>Worst value</i>
MOPSO	Distance	0.0139	0.0181	0.0236	0.0523	0.0639	0.0704
	Spread	0.9420	0.9586	0.9691	0.8303	0.8537	0.8736
MOGSA	Distance	0.0101	0.0120	0.0137	0.0415	0.0542	0.0620
	Spread	0.9297	0.9479	0.9582	0.8408	0.8522	0.8721
MOAEFA	Distance	0.0076	0.0106	0.0135	0.0320	0.0428	0.0589
	Spread	0.9396	0.9448	0.9564	0.7334	0.7492	0.7684
PSEFHO	Distance	0.0027	0.0042	0.0051	0.0089	0.0113	0.0142
	Spread	0.8918	0.9090	0.9170	0.6807	0.6904	0.7016

The outcomes yielded from PSEFHO, MOAEFA, MOGSA, and MOPSO are summarised in Table 4. The proposed PSEFHO optimises the objectives more efficiently as compared with other algorithms and yielded cost and voltage deviation as \$20,747,441.36 and 7.3221 p.u. Figure 6 presents the relationship between the reactive power output of the shunt capacitors and changes in marginal prices. The load bus

voltages for different hours are shown in Figure 7 which are maintained within the specified limits.

Table 3 Objectives comparison for different cases in IEEE 118-bus system

<i>Cost (\$) and voltage deviation (p.u.)</i>	<i>Case A</i>	<i>Case B</i>	<i>Case C</i>
Active thermal generation cost	3,018,791.90	3,001,673.25	3,004,202.18
Reactive thermal generation cost	938,065.60	928,402.07	934,870.70
Active wind generation cost	446,235.56	374,676.60	396,611.25
Reactive wind generation cost	119,913.98	128,786.57	124,776.95
Active solar generation cost	22,174.96	76,878.59	72,345.23
Over and under-estimation cost, wind	6,976.64	6,285.87	5,403.43
Over and under-estimation cost, solar	1,767.55	2,979.58	2,983.21
Lost opportunity cost, thermal	6,149.57	6,178.02	5,952.08
Lost opportunity cost, wind	1,978.32	1,941.51	1,966.15
VAr supply cost	4,152.72	5,668.72	4,866.40
Depreciation cost	81.07	81.07	81.07
Total cost	4,566,287.87	4,533,551.85	4,554,058.75
Total voltage deviation	1.3868	1.3485	1.3542

Table 4 Objectives comparison for executed algorithms in IEEE 300-bus system

<i>Cost (\$) and voltage deviation (p.u.)</i>	<i>MOPSO</i>	<i>MOGSA</i>	<i>MOAEFA</i>	<i>PSEFHO</i>
Active thermal generation cost	16,850,313.80	16,785,875.88	16,738,691.16	16,733,111.41
Reactive thermal generation cost	2,205,216.73	2,209,949.54	2,162,221.68	2,144,798.81
Active wind generation cost	1,434,432.90	1,488,681.97	1,519,910.24	1,447,122.05
Reactive wind generation cost	272,446.29	251,870.32	242,737.94	262,346.74
Active solar generation cost	65,146.26	65,111.88	65,290.62	65,034.58
Over and under-estimation cost, wind	13,080.68	14,787.33	12,479.04	13,410.56
Over and under-estimation cost, solar	2,384.44	2,390.46	2,384.05	2,384.11
Lost opportunity cost, thermal	56,845.61	56,865.89	56,394.94	56,379.70
Lost opportunity cost, wind	4,076.72	3,777.07	3,693.83	3,851.77
VAr supply cost	21,038.97	23,268.64	25,293.98	18,612.48
Depreciation cost	389.15	389.15	389.15	389.15
Total cost	20,925,371.55	20,902,968.13	20,829,486.63	20,747,441.36
Total voltage deviation	8.0244	7.9326	7.8821	7.3221

The reference Pareto optimal front and the Pareto fronts obtained by executed algorithms are shown in Figure 8. The best distance and spread metric values are yielded as 0.0089 and 0.6807, respectively by the proposed PSEFHO and are listed in Table 2. These values are smaller than the values yielded by other algorithms, thus, PSEFHO outperforms other algorithms.

The objective values obtained by PSEFHO for different cases are summarised in Table 5. The total cost yielded in case 1 is \$20,697,250.31 which is higher than those obtained in other cases. This increased cost is due to increased thermal generation cost as solar PV is not producing enough real power owing to less solar irradiation in Winters. Whereas minimum total cost is obtained in case 2, i.e., \$20,565,947.15 due to

high solar irradiance in the Spring season. The lowest voltage deviation is also observed in case 2, i.e., 6.5043 p.u owing to higher VAr generation.

Figure 6 Reactive power from shunt capacitor relative to marginal price for IEEE 300-bus system (see online version for colours)

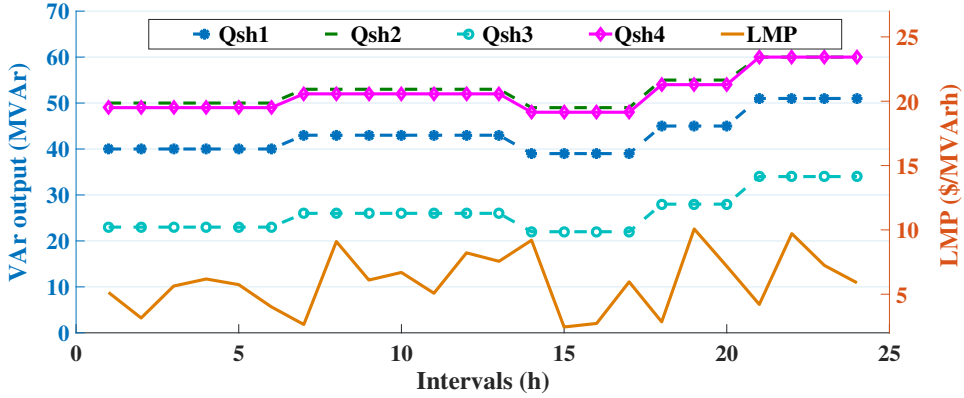
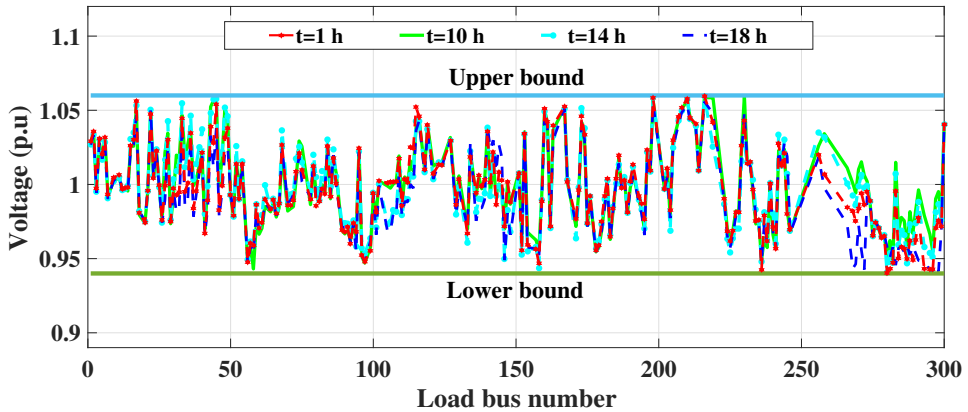


Figure 7 Voltage variation at PQ buses over time for IEEE 300-bus system (see online version for colours)



This observation underscores that when RES can produce a greater output as in spring season, the burden on thermal units decreases. This reduction not only enhances the stability of the power system but also proves to be cost-effective. Furthermore, the system's reliability is evident in the scenario where RES cannot meet its forecasted output during the Winter season. In such cases, thermal units can ramp up production to compensate, ensuring a stable supply. While this does incur higher costs, the system's reliability is bolstered by maintaining consistent supply levels.

The computational time required by executed algorithms is detailed in Table 6, utilising both conventional and sparse matrix implementations of the Newton power flow method. A noteworthy observation from the table is the significantly reduced time taken by the sparse matrix variant of the Newton method, as compared to the conventional approach. Furthermore, the developed algorithm exhibits significantly faster execution

times compared to MOPSO and MOGSA. Although it takes more time than MOAEFA, it yields superior and more accurate solutions.

Figure 8 Pareto optimal fronts yielded by implemented algorithms for IEEE 300-bus system (see online version for colours)

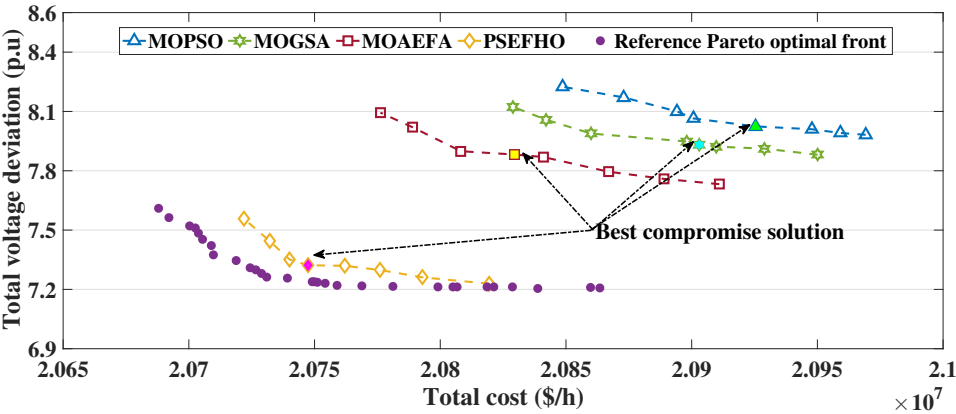


Table 5 Objectives comparison for different cases in IEEE 300-bus system

	Case A	Case B	Case C
Active thermal generation cost	16,730,275.88	16,500,482.20	16,590,204.49
Reactive thermal generation cost	2,096,187.64	2,081,957.52	2,060,694.30
Active wind generation cost	1,493,853.68	1,566,406.16	1,493,035.81
Reactive wind generation cost	245,604.13	224,220.92	250,439.73
Active solar generation cost	29,014.58	101,014.60	95,385.68
Imbalance penalty cost, wind	14,350.41	12,391.34	13,801.00
Imbalance penalty cost, solar	1,550.87	2,536.95	2,574.27
Lost opportunity cost, thermal	55,417.60	54,492.56	54,359.24
Lost opportunity cost, wind	3,715.26	3,443.27	3,772.49
VAR supply cost	26,891.11	18,612.48	21,841.29
Depreciation cost	389.15	389.15	389.15
Total cost	20,697,250.31	20,565,947.15	20,586,497.45
Total voltage deviation	7.4651	6.5043	7.3507

Notes: Cost in \$ and total voltage deviation in p.u.

Table 6 Computation time by implemented algorithms for both test systems

Test systems	Computation time (s)							
	Conventional load flow				Proposed sparse matrices load flow			
	MOPSO	MOGSA	MOAEFA	PSEFHO	MOPSO	MOGSA	MOAEFA	PSEFHO
IEEE 118-bus	2,438.85	2,164.33	1,287.41	1,455.32	992.54	872.89	447.71	582.08
IEEE 300-bus	17,287.26	15,372.52	9,496.15	10,765.55	6,138.68	5,380.90	2,776.85	3,611.64

5 Conclusions

This paper employs the PSEFHO algorithm to address the dynamic bi-objective challenge of RPCAS procurement in a deregulated system, incorporating uncertainty related to RES. The algorithm's performance is evaluated across different weather conditions and the results indicate that PSEFHO produces a Pareto optimal front characterised by superior uniformity and distribution, as evidenced by statistical performance metrics, in comparison to other implemented algorithms.

Additionally, during the spring season, the study observes minimum values for both cost and fluctuations in voltage owing to higher solar irradiation leading to higher solar generation cost, less thermal real generation cost, and enhanced reactive power production.

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