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ECONOMIC DISPATCH UNDER UNEXPECTED FORECAST ERRORS IN MICRO GRID

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Abstract : Conventional power plants operate under more predictable conditions, while wind farms and solar photovoltaic (PV) systems are influenced by variable factors such as wind speed and sunlight, which complicates the dispatching process. This study proposes an optimal scheduling method that leverages a modified inertia weight in the particle swarm optimization (PSO) algorithm. To improve solution diversity, an initial population is generated to expand the search space and enhance the algorithm's exploration of potential solutions. The modified inertia weight further boosts the PSO algorithm's global search capabilities, increasing scheduling efficiency. Additionally, the microgrid coordinates power generation to minimize overall costs. Renewable generation variability is modeled based on forecast data, with simulation results showcasing the effectiveness of this approach.

IndexTerms **– Mircogrid, IPSO.**

I. INTRODUCTION

Microgrid is a combination of interconnected loads and Distributed Energy Generation resources(DGs and DRESs),which operates in certain bounded electrical limits. Microgrid acts as a single controllable unit to connect and disconnect from the main utility grid. Renewable distributed generators in Microgrids are capable to improve the system performance, resiliency, reliability and load management. Working in both connected and islanded mode is one of the main characteristic of microgrid grid. Many of the energy management problems of the system can be solved by the tools provided by microgrid while operating in island mode.Optimal scheduling is a normal operation in power system by exchange of power among all generating units to fulfil load conditions. In recent years renewable energy and green energy fields have evolved as new versions of generations. These renewable energy sources with Distributed Generators(DGs) are used to solve many economic load dispatch problems in the system .

A microgrid is a localized and self-contained energy system that can generate, store,and distribute electrical power within a specific geographical area. It operates independently or in conjunction with the larger grid, and its purpose is to enhance the reliability, resilience, and efficiency of energy supply for a community, facility or group of users. Microgrids are designed to manage a variety of energy resources, including renewable sources like solar panels, wind turbines and battery storage as well as conventional generators such as natural gas or diesel.

1.1 CONCEPT OF MICROGRID

The concept of a microgrid is rooted in the need for more sustainable and adaptable energy solutions in a rapidly changing world. By integrating renewable energy sources and advanced control systems, microgrids offer several advantages:

- Enhanced Reliability: Microgrids can operate independently from the main grid, providing a reliable source of electricity even during grid outages or disturbances. This capability is especially crucial in critical facilities like hospitals, data centers, and military bases.
- Resilience: Microgrids are designed to withstand and recover from various disruptions, including natural disasters, cyberattacks, and physical damage to the grid. They can isolate themselves from the main grid to protect against disturbances and continue providing power to local users.
- Energy Efficiency: Microgrids can optimize energy use by intelligently balancing supply and demand within their boundaries. They can employ techniques such as demand response and load shedding to reduce energy consumption during peak periods.
- Integration of Renewable Energy: Microgrids often incorporate renewable energy sources, reducing greenhouse gas emissions and contributing to a cleaner energy . This supports sustainability goals and reduces reliance on fossil fuels.
- Grid Support: Microgrids can also provide support to the main grid by acting as distributed energy resources. During periods of high demand or grid instability, microgrids can export surplus power or provide grid services like frequency regulation.

Basically microgrid has two types of operations

(i) Grid connected
(ii) Islanding mode.

In island modes, microgrid supply local load independently while in grid connected modes, there is power exchange between microgrid and grid. Microgrid is also classified as AC and DC microgrid based on output from Distributed Generations (DGs).

Microgrid incorporate various green energy sources like Photovoltaic(PV), Wind Turbine(WT), biomass, ocean energy etc.

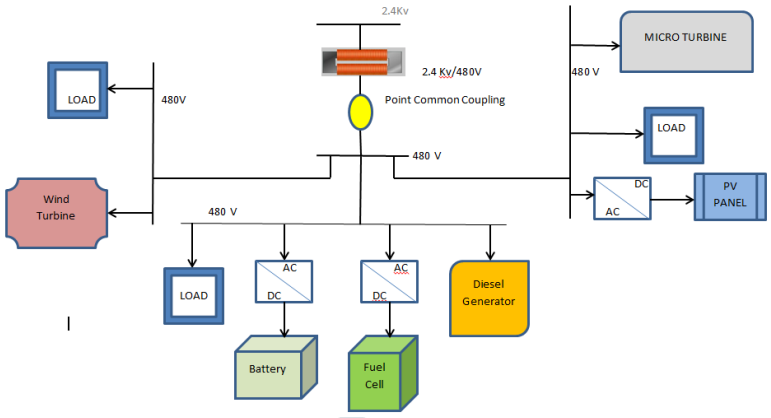


Fig. 1.1: Design of Microgrid

Presently researchers emphasis more on DC microgrids because of high utilization of solar Photovoltaic(PV) generation, Battery Energy Storage System(BESS), whose output power is in DC. Fig. 1.1 shows a typical microgrid consisting diesel generators, microturbines, fuel cells along with renewable generators like wind and solar PV cells.

1.2 OPTIMAL SCHEDULING OF MICROGRID

Power system optimal scheduling focuses at determining the optimal total cost for microgrid operation considering all constraints. In past several standard techniques have been given to solve Economic Dispatch (ED) problems but Particle Swarm Optimization (PSO) has many advantages over other proposed methods because PSO has simple process, high convergence speed and robust.

1.2.1 PARTICLE SWARM OPTIMIZATION(PSO)

Particle Swarm Optimization is an evolutionary computation technique developed by Eberhard and Kennedy in 1995. This approach draws inspiration from the social behaviors of bird flocking and fish schooling. PSO employs a population of individuals referred to as particles, each of which traverses the problem's hyperspace with initial positions and velocities. PSO is rooted in stochastic optimization and has shown success in addressing a variety of optimization problems, including Economic Dispatch (ED). Notably, PSO shares similarities with Genetic Algorithms (GA) and starts with a population of random solutions, working to find the optimal solution.

In the PSO method, each particle initially possesses a set position and velocity. These particles continually update their positions by exploring the search space until they discover the best solution, which remains unchanged. In this multidimensional search space, a particle's best position is called P_{Best}, while the best position across the entire population is known as G_{Best}.

The equations for updating a particle's new velocity (V^{d+1}) and position ((X^{d+1}) are as follows:

$$V_i^{d+1} = V_i^d + C1 \cdot rand1 \cdot \left(P_{Besti}^d - X_i^d\right) + C2 \cdot rand2 \cdot \left(G_{Best}^d - X_i^d\right) \quad (1.1)$$

$$X_i^{d+1} = X_i^d + V_i^{d+1} \quad (1.2)$$

Here

V_i^d = Velocity and position of particle i in dimension space
P_{Besti}^d = best position of an individual particle i in dimension space
G_{Best}^d = best position of the group in dimension space
rand1 & rand2 = two random numbers with a uniform distribution in the range of [0, 1]
C1 & C2 = two positive constants called cognitive and social acceleration

1.2.2 ANALYSIS OF FORECAST ERROR(FE)

Predicting power load for the day ahead is crucial in managing power system operations during the unit commitment process [1]. Additionally, it plays a vital role in studies related to integrating renewable energy. In these studies, the combined uncertainties of load and renewable energy forecasts contribute to net load uncertainty, which must be effectively addressed through economic dispatch or appropriate reserves. By comprehending potential errors in load forecasting, informed decisions can be made regarding the required reserve levels to compensate errors that may arise.

The analysis of Forecast Errors (FE) involves calculating the difference between actual power output and forecasted power output:

$$FE(t) = P(t) - P\hat{}(t) \quad (1.3)$$

Where

P(t) = actual output power

$P^{\wedge}(t)$ = forecasted output power

Minimizing forecast errors is crucial for achieving cost-effective power supply and demand management.

II PROBLEM FORMULATION

Basic Economic Dispatch(ED) problems introduce constraints distinct from power generation capacity limits. These constraints include operating zones, ramp rate limitations, multiple fuel options, and valve point effects. These factors necessitate a comprehensive formulation of the ED problem. To address the challenges posed by non-convexity, Dynamic Programming (DP) has been proposed, though it faces dimensional issues. Moreover, non-smooth optimization problems emerge, particularly concerning valve-point and multi-fuel considerations, making it challenging to obtain a global solution.

2.1 TOTAL GENERATION COST

The core challenge of the ED problem is to optimize power generation to minimize total generation costs while satisfying both equality and inequality constraints. In the context of micro grids, the primary goal is cost reduction while accounting for dispatchable and undispatchable generation units, loads, and batteries. Dispatchable units, such as distributed generators , complement undispatchable units like Distributed Renewable Energy Sources (DRES). DRES outputs are contingent on weather conditions, including wind velocity, solar temperature, and irradiance. Achieving optimal total cost necessitates coordinated operation between dispatchable and undispatchable units, striving to satisfy all constraints.

The mathematical formulation for minimizing Total Cost (TC) is expressed as:

$$TC = \sum_{i=1}^{N_G} C_{Gi}\,(P_{Gi}) \tag{2.1}$$

The objective function to minimize total cost(TC) enlisted below

$$\min TC = \left\{ \begin{array}{c} \sum_{i=1}^{N_D} C_{Di}(P_{Di}) + \sum_{i=1}^{N_{MT}} C_{MTi}(P_{MTi}) \\ + \sum_{i=1}^{N_{FC}} C_{FCi}(P_{FCi}) + \sum_{i=1}^{N_B} C_{Bi}(C_{BCi} + C_{BDi}) \\ + \sum_{i=1}^{N_w} C_{O,Wi}(P_{Wi} - P_{Wi,av}) + C_{U,Wi}(P_{Wi,av} - P_{Wi}) \\ + \sum_{i=1}^{N_{PV}} C_{O,PVi}(P_{PVi} - P_{PVi,av}) + C_{U,PVi}(P_{PVi,av} - P_{PVi}) \\ + \sum_{i=1}^{N_L} C_{O,Li}(P_{Li} - P_{Li,av}) + C_{U,Li}(P_{Li,av} - P_{Li}) \end{array} \right\} \tag{2.2}$$

The generator's cost function for each unit in simplified form can be given by a function of the quadratic equation

$$C_{Gi}(P_{Gi}) = \alpha_i + \beta_i(P_{Gi}) + \Upsilon_i(P_{Gi})^2 \tag{2.3}$$

Where:

C_{Gi} = Cost function of generators

$\alpha_i, \beta_i, \Upsilon_i$ = Cost coefficients of generator

P_{Gi} = Electrical output of generators

N = Number of generator sets

To minimize the total system cost, the total generating power (P_i) should match the total load demand (P_L) and losses .Equality constraints are therefore

$$\sum_{i=1}^{NG} P_{Gi} = P_L + \text{Losses} \tag{2.4}$$

In this paper author match the generating power with total load without accounting for network losses for simplicity.

Each generator operates within its minimum and above-minimum power for inequality constraints. The generators do not exceed their maximum output power. The system constraints encompass:

$$P_{DGmin} \le P_{DG} \le P_{DGmax} \tag{2.5}$$

$$SOC_{min} \le SOC \le SOC_{max} \tag{2.6}$$

$$0 \le P_{PV} \le P_{PVmax} \tag{2.7}$$

$$0 \le P_W \le P_{Wmax} \tag{2.8}$$

$$0 \le P_L \le P_{Lmax} \tag{2.9}$$

$$0 \le P_{BC} \le P_{BCmax} \tag{2.10}$$

$$0 \le P_{BD} \le P_{BDmax} \tag{2.11}$$

Constraints (2.5) address DGs' power limitations, (2.6) establishes battery state of charge limits, and (2.7),(2.8)and(2.9) pertain to wind, PV, and load constraints. Constraints (2.10) & (2.11) define battery charging and discharging capacity at maximum power.

2.2 UNCERTAINITY

Variability in wind velocity, solar temperature, and irradiance introduces uncertainties in power output. To enhance system efficiency in the presence of uncertainty, researchers focus on improving wind speed forecasts, as power output heavily depends on wind velocity. Forecast errors (FE) can be substantial in existing methods, leading to reduced reliability. Analyzing forecast data early on can mitigate the impact of uncertainty on power supply and demand costs.

The challenge of global warming and carbon emissions drives the integration of available renewable sources such as ocean power, wind power, tidal power, and PV power into the existing energy system. The generation limits of wind and PV change over time, known as variability, and their accuracy is subject to uncertainty. Addressing uncertainty is crucial for optimal scheduling, particularly when it depends on unpredictable weather conditions.

The mathematical model for the overestimation and underestimation can be formulated from objective function (2.2) as follows:

$$TC_{Wind} = \sum_{i=1}^{N_w} C_{O,Wi}\left(P_{Wi} - P_{Wi,av}\right) + C_{U,Wi}\left(P_{Wi,av} - P_{Wi}\right) \quad (2.12)$$

$$TC_{PV} = \sum_{i=1}^{N_{PV}} C_{O,PVi}\left(P_{PVi} - P_{PVi,av}\right) + C_{U,PVi}\left(P_{PVi,av} - P_{PVi}\right) \quad (2.13)$$

$$TC_{Load} = \sum_{i=1}^{N_L} C_{O,Li}\left(P_{Li} - P_{Li,av}\right) + C_{U,Li}\left(P_{Li,av} - P_{Li}\right) \quad (2.14)$$

The source of uncertainty in wind power is speed variability, in photovoltaic power is irradiation variability, and in load is consumption variability. Two primary sources of uncertainty exist: forecast error and interruptions in supply from the main grid. Forecast errors encompass both overestimation and underestimation of rated power for renewable sources and load demand. Overestimation leads to excess power generation, while underestimation results in a deficit. Accurate forecasting is essential to minimize forecast errors and, consequently, reduce overall power supply and demand costs.

III RESEARCH METHODOLOGY

3. IMPROVED PARTICLE SWARM OPTIMIZATION(IPSO)

Following modifications are proposed in standard PSO to improve its efficiency.

3.1 INITIALIZATION OF POPULATION FOR PSO BASED ON TENT MAPPING FUNCTION

The performance of meta-heuristic algorithms largely relies on the quality of their initial solutions. As such, it is essential for the initial population to be uniformly distributed throughout the search space. In standard Particle Swarm Optimization (PSO), the process begins with a set of randomly generated solutions within the feasible region of the problem. However, this randomness may limit the diversity of initial solutions, potentially affecting both convergence speed and the quality of the final solutions.

One method to address this issue is to use chaotic maps rather than random selection. Due to stochastic nature of the proposed chaotic approach, it can generate an initial population with greater diversity across the search space. The tent map function is used to produce a chaotic initial population for performance improvement of the conventional PSO algorithm [24]. The process unfolds as follows:

$$s_{k+1} = \begin{cases} \frac{s_k}{0.7}, & if\ s_k < 0.7 \\ \frac{1-s_k}{0.3}, & if\ s_k \geq 0.7 \end{cases} \quad (3.1)$$

For a given initial value, the chaotic vector $\vec{S} = (s_1, s_2, \ldots\ldots\ldots\ldots s_d)$ is obtained by equation (3.1) for (d − 1) iterative loops, where d represents the dimension of the search space. By insinuate the chaotic sequence, the i^{th} initial individual $\overrightarrow{X_i}$ can be obtained using the following eqn [24]:

$$\overrightarrow{X_i} = \vec{S} * \left(\vec{X}_{ub} - \vec{X}_{lb}\right) + \vec{X}_{lb} \quad (3.2)$$

$\vec{X}_{ub}=(x_1^{ub}, x_2^{ub}, \ldots\ldots\ldots x_d^{ub})$ and $\vec{X}_{lb}=(x_1^{lb}, x_2^{lb}, \ldots\ldots\ldots x_d^{lb})$ represent the upper and lower boundaries of the proposed optimization problem, respectively. In the population initialization stage, each individual particle is generated by applying Equations (3.1) and (3.2), resulting in an initial population with improved diversity.

3.2 IMPROVED INERTIA WEIGHT OF PSO

PSO offers numerous advantages, such as ease of execution and fast convergence. To strike a balance between convergence speed and maintaining particle diversity, Improved Inertia Weight PSO (IIW-PSO) introduces an inertia weight. This improvisation enhances convergence speed while ensuring an accurate solution. In PSO, a swarm consists of a population of particles, each with a position and velocity. The updated position of a particle represents a solution in the problem space, while its velocity guides it from one position to the next. The IIW-PSO method is used to obtain optimal solutions in Economic Dispatch problems. The process starts with a broad set of random solutions, which are progressively refined over several iterations. The velocity (V_i^{d+1}) and position (X_i^{d+1}) of particles in PSO are determined by the equations 1.1 and 1.2.

To further enhance convergence, the particle constriction factor M is included in equation 1.1. The new updated velocity equation is given as follows:

$$V_i^{d+1} = M(V_i^d + C1 \cdot rand1 \cdot \left(P_{Besti}^d - X_i^d\right) + C2 \cdot rand2 \cdot \left(G_{Best}^d - X_i^d\right)\left(G_{Best}^d - X_i^d\right)) \quad (3.3)$$

The value of M depends on the function δ,

$$M = \frac{2}{\left|2 - \delta - \sqrt{\delta^2 - 4\delta}\right|} \quad (3.4)$$

where δ = C1 + C2. To maintain stability, δ should be greater than 4.0, with a value of δ around 4.1 providing fast response and better stability, aiming for a perfect solution within the range of $4.1 \leq \delta \leq 4.2$.

The value of the constriction factor (M) has a significant impact on system convergence. Initially, particles are far apart, but as the algorithm progresses, their distances become smaller. The inertia weight (w) is a critical parameter in PSO that balances local and global searches. By selecting the optimal value for w, an optimal solution can be achieved within a few iterations. The updated velocity with inertia weight (w) is expressed as:

$$V_i^{d+1} = w.V_i^d + C1 \cdot rand1 \cdot \left(P_{Besti}^d - X_i^d\right) + C2 \cdot rand2 \cdot \left(G_{Best}^d - X_i^d\right)\left(G_{Best}^d - X_i^d\right) \quad (3.5)$$

Inertia weight (w) is determined by the equation:

$$w = w_{max} - \frac{(w_{max} - w_{\min}) \cdot d}{d_{max}} \quad (3.6)$$

Where d = Current iteration number.

The value of w impacts the system's global and local search capabilities. Two control parameters can be used to enhance system performance: adaptive control and time-varying control. The updated inertia weight (w_u) is expressed as:

$$w_u = w_{min} + \frac{(w_{max} - w_{\min}) \cdot (d_{max} - d)}{d_{max}} \quad (3.7)$$

Where

d = Current iteration number

d_{max} = maximum iterations

w_{max} & $w_{\min}$ = initial and final value of inertia weight

To increase global search capacity, a chaotic weight (w_c) is introduced, calculated as

$$w_c = w_u \cdot q_d \quad (3.8)$$

where q_d represents chaotic parameters at iteration d.

The chaotic parameter q_d can be defined by equation

$$q_d = 4\, q_{d-1}(1 - q_{d-1}) \quad (3.9)$$

System given by equation (3.9) represent chaotic behaviour where initial value of q_d selected randomly with in range (0,1).

The values of cognitive learning factor (C1) and social learning factor (C2) significantly influence system performance. Lower values cause particles to deviate from the solution, while higher values make particles converge more rapidly. In this modified method,the cognitive learning factor (C1) and social learning factor (C2) are determined as c_{m1} and c_{m2}. Author set values of both c_{m1} and c_{m2} as 2.05 to adjust these parameters.

The improved velocity (V_i^{d+1}) and position (X_i^{d+1}) of the proposed method are presented by the following equations

$$V_i^{d+1} = M(w_c \cdot V_i^d + c_{m1} \cdot rand1 \cdot (P_{Besti}^d - X_i^d) + c_{m2} \cdot rand2 \cdot (G_{Best}^d - X_i^d)(G_{Best}^d - X_i^d)) \quad (3.10)$$

$$X_i^{d+1} = X_i^d + V_i^{d+1} \quad (3.11)$$

The overall IPSO optimisation process is represented in Fig 2

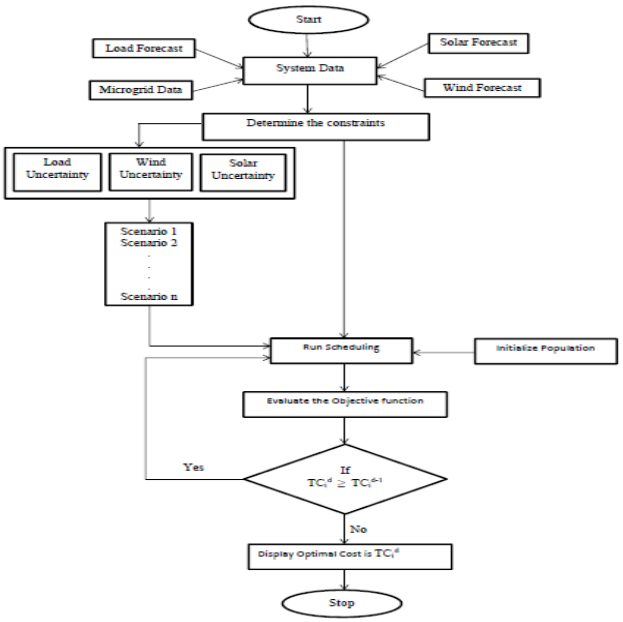


Fig. 3.1 Proposed IPSO

IV. RESULTS AND DISCUSSION

4.1 CASE STUDY

Optimal scheduling for a microgrid is analyzed under four different scenarios.

(i) First scenario : In this author assumes the operation is based on expected forecast conditions.

(ii) Second scenario : This is accounts for 20% and 30% unexpected forecast errors (FEs) in Distributed Renewable Energy Sources (DRESs) due to uncertainties.

(iii) Third scenario : In this the focus shifts to load demand with 5% and 10% unexpected forecast errors.

(iv) Fourth scenario : In this author combines the errors in forecast of both Distributed Renewable Energy Sources and demand in load.

The standard operation problem have the focus on finding the optimal schedule for Distributed Generators (DGs), battery storage, and exchange of power with the main grid. Adjustments to the schedule are necessary if there is a mismatch between supply and demand. The microgrid must ensure adequate capacity remains online. If there is a mismatch between supply and load, the optimal schedule needs to be adjusted. This adjustment can be made in three ways:

(i) Modify the unit commitment of dispatchable generation units and update the Energy Storage (ES) scheduling.

(ii) Link to the grid.
(iii) Curtailment of the load.
In this study, we focus on the first two actions and disregard load curtailment.

The objective of standard operation is to reduce the operating costs of dispatchable units and the expenditure associated with exchange of power with the primary grid which results in minimum overall cost of the microgrid. The scheduling period spans 24 hours, divided into 1-hour intervals.
Table 4.1 presents the parameters for the Distributed Generators (DGs), while Table 4.2 outlines the power output of solar PV generation and wind power generation systems .Table 4.3 presents day-ahead forecasted total demand along with day-ahead market rates of energy.

Table 4.1 Parameters of dispatchable generators

Table 4.2 Output power of PV and wind

Unit type	$\mathbf{P_{min}(kW)}$	$\mathbf{P_{max}(kW)}$	**Start-up cost** ($)	**Operating cost**		
				$\boldsymbol{\alpha_i}$($)	β_i($/MW)	$\Upsilon_i(\$/MW^2)$
Diesel	20	60	3.0	1.30	0.0304	0.00104
Microturbine	10	30	2.0	0.40	0.0397	0.00051
Fuel cell	10	30	1.50	0.38	0.0267	0.00024

		4		4	3
5	0	27.7421	17	14.1823	24.2732
6	0	30.1540	18	4.6705	26.2555
7	0.1617	28.6452	19	0.1836	26.7732
8	1.17726	23.3767	20	0	26.2159
9	5.2978	21.7503	21	0	32.8428
10	11.6044	34.8202	22	0	36.0156
11	36.6382	27.1748	23	0	37.2312
12	42.6778	30.1965	24	0	44.1215

Table 4.3 Day-ahead market prices and Forecast load demand

Hour	Price,$/ kWh	Load, kW	Hour	Price,$/ kWh	Load, kW
1	8.65	124.7103	13	26.82	189.9998
2	8.11	123.9769	14	27.35	187.0655
3	8.25	126.9111	15	13.81	192.2006
4	8.1	124.7103	16	17.31	194.4014
5	8.14	128.3783	17	16.42	187.0655
6	8.13	135.432	18	9.83	185.5983
7	8.34	146.718	19	8.63	183.3975
8	9.35	178.2624	20	8.67	187.0655
9	12	186.3319	21	8.35	190.7334
10	9.19	190.7334	22	16.44	181.9303
11	12.3	195.8685	23	16.19	161.3898
12	20.7	189.9998	24	8.87	134.9806

4.1.1 PERFORMANCE WITH EXPECTED FORECAST CONDITIONS(CASE-1)

In this scenario, no uncertainties are accounted for in any of the generated outputs of solar power, wind power, or load demand. The maximum capacity for distributed generators (DGs) is 120 kW, while the distributed renewable energy systems (DRESs) can supply up to 51.4829 kW from wind power sources and 42.6778 kW from solar power sources. Maximum supply capacity of the battery is 50 kW. This scheduling approach incorporates all relevant constraints for DGs, DRESs, and the battery, and it is optimized using the IPSO method. A detailed comparative results for both the IPSO and standard PSO methods is presented in Fig 4.1. The total cost for a 24- hour operation calculated with IPSO is $189,640.1, while the standard PSO yields $193,390.5.

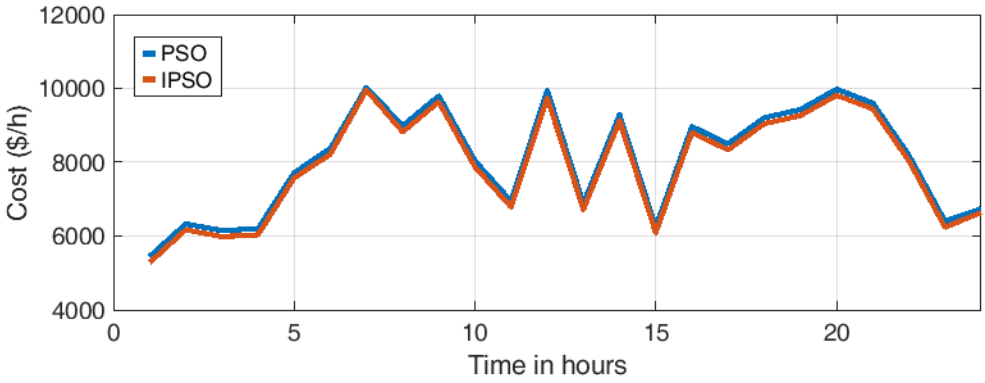
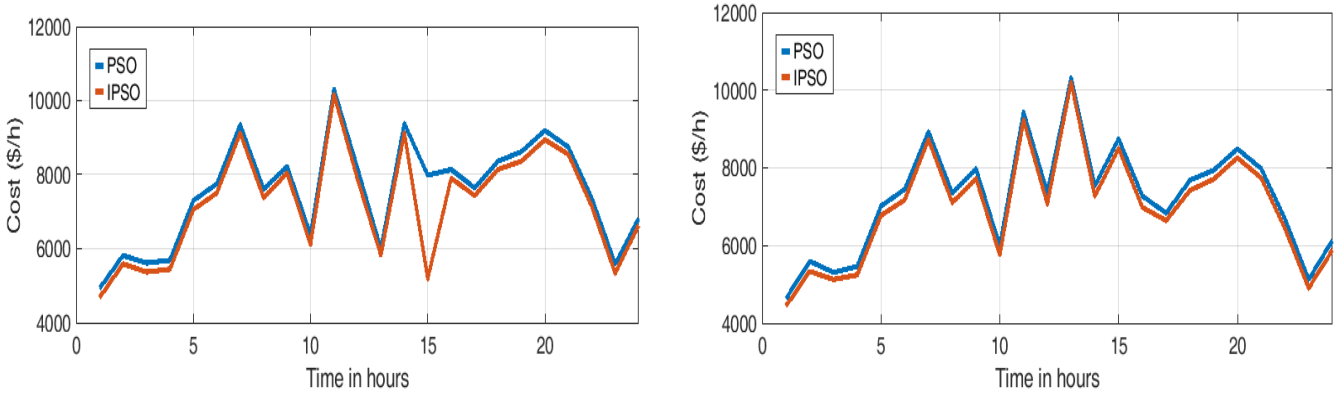


Fig. 4.1: Cost comparison when expected FE (Case-1)

4.1.2 PERFORMANCE WITH UNEXPECTED FORECAST CONDITIONS IN DRES ONLY (CASE-2)

In this analysis, author account for unexpected forecast errors of 20% and 30% in distributed renewable energy systems (DRESs). Forecast data from Table 4.2 is utilized for the scheduling, which is optimized using the IPSO method. The total costs derived with IPSO are $172,963.3 for a 20% forecast error and $167,680.5 for a 30% forecast error. Using standard PSO, the costs are $181,007.8 for a 20% error and $173,266.8 for a 30% error. A comparative summary of the total costs for both methods is presented in Fig. 4.2.

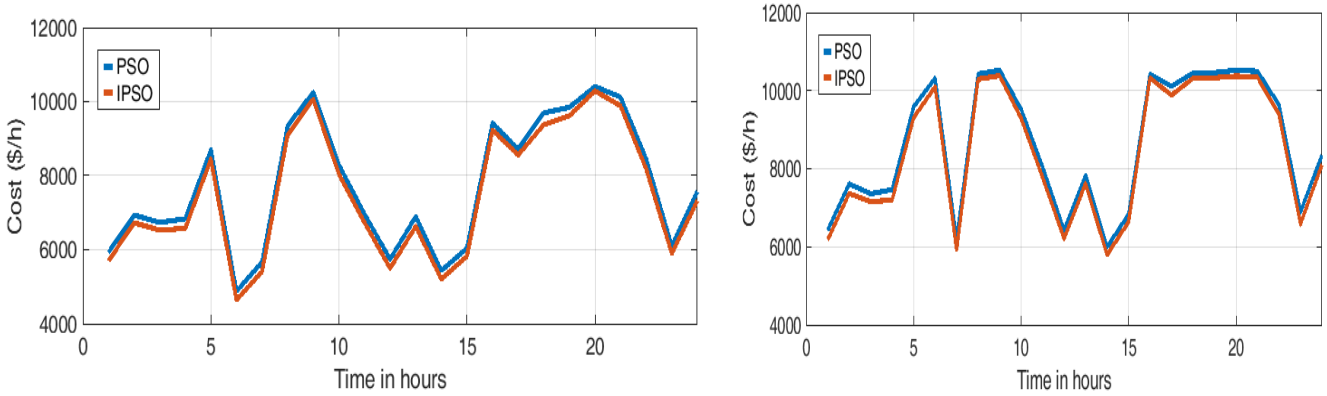


(a) 20% U-FE In DREs (b) 30% U-FE In DREs

Fig. 4.2: Cost comparison when unexpected FE(U-FE) are in DREs only (Case-2)

4.1.3 PERFORMANCE WITH UNEXPECTED FORECAST CONDITIONS IN LOAD DEMAND ONLY (CASE-3)

This section is dedicated for 5% and 10% unexpected forecast errors in load demand. The resulting total costs for optimal scheduling with IPSO are $179,486.5 for a 5% forecast error and $202,900.9 for a 10% forecast error. In comparison, the total costs using PSO are $184,969.7 for a 5% forecast error and $207,885.7 for a 10% forecast error. A detailed comparison of the total costs for both methods is presented in Fig 4.3

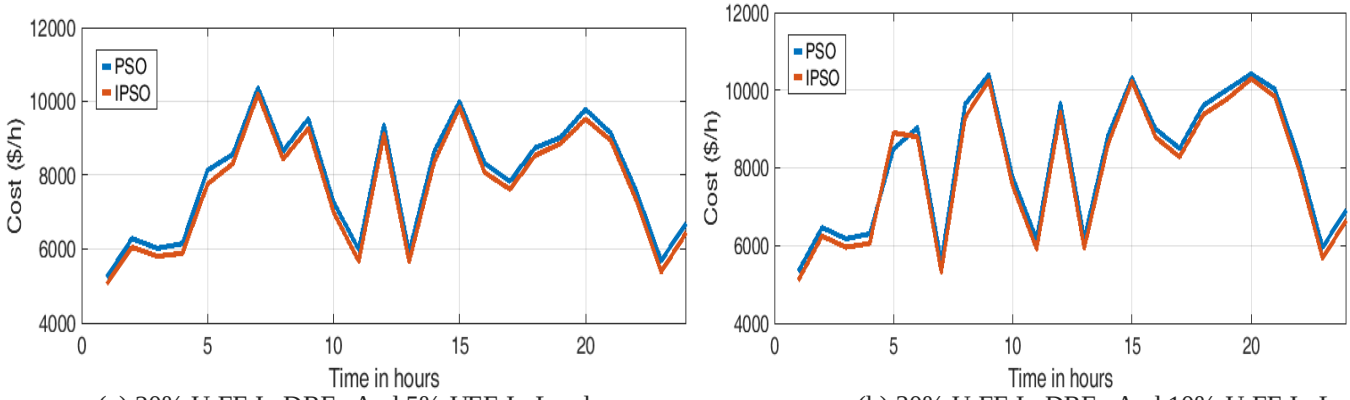


(a) 5% U-FE In Load (b) 10% U-FE In Load

Fig. 4.3: Cost Comparison When Unexpected FE(U-FE) Are In Load Only(Case-3)

4.1.4 PERFORMANCE WITH UNEXPECTED FORECAST CONDITIONS IN BOTH DRES AND LOAD DEMAND (CASE-4)

In this operation, we examine scenarios with combined forecast errors, specifically with 5% unexpected forecast errors in load demand and 20% unexpected forecast errors in distributed renewable energy sources (DRESs), as well as 10% forecast errors in load demand and 30% forecast errors in DRESs. The IPSO method is applied to solve the economic dispatch (ED) problem by optimizing the system's cost function while satisfying all constraints. With IPSO, the total cost is $183,140.5 for a 5% forecast error in load demand and a 20% forecast error in DRESs, and $190,218.2 for a 10% forecast error in load demand and a 30% forecast error in DRESs. In contrast, using PSO, the total cost is $188,959.2 for a 5% forecast error in load demand and a 20% forecast error in DRESs, and $195,023.9 for a 10% error in load demand and a 30% error in DRESs. Fig 4.4 provides a detailed comparison of total costs between the PSO and IPSO methods.



(a) 20% U-FE In DREs And 5% UFE In Load (b) 30% U-FE In DREs And 10% U-FE In Load

Fig. 4.4: Cost Comparison When Unexpected FE(U-FE) Are In DREs & Load Both(Case-4)

4.2 DISCUSSION

Figure 4.1 depicts a comparison of costs under expected forecast conditions, showing projected costs based on accurate forecast assumptions. This figure represents a baseline where the forecasts align closely with actual outcomes, providing insight into cost levels when there is minimal forecast deviation.

Figure 4.2 illustrates the impact of unexpected forecast errors (U-FE) in distributed renewable energy systems (DREs). This figure demonstrates how increased U-FE, representing unanticipated variations or errors in DRE forecasts, leads to higher costs.Fig 4.2a represents 20% U-FE in DREs and Fig 4.2b represents 30% U-FE in DREs. As U-FE rises, costs increase, likely due to the need for additional balancing or reserve energy to meet demand under these unexpected conditions.

Figure 4.3 shows the effect of Unexpected Forecast Errors (U-FE) in Load in which Fig 4.3a represents 5% U-FE in load and Fig 4.3b represents 10% U-FE in load. Here, deviations from expected load forecasts have a significant impact on costs, with cost variations that are larger than those caused by U-FE in Distributed Renewable Energy systems (DREs). This suggests that inaccuracies in load forecasting have a more pronounced effect on costs, possibly due to the need for immediate compensatory measures in energy supply.

Figure 4.4 illustrates the combined effect of U-FE in both DREs and load, revealing a clear increase in per-hour costs. This combined scenario highlights the compounded impact of forecast errors in both areas, as the unpredictability in both DREs and load makes balancing supply and demand more challenging, resulting in even higher operational costs.

Figure 4.4a represents combination of 20% U-FE in DREs and 5% U-FE in Load and Fig 4.4b represents combination of 30% U-FE in DREs and 5% U-FE in Load. These figures underscore how both DRE and load forecast accuracy are critical to controlling costs, with errors in load forecasts having a particularly strong effect, especially when combined with DRE inaccuracies.These comparisons highlight the financial impact of forecast accuracy: maintaining expected conditions keeps costs stable, whereas forecast errors in DREs contribute to increased costs, underscoring the importance of accurate forecasting in energy cost management.

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