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Multi-Objective Economic Load Dispatch Optimization of Integrated Thermal-Renewable-Battery Energy Storage Systems Under Renewable Energy Uncertainty

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ABSTRACT

The increasing integration of renewable energy sources into modern power systems introduces operational uncertainties that complicate Economic Load Dispatch (ELD), particularly in balancing generation costs, environmental emissions, and supply reliability. This study investigates the multi-objective economic load dispatch optimization of an integrated thermal–renewable–battery energy storage system (BESS) under renewable energy uncertainty using Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Differential Evolution (DE). The proposed framework coordinates three thermal generating units, solar photovoltaic, wind energy, and battery storage over a 24-hour scheduling horizon. A total of 96 decision variables is considered, incorporating generator operating limits, ramp-rate constraints, battery charging and discharging limits, transmission losses, and power balance requirements. Renewable energy uncertainty is modelled through probabilistic scenarios with temporally correlated solar and wind forecast errors, while the optimization considers operating cost and thermal carbon dioxide emissions as competing objectives. The simulation results demonstrate effective coordination of generation resources, with power balance residuals of approximately (10^{-14}) MW, confirming numerical consistency. Independent validation further indicates improved supply reliability under scenario-based scheduling compared with mean-availability scheduling. Comparative analysis of the selected compromise solutions reveals that PSO achieves the lowest daily thermal emissions of 6,404.82 tones/day, compared with 6,594.45 tonnes/day for GA and 6,765.81 tonnes/day for DE, representing approximately 2.88% and 5.34% reductions, respectively. The findings establish the effectiveness of metaheuristic optimization and scenario-based modelling in coordinating conventional generation, renewable energy, and battery storage under uncertain operating conditions, thereby supporting more economical, reliable, and environmentally sustainable power system operation.

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INTRODUCTION

Research into Economic Load Dispatch (ELD) in integrated thermal, solar, and wind power generation systems has gained considerable attention due to the increasing need for cost-effective and sustainable electricity production. Several studies have investigated different optimization techniques to determine the most efficient combination of conventional and renewable energy sources. Nevertheless, traditional optimization approaches may produce less accurate solutions or fail to adequately address complex operating conditions, such as valve-point loading effects. Similarly, soft

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computing techniques may encounter challenges associated with slow convergence, extensive parameter adjustments, and premature convergence to local optima, thereby limiting their effectiveness in exploring the entire search space [1].

Electricity plays a fundamental role in supporting modern technological advancement, particularly in India, where the availability and distribution of energy resources differ considerably across geographical regions [2]. Consequently, an interconnected power network is necessary to facilitate reliable electricity transmission and distribution according to varying demand requirements. The appropriate scheduling and coordination of generating units are therefore essential for responding to load variations and minimizing overall generation costs [1], [3]. However, the presence of valve-point effects, multiple fuel options, and various generating-unit operating constraints increases the complexity of the ELD problem, whose primary objective is to minimize generation expenditure while satisfying system operating requirements [3].

Meanwhile, renewable energy technologies provide significant advantages, including reduced energy costs, lower greenhouse gas emissions, environmental protection, and improved utilization of available natural resources [1]. Among these alternatives, wind energy has emerged as one of the fastest-growing and most cost-effective renewable energy technologies, while solar photovoltaic (PV) systems directly transform solar radiation into electrical power [4]. Furthermore, solar and wind resources are widely available across different geographical locations, making their integration into modern electricity generation systems a promising approach to improving energy sustainability and reducing dependence on conventional fossil-fuel-based generation [5].

Renewable energy technologies provide considerable potential for improving the performance, reliability, and sustainability of modern electrical power systems. In this regard, the study investigates an integrated power generation framework comprising solar, wind, and conventional steam-based generating units [6] . Nevertheless, incorporating renewable energy resources into the generation mix increases the complexity of the Economic Dispatch (ED) problem because of their intermittent characteristics and fluctuating power outputs [1]. This study therefore considers solar and wind energy as the major renewable sources, with particular emphasis on the uncertainty associated with wind power generation. Such uncertainty arises from the stochastic variations in wind speed, which make the available wind power difficult to predict accurately and introduce additional challenges into the mathematical formulation and optimization of the Economic Load Dispatch (ELD) problem [7].

The objective functions associated with Economic Load Dispatch (ELD) problems frequently possess non-linear and non-smooth characteristics, making the identification of globally optimal solutions increasingly challenging. To overcome these computational difficulties, several researchers have adopted soft computing and meta-heuristic optimization techniques, including Particle Swarm Optimization (PSO) and the Artificial Bee Colony (ABC) algorithm, Genetic Algorithm (GA) and Differential Evolution (DE) [8]. Previous investigations have also incorporated reliability assessment by evaluating different reliability indices within the ELD framework [9].Similarly, the Artificial Collaborative Search (ACS) algorithm has been employed to solve non-convex ELD problems involving valve-point loading effects [10] Other optimization approaches, such as the Shrunken Gaussian Distribution Quantum-behaved Optimization algorithm, have been developed to address ELD problems involving multiple operational constraints [11].

Furthermore, researchers have investigated alternative meta-heuristic techniques, including the Equilibrium Optimizer (EO), Cuckoo Optimization Algorithm (COA), and their hybrid combinations, to improve optimization performance [12]. More recent contributions have extended these optimization strategies to accommodate integrated renewable and conventional thermal power generation systems,

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thereby expanding the available approaches for solving complex ELD problems under different operating conditions[13],[14-21].

This research addresses overlooked challenges in ELD by developing a multi-objective ELD of Thermal renewable BESS power system under renewable energy uncertainty using PSO, GA and DE. The remaining of the paper is segmented as follows where section two discussed on Literature review, section three methodology and finally, section five focused on results and discussion. Finally, it will rounded up by conclusion and references

THE PARADIGM SHIFT: ADAPTIVE AND COMPUTATIONAL INTELLIGENCE-BASED SCHEMES

The limitations of traditional schemes have driven research towards more intelligent, adaptive solutions. The advent of Wide Area Measurement Systems (WAMS) and Phasor Measurement Units (PMUs) has been a game-changer [5].

METHODOLOGY

This section described the procedure that was followed to achieved the stated aim of the work

Mathematical Model of the Integrated Thermal, Renewable and BESS

The polynomial generation cost and power balance structure follow established optimal power flow formulations.

The model for the total operating cost was given as:

$$F_1 = \sum_t \Delta t \left[\sum_i \left(a_i + b_i P_{i,t} + c_i P_{i,t}^2\right) + c_s P_{s,t} + c_w P_{w,t} + c_\beta (Pch_{,t} + Pdis_{,t})\right] \quad (1)$$

Here, F_1 is total operating cost; $P_{i,t}$ is thermal generator output; a_i, b_i, and c_i are fuel cost coefficients; $P_{s,t}$ and $P_{w,t}$ are dispatched solar and wind power; c_s and c_w are renewable operating cost coefficients; c_β is the battery throughput cost coefficient; and Δt is the interval duration.

The total carbon emission was given as;

$$F_2 = \sum_t \Delta t \sum_i \left(\alpha_i + \beta_i P_{i,t} + \gamma_i P_{i,t}^2\right) \quad (2)$$

F_2 represents operational thermal CO_2 emissions in tonnes. The coefficients α_i, β_i, and γ_i describe each generator's emission characteristics. Renewable and battery lifecycle emissions are excluded.

The Power balance and transmission losses of the system was given as;

$$\sum_i P_{i,t} + P_{s,t} + P_{w,t} + Pdis_{,t} - Pch_{,t} = PD_{,t} + PL_{,t} \quad (3)$$

$$PL_{,t} = P_t^T B P_t \quad (4)$$

$$Pcurt_{,t} = P_{s,available,t} - P_{s,t} + P_{w,available,t} - P_{w,t} \quad (5)$$

$Pcurt_{,t}$ represents total renewable curtailment.

The battery power and energy constraints was given as;

$$Pdis_{,t} = max(P_{\beta,t}, 0)$$

$$Pch_{,t} = max(-P_{\beta,t}, 0)$$

$$-Pch,max \leq P_{\beta,t} \leq Pdis,max$$

$PD_{,t}$ is demand, $PL_{,t}$ is the approximate transmission loss, P_t is the thermal generation vector, and B is a symmetric loss coefficient matrix with units MW^{-1}.

The thermal generator constraints were given as;

$$P_i,min \leq P_{i,t} \leq P_i,max$$

$$-RD_i \Delta t \leq P_{i,t} - P_{i,t-1} \leq RU_i \Delta t$$

RU_i and RD_i are ramp limits in MW/h. The first interval is constrained relative to a specified initial generator output.

The renewable availability constraints were given as;

$$0 \leq P_{s,t} \leq P_{s,available,t}$$

$$0 \leq P_{w,t} \leq P_{w,available,t}$$

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$$E_{t+1} = E_t + \Delta t(\eta chPch,_t - Pdis,_t/\eta dis)$$

$$Emin \leq E_t \leq Emax$$

$$SOC_t = 100E_t/Ecapacity$$

$$E_1 = Einitial; \quad E_{t+1} = Einitial\, at\, t = T$$

Positive $P_{\beta,t}$ denotes discharge; negative $P_{\beta,t}$ denotes charging. E_t is stored energy, while ηch and ηdis are charging and discharging efficiencies. Explicit energy updates are necessary in time-dependent storage scheduling.

The Baseline compromise objective was given as;

$$J = w(F_1/Cref) + (1 - w)(F_2/Mref) \quad (6)$$

Here, w is the cost preference weight, and Cref and Mref are fixed positive normalization scales. This baseline produces one compromise schedule; it does not generate a Pareto frontier.

Mathematical Modeling of the Renewable Energy Uncertainty

The Temporally correlated forecast error was given as;

$$z_{s,t} = \rho z_{s,t-1} + \sqrt{(1 - \rho^2)}\varepsilon_{s,t} \quad (7)$$

Here, $z_{s,t}$ is the standardized forecast error for scenario s and interval t, ρ is the temporal correlation coefficient, and $\varepsilon_{s,t}$ is a standard Gaussian innovation. Separate correlation parameters are used for solar and wind.

The uncertain solar availability was given as;

$$Psolar,_{s,t} = min[Psolar, rated, max(0, Psolar, forecast,_t(1 + \sigma solar\, zsolar,_{s,t}))] \quad (8)$$

The parameter σsolar controls relative forecast uncertainty. This equation assumes constant conversion efficiency, so relative irradiance errors translate directly into relative photovoltaic power errors. Nighttime output remains zero.

The Uncertain wind speed and power was given as;

$$v_{s,t} = max[0, vforecast,_t(1 + \sigma wind\, zwind,_{s,t})] \quad (9)$$

$$Pwind(v) = 0, \quad v < vci\, or\, v \geq vco$$

$$Pwind(v) = Prated(v^3 - vci^3)/(vr^3 - vci^3), \quad vci \leq v < vr$$

$$Pwind(v) = Prated, \quad vr \leq v < vco$$

Here, vci, vr, and vco are cut-in, rated, and cut-out wind speeds, respectively.

The Scenario probabilities was given as;

$$\pi_k = n_k/N \quad (10)$$

$$\sum_k \pi_k = 1 \quad (11)$$

N is the number of original Monte Carlo trajectories, and n_k is the number assigned to retained representative k.

The shared generation and battery schedule was given as;

$$P_{i,t,s} = P_{i,t} \quad (12)$$

$$P_{\beta,t,s} = P_{\beta,t} \quad (13)$$

Thermal generation and battery power are identical across scenarios. Scenario-dependent actions are renewable utilization, renewable curtailment, and emergency load shedding.

The Scenario power balance was given as;

$$\sum_i P_{i,t} + Psolar,used,_{s,t} + Pwind,used,_{s,t} + Pdis,_t + U_{s,t} = PD,_t + PL,_t + Pch,_t \quad (14)$$

$U_{s,t}$ is unserved demand in MW. It is penalized rather than treated as generation.

For the prescribed balancing policy:

$$R_t = PD,_t + PL,_t - \sum_i P_{i,t} - P_{\beta,t} \quad (15)$$

$$A_{s,t} = Psolar,_{s,t} + Pwind,_{s,t} \quad (16)$$

$$Prenewable,used,_{s,t} = min(R_t, A_{s,t}) \quad (17)$$

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$$U_{s,t} = max(R_t - A_{s,t}, 0) \quad (18)$$

The constraint $R_t \geq 0$ prevents surplus thermal and battery injection. Solar and wind utilization are allocated proportionally to their available outputs.

The expected economic and environmental objectives was given as;

$$F_1 = \sum_s \pi_s [Coperating_{,s} + VOLL \sum_t U_{s,t} \Delta t] \quad (19)$$

$$F_2 = \sum_s \pi_s M_s \quad (20)$$

VOLL is the assumed value of lost load in USD/MWh. M_s is thermal CO_2 emissions. Because thermal schedules are shared, emissions are identical across scenarios for a given schedule.

The reliability and risk indicator was given as;

$$EENS = \sum_s \pi_s \sum_t U_{s,t} \Delta t \quad (21)$$

$$Pshortage = \sum_s \pi_s I(max_t U_{s,t} > \varepsilon) \quad (22)$$

$$CVaR\alpha(C) = q\alpha + [\sum_s \pi_s max(C_s - q\alpha, 0)]/(1-\alpha) \quad (23)$$

EENS is expected energy not served, Pshortage is the probability of at least one shortage during the day, and CVaR measures upper-tail daily cost. CVaR is reported as an assessment metric; it is not included in the optimization objective.

Mathematical Model for PSA, GA and DE implementation

The Decision vector was given as;

$$x = [P_{1,1}, \ldots, P_{n,t}, \ldots, P_{n,t}; P_{\beta,1}, \ldots, P_{\beta,t}] \quad (24)$$

More precisely, the code stores three thermal outputs and one signed battery power for each of 24 hours, giving 96 decision variables. Positive battery power represents discharge; negative power represents charging.

The multi-objective problem is:

$$Minimize\ F(x) = [F_1(x), F_2(x)] \quad (25)$$

$$F_1(x) = \sum_s \pi_s [Coperating_{,s}(x) + VOLL \times EENS_s(x)] \quad (26)$$

$$F_2(x) = \sum_t \sum_i [\alpha_i + \beta_i P_{i,t} + \gamma_i P_{i,t}^2] \Delta t \quad (27)$$

Here, π_s is scenario probability, $Coperating_{,s}$ is operating cost, $EENS_s$ is scenario unserved energy, and VOLL is its economic penalty. Thermal generation and battery schedules remain shared across scenarios.

All generator, ramp, battery, energy balance, and terminal energy constraints from Objective 2 are retained.

The Pareto dominance was given as;

$$x^a \prec x^b if: \quad (28)$$

$$F_j(x^a) \leq F_j(x^b), \quad (29)$$

for every objective j,
with strict inequality for at least one objective.

Nondominated sorting identifies solution quality, while crowding distance promotes diversity across the approximate Pareto front. This selection principle follows the NSGA-II framework. The Particle Swarm Optimization model utilized was given as;

$$v_i^{k+1} = \omega^k v_i^k + c_1 r_1 \odot (p_i^k - x_i^k) + c_2 r_2 \odot (g_i^k - x_i^k) \quad (30)$$

$$x_i^{k+1} = Repair(x_i^k + v_i^{k+1}) \quad (31)$$

Here, v_i is particle velocity, ω is inertia, c_1 and c_2 are acceleration coefficients, p_i is personal best, and g_i is an archive leader. The vectors r_1 and r_2 contain independent uniform random values; $\odot$ denotes elementwise multiplication.

The Genetic Algorithm model utilized was given as;

$$xchild = \lambda \odot xparent,A + (1-\lambda) \odot xparent,B \quad (32)$$

$$xmutated = Repair(xchild + m \odot \sigma \odot z) \quad (33)$$

The vector λ controls arithmetic crossover, m identifies mutated variables, σ controls mutation magnitude, and z contains standard Gaussian values. Parent and offspring populations undergo Pareto ranking and crowding-based survival.

The Differential Evolution (DE) model was given as;

$$v_i = x_{r1} + FDE(x_{r2} - x_{r3}) \quad (34)$$

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$$u_{i,j} = v_{i,j}, if\ r_j \leq CR\ or\ j = jrandom \quad (35)$$

$$u_{i,j} = x_{i,j}, \quad (36)$$

otherwise

The distinct indices r_1, r_2, and r_3 exclude the target individual. FDE is the differential scale, and CR is crossover probability. The implementation extends differential mutation and binomial crossover with Pareto-based environmental selection.

The model for Selecting a representative compromise was given as;

$$S(x) = \theta F_1(x)/Cref + (1 - \theta)F_2(x)/Mref \quad (37)$$

The code selects the smallest S from each archive using θ = 0.5 and identical fixed normalization scales. This preference score selects schedules for reporting; it does not replace Pareto selection during the search.

Modeling of the Comparative indicators

The expected operating cost and emissions was given as;

$$Cexpected = \sum_s \pi_s Coperating_{,s} \quad (38)$$

$$Cpenalized = Cexpected + VOLL \times EENS \quad (39)$$

$$MCO_2 = \sum_t \sum_i (\alpha_i + \beta_i P_{i,t} + \gamma_i P_{i,t}^2)\Delta t \quad (40)$$

Here, π_s is scenario probability, VOLL is the unserved-energy penalty, and MCO_2 is operational thermal emissions. Operating cost and penalized cost are reported separately.

The Reliability assessment was given as;

$$EENS = \sum_s \pi_s \sum_t U_{s,t} \Delta t \quad (41)$$

$$Pshortage = \sum_s \pi_s I(max_t U_{s,t} > \varepsilon) \quad (42)$$

$U_{s,t}$ represents unserved demand. Pshortage measures the probability of at least one shortage during the simulated day; it is not an annual reliability index.

The repeated-trial consistency was given as;

$$\mu q = (1/R)\sum_r q_r \quad (43)$$

$$sq = \sqrt{[\sum_r (q_r - \mu q)^2/(R - 1)]} \quad (44)$$

Here, q_r is a performance indicator from trial r, R is the number of trials, μq is its mean, and sq is its sample standard deviation.

The Hypervolume was given as;

$$HV(A) = Area[\cup_a \in A\ [a_1, r_1] \times [a_2, r_2]] \quad (45)$$

A contains normalized nondominated objective vectors, and r is a common reference point worse than those vectors. Higher hypervolume is preferable.

The code uses r = [1.1, 1.1] after applying common normalization bounds within each case. The Inverted generational distance was given as;

$$IGD(A, Z) = (1/|Z|)\sum_z \in Z\ min_a \in A\ \|z - a\|_2 \quad (46)$$

Z is the pooled empirical reference front, and A is an algorithm's normalized validation front. Lower IGD is preferable. Because normalization and references are constructed separately for each case, absolute HV and IGD values were compared between algorithms within the same case.

The Constraint satisfaction was given as;

$$Vmax = max[0, max_j g_j(x), max_k |h_k(x)|, maximum\ bound\ violation] \quad (47)$$

Constraints follow $g_j(x) \leq 0$ and $h_k(x) = 0$. A schedule is accepted when Vmax does not exceed the specified tolerance

RESULT AND DISCUSSIONS

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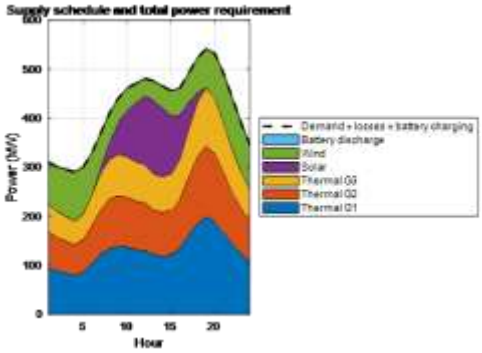


Figure 1: supply schedule and total power requirement

Figure 1 illustrates the relationship between the total power requirement and the combined supply from thermal generators, renewable energy sources, and the battery energy storage system (BESS). The generation schedule varies throughout the day to accommodate changing demand and available renewable power. The battery provides additional flexibility by charging or discharging when necessary. Overall, the figure demonstrates the importance of coordinating conventional generation, renewable energy utilization, and energy storage to satisfy demand while accounting for transmission losses and operational constraints.

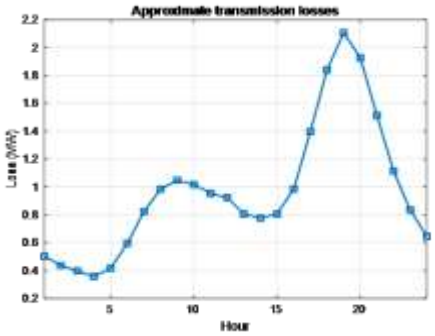


Figure 2: Approximate transmission losses

Figure 2 presents the estimated transmission losses across the simulated 24-hour period. These losses vary with the operating conditions and distribution of thermal generator outputs. Higher generation and power transfer levels may increase network losses, making their consideration essential in economic dispatch. Incorporating transmission losses into the optimization model allows the dispatch algorithm to determine generation schedules that satisfy demand more realistically. The results emphasize that minimizing generation costs alone may not produce the most efficient operating schedule when network losses are significant.

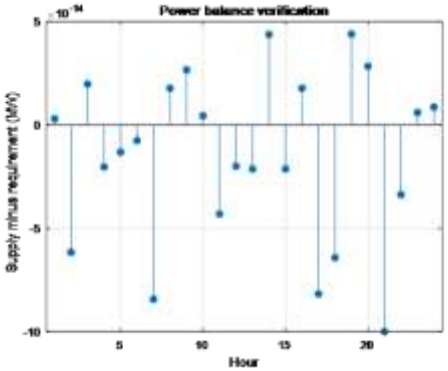


Figure 3: Power balance verification

Figure 3 verifies the accuracy of the simulated power balance by displaying the residual between total power supplied and total power required, including transmission losses. The residuals are approximately \(10^{-14}\) MW, indicating that the power balance is satisfied within numerical precision. This result supports the numerical consistency of the implemented dispatch model. However, power-balance satisfaction alone does not establish that every generator, battery, or renewable operating constraint is satisfied; those constraints require separate verification.

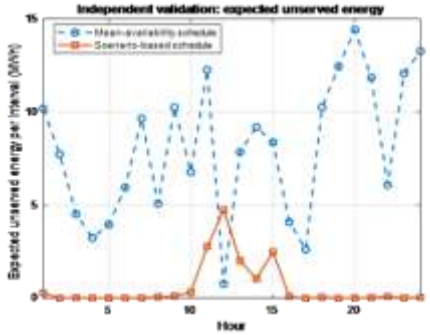


Figure 4: independent validation: expected unserved energy

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Figure 4 compares expected unserved energy for the scenario-based dispatch schedule and the mean-availability schedule. The scenario-based approach produces substantially lower expected unserved energy, indicating better performance under the modeled renewable uncertainty. This suggests that incorporating variations in solar and wind availability can improve supply reliability compared with relying solely on average renewable forecasts. The result highlights the value of probabilistic scenario modeling in economic dispatch. However, the improvement applies to the assumptions and operating conditions represented in the simulation and requires further testing for broader generalization.

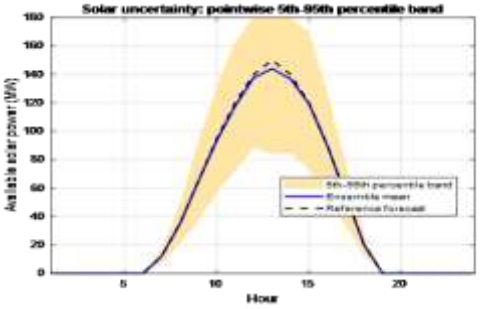


Figure 5: Solar uncertainty: point-wise 5th-95th percentile band

Figure 5 illustrates the uncertainty associated with solar photovoltaic power availability throughout the simulated day. Solar generation increases during daylight hours, reaches its maximum around midday, and decreases towards sunset, remaining zero during nighttime. The shaded percentile band represents the range between the 5th and 95th percentiles of simulated solar output, showing the potential variability around expected production. This variation demonstrates why renewable uncertainty should be incorporated into dispatch optimization to improve scheduling decisions and reduce the risk of power shortages.

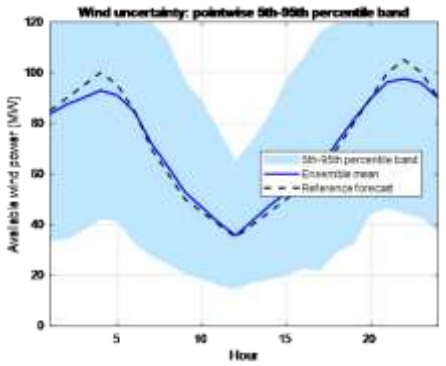


Figure 6: wind uncertainty: pointwise 5th-95th percentile band

Figure 6 presents the variability of wind power availability over the 24-hour simulation period. Unlike solar generation, wind output can fluctuate throughout both daytime and nighttime, depending on wind conditions. The 5th–95th percentile band represents the uncertainty range obtained from the modeled scenarios. A wider band indicates greater variability in available wind power, which can complicate generation scheduling. Incorporating this uncertainty into economic dispatch enables better coordination of thermal generators and battery storage to maintain supply-demand balance under changing wind conditions.

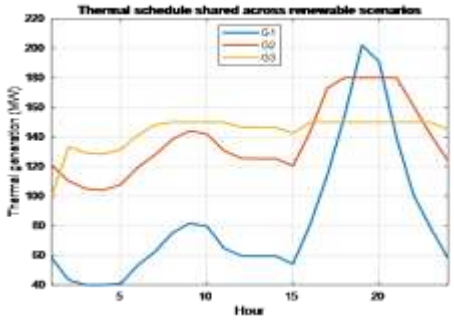


Figure 7: Thermal Schedule Shared across Renewable Scenarios

Figure 7 shows the scheduled outputs of the three thermal generators across the simulated 24-hour period. Although their generation levels vary over time, the thermal schedules remain

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identical across renewable scenarios. This reflects the model's shared-schedule assumption, which requires thermal generation decisions to remain consistent despite uncertainty in renewable availability. Such coordination simplifies operational planning while allowing renewable utilization, curtailment, and emergency load shedding to respond to individual scenarios. The results illustrate how thermal generators provide a scheduled generation foundation for a renewable-rich power system.

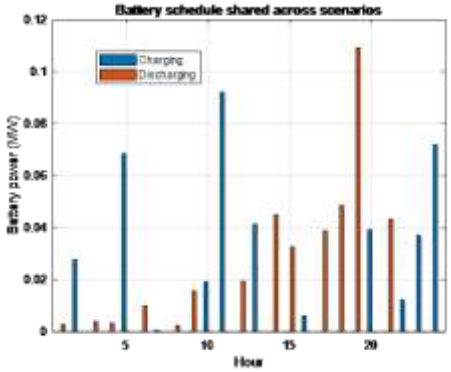


Figure 8: Battery schedule shared across scenarios

Figure 8 presents the battery energy storage system charging and discharging schedule throughout the simulated day. Positive battery power represents discharging, which supplies additional electricity to the system, while negative power represents charging, which stores excess energy for later use. The schedule illustrates how storage can support the integration of intermittent renewable generation and help maintain the balance between supply and demand. Because the battery schedule is shared across scenarios, it remains consistent under different renewable conditions. Its effectiveness depends on battery power limits, energy capacity, charging and discharging efficiencies, and terminal energy requirements.

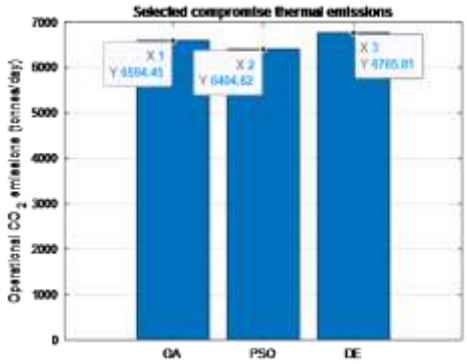


Figure 9: selected compromise thermal emissions

Figure 9 compares the thermal emissions associated with the selected compromise solutions from the three optimization algorithms. The reported emissions are approximately 6,594.45 tonnes/day for Genetic Algorithm (GA), 6,404.82 tonnes/day for Particle Swarm Optimization (PSO), and 6,765.81 tonnes/day for Differential Evolution (DE). PSO records the lowest emissions among the selected solutions, followed by GA and DE. These results suggest that PSO performs better environmentally for the selected compromise schedules. However, a complete assessment should also consider operating costs, constraint satisfaction, and the trade-off between economic and environmental objectives.

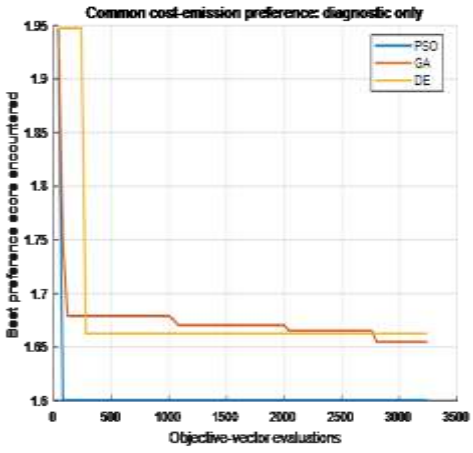


Figure 10: common cost-emission preference: diagnostic only

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Figure 10 compares the convergence behavior of PSO, GA, and DE using a common cost–emission preference score. The score combines normalized economic cost and emissions into a single diagnostic measure, with lower values indicating a more favorable compromise. The plotted trends show how each algorithm improves its selected solution during the optimization process. Differences in convergence patterns provide insight into the algorithms' search behavior and potential efficiency. However, this preference score is used for comparison and diagnosis; it does not replace the multi-objective Pareto-based selection process used during optimization.

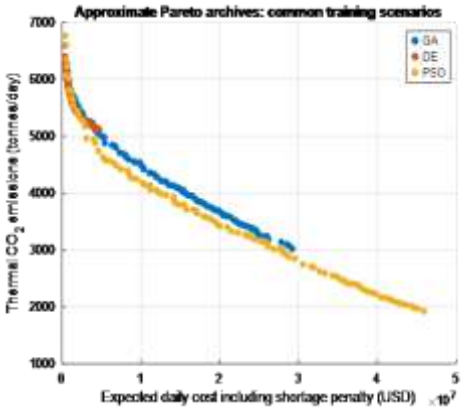


Figure 11: Approximate pareto archives: common training scenarios

Figure 11 presents the approximate Pareto fronts generated by the optimization algorithms under common training scenarios. Each point represents a non-dominated solution involving a particular combination of expected operating cost and thermal emissions. The distribution of points illustrates the trade-off between the two objectives: a solution with lower emissions may incur a higher operating cost, while a cheaper solution may produce more emissions. Comparing the fronts helps assess the diversity and quality of solutions obtained by each algorithm. The figure supports informed selection of compromise schedules according to the preferred balance between economic and environmental performance.

CONCLUSION

This study addressed the challenges of economic load dispatch in integrated thermal–renewable power systems arising from renewable energy uncertainty, generation cost, environmental emissions, and supply reliability. A multi-objective optimization framework incorporating thermal generators, solar PV, wind energy, and battery energy storage was developed using Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Differential Evolution (DE) over a 24-hour scheduling horizon. The simulation results confirmed power balance accuracy, with residuals of approximately MW. PSO achieved the lowest daily thermal emissions of 6,404.82 tonnes, outperforming GA (6,594.45 tonnes) and DE (6,765.81 tonnes). Overall, scenario-based optimization demonstrated improved modeled supply reliability and effective resource coordination under renewable uncertainty.

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