Scientific Reports

https://doi.org/10.1038/s41598-026-41270-3

Article in Press

Weighted cost emission dispatch optimization using GA–APO hybridization under priority sensitive scheduling for thermal power systems

Received: 18 September 2025

Accepted: 19 February 2026

Published online: 05 March 2026

Cite this article as: Srinivas C., Reddy M.R.P., Kumar V. *et al.* Weighted cost emission dispatch optimization using GA–APO hybridization under priority sensitive scheduling for thermal power systems. *Sci Rep* (2026). https://doi.org/10.1038/s41598-026-41270-3

Chodagam Srinivas, M. Rama Prasad Reddy, Vineet Kumar, Vineet Kumar, Ark Dev & Negasa Muleta

Weighted Cost Emission Dispatch Optimization Using GA–APO Hybridization under Priority Sensitive Scheduling for Thermal Power Systems

Chodagam Srinivas[1], M. Rama Prasad Reddy[2], Vineet Kumar[1], Vineet Kumar[3], Ark Dev[4], Negasa Muleta*[5]

[1]Department of Electrical & Electronics Engineering, Madanapalle Institute of Technology & Science, Andhra Pradesh, India

[2]Department of Electrical & Electronics Engineering, G. Pullaiah College of Engineering and Technology, Kurnool, Andhra Pradesh, India

[3]Department of Electrical Engineering, Netaji Subhas University of Technology, Dwarka, New Delhi, India

[4]Department of Electronics and Communication Engineering, SR University, Telangana, Warangal, 506371, India

[5]Centre of Electrical System and Electronics, College of Electrical Engineering and Computing, Adama Science and Technology University, Adama, Ethiopia

*__Corresponding Author:__ Negasa Muleta (negasa.muleta@astu.edu.et)

Abstract: Modern utilities operate in an environment where fuel expenditure cannot be viewed in isolation from the environmental impact of generation. This creates a scheduling problem that is harder to address with traditional single objective tools, especially when the fuel and emission characteristics of thermal units do not behave smoothly. In this work, a two-stage solution strategy is developed for the economic–emission dispatch problem. The idea is straightforward: use a Genetic Algorithm (GA) to search widely for feasible production patterns and then pass its best candidate to an Arctic Puffin Optimization (APO) based refinement step, which adjusts the schedule locally and attempts to settle it closer to a desirable operating point. The economic and environmental indices are combined through a weighted formulation so that the dispatch can be steered toward cost saving, emission reduction, or an intermediate compromise without reworking the underlying model. Proposed method is tested on three generators thermal power plant with 24 hours scheduling. Under different conditions, the proposed algorithm performed satisfactory by maintaining the results within the operational limits. Comparative study validates the effectiveness of the proposed design over GA approach. In cost-priority operation the hybrid approach achieves up to 1.88% reduction in total operating cost compared to GA. In emission priority condition the proposed GA-APO reduced the emission consumption nearly 0.21% and in balanced case cost per MWh reduced nearly 0.68%.

Keywords: Arctic Puffin Optimization (APO), Cost–Emission Trade-off, Forecasted Load Management, Load Scenario Analysis, Priority-based Dispatch Strategy.

1. Introduction

1.1 Background and Problem Context

The economic dispatch problem began as a fairly straightforward exercise: schedule thermal generators so that the system demand is supplied at minimum fuel cost. For many years this narrow viewpoint worked because power systems operated in a predictable and relatively sheltered environment. Loads were stable, generation portfolios were simple, and utilities were not expected to demonstrate anything beyond operational efficiency. That setting has changed considerably. Environmental regulations now influence almost every operational decision, and system operators must weigh fuel expenditure against the environmental consequences of each schedule. Once emissions are acknowledged as part of the objective, the dispatch task immediately becomes more involved because the factors that minimise cost are not always the same as those that limit pollution. The technical behaviour of generators has also changed a lot compared to what older dispatch models assumed. Earlier studies usually worked with simple quadratic curves for fuel cost, but real units today do not follow such smooth patterns. In fuel cost curves the characteristics becomes non-linear due to the presences of valve-point effects, fuel-switching options, and operating limits. It causes drastic changes in the generator output with small deviations in the cost and emission. Today, many large thermal power plants are combined with solar (PV) and wind energy systems. Since, power demand is uncertain in nature and the output of solar and wind can change when load demand increases, at that time the operational limits used in economic load dispatch are also affected. Considering all these factors interaction, the dispatch problem cannot be treated as a simple fuel saving exercise. In real time for scheduling problems has to consider the environmental economic load dispatch (EELD), at the same time need to consider the uncertainty in the demand pattern due to usage of EV charging stations. It shows that EELD must operate by satisfying many constraints.

1.2 Motivation and Research Gap

Although, the research on economic–emission dispatch (EED) and multi-objective economic dispatch has grown rapidly due to economic reasons, certain shortcomings continue to appear when these methods are examined under conditions that resemble real system operation. In [1], authors proposed combined thermal generation with wind, solar, and run-of-river hydro in a unified EED framework and illustrated how emission constraints reshaped generator participation in mixed portfolios. A similar work addressing the emission dispatch in a day-ahead strategy for scheduling to clear emission controlled dispatch in thermal power plants is reported in [2]. Authors in [3], addressed the EELD problem in thermal power plants by considering the valve point effect and transmission line losses by using equilibrium optimization algorithm (EOA). In [4], a comprehensive survey on ELD problems is presented, emphasizing how additional constraints have progressively transformed the traditional quadratic cost model—incorporating factors such as valve-point effects, non-smooth cost functions, and uncertainties in load demand arising from EV charging stations and demand response strategies. Authors in [5], examined multi-area ED in networks with significant renewable penetration and shown that their hierarchical consensus approach can coordinate tie-line flows efficiently even in large systems. In [6], economic dispatch in cyber-physical power systems is examined, and it is demonstrated that a distributed, carbon-aware scheduling strategy can withstand cyberattacks while remaining aligned with emission-trading rules. Constraint-rich nature of economic dispatch has also been explored. For instance, in [7], prohibited operating zones (POZs), valve-point loading effects, and multi-fuel operating conditions using computational intelligence tools capable of maintaining feasible solutions despite the presence of difficult non-linearities is discussed. A memetic (hybrid) version of the salp swarm algorithm (SSA) for ELD problems with severe constraints, showing faster convergence and good solution robustness is reported in [8]. Hybrid Jaya-teaching-learning method for ELD, improving over baseline metaheuristic techniques especially under non-smooth cost function situations is discussed in [9]. A similar work reporting a novel metaheuristic optimization called the generalized normal distribution optimization (GNDO) is applied to ED problems both with and without integrated renewable energy sources is reported in [10]. Authors in [11], presented a low-carbon economic dispatch model for combined heat and power micro-grid systems, integrating China's carbon trading scheme and multiple forms of flexible loads (shiftable, transferable, cutable). The model achieved both large emission reductions and cost savings versus conventional dispatch. In [12], a hybrid algorithm combining slime mould algorithm with genetic algorithm (GSMA) for ELD in microgrids is proposed. In scenarios including wind, photovoltaic, storage, and fuel generation, GSMA outperformed a number of common metaheuristics. In [13], a short-term scheduling in mixed-generation system is investigated. The results indicate that the feasibility of the final schedule can shift quite a bit depending on how much renewable energy is actually available at each hour. A thermal-solar-wind-battery (TSWB) integrated system model for 24 hourly hybrid dynamic EED generation scheduling using chaos based arithmetic optimization algorithm is reported in [14]. Despite the advantages associated with hybrid optimizations, they struggle when operating conditions change quickly. In several reported cases, the quality of the solution drops as soon as dispatch priorities are shifted in real time, an issue already pointed out in earlier work [15]. Power system optimisation is becoming harder because of renewable variability, storage participation, and the fact that operators may change operating preferences frequently as studied in [16-18]. Considering real time test systems, particularly the IEEE 57 and 118 bus systems, [19] investigates the probabilistic optimal power flow framework targeting cost & emission reduction while simultaneously enriching voltage profile & stability using Quasi Oppositional Sine Cosine algorithm. A similar work proposes a chaotic hippopotamus optimization algorithm (CHOA) to solve dynamic ELD over 24 hours in hybrid systems incorporating wind, solar, and electric vehicles, minimizing fuel cost and power loss under practical constraints is reported in [20]. Authors in [21] proposed an ELD formulation considering valve-point effects and solved it using an advanced self-adaptive multi-population quadratic approximation-guided Jaya (SMP-JaQA) algorithm on a 160-unit generator system, demonstrating lower operating costs and improved robustness. A work aimed to achieve efficient power generation while minimizing emissions and voltage deviations, as well as maintaining transmission line voltage stability is reported in [22]. In this work, a combined heat and power economic dispatch (CHPED) system is integrated into the IEEE-57 bus network to ensure optimal power flow across transmission lines while satisfying the load demand. In [23], the authors evaluate their proposed algorithm on both hydro–thermal scheduling (HTS) and wind–solar–electric vehicle-based HTS (HTWSVS) considering three distinct case studies. The formulation incorporates key nonlinearities, including the valve-point effects of thermal units, transmission losses, hydro reservoir spillage rates, and the uncertainties associated with wind, solar, and electric-vehicle sources. Their findings highlight that the chaotic quasi-opposition-based whale optimization technique delivers superior performance and reliability when applied to realistic and practical power system scheduling problems. Recently, several studies addressed dynamic economic and emission dispatch by integrating renewable energy sources and electric vehicles systems. Dasgupta et al. [24] proposed a quasi-oppositional chaotic sine–cosine algorithm to reduce the cost and emission for hybrid thermal–wind–solar DEED under dynamic conditions.

Renewable integration within optimal power flow based combined heat and power dispatch has also been tested in [25], where chaotic

oppositional learning enhanced convergence and robustness in IEEE test systems.
From the literature, it has been identified that, techniques that emphasise exploration such as PSO-based hybrids or Differential Evolution supported models can map the wider search space well but often fail to refine solutions once they reach difficult regions of the cost–emission landscape. On the other hand, algorithms that lean more toward exploitation including SSA variants, GNDO, or different teaching–learning approaches often settle too quickly into local zones of the search space, especially when strong non-linear effects like valve-point behaviour or strict emission limits are present.

Although several hybrid optimization frameworks aim to balance exploration and exploitation, many reported approaches rely on aggressive local search strategies that can cause instability or feasibility violations when dispatch preferences change. In addition, most existing EED models require reformulation or parameter retuning to switch between cost-dominant, emission-dominant, and balanced operating modes, which limits their practicality for real-time or policy-responsive decision-making.
Therefore, a clear research gap exists for an optimization framework that: i) maintains global search diversity while achieving stable convergence near operational constraints, ii) adapts smoothly to dynamic shifts in cost–emission priorities without requiring model restructuring, and, iii) provides reliable refinement under complex, constraint-rich EED conditions.
The above discussed points are showing clear gaps in the existing works and these points are addressed in this work. An optimisation framework is required that maintains global diversity, adapts smoothly to shifts in dispatch priorities, and refines candidate solutions with behaviour-driven precision when operating near constraint boundaries. The hybrid GA–APO framework developed in this work is shaped by this requirement, combining GA's broad search capability with APO's focused refinement to offer a more stable and priority-responsive solution for modern EED.
The present study is tested on a three-unit thermal system, the objective is to evaluate the behaviour and stability of the proposed hybrid optimization framework under tightly constrained conditions, which are representative of real-world operational challenges encountered in larger power systems.

1.3 Methodological Innovation and Proposed Approach

This work is based on an idea that a single optimization method does not perform well in every stage of the dispatch search. When the search starts, the solution must move widely across the space so that it does not get stuck early. Later, the search needs more careful adjustments, especially when generator limits or cost–emission interactions make the problem sensitive. For this reason, a simple two-step hybrid approach is used. In the first step, the GA is applied because it can generate a broad mix of possible schedules. The GA helps in scanning different regions and gives a starting point that is usually feasible. After the GA finishes, the best schedule from its population is taken as the input for the second step. The next stage is based on the APO. The APO works in a more focused manner and updates the solution using its foraging-type, sliding, and group-movement behaviour. These updates help in improving the solution near its neighbourhood, which the GA alone may not handle well. To allow different system priorities, the dispatch model is written in a weighted form. By changing these weights, the same formulation can be used for cost-priority, emission-priority, or balanced operation without rewriting the model. This shows the flexibility of the operator to focus on various conditions like generator cost minimization, emission control or both cost and emission balance. The proposed hybrid model examined on 24-hour schedule with different priorities between cost and emission combinations as per operator requirements.

1.4 Key Findings and Scientific Contributions

Simulation results obtained using MATLAB validate the effectiveness of the proposed GA-APO optimization over 24-hour scheduling. Improvement can be observed in all three key indices i.e. cost-priority, emission-priority, and balanced operation. The hybrid optimization does not only provide faster solution but also manages the constraint violation better and also keeps the dispatch schedule with acceptable limits.

The key highlights of this work are as follows:

i. Hybrid search mechanism:

   While, GA explores the search space, the APO improves the solution. This approach manages the rough and non-smooth behaviour of MOED problems.

ii. Priority-based objective settings:

   In practice, the priorities often change with policies or fuel price. The weighing factors shift the focus between cost and emissions without changing the model.

iii. Full-day performance evaluation:

In this work, the proposed approach is validated for 24 hours assuring the efficacy of the hybrid method in handling load changes, and keeping the cost and emissions balanced.

iv. Comparison with standard GA:

Upon comparison with traditional GA, it has been found that the proposed hybrid optimization results in lower cost and steadier results. It works well with all weight choices, which means it is dependable even when priorities vary.

2. Mathematical Formation

This study treats ELD as a problem with two objectives: lowering fuel cost and reducing emissions. The system must meet demand and keep each generator within its limits. The model includes realistic non-linear features to match the real thermal power plant working.
The fuel cost for each thermal generating unit is expressed using a quadratic cost model:

$$F(P_i) = a_i + b_i P_i + c_i P_i^2 \quad (1)$$

where P_i is the output of generator *i (MW)*, a_i, b_i, c_i are cost coefficients associated with the *i*th generator (Rs./MW^2, Rs./MW, and Rs. respectively). The quadratic form captures heat rate characteristics of thermal units. The a_i term represents non-linear incremental cost, while b_i and c_i account for proportional and fixed operating costs.

Using a composite quadratic–logarithmic model, pollutant emissions from generator i are represented as follows,

$$E_i(P_i) = \alpha_i P_i^2 + \beta_i P_i + \gamma_i + \zeta_i \ln(P_i + \epsilon) \quad (2)$$

where α_i, β_i, and γ_i represent emission coefficients (Kg/CO_2/MW^2, Kg/CO_2/MW, Kg/CO_2), ζ_i represents coefficient capturing nonlinear chemical behaviour, and ϵ represent small constant to avoid singularity. It should be noted that equation (2) has two components: quadratic and logarithmic. The quadratic component represents the fuel dependent emissions, while the logarithmic component represents high emission zones at low output levels due to incomplete combustion. This combined form provides a realistic approximation for CO_2 and NOx characteristics.

2.1 Composite Multi-Objective Function

In order to incorporate the trade-off between cost and emission, a weighted composite objective function is formulated as,

$$\text{Min J} = w_1\sum_{i=1}^{n} F_i(P_i) + w_2\sum_{i=1}^{n} E_i(P_i) \quad (3)$$

where w_1 and w_2 are weights of cost and emission priority respectively.

Based on the policy like cost priority, Environment concern, and considering a balanced approach mentioned below:

- Balanced Dispatch: w_1=w_2=1.
- Cost-Priority w_1 = 1.5, w_2 = 0.5.
- Emission-Priority Dispatch: w_1 = 0.5, w_2 = 1.5.

These weights will not impact the optimization but it focused on objective weightage.

2.2 Operational Constraints

The optimization is driven by following physical and engineering constraints.

a) Power Balance Constraint

Power balance signifies that the total generation should match the total demand while accounting for network losses, preserving steady-state system equilibrium.

$$\sum_{i=1}^{N} P_i = P_D + P_{loss} \quad (4)$$

where P_D= system demand (MW), P_{loss}= transmission loss (MW), estimated using B-coefficient loss formulas. This constraint ensures that total generation equals demand plus losses, preserving steady-state power balance.

b) Generator Operating Limits

Prevents overloading, under loading, and thermal stresses on generating units. These bounds reflect physical and safety constraints.

$$P_i^{min} \le P_i \le P_i^{max} \quad (5)$$

where P_i^{min} and P_i^{max} are the minimum and maximum allowable outputs.

c) Emission Cap

$$\sum_{i=1}^{N} E_i(P_i) \le E_{max} \quad (6)$$

is included where environmental policies mandate emission ceilings.

d) Security and Feasibility Penalties

Violations of any constraint are incorporated into the objective using adaptive penalty factors:

$$J' = J + \lambda_1|\Delta P| + \lambda_2\sum_i \max(0, P_i - P_i^{max}) + \lambda_3 \sum_i \max(0, P_i^{min} - P_i) \quad (7)$$

where ΔP is power mismatch and λ_1, λ_2, λ_3 are penalty weights.

The study tests the GA–APO method using a 24-hour demand scenario. Three dispatch priorities are used to reflect different dispatches:

- Balanced Dispatch: Equal emphasis on minimizing cost and emission, achieved by setting weighting factors w_1=w_2=1.

- Cost-Priority Dispatch: Greater importance is assigned to generation cost ($w_1 = 1.5$, $w_2 = 0.5$), reflecting economically constrained conditions.
- Emission-Priority Dispatch: Environmental impact is prioritized over cost ($w_1 = 0.5$, $w_2 = 1.5$), aligning with low-carbon operation objectives.

Based on current policy, economic needs, and regulations, the multi-objective function weights can be changed. By changing the weights, the objective function can provide required solutions without violating any constraints.

3. Methodology

In this study a hybrid optimization technique is made by combining the two techniques GA and APO. The first one is the GA, which is fairly good at scanning a wide region of the search space without getting stuck too early. The second one is the APO algorithm, which tends to work better when the solution is already somewhere close to a good region and only requires finer adjustments. Because the ELD problem usually contains several local minima and strict operational limits, a single algorithm often fails to achieve both broad exploration and accurate refinement. For this reason, the proposed framework uses GA to generate an initial population of feasible schedules, and then passes the best schedule to APO for further improvement. The whole process is carried out on the weighted multi-objective formulation discussed earlier.

3.1 Priority-Sensitive Multi-Objective Dispatch Formulation

The dispatch model is expressed as a weighted combination of cost and emission functions. Instead of creating different models for different priorities, the same mathematical structure is retained, and the emphasis is controlled through two weights (w_1, w_2). Three cases are considered in this study. The first is a balanced mode where both components are treated equally. The second is a cost-priority mode where economic operation is given slightly more importance, and the third is an emission-priority mode where the optimizer is guided more strongly toward cleaner operation.

This weighted approach is fairly common in real power system control rooms because operators often need to shift between different operating philosophies depending on external factors fuel price variations, environmental advisories, or regulatory limits. The idea here is similar: by modifying the weights, the model can move from one type of schedule to another without redesigning the entire optimization. A simple conceptual illustration, shown in Figure 1 helps explain how the weights influence the direction of the algorithm. In practice, such flexibility is useful because dispatch decisions are rarely made with a single fixed objective in mind.

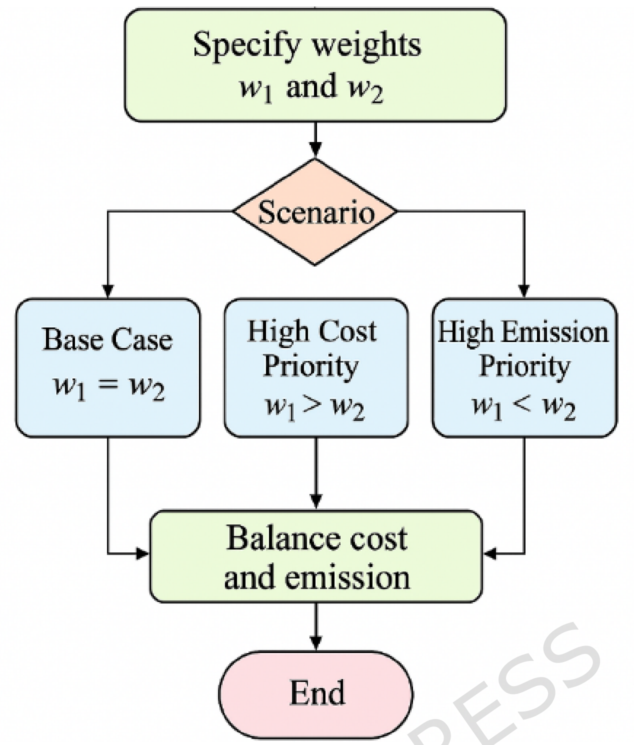

Figure 1: Priority-Based Multi-Objective Handling Strategy.

3.2 Genetic Algorithm for Global Exploration

The first stage of the hybrid method uses the GA. The GA has been widely applied to economic dispatch problems over the years mainly because it explores the search space broadly. In this model, each individual in the GA population represents a complete set of generator outputs over the 24-hour horizon. The encoding is straightforward: each chromosome is a real-valued vector, and every value is kept within the physical limits of the respective generating unit. The initial population is generated randomly so that a wide range of operating patterns is represented. The fitness evaluation is performed using the same weighted objective function described earlier. A roulette-wheel selection method is used since it provides a fair balance between promoting good solutions and keeping enough diversity in the pool. For generating new individuals, an arithmetic crossover operator is applied. This type of crossover tends to produce offspring that fall between the parent solutions, which is suitable for continuous variables like generator outputs. A small mutation is added using a Gaussian perturbation. The mutation step is intentionally kept moderate because too much randomness tends to disturb feasibility, while too little can cause stagnation. The main purpose of this GA stage is not to find the exact optimal schedule but to identify a set of candidate regions where APO can subsequently perform a more focused search.

3.3 Arctic Puffin Optimization for Local Refinement

After the GA identifies a reasonably good dispatch pattern, the solution usually needs further polishing, especially because the economic–emission landscape has many small irregularities that GA alone does not always resolve well. For this second stage, the model employs the APO, which is better suited for making short-range adjustments. The intention is not to redo the entire search but to focus on the neighbourhood of the GA solution and make more careful corrections. A general flow of this refinement step is shown in Figure 2.

APO uses ideas taken from how puffins behave in nature, but in the algorithm these ideas simply act as ways to move the candidate solutions around. In practice, the method goes through three broad stages during refinement.

Exploration Phase (Foraging)

When APO starts, it does not immediately stay fixed around the solution passed from the GA stage. Instead, the candidates are allowed to wander slightly away from that point. This helps the algorithm look around the area rather than assuming that the GA solution is already close to the best answer. In economic–emission dispatch problems, the objective surface can change sharply because of limits on generator operation, so GA sometimes stops just before a better region. This initial spreading step gives the APO a chance to move into those areas and check whether an improvement is possible.

Exploitation Phase (Diving)

Once the algorithm has examined the nearby region, the search usually becomes more focused. In this stage, APO begins to make smaller and more careful adjustments. These small moves are often enough to reduce cost or emissions when the GA solution is already near a good point. This behaviour is especially useful near strict limits, where a slight change in output can help the schedule become feasible or reduce the total cost without disturbing other generators.

Information Exchange (Huddling)

Toward the end of the run, the candidates start to move in a more coordinated way. In nature, puffins tend to group together, and APO models this by letting the solutions follow the better-performing members of the population. This prevents unnecessary wandering and helps the search settle down. As a result, the solutions gradually become more similar, and the algorithm moves toward a stable final schedule.

Role of APO in the Hybrid Structure

APO is added after GA because GA can locate promising regions but does not always finish the job cleanly. It sometimes leaves small mismatches or slight violations near constraints. APO is better suited for this final stage because it can make small, targeted adjustments without losing feasibility. By the time APO completes its run, the dispatch curve usually becomes smoother, more consistent with system limits, and better balanced between cost and emissions compared to the direct GA output.

3.4 Hybrid Refinement of GA-Derived Solution

The choice to combine GA and APO in a two-step manner was based on several trial runs. When APO was run independently from a random starting point, it spent a large number of iterations moving through regions that were already known to be poor. This made the process slow and did not give any clear advantage. Using the best GA solution as the starting point worked much better. In this arrangement, GA handles the broad search and identifies a feasible operating zone, and the APO then works only on improving what GA has already found. This approach saves computation time and allow APO to concentrate on fine-tuning instead of fixing basic violations.

Local Adaptation and Constraint Handling

Tests highlighted that APO adjusts its steps when the search becomes difficult. Near high-penalty areas, it takes smaller steps to move back into a safe region. This happened near generator limits and sharp cost–emission changes. Other methods often overshoot, but APO stayed controlled. This helped the hybrid method stay within limits while still improving results, which is useful for a non-convex problem.

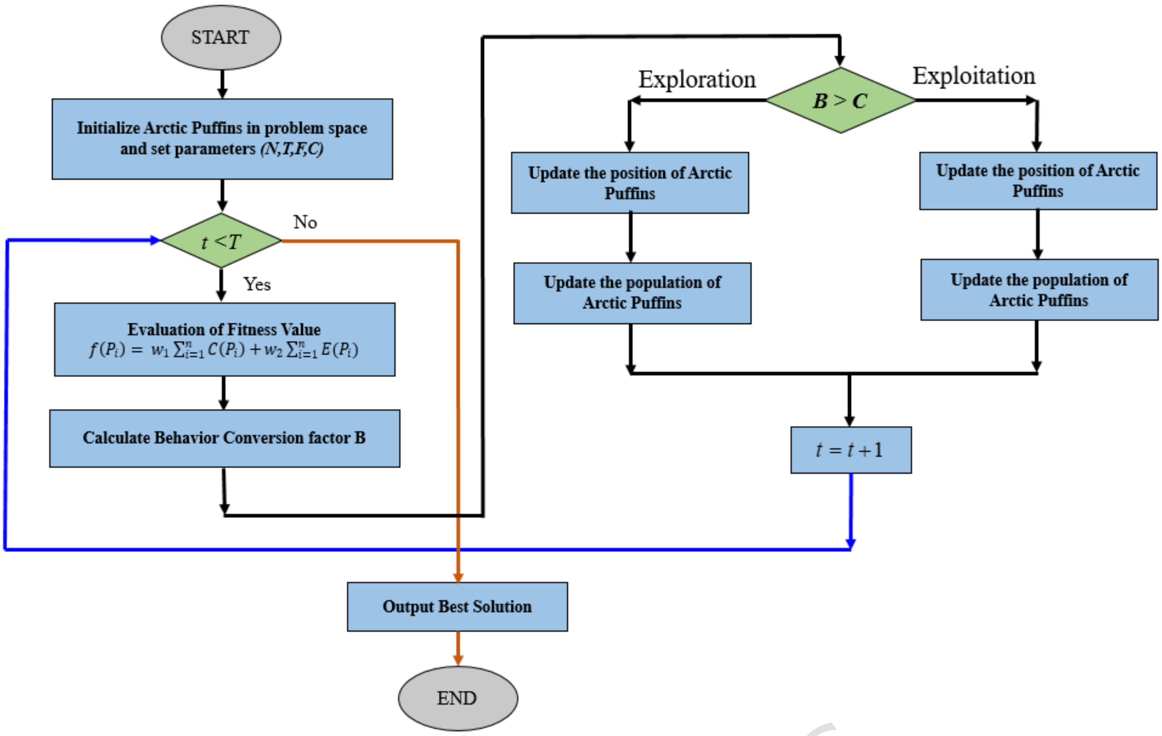

Figure 2: Flowchart of Arctic Puffin Optimization (APO)

Unlike simpler local search procedures, which often get stuck once the objective function becomes jagged or non-smooth, APO's design makes it more flexible. Depending on the progress made in a given iteration, it can broaden its search ("foraging") or shift toward deeper adjustments ("diving"). These two behaviours together prevented early stagnation in most runs, and the algorithm kept discovering improved schedules even when the initial GA solution was already quite strong.

Hybrid GA–APO Workflow

Because the economic–emission dispatch surface is non-convex and filled with discontinuities, the final framework was organised as a modular sequence. The GA carries out the heavy lifting during the global exploration stage. Its population operations: selection, crossover, and mutation tend to maintain enough diversity to reach promising regions without settling too quickly. By the final GA generation, the population usually contains at least one dispatch plan that balances cost and emission reasonably well. At that point, the best GA solution becomes APO's starting input. From here, APO works more like a specialist than a generalist. Its behaviour based updates, inspired by puffin foraging, gliding, and group huddling, allow the algorithm to probe the region around the GA candidate with more precision. In practice, much of APO's effort goes into cleaning up constraint margins and smoothing out the final trade-off between cost and emissions, especially in narrow feasibility zones where GA occasionally struggles.

The hybrid optimization algorithm unfolds as follows:

GA Phase:

The hybrid optimization begins with the GA, which is allowed to run for a fixed number of generations. In this stage, the aim is not to find the perfect schedule but to produce a collection of dispatch plans that are both feasible and diverse enough to explore different cost–emission patterns.

APO Initialization:

After GA finishes, the best-performing individual from its final population is taken out and used as the starting point for the refinement stage. By doing this, the APO avoids wasting effort on directions that GA has already ruled out.

APO Refinement:

The APO then works on this candidate, making small, adaptive adjustments. It reacts to the local landscape sometimes taking cautious steps near constraint boundaries, and at other times searching more widely if the region seems flexible. The goal here is mainly to tighten feasibility and smooth the cost–emission balance.

Final Output:

Once APO completes its cycles, the resulting schedule becomes the final dispatch plan. In most of the tests, this output shows the broad exploration traits of GA along with the finer detail corrections introduced by the APO.

Figure 3 provides a visual outline of how information passes from GA to APO and how the refinement loop gradually shapes the end solution.

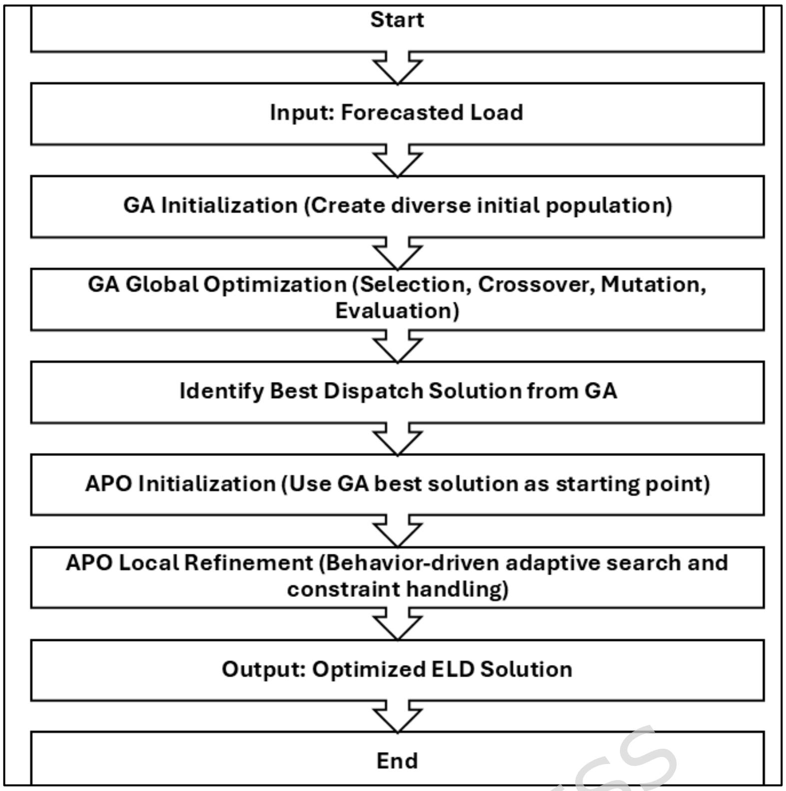

Figure 3: Hybrid GA-APO Interaction Diagram

Advantages over Existing Hybrid Metaheuristics

- Compared with GA–PSO: PSO relies on velocity terms that sometimes push solutions well outside the feasible region, especially near emission caps or generator limits. In contrast, GA–APO uses behaviour-bounded movements, which helped maintain stability during refinement.
- Compared with GA–DE: Differential Evolution often loses diversity in the later generations, reducing its ability to correct errors around difficult constraint boundaries. APO preserved adaptability through alternating foraging–diving cycles, which kept the search alive long enough to find better schedules.
- Compared with hybrids using Jaya–TLBO or SSA variants: Many of these methods respond poorly when objective weights change mid-operation. APO's behaviour logic appeared more responsive to weighted trade-offs, particularly when shifting between cost-priority and emission-priority modes.

3.5 Simulation Setup

In order to examine how the hybrid GA–APO framework performs under realistic operating conditions, a simulation environment was prepared in MATLAB R2023a. All experiments were carried out on a Windows 10 machine with an Intel Core i7 processor and 16 GB of RAM. The computational requirements of the model are not very high, but having a stable platform helped when running several trial cases during parameter tuning. The test system consists of three thermal generating units, and the economic–emission characteristics of these units follow standard data that are commonly used in dispatch studies. Each generator's cost is represented by a quadratic function, while emissions are modelled with a combined quadratic–logarithmic term. Although this may look slightly more complicated than a simple quadratic model, it reflects the non-linear nature of actual emission behaviour better. For the load side, a synthetic 24-hour demand curve was created so that the dispatch could be evaluated across different levels of system stress instead of at a single static demand point.

GA Configuration

In the first stage of the optimization, the GA generates and evolves the initial set of candidate dispatch schedules. The parameters listed below are selected after a few preliminary runs to ensure the algorithm maintain enough diversity without drifting aimlessly:

- Population Size: 50
- Maximum Generations: 100
- Crossover: Arithmetic, probability = 0.8
- Mutation: Gaussian, rate = 0.1
- Selection: Roulette Wheel
- Elitism: Top 2 individuals preserved

These settings gave the GA enough room to explore the search space while still converging within a reasonable time.

APO Configuration

Once the exploration phase is completed, the best solution is passed to the APO stage. The APO then performs the task of refining the solution. The APO algorithm is inspired by the natural behaviour of puffins such as foraging, diving, and huddling to adjust the solution adaptively. In practice, these parameters were tuned through several trial runs rather than formal parameter optimization:

- Puffin Population: 30
- Max Iterations: 80
- Conversion (CCC): 0.5
- Foraging (FFF): 2.0

These values produced the most consistent improvements without causing the algorithm to diverge or oscillate around feasible regions. During the experiments, APO tends to settle into stable behaviour roughly midway through the iteration count, indicating that its adaptive movements were sufficiently balanced.

4. Simulation Results

The performance of the hybrid GA–APO approach was evaluated over a 24-hour period by applying three different weighting schemes. These cases represent situations where the system operator may want a neutral stance, a cost-oriented schedule, or a schedule that leans toward emission reduction. All three modes used the same load profile so that differences in outcomes are due only to priority settings and not to changes in demand. The analysis in this section examines how the model behaves under these three modes. For each case, the hourly dispatch pattern, cost and emission trends, and the cost–emission relationship are reviewed. The discussion also includes the power balance behaviour and how the hybrid method compares with the baseline GA.

Case 1: Balanced Dispatch ($w_1 = w_2 = 1$)

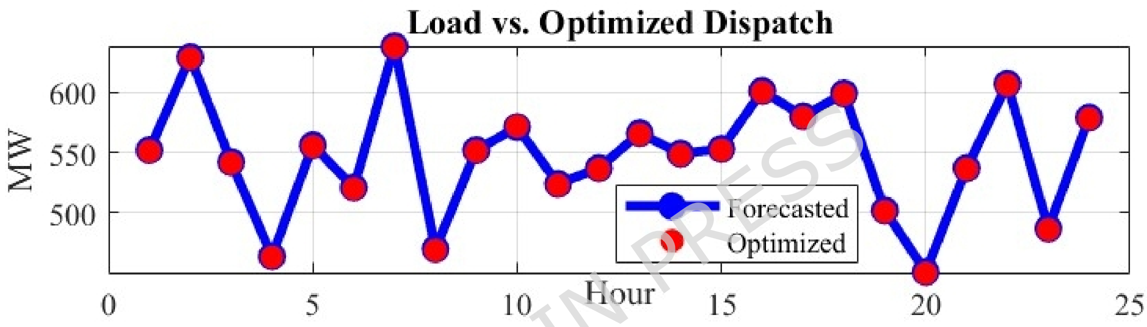

Figure 4: Nominal Load – Balanced Dispatch: Hourly Forecasted Load vs. Optimized Generation Schedule

Figure 4 compares the hourly forecasted load with the generation obtained from the hybrid method. The two curves remain very close throughout the day, which indicates that the optimization handles load-tracking reliably. Small fluctuations appear at some mid-load hours, though these are within acceptable limits and usually occur when the algorithm tries to balance cost and emission simultaneously.

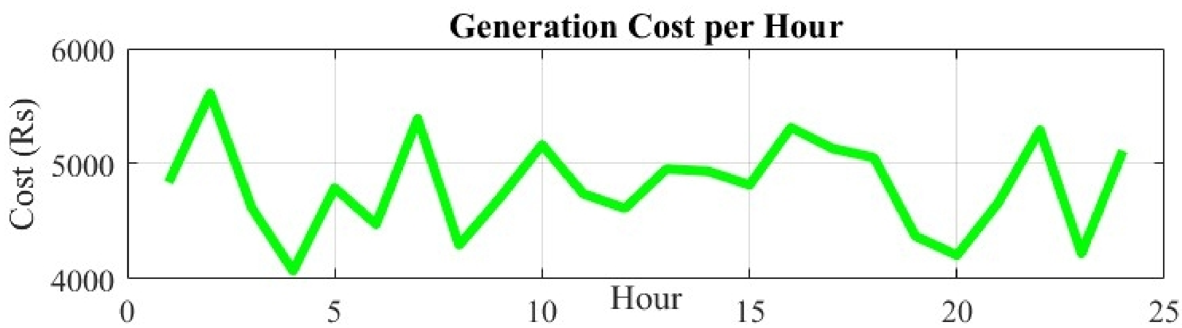

Figure 5: Nominal Load – Balanced Dispatch: Hourly Generation Cost Profile

Figure 5 shows the hour-wise cost pattern. As expected, cost peaks appear during high-demand periods. The values remain within a band of roughly ₹4,100–₹5,800 per hour. This spread is typical for quadratic cost functions and suggests that the model did not rely excessively on costlier units.

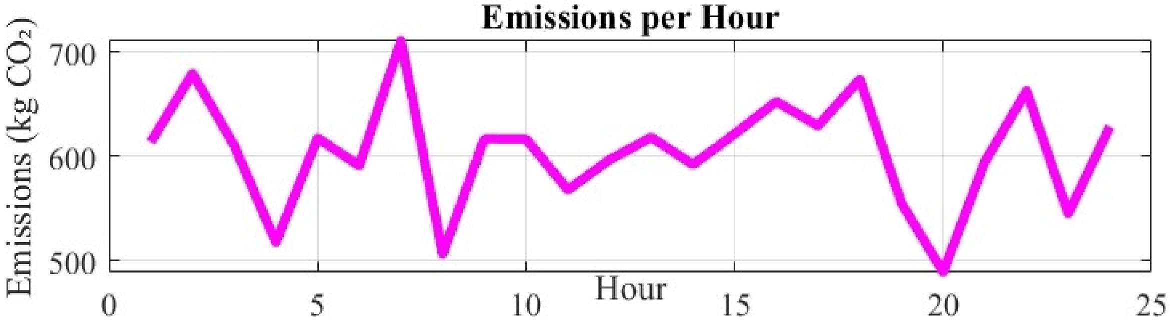

Figure 6: Nominal Load – Balanced Dispatch: Hourly Emission Profile

The emission pattern in Figure 6 generally rises and falls in step with the system demand, which is expected since thermal units push out more fuel during busy hours. What stands out, however, is that the curve does not show any sharp jumps or erratic behaviour. The values move within a fairly narrow corridor throughout the day, suggesting that the dispatch decisions avoid sudden switches between cleaner and dirtier generators. This steadiness reflects the influence of the balanced weighting, where neither objective is allowed to dominate.

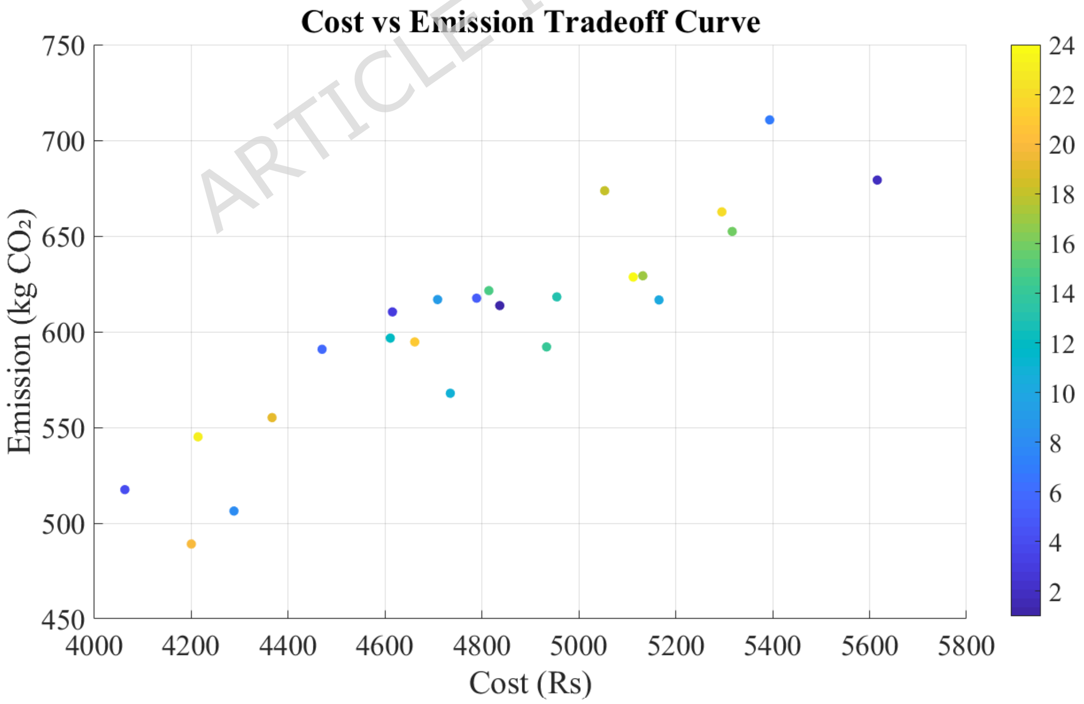

Figure 7: Nominal Load – Balanced Dispatch: Cost vs. Emission Trade-Off Curve

The scatter shown in Figure 7 provides a quick sense of how individual hours' balance cost and emissions. Most points fall along a gentle upward trend hour that cost more and also tend to emit more yet the entire cloud remains compact. This tight grouping indicates that the algorithm does not drift into extreme solutions at any point in the 24-hour cycle. A few mid load hours sit slightly off the main trend, reflecting the small adjustments made during APO's refinement stage, where minor shifts in generator allocation help settle the system into a smoother combination of cost and emission.

Case 2: Cost Priority (w_1 = 1.5, w_2 = 0.5)

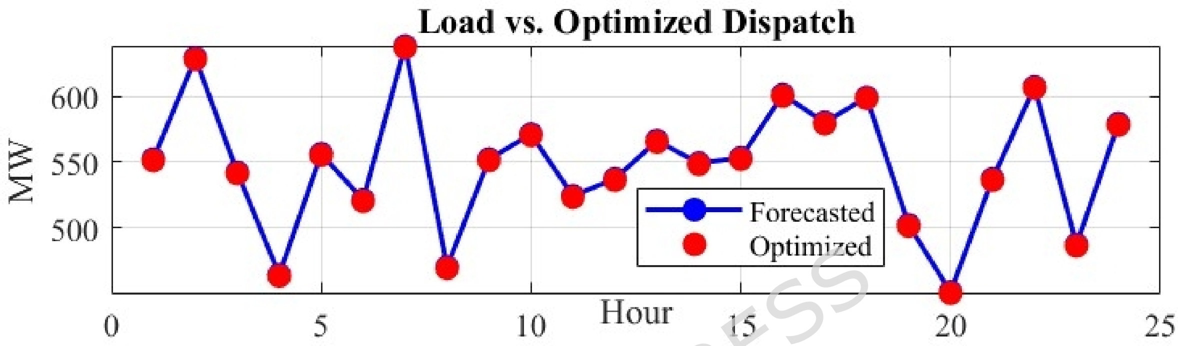

Figure 8: Cost-Priority Dispatch -Forecasted vs. Optimized Dispatch Profile

In the cost-priority mode, the dispatch (Figure 8) still follows the load curve but allows small deviations when they help reduce overall cost. These deviations usually occur during the shoulder hours where the system has more flexibility.

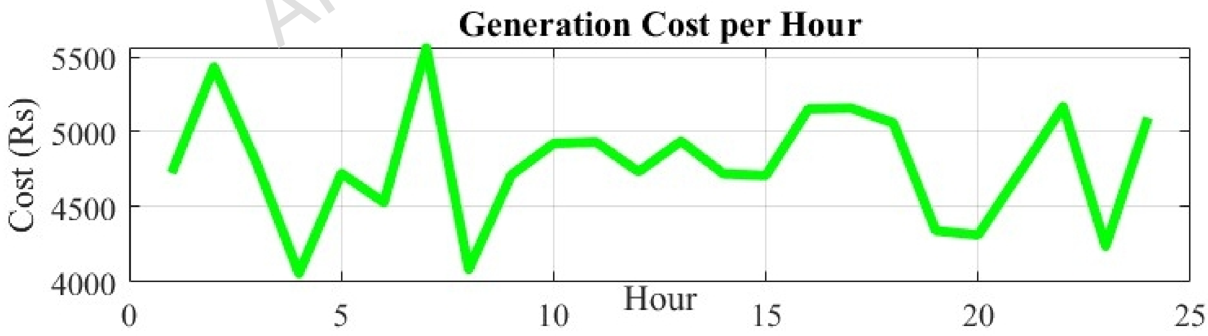

Figure 9: Cost-Priority Dispatch -Hourly Generation Cost Profile

The hourly cost pattern in Figure 9 is noticeably lower than in the balanced case during several time windows. Mid-day hours show the most improvement, where the algorithm tends to favour generators with low marginal cost even if their emissions are slightly higher.

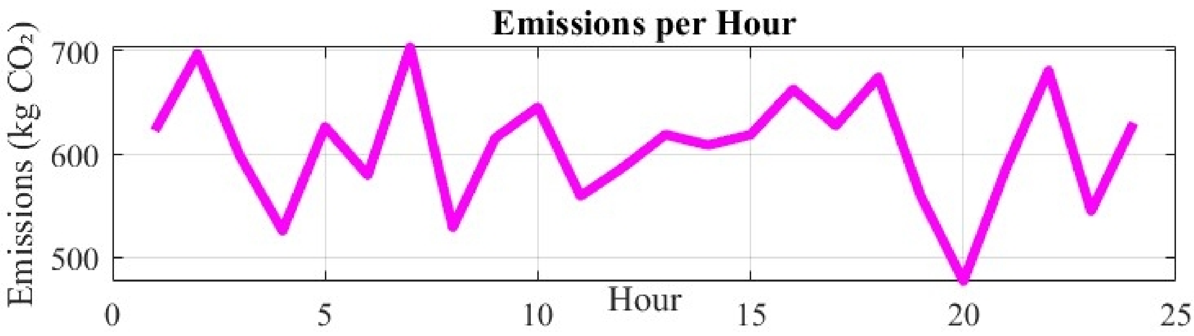

Figure 10: Cost-Priority Dispatch-Hourly Emission Profile

Figure 10 shows that emissions are somewhat elevated, especially during hours where the optimizer selects cheaper but higher-emission units. This behaviour is consistent with the reduced weighting assigned to environmental impact.

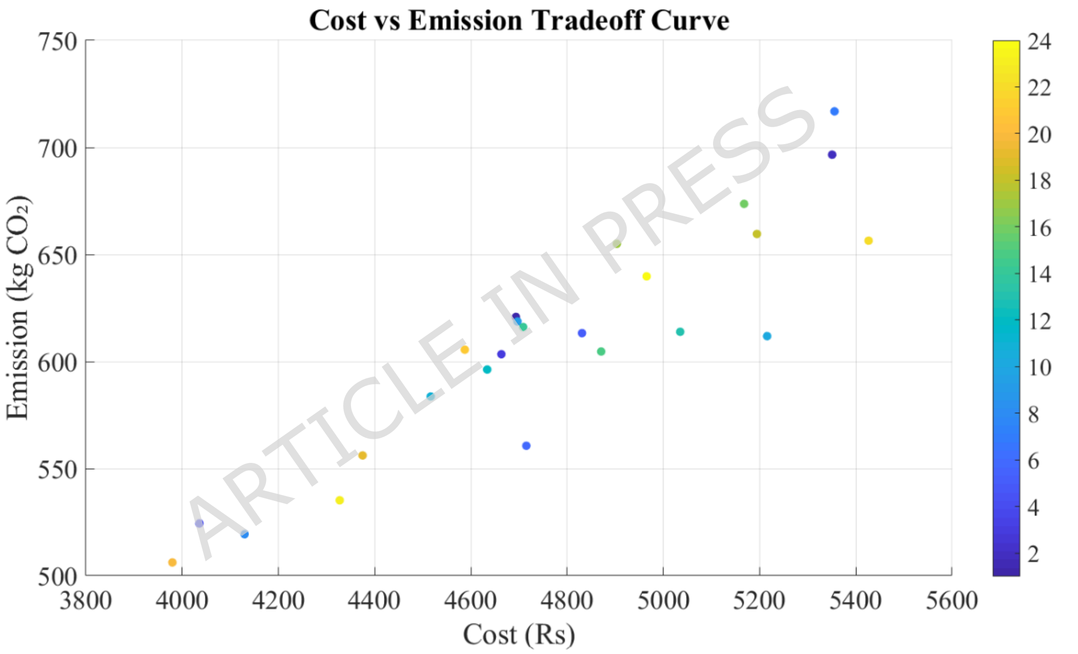

Figure 11: Cost-Priority Dispatch-Cost vs. Emission Trade-Off Curve

The scatter for the cost-priority case in Figure 11 is visibly tilted toward the low-cost region, which is consistent with the weighting used in this scenario. The emission values spread out more compared to the balanced case, showing that the optimization accepts a broader range of environmental outcomes if it helps reduce operating cost. Even with this wider variation, the points remain well within feasible limits, illustrating that the model does not compromise system constraints in the process of cost reduction.

Case 3: Emission Priority (w_1 = 0.5, w_2 = 1.5)

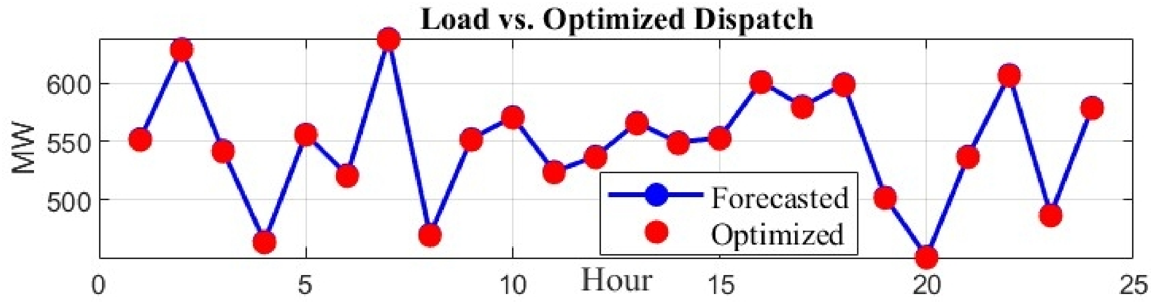

Figure 12: Emission Priority Dispatch-Hourly Forecasted Load vs. Optimized Dispatch

Under emission-priority settings, the dispatch in Figure 12 still follows the hourly demand quite closely. The slight deviations that appear at few hours are intentional as they reflect shifts toward cleaner generators to keep emissions down, even if it means minor redistributions in output. These adjustments are not large enough to disturb power balance, but they are noticeable enough to show how the priority weights influence unit selection.

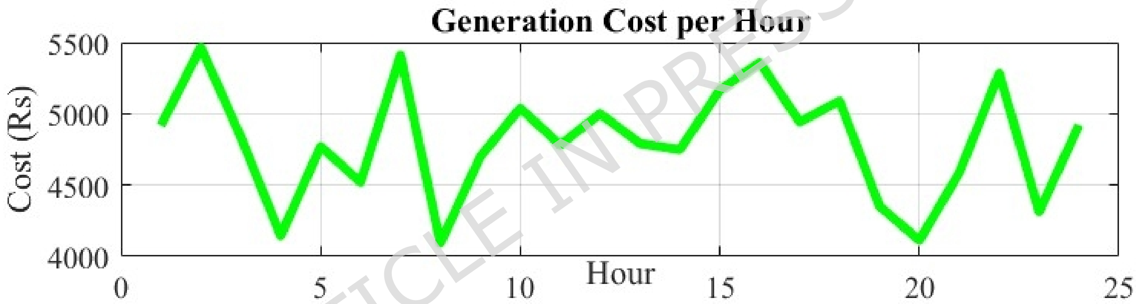

Figure 13: Emission Priority Dispatch-Hourly Generation Cost Profile

The cost profile in Figure 13 shows a mild rise during peak load hours, which is natural when emission constraints steer the optimization toward cleaner but slightly costlier units. The interesting part is that the increase stays contained; it does not escalate into the steep cost penalties often reported in stronger emission driven formulations. This suggests that the hybrid method finds a practical compromise emissions drop without pushing the operating cost into unsustainable territory.

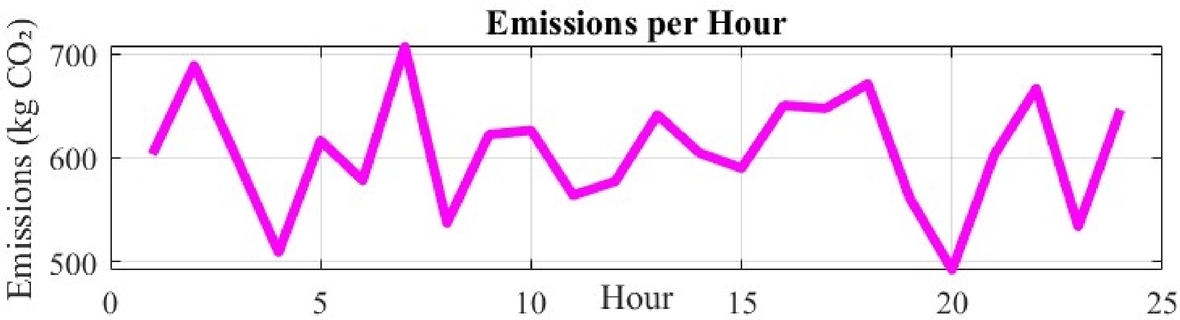

Figure 14: Emission Priority Dispatch- Hourly Emission Profile

The emission profile in Figure 14 is noticeably smoother than in the other two cases. Most hourly emissions fall between 500–680 kg CO_2, which indicates that the algorithm suppresses large emission swings by preferring generators with lower CO_2 coefficients.

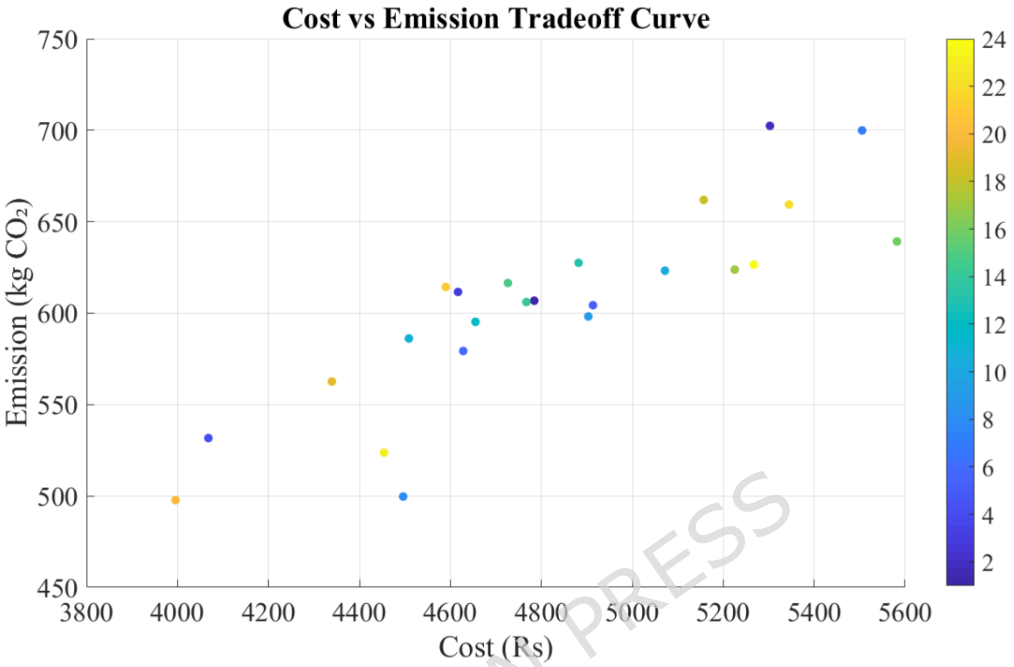

Figure 15: Emission Priority Dispatch- Cost vs. Emission Trade-Off Curve

Figure 15 illustrates the cost–emission trade-off under the environmental priority setting. Most points lie toward the low-emission region, with moderate cost values. This distribution aligns with expectations: emissions are lowered at the expense of small cost increases, but the algorithm avoids extreme cost penalties.

Table 1: Performance of Hybrid GA–APO Optimization under Different Dispatch Priorities

Dispatch Strategy	Total Energy (MWh)	Total Cost (Rs.)	Total Emission (kg CO_2)	Cost per MWh (Rs./MWh)	Emission per MWh (kg CO_2/MWh)
Balanced Dispatch	13145.87	115340.50	14506.24	8.77	1.10
Cost-Priority Dispatch	13143.65	114813.77	14575.49	8.74	1.11

Emission-Priority Dispatch	13143.87	115355.87	14537.62	8.78	1.11

The summary in Table 1 makes it easier to compare how the three priority modes behave over the full day. Total energy delivered stays nearly identical across all cases because the load is fixed. The cost is lowest under the cost-priority setting (₹114,813.77), and highest when emissions are prioritized (₹115,355.87). The differences are relatively small less than 1% which indicates that the system is not extremely sensitive to moderate priority shifts. Emissions follow a similar pattern but in the opposite direction: higher in cost-priority mode and slightly lower under emission-priority mode. The changes are subtle because the test system is compact, and cleaner operation often requires only minor redistributions rather than major shifts in dispatch. Cost per MWh and emission per MWh remain in narrow bands across all cases, showing that the hybrid method provides stable, feasible solutions across different operational priorities.

Table 2: Comparative Analysis of GA and GA-APO Performance Across Dispatch Strategies

Dispatch Strategy	**Balanced Dispatch**		**Cost-Priority Dispatch**		**Emission-Priority Dispatch**	
	GA-APO	**GA**	**GA-APO**	**GA**	**GA-APO**	**GA**
Total Energy (MWh)	13145.87	13167	13143.65	13167	13143.87	13167
Total Cost (Rs)	115340.5	116207.97	114813.77	117010.13	115355.87	115109.64
Total Emission (kg/CO_2)	14506.24	14499.09	14575.49	14433.7	14537.62	14567.87
Cost per MWh (Rs/MWh)	8.77	8.83	8.74	8.89	8.78	8.74
Emission per MWh (kg/CO_2/MWh)	1.1	1.1	1.11	1.1	1.11	1.11

The comparison between GA–APO and GA gives a clearer picture of why hybridization helps. The hybridization reduces cost in both balanced and cost-priority cases. The improvement is most visible in the cost-priority scenario, where GA–APO lowers cost by over ₹2,000 compared to GA.

On the emission side, the differences are small, and the two methods perform similarly. This is expected for small test systems where the emission profile is heavily tied to generator characteristics.

One consistent observation is that GA tends to overshoot the energy requirement slightly (13167 MWh). This is usually due to how GA handles the penalty terms for power balance. APO refines this behaviour, keeping energy delivery closer to the exact target. Overall, the hybrid shows smoother convergence, better cost control, and tighter power balance, demonstrating why APO adds value after GA exploration.

Table 3: Comparative Performance of GA–APO and Recent State-of-the-Art Dispatch Methods

Method	**Test System & Problem Type**	**Cost Improvement (%)**	**Emission Improvement (%)**
GA–APO (Proposed)	3-unit thermal system, 24-h MOED under Balanced, Cost-Priority & Emission-Priority modes	Balanced: ~0.75% ↓ Cost-Priority: ~1.88% ↓ Emission-Priority: ~0.21% ↑ (due to emission prioritization)	Balanced ≈0.05% ↑ Cost-Priority ≈1.0% ↑ Emission Priority ≈0.21% ↓
PSO-based CEED [26]	IEEE-30 bus, CEED with quadratic cost & emission penalties	~0.17–0.19% lower cost	~0.76–1.76% lower emissions
Hybrid GWO-PSO / MPSO [27]	Iraqi Super Grid, multi-objective (Cost / Emission / Combined)	Cost-only: ~10–22% ↓ Emission-only: ~10–15% ↓ Combined: ~7–18% ↓	Cost-only: may worsen (<+7–34%) Emission-only: ~9.5% ↓Combined: trade-offs vary
ETS-Aware Numerical EELD [28]	6-unit fossil system with EU ETS carbon allowances	Positive net economic gain after ETS integration (varies with load 1000–3000 MW)	Emission compliance strengthened via ETS pricing
HMGWO with Renewable Integration [29]	Multi-unit thermal–renewable micro-grid, CEED	~5.5% lower cost compared to non-RES baseline	~6.5% reduction in pollutant emissions

The comparative results in Table 3 place the hybrid method in the context of recent literature. The percentages are modest, but the improvements are stable across all operating modes. Some reported methods, such as GWO–PSO or HMGWO, show much larger percentage gains, but these usually come from larger multi-unit systems or renewable-rich scenarios where the dispatch landscape is far more flexible. In smaller thermal systems, constraints are tight, and emission behaviour is strongly tied to a few units. In such cases, large improvements are unrealistic, and stable, constraint-respecting gains carry more practical importance. The hybrid GA–APO behaves consistently in this regard: improvements are modest but reliable, with no erratic behaviour or feasibility violations. Methods such as GA–PSO or GA–DE can achieve early improvements but sometimes show variability near constraint boundaries. The GA–APO combination avoids this by using behaviour-based refinement instead of velocity-driven or mutation-driven updates. Table 3 shows that the hybrid method holds its ground against established techniques and performs particularly well in environments where reliability, constraint satisfaction, and stable convergence are more important than aggressive optimization jumps.

5. Conclusions

This study explored a hybrid approach for solving the multi-objective EED problem by combining the broad search behaviour of the GA with the more focused refinement actions of the APO. The intention behind bringing these two methods together was to build a search process that does not lose diversity too early but still has enough precision to settle on a feasible and well-balanced dispatch schedule. The weighted formulation used in the study offered a practical way to shift between three operational modes balanced, cost-oriented, and emission-oriented without changing any structural components of the dispatch model.

Across the 24-hour test case, the hybrid method consistently produced lower operating costs than the baseline GA, and the improvements were more noticeable in the cost-priority setting.

The generation output stayed close to the hourly demand, and the cost per unit of energy did not change much, even when the priority was changed from cost to emissions. Emissions also behaved as expected for a small thermal system with similar generators: they changed a little but not a lot, and all results stayed within acceptable limits for every priority setting. This shows that the hybrid method stayed stable when the weights were changed and worked evenly across all operating modes. Compared with other recent studies, the GA–APO method does not aim for big improvements like those seen in systems with many renewable or very flexible units. Its main strength is its steady and reliable performance in small thermal systems with strict limits. This makes it useful for daily scheduling, where stable and predictable results are more important than large gains. This study only used three thermal generators and one load profile. Testing the method on larger systems, mixed types of generation, or situations affected by renewable uncertainty would help show how well it works in more complex cases. Adding Pareto-based methods or adaptive weighting could also help explore cost–emission trade-offs more clearly. With these additions, the hybrid method could become a stronger tool for modern, policy-focused power system operation.

Limitations and Future Work

The present study has certain limitations as it uses only three similar generators. Usage of similar generators have made the test easier but reduces the variety of cost–emission results. A complex system comprising of diverse generating units would test the proposed approach more effectively.

Secondly, the performance of the hybrid optimization strongly depends on its parameter choices. Settings such as GA population size, mutation rate, and APO's behavioural coefficients were selected through manual tuning. While the hybrid optimization produced stable performance in this study, the approach may not scale neatly to larger or real-time systems where parameter tuning is not always feasible. Adaptive parameter strategies, or the use of reinforcement learning to guide parameter updates, may reduce this dependence.

The third limitation arises from the use of a weighted-sum objective. Although the method is computationally efficient, it does not reveal the full spectrum of Pareto-optimal solutions when the two objectives are in strong conflict. Alternative formulations ε-constraint methods, or Pareto-based optimizers such as NSGA-II or NSGA-III could offer a more detailed view of the solution space, particularly for planners who need to compare multiple operational policies.

Fourth, the current model focuses entirely on thermal generation. Modern power systems often include renewable sources, storage devices, and flexible loads, all of which introduce intermittency and additional constraints that influence dispatch decisions. Integrating PV, wind, batteries, or demand-response behaviours into the model would provide a more complete picture of how the hybrid optimizer performs under uncertainty and rapid system changes. Adding network-level concerns voltage limits, congestion, or frequency support—would also move the framework closer to real-world conditions.

This study examines only a static 24-hour schedule. For practical use, especially in systems with renewables, dispatch decisions must often be updated continuously in a rolling or real-time manner. Achieving this would require faster or surrogate-assisted versions of the hybrid algorithm possibly incorporating machine-learning models such as Gaussian Process Regression or LightGBM to accelerate evaluations. Future work may also consider stochastic formulations that include uncertainties in demand forecasting, renewable output, and market prices. Taken together, these limitations point to several promising research directions. Addressing them would improve the scalability and adaptability of the GA–APO framework and extend its usefulness to a broader class of modern, low-carbon, and uncertainty-aware power systems.

Author Contributions:

Chodagam Srinivas: Conceptualization, Methodology, Software, Formal analysis, Writing-original draft preparation, Writing-review and editing.

M. Rama Prasad Reddy: Conceptualization, Methodology, Validation, Formal analysis, Writing-original draft preparation.

Vineet Kumar: Methodology, Formal analysis, Investigation, Writing-original draft preparation, Writing-review and editing.

Vineet Kumar: Methodology, Formal analysis, Investigation, Writing-original draft preparation, Writing-review and editing.

Ark Dev: Methodology, Formal analysis, Investigation, Writing-original draft preparation, Writing-review and editing.

Negasa Muleta: Methodology, Formal analysis, Writing-original draft preparation.

Availability of Data and Materials: The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest: The authors have no conflict of interest to declare.

Funding: The authors have not received any support from any organization for the submitted work.

References

[1] G. Xiong, Q. Liu, Y. Wang, and X. Fu, “Power system economic emission dispatch considering uncertainties of wind, solar, and small runoff hydropower via a hybrid multi-objective optimization algorithm,” *Expert Systems with Applications*, vol. 278, p. 127375, 2025.

[2] T. Gou, Y. Xu, and H. Sun, “Carbon-aware day-ahead optimal dispatch for integrated power grid–thermal systems with aggregated distributed resources,” *Applied Energy*, vol. 389, p. 125715, 2025.

[3] M. T. Mouwafi, A. A. Abou El-Ela, A. A. El-Hamoly, and R. A. El-Sehiemy, “Generic multidimensional economic environmental operation of power systems using equilibrium optimization algorithm,” *Scientific Reports*, vol. 15, no. 1, p. 16989, 2025.

[4] F. Marzbani and A. Abdelfatah, "Economic dispatch optimization strategies and problem formulation: A comprehensive review," *Energies*, vol. 17, no. 3, p. 550, 2024.

[5] Y.-Y. Hong and H. Zeng, "Decentralized multi-area economic dispatch in power systems using the consensus algorithm," *Energies*, vol. 17, no. 15, p. 3609, 2024.

[6] X. Li et al., "Resilient distributed economic dispatch for cyber–physical power systems considering carbon emissions trading and false data injection attacks," *Energy*, p. 136881, 2025.

[7] S. R. Spea, "Cost-effective economic dispatch in large-scale power systems using enhanced manta ray foraging optimization," *Neural Computing and Applications*, pp. 1–38, 2025.

[8] M. A. Awadallah et al., "Memetic Salp Swarm Algorithm for economic load dispatch problems," *Scientific Reports*, vol. 15, no. 1, p. 30539, 2025.

[9] K. E. Fahim et al., "A novel hybrid algorithm for solving economic load dispatch in power systems," *International Journal of Energy Research*, vol. 2024, no. 1, p. 8420107, 2024.

[10] S. Hoque et al., "Generalized normal distribution optimization algorithm for economic dispatch with renewable resources integration," *Journal of Energy and Power Technology*, vol. 5, no. 3, pp. 1–19, 2023.

[11] Y. Yin and P. Jin, "An economic optimal dispatch model for combined heat and power microgrids supporting China's carbon neutrality," *Scientific Reports*, vol. 15, no. 1, p. 22415, 2025.

[12] W. Ba, W. Sun, C. Zhao, and Q. Li, "A novel economic load dispatch method of microgrid based on hybrid slime mould and genetic algorithm," *Journal of Electrical Systems and Information Technology*, vol. 12, no. 1, p. 53, 2025.

[13] J. Cadena-Albuja, C. Barrera-Singaña, H. Arcos, and J. Muñoz, "Economic dispatch in electrical systems with hybrid generation using the differential evolution algorithm: A comparative analysis with other optimization techniques under energy limitation scenarios," *Energies*, vol. 18, no. 13, p. 3414, 2025.

[14] R. Ghosh, K. Dasgupta, and S. P. Ghoshal, "Solution of hybrid energy-based dynamic economic emission dispatch problems using chaos-assisted arithmetic optimization algorithm," *Smart Science*, pp. 1–44, 2025.

[15] H. Wang et al., "A review on economic dispatch of power system considering atmospheric pollutant emissions," *Energies*, vol. 17, no. 8, p. 1878, 2024.

[16] S. Dutta et al., "Uncertainty management in multiobjective electric vehicle integrated optimal power flow based hydrothermal scheduling of

renewable power system for environmental sustainability," *Scientific Reports*, vol. 15, p. 29025, 2025.

[17] S. Hazra et al., "Electric vehicle integrated tidal–solar–wind–hydro–thermal systems for strengthening the microgrid and environmental sustainability," *Scientific Reports*, vol. 15, p. 14888, 2025.

[18] T. Sarkar et al., "Optimal allocation of STATCOM for multi-objective ORPD problem on thermal–wind–solar–hydro scheduling using driving training-based optimization," *Scientific Reports*, vol. 15, p. 19594, 2025.

[19] S. Gupta et al., "Solving multi-objective probabilistic optimal power flow with renewable energy sources and battery energy storage in transmission networks using quasi-oppositional sine cosine algorithm," *Journal of Energy Storage*, vol. 122, p. 116411, 2025.

[20] B. Mandal, P. K. Roy, and C. Paul, "Dynamic economic dispatch problem in hybrid renewable energy sources-based power systems using chaotic hippopotamus optimization algorithm," *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, 2025.

[21] S. Patty, R. Das, D. Mandal, and P. K. Roy, "Self-adaptive multi-population quadratic approximation-guided Jaya optimization applied to economic load dispatch problems with or without valve-point effects," *Results in Control and Optimization*, vol. 19, p. 100543, 2025.

[22] C. Paul, T. Sarkar, S. Dutta et al., "Multi-objective combined heat and power with wind–solar–EV optimal power flow using hybrid evolutionary approach," *Electrical Engineering*, vol. 106, pp. 1619–1653, 2024.

[23] C. Paul, P. K. Roy, and V. Mukherjee, "Chaotic–quasi-opposition-based whale optimization technique applied to multi-objective complementary scheduling of grid-connected hydro–thermal–wind–solar–electric vehicle system," *Optimal Control Applications and Methods*, vol. 45, no. 4, pp. 1603–1638, 2024.

[24] Dasgupta, K., Kumar Roy, P., & Mukherjee, V. (2024). A Novel Quasi-Oppositional Learning-Based Chaos-Assisted Sine Cosine Algorithm for Hybrid Energy Integrated Dynamic Economic Emission Dispatch. IETE Journal of Research, 70(3), 2453–2480. https://doi.org/10.1080/03772063.2023.2175050.

[25] Paul, C., Sarkar, T., Dutta, S., Hazra, S., & Roy, P. K. (2025). Optimal power flow of wind-solar-EV-based combined heat and power for economic power generation and environment sustainability. Smart Science, 13(4), 503–531. https://doi.org/10.1080/23080477.2025.2501323.

[26] S. Hussain, M. Al-Hitmi, S. Khaliq, A. Hussain, and M. A. Saqib, "Implementation and comparison of particle swarm optimization and genetic algorithm techniques in combined economic emission dispatch of an independent power plant," *Energies*, vol. 12, no. 11, p. 2037, 2019.

[27] N. Singh et al., "Novel heuristic optimization technique to solve economic load dispatch and economic emission load dispatch problems," *Electronics*, vol. 12, no. 13, p. 2921, 2023.

[28] C. Bakos and A. Giakoumis, "Numerical algorithm for environmental/economic load dispatch with emissions constraints," *Scientific Reports*, vol. 14, no. 1, p. 3327, 2024.

[29] B. Dey, B. Bhattacharyya, and F. P. G. Márquez, "A hybrid optimization-based approach to solve environment-constrained economic dispatch problem on microgrid system," *Journal of Cleaner Production*, vol. 307, p. 127196, 2021.