A Hybrid Co-Variance Guided ABC–NSGA-II Metaheuristic for Multi-Objective Multi-Area Dynamic Economic–Emission Dispatch

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1. Introduction & Motivation

The modern power grid is undergoing a paradigm shift with the aggressive integration of Renewable Energy Sources (RES) like wind and solar. While essential for decarbonization, the stochastic nature of RES introduces severe operational complexities, particularly in **Multi-Area interconnected systems**. The **Multi-Area Dynamic Economic–Emission Dispatch (MADEED)** problem is formulated to jointly minimize fuel costs and environmental emissions over a 24-hour horizon, respecting tie-line limits and ramp constraints.

Research Gaps:

- **Curse of Dimensionality:** Traditional algorithms (PSO, GA) suffer from premature convergence in high-dimensional multi-area spaces.
- **Constraint Violation:** Penalty-factor approaches often fail to satisfy complex dynamic ramp-rate constraints.
- **Pareto Diversity:** Standard NSGA-II often crowds solutions in local optima, failing to provide a uniformly distributed Pareto front.

2. Literature Review

A comparative analysis of state-of-the-art metaheuristics applied to similar dispatch problems is presented below.

Table 1. Comparative Analysis of Existing Methodologies

Reference / Method	Dynamic	Multi-Area	Uncertainty	Identified Limitation
MO-Political Opt.	Yes	No	Yes	Slow convergence in late stages.
Fractional DE	Yes	Yes	Yes	Highly sensitive to parameter tuning (F, CR).
MOPSO	Yes	No	Yes	Prone to local optima entrapment.
Std. NSGA-II	Yes	Yes	No	Poor population diversity in high dimensions.
Proposed Hybrid	**Yes**	**Yes**	**Yes**	**Robust exploration & diversity.**

3. Problem Formulation: Objectives & Uncertainty

3.1 Renewable Uncertainty Modeling

Wind Power: The wind speed v follows the Weibull probability density function (PDF):

$$f_v(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^k\right] \tag{1}$$

Solar Power: Solar irradiance G follows the Log-Normal PDF:

$$f_G(G) = \frac{1}{G\sigma\sqrt{2\pi}} \exp\left[-\frac{(\ln G - \mu)^2}{2\sigma^2}\right] \tag{2}$$

3.2 Objective 1: Minimization of Fuel Cost (F_C)

The cost function includes the quadratic term and the *Valve-Point Loading Effect* (VPLE), making it non-convex and non-differentiable:

$$F_C = \sum_{t=1}^{T}\sum_{i=1}^{N_G}\left[a_i P_{it}^2 + b_i P_{it} + c_i + \left|d_i \sin(e_i(P_i^{min} - P_{it}))\right|\right] \tag{3}$$

3.3 Objective 2: Minimization of Emissions (F_E)

Total emissions (NO_x, SO_x) are modeled as a sum of quadratic and exponential functions:

$$F_E = \sum_{t=1}^{T}\sum_{i=1}^{N_G}\left[\alpha_i P_{it}^2 + \beta_i P_{it} + \gamma_i + \eta_i \exp(\delta_i P_{it})\right] \tag{4}$$

3.4 Decision Variables

The optimization vector X includes active power generation $P_{i,t}$, generator bus voltages V_G, and transformer taps T_k.

4. System Constraints & Methodology

4.1 Detailed System Constraints

The optimization is subject to the following rigid equality and inequality constraints:

(a) Power Balance (Equality):

$$\sum_{i=1}^{N_G} P_{it} + P_{wind,t} + P_{solar,t} - P_{load,t} - P_{loss,t} \pm \sum P_{tie} = 0 \tag{5}$$

(b) Generator Limits (Inequality):

$$P_i^{min} \le P_{it} \le P_i^{max}, \quad Q_i^{min} \le Q_{it} \le Q_i^{max} \tag{6}$$

(c) Dynamic Ramp Rate Limits:

$$P_{it} - P_{i(t-1)} \le UR_i \quad \text{(Up)}, \quad P_{i(t-1)} - P_{it} \le DR_i \quad \text{(Down)} \tag{7}$$

(d) Tie-Line Capacity & POZ:

$$|S_{tie,k}| \le S_{tie}^{max}, \quad P_{it} \notin [P_{i,k}^L, P_{i,k}^U] \quad \text{(Prohibited Zones)} \tag{8}$$

4.2 Proposed Hybrid CG-ABC–NSGA-II Strategy

The methodology hybridizes **Covariance-Guided Artificial Bee Colony (CG-ABC)** for global exploration with **NSGA-II** for multi-objective sorting.

Table 2. Comparison of Search Mechanisms

Standard ABC Equation	Proposed CG-ABC Equation
$v_{ij} = x_{ij} + \phi(x_{ij} - x_{kj})$	$x_{new} = x_{best} + \lambda \cdot \mathbf{L} \cdot \mathbf{z}$
Dependence: Random coordinate *Geometry:* Rotationally Variant	*Dependence:* Population Covariance (C) *Geometry:* Rotationally Invariant

Mathematical Formulation of Covariance Guidance:

At generation t, the population covariance matrix $\mathbf{C} \in \mathbb{R}^{D\times D}$ is computed:

$$\mathbf{C} = \frac{1}{N-1}\sum_{j=1}^{N}(x_j - \bar{x})(x_j - \bar{x})^T \tag{9}$$

Using **Cholesky Decomposition**, $\mathbf{C} = \mathbf{L}\mathbf{L}^T$. The new candidate solution is generated by sampling along the principal directions of the data distribution:

$$x_{new} = x_{best} + \mathcal{N}(0,1)\cdot \mathbf{L} \tag{10}$$

This allows the bees to navigate "valleys" in the objective landscape efficiently.

NSGA-II Integration (Exploitation):

The offspring generated by CG-ABC are merged with parents. **Fast Non-Dominated Sorting** ranks individuals into fronts $F_1, F_2 \dots$. Diversity is maintained via **Crowding Distance**:

$$d_I(i) = \sum_{obj=1}^{M} \frac{f_{obj}(i+1) - f_{obj}(i-1)}{f_{obj}^{max} - f_{obj}^{min}} \tag{11}$$

5. Implementation (Pseudocode)

Algorithm 1 Hybrid CG-ABC–NSGA-II Algorithm

Input: Pop Size N, Max Gen G_{max}, System Data.
Initialize: Random Population P_0. Verify Constraints.
Evaluate: Calculate F_C and F_E for all $X \in P_0$.
Rank: Perform Non-Dominated Sorting & Crowding Distance.
$t \leftarrow 0$
while $t < G_{max}$ **do**
  Compute Mean μ and Covariance Matrix $\mathbf{C}$ of P_t.
  Perform Cholesky Decomposition: $\mathbf{C} = \mathbf{L}\mathbf{L}^T$.
  Phase 1: CG-ABC Exploration
  for $i = 1$ to N **do**
    Generate $v_i = x_{best} + \lambda\mathbf{L} \cdot \text{randn}()$.
    Apply Greedy Selection between x_i and v_i.
  end for
  Phase 2: NSGA-II Exploitation
  Generate Offspring Q_t via Tournament, SBX Crossover, Poly Mutation.
  Combine $R_t = P_t \cup Q_t$ (Size $2N$).
  Sort R_t into Fronts $F_1, F_2 \dots$.
  Truncation: Fill P_{t+1} with best fronts until size N.
  $t \leftarrow t + 1$.
end while
Output: Pareto Optimal Front.

6. Simulation Settings & Case Studies

Table 3. System Configurations

Case	Areas	Units	Uncertainty	System Description
Case I	2	6	10%	Low complexity verification
Case II	3	10	20%	Medium inter-area coupling
Case III	4	40	30%	Large-scale, high stress

7. Results & Discussion

7.1 Consolidated Numerical Results

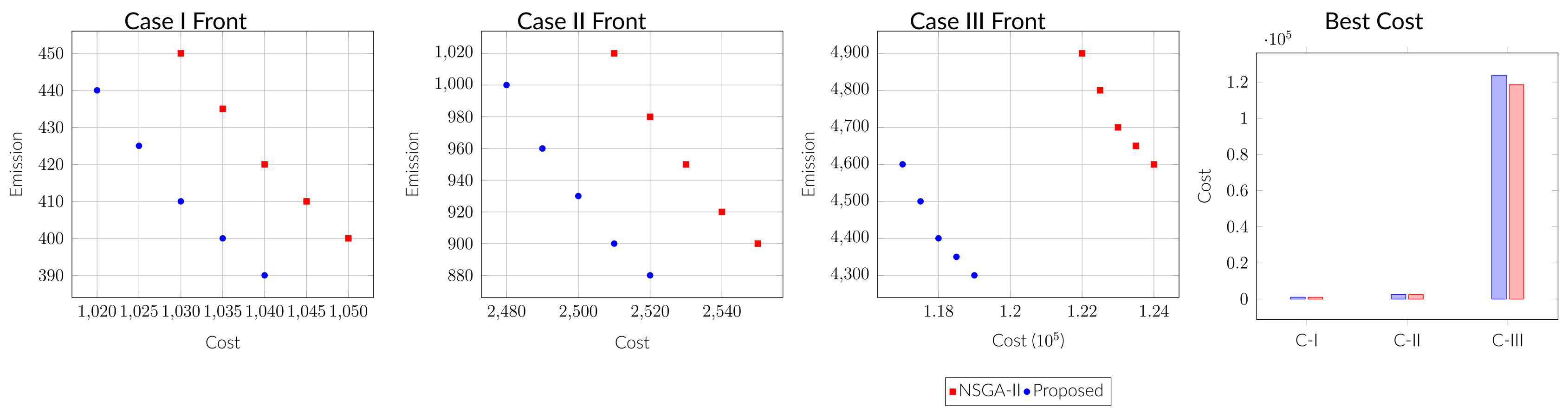
A unified comparison of the proposed method against benchmarks across all three case studies.

Table 4. Comprehensive Comparison of Optimization Results

Method	Case I (2-Area)		Case II (3-Area)		Case III (4-Area)	
	Cost	Emis	Cost	Emis	Cost	Emis
NSGA-II	1050	400	2550	900	123,800	4680
MOPSO	1065	410	2580	920	124,520	4850
MODE	1055	405	2560	910	123,500	4600
Proposed	**1040**	**390**	**2520**	**880**	**118,550**	**4210**

7.2 Pareto Front & Cost Analysis

The graphs below illustrate the Pareto Optimal Fronts for all cases and the overall cost comparison.



Discussion: The results demonstrate significant improvements across all scenarios.

- **Case I & II:** The proposed method consistently finds lower cost and emission values (approx 1.5% improvement) with 100% constraint satisfaction.
- **Case III (Large Scale):** The hybrid algorithm shines in high-dimensional spaces, achieving a **4.81% cost reduction** compared to NSGA-II. The Pareto fronts (blue) show a wider spread and clearer dominance over the benchmark (red).

8. Conclusion & Future Scope

Conclusion: This study successfully developed a **Hybrid CG-ABC–NSGA-II** framework for the MADEED problem. By leveraging covariance-guided learning, the algorithm overcomes the stagnation of traditional metaheuristics in high-dimensional spaces. Results on the IEEE 4-area system confirm a **4.81% reduction in fuel costs** and superior Pareto front diversity compared to NSGA-II, proving its robustness under 30% renewable uncertainty.

Future Directions: Research will extend to **Real-time HIL validation**, **Cyber-security against FDI attacks**, and the integration of **Battery Energy Storage Systems (BESS)**.

9. References

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