

Optimization Techniques for Renewable Energy Distribution in Smart Grids

Dr. Deepti Raut; Vidya Tidole,
G H Raison Skill Tech University,

Abstract

Sustainable energy management requires the integration of renewable energy sources like solar and wind into smart grids, but this is difficult because of their intermittent and unpredictable nature. Conventional optimization techniques, such as linear and convex programming, offer deterministic answers but are not flexible enough to deal with uncertainty. Although metaheuristic algorithms are flexible, they frequently have issues with scalability and convergence. In order to reduce operating costs, maximise renewable utilisation, and preserve grid stability, this research suggests a hybrid optimisation framework that blends deterministic optimisation with metaheuristic techniques. The hybrid model outperforms traditional approaches, yielding cost reductions of up to 20% and better renewable integration, according to simulation studies using real-world datasets. In order to advance sustainable energy systems, the findings provide policymakers and industry stakeholders fresh perspectives.

Keywords: Renewable energy, smart grids, optimization, metaheuristics, sustainability, hybrid models.

1. Introduction:

In order to attain sustainability objectives and lower greenhouse gas emissions, the global energy sector is shifting to renewable sources. This shift is largely dependent on smart grids, which incorporate cutting-edge control and communication technology. However, energy distribution is complicated by variations in wind speed and solar irradiation, making it difficult to balance supply and demand while preserving grid stability (Liu et al., 2023).

In order to overcome these obstacles, optimisation techniques are essential. To reduce expenses and guarantee effective energy dispatch, deterministic techniques like linear programming (LP) and convex optimisation have been extensively used (Conejo et al., 2010; Boyd & Vandenberghe, 2004). However, these techniques rely on steady inputs, which limits their usefulness in grids that are dominated by renewable energy. While metaheuristic algorithms, such as genetic algorithms (GA) and particle swarm optimisation (PSO), offer flexibility in managing uncertainty, they frequently encounter problems with scalability and convergence (AlRashidi & El-Hawary, 2009; Mohammadi-Ivatloo et al., 2017).

Hybrid techniques are becoming increasingly important, according to recent studies. In their thorough analysis of optimisation algorithms in smart grids, Aslam et al. (2024) highlighted the necessity of adaptive frameworks that integrate stochastic and deterministic techniques. In microgrid scheduling, Zhang et al. (2022) showed that hybrid GA-LP models perform better than standalone methods.

In this work, a hybrid optimisation approach combining metaheuristic adaptability with deterministic scheduling is presented. Its capacity to dynamically adjust to renewable variability while preserving grid stability and cost effectiveness is what makes it distinctive. This study attempts to give policymakers, researchers, and industry stakeholders practical insights by applying the model to real-world information.

2. Literature Review

Over the past ten years, optimisation in smart grids has changed dramatically. Early research concentrated on linear programming models that reduced operating expenses in situations with deterministic demand (Wood & Wollenberg, 2012). Later, convex optimisation

appeared, providing better stability analysis and global optimality, especially in demand-side management (Boyd & Vandenberghe, 2004).

Because they can deal with uncertainty, metaheuristic algorithms became popular. While PSO has been used to represent adaptive search processes in stochastic contexts, GA has been used to optimise energy scheduling by evolving solutions through crossover and mutation (Kennedy & Eberhart, 1995; AlRashidi & El-Hawary, 2009). Although these techniques showed increased flexibility, they frequently encountered difficulties with computational scalability and convergence speed.

Hybrid techniques are emphasised in recent research. Research integrating LP with GA or PSO has demonstrated encouraging outcomes in microgrid optimisation (Zhang et al., 2022). For smart grids, reinforcement learning-based optimisation frameworks have also been presented (Wei et al., 2019), but they are more concerned with control than mathematical optimisation.

The gap is in creating a mathematically sound hybrid optimisation model that specifically takes grid stability, scalability, and renewable intermittency into account. By developing such a model and verifying it using actual datasets, our study makes a contribution.

3. Materials and Methods

Mathematical Formulation

We define the optimization problem as follows:

• Decision Variables:

$P_i(t)$: Power generated by source i at time t .

$D(t)$: Demand at time t .

$C_i P_i(t)$: Cost function for source i .

$R_i(t)$: Renewable availability at time t .

• Objective Function:

$$\min Z = \sum_{t=1}^T \sum_{i=1}^n C_i(P_i(T)) - \alpha \eta(T)$$

Where $\eta(T)$ is renewable utilization ratio, and α is a weighting factor balancing cost vs. efficiency.

• Constraints:

$$\sum_{i=1}^n P_i(t) \geq D(t), 0 \leq P_i(t) \leq P_i^{max}(t), P_i(t) \leq R_i(t)$$

4.2 Optimization Techniques

• **Linear/Convex Programming:** Provides deterministic baseline scheduling.

• **Metaheuristics:** GA and PSO handle stochastic inputs and variability.

• **Hybrid Framework:** Combines deterministic scheduling with metaheuristic adaptability for real-time adjustments.

4.3 Simulation Setup

• **Datasets:** Solar irradiance and wind speed data from India’s renewable energy monitoring stations.

• **Tools:** MATLAB and Python optimization libraries.

Performance Metrics Comparison:

Method	Cost reduction percentage	Renewable utilization ratio	Stability Deviation
Linear Programming	Baseline	60-65	Low
Metaheuristics	10-12	70	Medium
Hybrid Optimization	15-20	75-80	Low

4. Results and Discussion

The hybrid optimization framework was tested against classical LP and standalone metaheuristics.

• **Cost Reduction:** Hybrid optimization achieved 15–20% lower costs compared to LP and ~10% lower than metaheuristics alone.

• **Renewable Utilization:** Increased to 75–80%, compared to ~65% for LP and ~70% for metaheuristics.

• **Grid Stability:** Deviations remained within acceptable limits .

5. Conclusion and Future Scope

The results confirm that hybrid optimization

provides a balanced solution, combining the stability of deterministic methods with the adaptability of metaheuristics. The framework is particularly effective under high renewable penetration scenarios, where variability is most pronounced.

This research introduces a novel hybrid optimization framework for renewable energy distribution in smart grids. By addressing variability and uncertainty, the model enhances cost efficiency, reliability, and sustainability. Future research will explore integration with predictive machine learning models and application to multi-source renewable systems.

6. References

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