



COMPARATIVE ASSESSMENT OF CONVENTIONAL AND METAHEURISTIC APPROACHES FOR OPTIMAL POWER FLOW: BENCHMARK RESULTS ON FIVE-BUS AND IEEE 30-BUS SYSTEMS

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ABSTRACT

Optimal Power Flow can be solved using classical mathematical programming as well as intelligent and metaheuristic search methods. This paper presents a comparative assessment based on the benchmark formulation, methodology and numerical results. Conventional approaches considered in the source include gradient, linear programming, nonlinear programming, quadratic programming, Newton-based and interior-point methods, while intelligent approaches include evolutionary algorithms, ant-colony optimization (ACO), particle swarm optimization (PSO), neural-network methods and fuzzy approaches. The numerical comparison focuses on two directly reported benchmark sets: a five-bus case comparing the gradient-method result with PSO, and an IEEE 30-bus case comparing genetic algorithm (GA), differential evolution (DE), ACO and PSO. For the five-bus system, the reported generation cost changes from 1599.98 to 1597.71 \$/h and loss from 3.0524 to 2.3407 MW when moving from the reported gradient solution to PSO. For the IEEE 30-bus system, the reported costs are 803.7075 \$/h (GA), 811.8780 \$/h (DE), 803.1216 \$/h (ACO), and 801.8436 \$/h (PSO). The paper discusses algorithm characteristics, constraint handling, benchmark evidence and limitations of direct cross-method comparison.

Keywords—Optimal Power Flow, conventional optimization, metaheuristic optimization, gradient method, genetic algorithm, differential evolution, ant colony optimization, particle swarm optimization, IEEE 30-bus.

1. Introduction

Optimal Power Flow (OPF) is formulated to optimize one or more operating objectives subject to the nonlinear AC power-flow equations and equipment operating limits. The thesis groups OPF solution procedures into conventional and non-conventional/intelligent methods. Classical methods use mathematical structure such as derivatives, linearization, quadratic models or barrier/interior-point formulations, whereas

metaheuristics search the solution space using population, memory or nature-inspired mechanisms [1–3].

A comparative study is useful because no single algorithmic family is appropriate for every OPF formulation. Conventional methods can exploit analytical structure efficiently, while metaheuristics can operate without explicit derivatives and can accommodate nonlinear, non-smooth or complex penalty formulations. However, metaheuristic

results are sensitive to population size, parameter settings, stopping rules and constraint-handling strategies [2], [3], [5], [8].

2. OPF Mathematical Model

The study uses fuel-cost minimization as the principal objective. The general constrained OPF problem is written as [1], [2]:

minimize $f(x, u)$

subject to $g(x, u) = 0, h(x, u) \leq 0$

Here x contains dependent state variables such as slack-bus active power, load-bus voltages, generator reactive powers and line loadings; u contains control variables such as generator active powers (except the slack unit), generator voltages, transformer taps and shunt VAR compensation.

2.1 Constraint Categories

Table 1. Constraint Categories in the OPF Formulation

Category	Examples
Equality	Active and reactive AC power-balance equations
Generator limits	P_G, Q_G and generator-voltage bounds
Network security	Load-bus voltage magnitude and line/transformer loading
Control-device limits	Transformer tap and shunt VAR limits

2.2 Penalty-Based Constraint Handling

The source transforms selected hard inequality violations into penalty terms added to the objective. For a variable x , the penalty is zero when $x_{\min} \leq x \leq x_{\max}$ and grows quadratically when x

is outside the permitted interval. This permits a metaheuristic particle to be evaluated through a single scalar fitness value while strongly discouraging infeasible operating points [5], [8].

3. Classification of OPF Solution Methods

Table 2. Classification of OPF Solution Methods

Family	Methods identified in the thesis	General computational characteristic
Conventional / mathematical	Gradient, linear programming, nonlinear programming, quadratic programming, Newton, interior point, mixed-integer programming, network-flow programming	Exploit mathematical structure; often require derivatives, linearization or a specific problem form
Intelligent / metaheuristic	Evolutionary algorithms, GA/EP/ES, ACO, PSO, tabu search	Population/memory-based search; generally derivative-free
AI / decision-oriented	Optimization neural networks, fuzzy set theory, AHP	Useful for nonlinear optimization, uncertainty and decision-making formulations

The thesis notes that conventional methods can become difficult as OPF size and nonlinearity increase, whereas intelligent methods can be flexible with objective functions and inequality constraints. These are methodological observations rather than universal performance guarantees [2], [3], [9], [18], [21].

4. Methodological Characteristics

4.1 Conventional Approaches

Gradient and reduced-gradient methods: Use local gradient information to determine search directions. They are mathematically structured but depend on derivative information and may

encounter slow convergence in nonlinear formulations [2], [3].

Linear programming: Linearizes the objective and constraints. It is computationally attractive for large practical applications, but approximation can reduce fidelity relative to the full nonlinear AC model [2], [3].

Quadratic programming: Uses a quadratic objective with linear constraints and therefore matches the common quadratic generator-cost representation well when the remaining model is suitably approximated [2].

Newton-based methods: Use first- and second-order information, including Hessian-related calculations, to satisfy optimality conditions. They can be efficient near a solution but require substantial model derivatives [3].

Interior-point methods: Introduce barrier concepts and have been applied to linear, quadratic and nonlinear OPF formulations; the thesis identifies them as an important conventional family [3].

4.2 Metaheuristic Approaches

Genetic Algorithm (GA): Population-based evolutionary search using selection, crossover and mutation. Fitness-function design and constraint representation are important for OPF [7].

Differential Evolution (DE): Population-based evolutionary search in which vector differences are

used to generate candidate solutions; it is suitable for continuous optimization [12].

Ant Colony Optimization (ACO): Nature-inspired search based on collective path-selection behavior and pheromone-like information. Its representation and parameterization must be adapted to continuous OPF variables [14], [16].

Particle Swarm Optimization (PSO): Particles update position and velocity using individual and swarm experience. The source implementation uses inertia weight, cognitive and social acceleration terms and penalty-based constraint handling [4-8].

5. Benchmark Systems and Experimental Basis

The comparison is based on the numerical cases reported in the thesis rather than a newly rerun common software environment. This distinction is important: the reported values should be treated as source benchmark results, while a strict modern comparative experiment would require implementing every algorithm with identical network data, objective function, constraint treatment, stopping criteria and repeated random seeds [5–8].

5.1 Five-Bus Case

The five-bus system has three thermal generators at buses 1–3 and seven branches. The generator active-power limits are 10–85 MW, 10–80 MW and 10–70 MW. The base demand is 150 MW.

Table 3. Optimal Power Flow Results for the Five-Bus System: Gradient Method (Without PSO) Versus PSO

Method/Result	P ₁ (MW)	P ₂ (MW)	P ₃ (MW)	Cost (\$/h)	Loss (MW)
Gradient / without PSO	33.4701	64.0974	55.1011	1599.98	3.0524
PSO	33.09028	64.4269	54.8553	1597.71	2.3407

5.2 IEEE 30-Bus Case

The IEEE 30-bus system contains six generators at buses 1, 2, 5, 8, 11 and 13 and 41 branches. The reported control-variable limits

include generator active-power bounds, generator-voltage bounds, transformer tap settings and shunt VAR compensation. Load-bus voltage is constrained to 0.95–1.10 pu.

Table 4. Optimal Power Flow Results for the IEEE 30-Bus System: Comparison of GA, DE, ACO and PSO

Method	P ₁	P ₂	P ₅	P ₈	P ₁₁	P ₁₃	Cost (\$/h)
GA	179.367	44.24	24.61	19.9	10.71	14.09	803.7075
DE	177.3	49.18	12.24	11.19	21.23	21.74	811.8780
ACO	177.863	43.8366	20.893	23.1231	14.0255	13.1199	803.1216
PSO	176.7327	48.8339	21.4524	21.6692	12.0886	12.0000	801.8436

6. Comparative Analysis

The five-bus comparison indicates that the reported PSO solution has a 2.27 \$/h lower generation cost and a 0.7117 MW lower loss than the reported gradient-method result. The corresponding percentage changes, calculated from the reported values, are approximately 0.142% lower cost and 23.31% lower loss [5].

In the IEEE 30-bus comparison, the four reported metaheuristic implementations produce different generator dispatch patterns and costs. The cost spread between the highest and lowest reported values is 10.0344 \$/h, illustrating that algorithm choice and parameterization can materially affect the reported objective for the same benchmark formulation [7], [12], [14].

Table 5. Summary of Comparative Metrics for the Five-Bus and IEEE 30-Bus Cases

Metric	Five-bus comparison	IEEE 30-bus comparison
Compared methods	Gradient vs PSO	GA, DE, ACO, PSO
Objective	Fuel/generation cost	Fuel/generation cost
Additional reported metric	Transmission loss	Generator dispatch
Constraint approach	AC power flow + limits/penalties	AC power flow + limits/penalties
Source software	MATLAB	MATLAB

7. Discussion

Several methodological points follow from the reported cases. First, the objective value alone is insufficient to characterize an OPF solution; feasibility of voltage, reactive-power and branch-loading constraints must also be checked. Second, conventional and metaheuristic methods solve the optimization problem through different computational mechanisms, so direct numerical comparisons are meaningful only when the underlying OPF formulation is identical. Third, stochastic methods should ideally be evaluated over multiple independent runs and reported using best, mean and standard deviation, together with computational time and constraint-violation statistics. The original thesis provides benchmark outputs but does not provide a complete repeated-

run statistical study for all compared algorithms [18-21].

8. Limitations and Reproducibility

The numerical values in this manuscript are transcribed from the source thesis. The thesis reports PSO implementations in MATLAB 7.1, with 100 particles and up to 100,000 iterations for the five-bus case and 10 particles with a 500-iteration maximum for the IEEE 30-bus case. The GA, DE and ACO values are reported as comparison results in the thesis, but the available thesis text does not provide a complete description of their implementation settings. Accordingly, this paper does not claim that the four algorithms were independently rerun under a common modern software framework.

9. Conclusion

This paper organizes the conventional and metaheuristic OPF approaches documented in the thesis and presents the reported benchmark results in a research-paper format. The study demonstrates how a common AC-OPF formulation can be addressed by gradient-based and population-based methods. The reported cases show meaningful differences in generation cost, loss and generator dispatch. A follow-on experimental study should implement gradient/Newton/interior-point, GA, DE, ACO and PSO under identical IEEE benchmark data and constraints, use multiple random seeds for stochastic methods, and report cost, loss, voltage deviation, constraint violations, convergence iteration and execution time.

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