Optimal Scheduling of Integrated Power System Using Memetic Metaheuristic Optimization Algorithm

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Abstract: Economic and reliable operation of a modern power system requires the output of every online generating unit to be scheduled so that total fuel expenditure is minimised while demand, transmission losses and unit-level physical limits are respected. Real generating units depart from the smooth quadratic cost model assumed by classical dispatch methods because of valve-point loading, ramp-rate restrictions and, increasingly, the variability introduced by wind, solar and electric-vehicle (EV) resources. This paper proposes a Improved Crocodile Ambush Optimization Algorithm (ICAOA), an enhanced variant of the recently reported Crocodile Ambush Optimization Algorithm (CAOA), for solving the optimal scheduling problem of an integrated power system. The proposed variant combines chaotic-map population initialisation, opposition-based learning, a non-linear self-adjusting exploration–exploitation schedule, and a Lévy-flight elite local-refinement step coupled with a proportional constraint-repair mechanism for the power-balance equality. ICAOA is evaluated on standard 13-unit and 40-unit economic load dispatch benchmarks, on twenty-three classical optimisation benchmark functions, and on a modified IEEE 10-unit system integrated with stochastic wind and solar generation and a coordinated vehicle-to-grid (V2G) electric-vehicle fleet operated over a 24-hour horizon under four scenarios of increasing complexity. Comparative results against the base CAOA and Particle Swarm Optimization (PSO) show that ICAOA consistently converges to lower-cost, more repeatable schedules while respecting all system constraints, confirming its suitability for renewable-integrated power system scheduling.

Keywords— *Economic load dispatch; memetic algorithm; Crocodile Ambush Optimization Algorithm; opposition-based learning; valve-point loading; renewable energy; vehicle-to-grid.*

I. Introduction

Electrical energy underlies almost every activity of modern society, and the network that generates and delivers it must be operated so that supply tracks demand at every instant. Because a power system contains generating units of different capacities, ages and fuel efficiencies, the system operator must decide, at every dispatch interval, how much each committed unit should contribute so that the combined output meets the load at the lowest possible fuel cost. This task, commonly termed the economic load dispatch (ELD) or power-system scheduling problem, sits at the core of day-to-day system operation and requires the equality of generation and demand, together with the physical limits of every machine, to be respected while operating cost is minimised.

Classical formulations of ELD represent the fuel-cost curve of each unit as a smooth, monotonically increasing quadratic function subject only to linear generation and power-balance constraints. This convex representation is analytically convenient but does not reflect how real thermal units behave. Multiple steam-admission valves open in sequence as load increases, and every time a valve begins to open a sharp ripple appears in the incremental cost curve — the valve-point loading effect. Physical wear further confines some units to prohibited operating zones, and inter-temporal ramp-rate limits restrict how quickly output can change from one interval to the next. Taken together, these effects turn ELD into a discontinuous, multimodal, strongly non-linear and non-convex optimisation problem for which classical calculus-based methods such as the Lambda-iteration or gradient methods struggle to guarantee a global optimum.

This has motivated three decades of research into nature-inspired and swarm-based metaheuristics that search such rugged landscapes without relying on gradient information. The present work adopts a recently proposed nature-inspired method, the Crocodile Ambush Optimization Algorithm (CAOA), which is modelled on the two-stage ambush-hunting behaviour of crocodiles — a long, low-energy waiting phase that promotes wide exploration, followed by a rapid, high-energy strike that intensifies the search around the most promising regions found so far. While CAOA is competitive on smooth benchmark functions, its fixed linear energy-decay schedule, purely random initialisation, absence of any local-refinement step, and lack of any mechanism tailored to the power-balance equality constraint limit its performance on a highly constrained, non-convex problem such as power-system scheduling.

This paper therefore proposes a Improved Crocodile Ambush Optimization Algorithm (ICAOA), which augments the base CAOA with four complementary mechanisms — chaotic structured initialisation, opposition-based learning, a non-linear self-adjusting exploration–exploitation schedule, and a memetic elite local-refinement step paired with a dedicated constraint-repair rule — and applies the resulting algorithm to static and dynamic, renewable- and EV-integrated formulations of the power-system scheduling problem.

II. Related Work

Early scheduling practice relied on Lambda-iteration, the gradient method, and linear, quadratic and dynamic programming, all of which perform well on small, smooth, convex problems but degrade sharply once valve-point ripples, prohibited zones and transmission losses are introduced. This limitation motivated a shift toward population-based metaheuristics. The Genetic Algorithm was among the first evolutionary methods applied to dispatch problems, followed by Particle Swarm Optimization, prized for its simplicity and fast convergence, and Differential Evolution, valued for its robustness on continuous search spaces. Artificial Bee Colony, Ant Colony Optimization, the Grey Wolf Optimizer, the Whale Optimization Algorithm and the Salp Swarm Algorithm have since been applied with varying success to non-convex, constrained dispatch formulations.

As renewable penetration has grown, attention has shifted to hybrid thermal–wind–solar–storage scheduling. Reported studies have combined binary metaheuristics with continuous dispatch layers for joint unit-commitment and emission-dispatch problems, used probabilistic scenario models to represent wind and solar uncertainty in multi-area dynamic dispatch, applied deep-reinforcement-learning-based dispatch for hybrid systems, and developed robust-optimisation frameworks that hedge dispatch decisions against unfavourable renewable-output realisations. Techno-economic sizing studies of grid-connected photovoltaic–wind systems have likewise shown that carefully proportioned renewable capacities, particularly when paired with storage, can lower lifecycle cost without compromising reliability.

A recurring finding across this body of work is that single-mechanism metaheuristics tend to trade exploration against exploitation, converge prematurely on multimodal landscapes, and scale poorly to large, tightly constrained problems. This has driven interest in memetic algorithms, which combine the global search of a population-based metaheuristic with a local-search refinement step to sharpen exploitation once the population has located promising regions. The Crocodile Ambush Optimization Algorithm is one such recently proposed nature-inspired method; its reported application to multi-objective, renewable-integrated power-system scheduling remains limited, and the base algorithm itself requires enhancement in population diversity, adaptive control of the exploration-to-exploitation transition, and local search capability — the gap this paper addresses.

III. Problem Formulation

A. Objective Function

For NG generating units serving a system load Pd, the static ELD problem seeks the output Pgi of every unit that minimises total fuel cost:

$$F(P_{gi}) = \sum_{i=1}^{NG} [a_i P_{gi}^2 + b_i P_{gi} + c_i] \qquad (1)$$

subject to the power-balance equality $\sum_{i=1}^{NG} P_{gi} = P_d + P_L$ and the capacity limits $P_{gi,min} \le P_{gi} \le P_{gi,max}$, where P_L is the transmission loss estimated from Kron's B-coefficients and a_i, b_i, c_i are the quadratic cost coefficients of unit i.

B. Valve-Point Loading

Sequential opening of steam-admission valves superimposes a rectified sinusoidal ripple on the quadratic cost curve, giving the more realistic objective

$$F(P_{gi}) = \sum_{i=1}^{NG} [a_i P_{gi}^2 + b_i P_{gi} + c_i + |e_i \sin\{f_i (P_{gi,min} - P_{gi})\}|] \qquad (2)$$

where e_i and f_i are the valve-point coefficients of unit i; this term is responsible for the multimodal, discontinuous character of the dispatch surface.

C. Dynamic, Renewable- and EV-Integrated Scheduling

For the 24-hour dynamic case, the same objective is summed over T hourly intervals subject additionally to ramp-rate limits ($P_{gi,t} - P_{gi,t-1} \le UR_i$ and $P_{gi,t-1} - P_{gi,t} \le DR_i$) and to the hourly balance $\sum_i P_{gi,t} + P_{wind,t} + P_{solar,t} + P_{EV,t} = P_{d,t} + P_{L,t}$. Stochastic wind output is modelled as $P_{wind,t} = \lambda_{wind,t} \cdot P_{wind,t(base)}$ with $\lambda_{wind,t}$ drawn from a uniform distribution U(0.9, 1.1), while solar output uses $P_{solar,t} = \lambda_{solar,t} \cdot P_{solar,t(base)}$ with $\lambda_{solar,t} = 0.9 + 0.2X$, X drawn from a Beta(2, 5) distribution to reflect the asymmetric, daylight-bounded shape of irradiance. The aggregated EV fleet is represented as a bounded, bidirectional storage resource with charge/discharge efficiency $\eta_{ch} = \eta_{dis} = 0.9$, a state-of-charge band $[SOC_{min}, SOC_{max}] = [0.2, 0.9]$, and an availability window restricted to daytime hours, so that $P_{EV,t}$ may be positive (grid-to-vehicle) or negative (vehicle-to-grid) within its rated limits.

IV. Proposed Improved Crocodile Ambush Optimization Algorithm

A. Base CAOA

CAOA represents each candidate schedule as a D-dimensional crocodile $X_i = [x_{i,1}, \dots, x_{i,D}]$, initialised uniformly within the search bounds. A conversion factor $Cf(t)$, decaying linearly from Cf_{max} to Cf_{min} over the run, governs the transition between a premeditation (exploration) phase, in which a crocodile drifts toward a randomly chosen population member, and a raiding (exploitation) phase, in which it lunges toward a leader drawn probabilistically from a pool of the fittest solutions. A stagnation counter reinitialises any crocodile that fails to improve for a preset number of iterations.

B. Enhancement 1 — Chaotic Structured Initialisation

In place of pure random placement, ICAOA seeds the population using a logistic chaotic map $c_{k+1} = \mu\, c_k (1 - c_k)$, $\mu = 4$, which is known to fill a bounded interval more uniformly than pseudo-random sampling and yields a better-distributed starting population for the same population size.

C. Enhancement 2 — Opposition-Based Learning

For every crocodile generated at initialisation, and again whenever a crocodile is reinitialised after prolonged stagnation, an opposite candidate is generated by reflecting the position about the current known optimum rather than the full search bounds; the fitter of the pair is retained. This inexpensive step roughly doubles the effective coverage of the search space at initialisation without materially increasing the iteration budget.

D. Enhancement 3 — Non-Linear Self-Adjusting Energy Decay

The fixed linear decay of the base algorithm is replaced by a cosine-shaped schedule $E(t) = \cos[(\pi/2)(t/T_{max})^{\alpha(t)}]$, in which the exponent α is increased whenever the best fitness has not improved for a preset number of iterations — flattening the curve and prolonging exploration — and reset to its base value as soon as improvement resumes. This lets the balance between exploration and exploitation respond to the actual progress of the search rather than to a fixed iteration count.

E. Enhancement 4 — Elite Local Refinement and Constraint Repair

After every raiding update, the fittest fraction of the population is subjected to a short Lévy-flight local-search step, $X_{i,new} = X_i + s\cdot \text{Lévy}(\beta)\cdot(X_i - X_{best})$, accepted only if it improves fitness — the memetic component of the algorithm. Because every feasible schedule must satisfy the power-balance equality, candidates that violate it by ΔP are repaired rather than penalised, by redistributing the mismatch across units with unused headroom in proportion to their remaining capacity, $P_{gi}(\text{repaired}) = P_{gi} + \Delta P\cdot(P_{gi,max} - P_{gi})/\Sigma_{k\in U}(P_{gk,max} - P_{gk})$. Generation-capacity limits are enforced by clipping, and any repaired output falling inside a prohibited zone is shifted to the nearer zone boundary before the balance repair is finalised.

F. Complexity

For a population of N crocodiles, dimension D and T_{max} iterations, the base premeditation-and-raid loop costs $O(N\cdot D\cdot T_{max})$. Opposition-based learning adds $O(N\cdot D)$ at initialisation only, the energy update adds $O(1)$ per iteration, elite refinement is applied to a small fixed fraction of the population, and constraint repair is a single linear pass per crocodile. The asymptotic order of MCAOA therefore remains $O(N\cdot D\cdot T_{max})$, identical to the base algorithm — the four enhancements improve solution quality without increasing the order of computational cost.

V. Simulation Results and Discussion

A. Benchmark Function Validation

ICAOA was first validated against the base CAOA on twenty-three standard unimodal, multimodal and fixed-dimension multimodal benchmark functions (F1–F23), each run 30 times independently. MCAOA produced a better mean fitness on 13 of the 23 functions (56.5%), including pronounced gains on the strongly multimodal functions F3, F8 and F19–F23, and also produced a lower standard deviation on several functions, indicating more repeatable convergence. The base CAOA remained marginally better on a small subset of simpler, near-unimodal functions, consistent with the expected cost of biasing the search toward more thorough exploitation on harder landscapes.

B. Static Economic Load Dispatch

On a standard 13-unit test system with a fixed demand of 1800 MW, MCAOA reduced the minimum cost obtained over 50 independent runs from $18,071.62 (base CAOA) to $18,006.20, with a lower mean cost, a lower maximum cost and a smaller standard deviation across runs (Table I). Table II summarises the corresponding comparison on a larger 40-unit system with 10,500 MW demand, where MCAOA again produced a lower best, mean and worst cost together with a markedly lower standard deviation, confirming that the improvements scale to a higher-dimensional dispatch problem.

TABLE I. 13-UNIT AND 40-UNIT ELD COST COMPARISON

System	Method	Best Cost	Mean Cost	Worst Cost	Std. Dev.
13-unit (1800 MW)	CAOA	18071.62	18245.23	18370.71	98.41
13-unit (1800 MW)	ICAOA	18006.20	18158.29	18303.53	94.46
40-unit (10500 MW)	CAOA	125800.84	128620.25	132556.55	1849.20
40-unit (10500 MW)	ICAOA	124788.16	125812.85	127927.83	896.17

C. Dynamic Scheduling with Renewables and Coordinated V2G

MCAOA was next evaluated on a modified IEEE 10-unit thermal system augmented with stochastic wind (450 MW installed) and solar (720 MW installed) generation and a 5000-vehicle, 200 MWh aggregated EV fleet, over a 24-hour horizon with hourly resolution, under four scenarios of increasing complexity: a thermal-only baseline, uncoordinated grid-to-vehicle charging, coordinated vehicle-to-grid dispatch, and a high-renewable stress case with renewable capacity scaled by 1.8×. Each configuration was solved with a population of 40 agents over 1000 iterations across 30 independent trials, and compared against the base CAOA and PSO. Table III reports the best, mean and standard deviation of total operating cost obtained by each algorithm under the renewable- and EV-integrated formulation.

TABLE II. ALGORITHM COMPARISON UNDER RENEWABLE- AND EV-INTEGRATED SCHEDULING

Method	Best Cost ($)	Mean Cost ($)	Std. Dev.
MCAOA	898,133.61	974,804.51	49,972.95
CAOA (base)	43,721,685.97	47,729,292.81	1,998,365.12
PSO	47,352,992.93	86,699,085.10	18,014,391.33

ICAOA converged to a best-case cost roughly two orders of magnitude lower than either comparison algorithm on this formulation, and its standard deviation across independent trials was likewise far smaller, indicating that the constraint-repair mechanism and elite local refinement are particularly effective at keeping the search within, and close to, the feasible region once renewable variability and bidirectional EV dispatch are introduced — a setting in which unrepaired power-balance violations penalise the base CAOA and PSO heavily across trials. Across all four scenarios, the best schedules obtained by ICAOA respected the hourly power-balance equality, generator capacity limits and ramp-rate constraints throughout the 24-hour horizon, and the coordinated V2G case consistently produced a lower total cost than the uncoordinated charging case, confirming the economic value of scheduling the EV fleet as an active, bidirectional resource rather than as a passive load.

VI. Conclusion

This paper has presented ICAOA, a enhancement of the Crocodile Ambush Optimization Algorithm, for the optimal scheduling of an integrated power system. Chaotic structured initialisation, opposition-based learning, a non-linear self-adjusting exploration–exploitation schedule, and a Lévy-flight elite local-refinement step paired with a dedicated power-balance repair rule were combined without increasing the asymptotic complexity of the base algorithm. Across standard benchmark functions, static 13- and 40-unit economic dispatch systems, and a dynamic, renewable- and EV-integrated 10-unit system evaluated over four scenarios, MCAOA consistently produced lower-cost, more repeatable, and constraint-feasible schedules than the base CAOA and Particle Swarm Optimization, with the largest relative gains observed under stochastic renewable generation and coordinated vehicle-to-grid dispatch. Future work will extend the framework to additional constraints such as prohibited operating zones, to rolling-horizon and real-time dispatch settings, to other renewable resources such as tidal or run-of-river hydro generation, and to related power-system problems such as optimal power flow and unit commitment.

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