Eagle strategy-based crow search algorithm for UCP: integration of pumped storage units in smart grid environment

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ABSTRACT

This paper proposes a hybrid eagle strategy with crow search algorithm (ES-CSA) as local optimizer to solve the unit commitment problem (UCP) in power systems. The algorithm aims to minimize total operational costs while considering pumped storage units as spinning reserves. The proposed methodology combines the exploration capability of ES with CSA's local search efficiency to determine optimal generator scheduling and power dispatch. The approach is validated using standard test cases from the literature, demonstrating improved convergence and cost reduction compared to existing methods. Results confirm the effectiveness of integrating pumped storage units in reducing overall system costs while maintaining reliable operation.

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1. INTRODUCTION

The global transition toward sustainable energy systems has intensified the challenges of power grid management, particularly as electricity demand continues to surge with rapid urbanization and technological advancement. Smart grid technology has emerged as a crucial solution for reducing losses and enhancing system stability, while promoting dependability and efficient regulation of electrical energy supply [1]. The integration of smart devices, however, creates significant data interchange between various grid components, which can impact response and processing times [2].

Modern smart grids represent an evolution of electrical networks that connect highly efficient, decentralized renewable energy sources. Through advanced communication and control technology, these systems fulfill consumer demands while reducing both costs and greenhouse gas emissions [3]. The transformation of traditional power grids into smart grids (SG) has been enabled by information and communication technology (ICT), creating networks where millions of electronic devices communicate through advanced metering infrastructure (AMI) [4].

The unit commitment problem (UCP) plays a vital role in this context, significantly contributing to cost reduction in electrical power production through strategic allocation of production costs based on real output power [5]. The UCP involves coordinating multiple generating units to meet forecasted electricity demand over a 24-hour period, requiring careful planning of generator operations to achieve minimum cost while satisfying operational constraints [6].

The complexity of the UCP stems from its considerable dimensions, nonlinear objective function, and coupling constraints. The problem can be decomposed into two distinct but interconnected components: unit commitment and economic dispatch. The economic dispatch aspect requires careful consideration to efficiently distribute electricity generated across the system [7]. This dual nature of the problem - combining unit commitment decisions about operational status with economic dispatch determinations about power output levels - creates a challenging optimization scenario.

This research introduces a novel eagle strategy based crow search algorithm (ES-CSA) as a solution for the UCP in smart grid systems. Our proposed algorithm minimizes system generation costs while simultaneously satisfying load demand and spinning reserve constraints. We demonstrate the effectiveness of our ES-CSA method through implementation on a power system with 10 power units.

The remainder of this paper is organized as follows: section 2 presents the mathematical formulation of the UCP. Section 3 introduces the fundamentals of ES and CSA algorithms. Section 4 discusses the computational results. Finally, section 5 provides concluding remarks.

2. METHOD

2.1. Formulation of unit commitment problem

The UCP encompasses determining the optimal operational schedule of generating units across discrete time intervals to meet demand while minimizing total operational costs [8]. This optimization must satisfy both load requirements and spinning reserve constraints, while respecting individual unit limitations including generation bounds and minimum up/down times.

The total production cost over the scheduling horizon comprises three primary components [9]. First, fuel costs are typically represented by quadratic polynomials derived from heat rate data and fuel pricing [10]. Second, startup costs vary with unit downtime duration, commonly modeled through either exponential cooling functions or binary hot/cold start classifications [11]. Finally, shutdown costs, primarily reflecting labor and maintenance expenses, are treated as fixed values for each generating unit.

2.2. Objective function

The UCP main goal is to minimize the total production cost function:

$$MinF_T = \sum_{i=1}^{N}\sum_{t=1}^{Nt}\Big[\big[F_i\big(P_i(t)\big)U_i(t) + ST_i(t)U_i(t)\big] + DC_i(t)\big(1 - U_i(t)\big)U_i(t-1)\Big] \tag{1}$$

where: $U_i(t)$ is the state of unit i at time t: a zero means that the plant is stopped, a 1 that it is in operation
$\mathrm{F_i}(\mathrm{P_i}(t))$ is the production cost of unit i at time t, in the most frequent case:

$$F_i(P_i(t)) = a_i + b_iP_i(t) + c_iP_i(t)^2 \tag{2}$$
$$i = 1, \dots\dots, N$$
$$t = 1, \dots\dots, Nt$$

where a_i, b_i, and c_i represent the unit cost coefficients.
$\mathrm{ST_i}(t)$ represents the cost of restarting unit i at time t, it depends on the time which unit i was turned $\mathrm{T_i^{off}}$, it can be represented by the following form:

$$STi(t) = \begin{cases} HSC_i \; si \; MDTi \le T_i^{OFF} \le MDTi + SCi \\ CSC_i \; si \; \mathrm{T_i^{OFF}} > MDTi + SCi \end{cases} \tag{3}$$

where CSC_i is (cold start cost) cold start cost of unit i ($), HSC_i is (hot start cost) hot restart cost of unit i ($), SCi is (cold start) cold restart time of unit i (hours), and $\mathrm{DC_i}(t)$ is the cost of shutting down unit i at time t, it is often constant.

2.3. Constraints

The UCP is subject to several essential operational constraints that ensure reliable and secure power system operation. These constraints govern power balance, spinning reserve requirements, generation limits, and unit operational timing restrictions, collectively forming the technical framework for optimization.

2.3.1. Technical and operational constraints

– Demand to be satisfied:

$$\sum_{i=1}^{N} P_i(t)\, U_i(t) = P_D(t) + P_L\,(t)\ t = 1, \dots \dots .., Nt \tag{4}$$

where P_D(t) is the system load demand at time t.

– Reserve to be guaranteed:

$$\sum_{i=1}^{N} P_i^{max}(t)\, U_i(t) \geq P_D(t) +\ P_R\,(t)\ t = 1, \dots \dots\ Nt \tag{5}$$

The losses through the transmission system can be approximated by:

$$P_L(t) = \sum_{i=1}^{N}\sum_{j=1}^{N} \mathrm{P_i}(t)\, B_{ij} P_j(t) + \sum_{i=1}^{N} B_{Oi}\, \mathrm{P_i}(t) + B_{OO} \tag{6}$$

where Pj minimum power of unit j (MW), Pj minimum power of unit j (MW), Bij element (i, j) of a square matrix of dimension (N×M), Bio element i of a vector of dimension N, and Boo constant losses (MW).

– Bounded power

$$P_i^{min} \leq \mathrm{P_i}(t) \leq P_i^{max}\ Si\ \mathrm{U_i(t)} = 1 \tag{7}$$

where P_i^{min} and P_i^{max} are the minimum and maximum generation limits of unit i. Minimum switch-on time. When a unit is started, it can only be switched off if the running time exceeds the minimum running time of that unit.

$$MUTi \leq\ \ \mathrm{T_i^{ON}}\ i = 1, \dots ; N \tag{8}$$

– Minimum extinction time

$$MDTi \leq\ \ \mathrm{T_i^{OFF}}\ i = 1, \dots ; N \tag{9}$$

– Maximum power elevation:

$$P_i(t) \leq min\ (P_i^{max}, P_i(t-1)\ - URi)\ Si\ U_i(t-1) = 1\ et\ U_i(t) = 1 \tag{10}$$
$$i = 1, \dots \dots, N$$
$$t = 1, \dots \dots, Nt$$

– Maximum power drop:

$$\mathrm{P_i}(t) \leq \max\,(P_i^{min}, \mathrm{P_i}(t-1)\ - \mathrm{DRi})\ \mathrm{Si}\ \mathrm{U_i(t-1) = 1\ et\ U_i(t) = 1} \tag{11}$$
$$i = 1, \dots \dots, N$$
$$t = 1, \dots \dots, Nt$$

The constraint (4) ensures power balance by equating total generation with the sum of demand and losses. The constraint (5) guarantees sufficient spinning reserve capacity to handle contingencies. The constraint (6) accounts for transmission system losses using the B-matrix coefficients. The constraint (7) ensures each generating unit operates within its minimum and maximum power limits when committed. The constraint (8) enforces minimum up-time requirements, ensuring units remain online for a specified duration once started. The constraint (9) guarantees minimum down-time requirements are met before restarting a unit. The constraint (10) ensures generation increases remain within ramp-up rate limits while constraint (11) maintains ramp-down rates within acceptable bounds for committed units.

2.3.2. Electric vehicles constraints

Recent advancements in vehicle-to-grid (V2G) technology have enabled electric vehicles (EVs) to participate actively in power system operations through bidirectional power flow capabilities. This integration is facilitated through aggregator entities that serve as intermediaries between system operators and multiple EV owners [12]-[15]. The aggregator model enables efficient coordination of distributed EV resources, particularly during periods of vehicle inactivity when owners can establish contractual agreements with system operators for load aggregation services.

From a system perspective, aggregated plug-in electric vehicles (PEVs) can be modeled as a distinctive generating unit with unique characteristics. The cost structure of PEV aggregation follows a quadratic function, reflecting the increasing marginal costs associated with expanding EV owner participation. This economic behavior aligns with traditional power system unit commitment frameworks while accounting for the distributed nature of EV resources.

$$f\big(P(m,t)\big) = a(m)P(m,t)^2 + b(m)P(m,t) + c(m) \quad (12)$$

Electric vehicle integration into the grid requires careful consideration of several key operational limits. First, we must maintain a minimum state of charge (SoC) to ensure EV owners have sufficient energy for unexpected travel needs. Second, grid stability and safety necessitate setting an upper boundary on the total power that EVs can feed back into the grid each hour. Third, since EVs have intermittent grid connectivity patterns throughout the day, we need to define specific time windows when vehicles are available for grid services. Finally, we must account for the maximum power capacity available from the aggregated PEV fleet during each operational period.

$$SOC(t,m) \geq SOC_{min} \quad (13)$$

$$PEV(t) = \sum_{m=1}^{M} P(t,m) \leq PEV_{max} \quad (14)$$

2.3.3. Pumped storage constraints

The operation of pumped storage systems presents unique characteristics in power system optimization, as these units incur minimal operational costs due to their fuel-free nature. Their integration into the UCP requires adherence to key operational bounds. Specifically, the generation output must be maintained within defined lower and upper limits to ensure system stability and efficient operation. Constraint (16) ensures the generation output of pumped storage units remains within specified minimum and maximum power limits during operation mode. Constraint (17) enforces similar bounds for pumping operation, maintaining power consumption within safe operational limits. Constraint (18) and (19) govern the spinning reserve contribution, ensuring it stays within defined boundaries while limiting the total sum of generation and reserve to the unit's maximum capacity. Constraint (20) enforces a fundamental operational rule that prevents simultaneous pumping and generation modes. Constraint (21) maintains the energy balance in the upper reservoir by accounting for pumping gains and generation losses through their respective efficiencies. Constraint (22) defines the allowable storage capacity range for the upper reservoir. Constraint (23) sets the initial stored energy level, while constraint (24) ensures a minimum final energy level in the upper reservoir at the end of the planning horizon.

$$0 \leq P_g(m,t) \leq P_{g-max}(m) \quad (15)$$

$$0 \leq P_p(m,t) \leq P_{p-max}(m) \quad (16)$$

$$0 \leq P_{g-SR}(m,t) \leq P_{g-max}(m) \quad (17)$$

$$0 \leq P_{p-SR}(m,t) \leq P_p(m,t) \quad (18)$$

$$P_g(m,t) + P_{g-SR}(m,t) \leq P_{g-max}(m) \quad (19)$$

$$u_p(m,t) + u_g(m,t) \leq 1 \quad (20)$$

$$E(m,t) = E(m,t-1) - P_g(m,t) + \eta_{ps}P_p(m,t) - \Big(\eta_{ps}.P_{p-SR}(m,t) + P_{g-SR}(m,t)\Big)re \quad (21)$$

$$E_{min}(m,t) \leq E(m,t) \leq E_{max}(m) \quad (22)$$

$$E(m,T) = E(m,0) \quad (23)$$

$$E_{min}(m,t) = E_{min}(m) + re(P_{p-SR}(m,t+1) + P_{g-SR}(m,t+1)) \quad (24)$$

3. METHODS

3.1. Crow search algorithm

The CSA represents an innovative metaheuristic optimization technique that simulates the intelligent behavior patterns of crow flocks. First introduced by Askarzadeh [16], this population-based algorithm has demonstrated remarkable effectiveness in addressing complex engineering optimization challenges. Crows exhibit sophisticated cognitive abilities, including facial recognition and strategic food-hiding behaviors, which form the foundation of this optimization approach [17]. The CSA methodology follows a systematic process organized in distinct stages:

a. Initialization
   - Generate initial population of crows in d-dimensional space
   - Each crow i maintains position $x^{i,iter}$ and memory $m^{i,iter}$
   - Evaluate initial fitness values
b. Position update process

$$x^{i,iter+1} = \begin{cases} x^{i,iter+1} + r_i \times fl^{i,iter} \times (m^{i,iter} - x^{i,iter}), \\ r_j \geq AP^{j,iter} A \text{ random positonofsearch spaceotherwise} \end{cases} \tag{25}$$

where APj; iter refers to crow j awareness probability, iter refers to iteration number, ri; rj refers to random numbers, fli; iter is the crow i flight length to denote crow j memory.
c. Memory update mechanism

$$m^{i,iter+1} = \begin{cases} x^{i,iter+1}, \text{if } f(x^{i,iter})\text{is better than } f(m^{i,iter}) \\ m^{i,iter}, \text{otherwise} \end{cases} \tag{26}$$

where f (*) stands for the objective function. Until the termination requirement is met, these procedures are repeated. The best position that the crow flock has memorized at that point is presented as the best solution.

The exploration and exploitation capabilities of the CSA are illustrated in Figure 1. The overall process of the CSA algorithm is summarized in the flowchart shown in Figure 2.

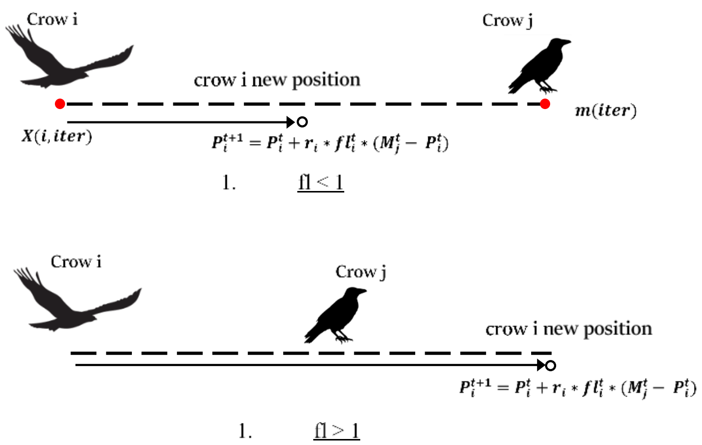

Figure 1. Exploration and exploitation of CSA

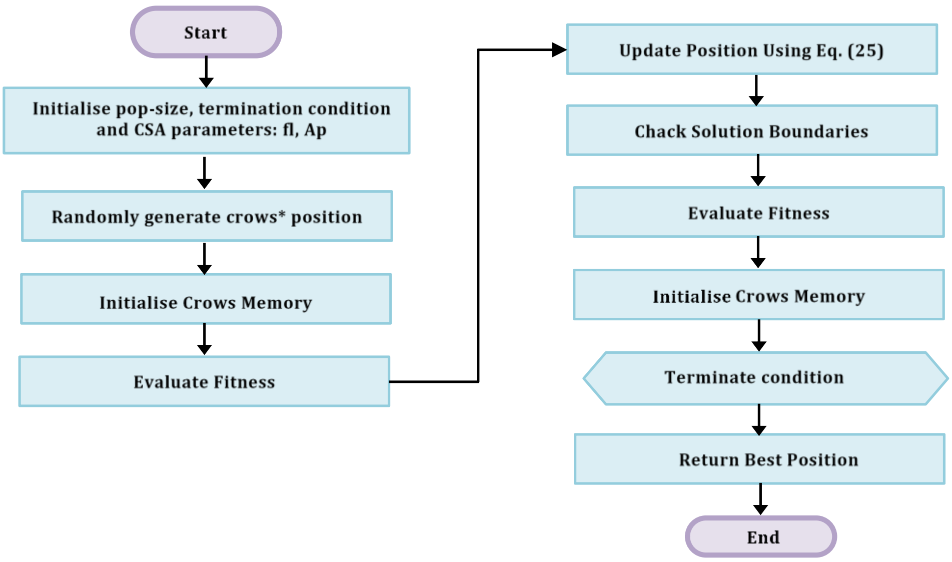

Figure 2. Flowchart of CSA

Algorithm 1. Crow search algorithm

Randomly initialize the position of a flock of (N_P) crows in the search space.
Evaluate the position of the Crows
Initialize the memory of each Crow
While ($iter \leq iter_{max}$) **do**
for i= 1: to N_P **do**
Randomly choose one of the crows to follow (for example, j)
Define an awareness probability
if ($r_j \geq AP^{j,\ iter}$) **then**
$x^{i,\ iter+1}=x^{i,\ iter}+r_i*fl^{i,\ iter}*\ (m^{j,\ iter}-x^{i,\ iter})$
else
$x^{i,\ iter+1}$=a random position of search space.
end if
end for
Check the feasibility of new positions
Evaluate the new position of the Crows
Update the memory of crows
end while

Recent studies have demonstrated CSA's effectiveness in various optimization scenarios [18], particularly in power system applications. The algorithm's success stems from its ability to balance exploration and exploitation through the awareness probability (AP) parameter and flight length mechanisms. The iterative process continues until meeting termination criteria, with the flock's best memorized position representing the optimal solution. This approach has proven particularly effective in handling nonlinear optimization problems with multiple constraints [17], [18].

3.2. Brief introduction to eagle strategy

ES represents a metaheuristic optimization approach introduced by Yang and Deb [19], which emulates the distinctive hunting behavior of eagles. This two-phase optimization technique draws inspiration from eagles' natural foraging patterns, combining global exploration with focused local search capabilities. The ES methodology consists of two primary phases:

a. Global exploration
   - Implements Levy flight patterns for broad search space exploration
   - Mimics eagles' random soaring behavior
   - Seeks promising regions in the solution space

b. Local search

$\boldsymbol{If}$ ($promising\_solution\_found$){
Perform intensive local search
Apply efficient local optimizer
Else
Restart global exploration

The algorithm alternates between these phases, systematically:
- Conducting global exploration to identify potential solutions
- Executing intensive local search when promising regions are discovered
- Restarting the process in new areas to maintain search diversity

This dual-phase approach has proven particularly effective for complex optimization problems [19], combining the benefits of broad exploration with focused exploitation of promising solution regions.

Algorithm 2. ES

Objective function f(x)
Initialization and random initial guess $x^{t=o}$
While (stop criterion) **do**
Global exploration by randomization (e; g; levy flights)
Evaluate the objectives and find a promising solution
Intensive local search via an efficient local optimizer
If (a better solution is found) then
Update the current best
End if
Update t=t+1
End while

3.3. Binary eagle startegy based crow search algorithm for unit commitment problem

The proposed methodology addresses the UCP through a two-phase approach that combines binary ES-CSA with the Lambda-iteration method [20]. In this framework, the unit scheduling optimization, which represents the more complex aspect of the problem, is handled by a binary version of ES-CSA in the first phase. The second phase employs the conventional Lambda-iteration method to resolve the economic load dispatch subproblem, creating a comprehensive solution strategy for the complete unit commitment challenge. In (27) convert (3) and (26) from continues to binary space:

$$x^{i,iter} = \begin{cases} 1 \text{ if } s(x^{i,iter}) \geq \text{rand}(), \\ 0 \text{ if otherwise} \end{cases} \tag{27}$$

where $s(x^{i,iter})=\frac{1}{y}$, $y=1+e^{-x^{i,iter}}$, and rand() is a random number from uniform distribution [0; 1] and $x^{i,iter}$ is the updated binary position at iter iteration.

3.3.1. Solution representation and initialization

In implementing the binary ES-CSA for UCP, the solution encoding plays a crucial role in algorithm effectiveness. Each solution, represented as an artificial crow in the algorithm, encodes the operational schedule of generating units across the planning horizon. The encoding structure utilizes a binary matrix format where each element represents the operational state of a generating unit: 1 for operational (ON) and 0 for non-operational (OFF) status. The solution structure is organized as a matrix U with dimensions NG × H, where NG represents the number of generating units and H denotes the planning horizon in hours. Each column of this matrix constitutes the system state for a specific hour, comprising the operational status of all units at that time point. This hourly collection of unit states forms what we define as a temporal segment of the complete schedule.

$$U = \begin{bmatrix} u_1^1 & u_1^2 & u_1^3 & \cdots & u_1^H \\ u_2^1 & u_2^2 & u_2^3 & & u_2^H \\ & \vdots & & \ddots & \vdots \\ u_N^1 & u_N^2 & u_N^3 & \cdots & u_N^H \end{bmatrix}$$

where u_i^h is unit on/off status of unit i at time h (u_i^h=1\0 for on/off).

The algorithm begins with the creation of an initial population set, where each solution Uj (j=1, 2, ..., NP) represents a potential unit commitment schedule. For every member of the population of size NP, the binary position uhi is generated using a uniform random distribution that assigns values of either 0 or 1 with equal probability (0.5). This randomization process ensures diversity in the initial population while maintaining the binary nature of the unit commitment decisions.

3.3.2. Generate new solutions

ES employs Levy flights as its primary mechanism in the first stage of optimization. These flights represent a specialized stochastic process characterized by non-Gaussian step distributions. The step lengths in Levy flights follow a unique probability distribution known as the Levy stable distribution, which enables more effective exploration of the search space through a combination of short and occasional long-distance movements. The generation of new solutions through Levy flights can be expressed as:

$$x^{i,iter+1} = x^{i,iter} + \alpha \oplus Levy(\lambda) \tag{28}$$

The Levy flight process adapts its movement through problem-specific step sizes that align with the search space dimensions. By sampling from a heavy-tailed Levy distribution, this approach generates a specialized random walk pattern that defines the search trajectory. The combination of step lengths and movement directions through component-wise multiplication creates a dynamic search behavior, allowing the algorithm to balance between detailed local searches and broader exploration through larger jumps in the solution space.

$$\text{Levy}(\lambda) = u = t^{-\lambda}, 1 \leq \lambda \leq 3 \tag{29}$$

In this research, we implement the Mantegna algorithm [19] to generate Levy flights effectively. The step length s can be calculated using Levy(λ)=s, which can be further expressed as:

$$x^{i,iter+1} = x^{i,iter} + \alpha \oplus s \tag{30}$$

The step length s in Levy flights can be computed using Mantegna's algorithm [21], which is expressed as:

$$s = \frac{\mu}{|v|}{}^{1}/_{\beta} \tag{31}$$

where u and v are drawn from normal distributions respectively. That is, $u \sim N(0,\sigma u^2)$ and $v \sim N(0,\sigma v^2)$ are calculated as follows: $\left(\frac{\Gamma(1+\beta).\sin(\frac{\pi\beta}{2})}{\Gamma\left(\frac{\beta+1}{2}\right).\beta.2^{(\frac{1-\beta}{2})}}\right)^{\frac{1}{\beta}}$ $,\sigma_{v\,,} = 1$. Here $0\leq \beta \leq 2$ and (:) is the Gamma function.

The second optimization stage implements a modified version of the CSA configured specifically for intensive local search operations. Although CSA fundamentally operates as a global optimization methodology, its search characteristics can be effectively refined for localized exploitation through strategic parameter adjustment. This adaptation is achieved primarily through the manipulation of two critical control parameters: awareness probability (AP) and flight length (fl).

The algorithm's search behavior transitions from global exploration to focused local exploitation through the reduction of the awareness probability to significantly lower values. This modification, coupled with an empirically determined optimal flight length (fl=2), enables precise exploration of promising solution regions. The synergistic interaction of these parameters produces superior optimization outcomes compared to conventional CSA implementations.

For application to the UCP, where solution variables are constrained to binary integers representing unit states (0/OFF, 1/ON), the inherently continuous nature of CSA necessitates additional adaptation. This binary constraint satisfaction is achieved through a specialized conversion mechanism that preserves the algorithm's search efficiency while maintaining the discrete nature of generator scheduling decisions.

4. RESULTS AND DISCUSSION

To evaluate the performance and effectiveness of the proposed ES-CSA [22], [23], extensive testing was conducted across multiple system configurations ranging from 20 to 100 generating units [24]. The experimental setup employed a 24-hour planning horizon with a spinning reserve requirement of 10% of the total load demand. For larger systems analysis (20, 40, 60, 80, and 100 units), the base 10-unit system was replicated with load demands scaled proportionally to system size.

The implementation was carried out in MATLAB on a computer equipped with a 2.26 GHz Intel processor and 2 GB RAM. Initial testing focused on a 10-unit system, with 24-hour load demand profiles presented in Table 1 and graphically represented in Figure 3. The generating unit specifications are detailed in Table 2, while Table 3 presents the algorithm parameters. These specifications include power limits (Pmin and Pmax), operating cost coefficients (ai, bi, ci), minimum startup and shutdown times, and startup costs (hot and cold) for each generating unit.

Table 1. Test load demand data for 10 generating unit system

Time (h)	1	2	3	4	5	6	7	8	9	10	11	12
Load (MW)	700	750	850	950	1000	1100	1150	1200	1300	1400	1450	1500
Time (h)	13	14	15	16	17	18	19	20	21	22	23	24
Load (MW)	1400	1300	1200	1050	1000	1100	1200	1400	1300	1100	900	800

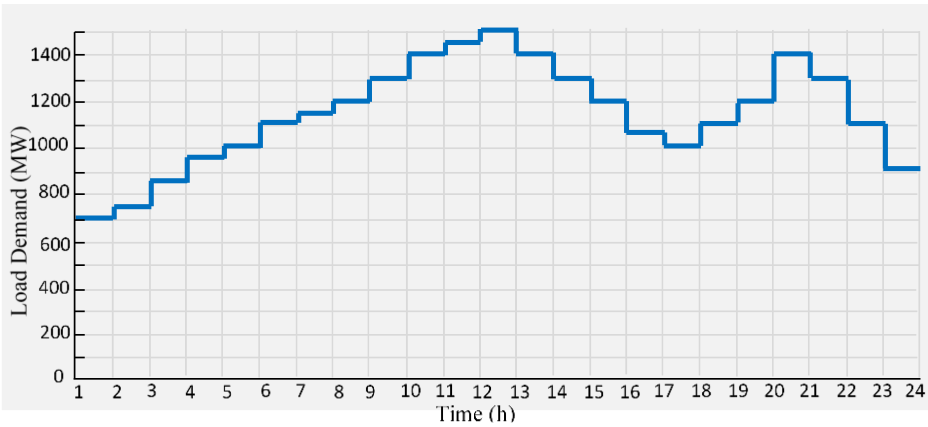

Figure 3. Test load demand curve for 10-unit system

Table 2. Test data for 10 generating unit system

Unit	P_{max} (MW)	P_{min} (MW)	ai [$]	bi[$/MW]	ci[$/MW2]	T_i^{ON} (h)	T_i^{OFF} (h)	HSC_i[$]	CSC_i[$]	SCi (h)	Start time
U1	455	150	1000	16.19	0 .00048	8	8	4500	9000	5	8
U2	455	150	970	17.26	0 .00031	8	8	5000	10,000	5	8
U3	130	20	700	16.6	0.00200	5	5	550	1100	4	-5
U4	130	20	680	16.5	0.00211	5	5	560	1120	4	-5
U5	162	25	450	19.7	0.00398	6	6	900	1800	4	-6
U6	80	20	370	22.26	0.00712	3	3	170	340	2	-3
U7	85	25	480	27.74	0.00079	3	3	260	520	2	-3
U8	55	10	660	25.92	0.00413	1	1	30	60	0	-1
U9	55	10	665	27.27	0.00222	1	1	30	60	0	-1
U10	55	10	670	27.79	0.00173	1	1	30	60	0	-1

Table 3. Parameters of ES-CSA [25]

Parameters/algorithms	CSA	ES-CSA
AP	0.2	0.2
Fl	2	2
β	-	1.5

The simulation results yielded commitment schedules and demand distributions, presented in Tables 4 and 5, with a total generation cost of $546,577 and startup cost of $3,910. Table 5 provides comprehensive hourly distribution data and cost analysis for all 10 generators throughout the 24-hour planning period, demonstrating that load requirements are successfully met.

Table 4. Commitment schedule for10 generating unit system

Time (h)	Commitment schedule (U1-U10)									
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10
1	1	1	0	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0	0	0
3	1	1	0	0	0	0	0	0	0	0
4	1	1	0	1	0	0	0	0	0	0
5	1	1	0	1	0	0	0	0	0	0
6	1	1	0	1	1	0	0	0	0	0
7	1	1	0	1	1	0	0	0	0	0
8	1	1	1	1	1	0	0	0	0	0
9	1	1	1	1	1	0	0	0	0	0
10	1	1	1	1	1	1	0	0	0	0
11	1	1	1	1	1	1	0	1	0	0
12	1	1	1	1	1	1	0	1	1	0
13	1	1	1	1	1	1	0	0	0	0
14	1	1	1	1	1	0	0	0	0	0
15	1	1	0	1	1	0	0	0	0	0
16	1	1	0	1	1	0	0	0	0	0
17	1	1	0	1	1	0	0	0	0	0
18	1	1	0	1	1	0	0	0	0	0
19	1	1	0	1	1	0	0	0	0	0
20	1	1	1	1	1	1	0	0	0	0
21	1	1	1	1	1	1	0	0	0	0
22	1	1	1	0	0	1	0	0	0	0
23	1	1	1	0	0	0	0	0	0	0
24	1	1	1	0	0	0	0	0	0	0
Total production cost ($) = $550487										

The convergence characteristics across different system instances are illustrated in Figure 4, demonstrating ES-CSA's robust convergence properties. The algorithm's effectiveness stems from its dual-stage approach: the initial stage employs Levy flights for extensive exploration and local optima avoidance, while the second stage utilizes CSA for intensive exploitation of promising regions. This strategic combination enables the discovery of superior solutions.

Table 5. Generation schedule for 10 generating unit system (PR(t)=0)

Time (h)	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	Demand (MW)	Start-up cost ($)	Cost of production ($/hr)
	Generation schedule (U1-U10) (MW)												
1	455	245	0	0	0	0	0	0	0	0	700	0	13683.14
2	455	295	0	0	0	0	0	0	0	0	750	0	14554.51
3	455	395	0	0	0	0	0	0	0	0	850	0	16809.46
4	455	365	0	130	0	0	0	0	0	0	950	560	18638.69
5	455	415	0	130	0	0	0	0	0	0	1000	0	19513.03
6	455	455	0	130	60	0	0	0	0	0	1100	900	21860.06
7	455	455	0	130	110	0	0	0	0	0	1150	0	22879.99
8	455	455	130	130	160	0	0	0	0	0	1200	1100	23522.48
9	455	455	130	130	130	0	0	0	0	0	1300	0	26184.08
10	455	455	130	130	162	68	0	0	0	0	1400	340	28768.57
11	455	455	130	130	162	80	0	38	0	0	1450	60	30699.08
12	455	455	130	130	162	80	0	55	33	0	1500	60	32713.19
13	455	455	130	130	162	68	0	0	0	0	1400	0	28768.57
14	455	455	130	130	130	0	0	0	0	0	1300	0	26184.08
15	455	455	0	130	160	0	0	0	0	0	1200	0	23918.36
16	455	440	0	130	25	0	0	0	0	0	1050	0	20896.67
17	455	390	0	130	25	0	0	0	0	0	1000	0	20020.84
18	455	455	0	130	60	0	0	0	0	0	1100	0	21860.06
19	455	455	0	130	160	0	0	0	0	0	1200	0	23918.36
20	455	455	130	130	162	68	0	0	0	0	1400	890	28768.57
21	455	455	130	130	110	20	0	0	0	0	1300	0	26589.08
22	455	455	130	0	0	60	0	0	0	0	1100	0	21976.99
23	455	315	130	0	0	0	0	0	0	0	900	0	17795.71
24	455	215	130	0	0	0	0	0	0	0	800	0	16053.43
	The sum of the production costs												546577$
	transition cost (generator start-up costs)												3910$
	Total cost ($/hr)												550487

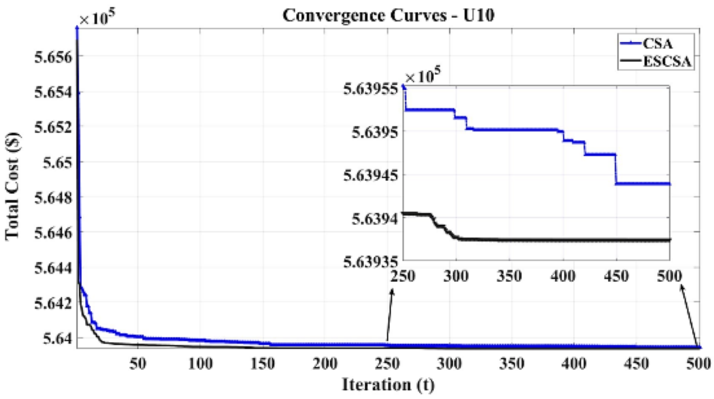

Figure 4. Convergence of ES-CSA system 10 unit

5. CONCLUSION

This research presents a comprehensive investigation into solving the UCP through a novel hybridization of ES-CSA. Our work establishes a detailed mathematical framework encompassing both the objective function and associated constraints of the UCP. The developed ES-CSA approach leverages the binary strategy characteristics of eagle behavior combined with the local search capabilities of CSA, creating a robust optimization method. Testing across multiple unit commitment scenarios, particularly with systems containing 10 generating units, demonstrates the algorithm's efficacy. A significant finding emerges in the economic performance of our approach: the ES-CSA consistently achieves lower overall production costs across the planning horizon compared to contemporary optimization techniques. Notably, the computational efficiency of our method shows a linear relationship with system size, making it particularly valuable for industrial applications. This scalability characteristic, combined with superior cost performance, positions ES-CSA as a promising solution for practical power system operations. The results validate our initial hypothesis and suggest that this hybrid approach offers a viable pathway for solving complex UCP in real-world power systems.

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