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Power system operational optimization using the kakapo optimization algorithm for dynamic economic dispatch

Introduction. *Metaheuristic algorithms are effective for solving complex power system optimization problems characterized by nonlinearity, multimodality, and high dimensionality. Nature-inspired strategies based on adaptive biological behaviors offer significant potential to enhance search efficiency and convergence reliability. The recently published kakapo optimization algorithm (KOA) is employed in this study to address the dynamic economic dispatch (DED) problem over a 24-hour horizon in multi-unit power systems.* ***Problem.*** *The DED problem extends conventional economic load dispatch into a multi-hour planning horizon, considering hourly load variations, generator ramp-rate limits, valve-point effects, and transmission losses. These characteristics render DED highly nonconvex and nonlinear, posing challenges to conventional and metaheuristic techniques. Maintaining a robust balance between global exploration and local exploitation is critical to prevent premature convergence or suboptimal generation schedules.* ***Goal.*** *To apply kakapo optimization algorithm for the dynamic economic dispatch problem, aiming to generate economically optimal and operationally feasible generation schedules over a 24-hour dispatch horizon while preserving population diversity and search stability.* ***Methodology.*** *KOA models two synergistic behavioral phases of the kakapo. Exploration is inspired by lek mating and acoustic signaling, where higher-fitness solutions emit stronger «calls» that probabilistically attract weaker candidates toward promising regions. Exploitation mimics freezing and camouflage strategies, performing fine-grained local adjustments around promising solutions with adaptive step sizes. KOA is applied to a standard five-unit system over 24 hours and benchmarked against nine well-known metaheuristics.* ***Results.*** *KOA achieves the lowest total generation cost, rapid convergence, and high robustness. Statistical performance metrics – including mean, best, worst, standard deviation, and rank – consistently favor KOA, confirming its effectiveness for multi-dimensional, multi-modal DED problems.* ***Scientific novelty.*** *KOA introduces a biologically inspired, self-adaptive search framework that balances exploration and exploitation without external control parameters.* ***Practical value.*** *The algorithm provides a reliable, versatile, and computationally efficient optimization tool for complex power system dispatch problems, with potential applications in renewable integration, multi-objective optimization, and real-time adaptive operations.* References 29, tables 4, figures 2.

Key words: **dynamic economic dispatch, kakapo optimization algorithm, metaheuristic optimization, power system operation, valve-point effects, economic load scheduling.**

Вступ*. Метаевристичні алгоритми є ефективним засобом розв'язання складних задач оптимізації електроенергетичних систем, що характеризуються нелінійністю, мультимодальністю та великою розмірністю. Природоорієнтовані стратегії, засновані на адаптивній біологічній поведінці, мають значний потенціал для підвищення ефективності пошуку та надійності збіжності. У даному дослідженні для розв'язання задачі динамічного економічного розподілу навантаження (DED) у багатогенераторних електроенергетичних системах на 24-годинному інтервалі застосовано нещодавно запропонований алгоритм оптимізації какапо (KOA).* ***Проблема****. Задача DED є розширенням класичної задачі економічного розподілу навантаження на багатогодинний часовий горизонт з урахуванням погодинних змін навантаження, обмежень швидкості зміни потужності генераторів, ефектів клапанних точок та втрат у мережі. Ці особливості роблять задачу DED сильно неопуклою та нелінійною, що створює труднощі для традиційних і метаевристичних методів. Для запобігання передчасній збіжності або отриманню неоптимальних графіків генерації необхідно забезпечити надійний баланс між глобальним пошуком і локальним уточненням.* ***Мета****. Застосувати алгоритм оптимізації какапо для задачі динамічного економічного розподілу навантаження з метою формування економічно оптимальних і технічно допустимих графіків генерації на 24-годинному інтервалі диспетчеризації зі збереженням різноманітності популяції та стабільності пошуку.* ***Методика****. Алгоритм KOA моделює дві взаємодоповнювальні поведінкові фази какапо. Етап дослідження простору пошуку ґрунтується на шлюбній поведінці на токовищі та акустичній сигналізації, за якої розв'язки з вищою пристосованістю генерують сильніші «сигнали», що з певною ймовірністю притягують слабші кандидати до перспективних областей пошуку. Етап уточнення імітує завмирання та маскування, виконуючи локальні коригування перспективних розв'язків за допомогою адаптивних кроків. Алгоритм застосовано до стандартної п'ятиагрегатної системи протягом 24 годин і порівняно з дев'ятьма відомими метаевристичними алгоритмами.* ***Результати****. KOA забезпечує найменшу сумарну вартість генерації, швидку збіжність та високу робастність. Статистичні показники ефективності, зокрема середнє значення, найкращий та найгірший результати, стандартне відхилення і ранг, стабільно підтверджують перевагу KOA, що свідчить про його ефективність для багатовимірних і мультимодальних задач DED.* ***Наукова новизна****. Алгоритм KOA пропонує біологічно натхнену самоадаптивну пошукову структуру, яка забезпечує баланс між глобальним пошуком і локальним уточненням без використання параметрів зовнішнього керування.* ***Практична значимість****. Алгоритм є надійним, універсальним та обчислювально ефективним інструментом оптимізації для складних задач диспетчеризації електроенергетичних систем і має потенціал застосування в задачах інтеграції відновлюваних джерел енергії, багатокритеріальної оптимізації та адаптивного керування в реальному часі.*. Бібл. 29, табл. 4, рис. 2.

Ключові слова: **динамічний економічний розподіл навантаження, алгоритм оптимізації какапо, метаевристична оптимізація, функціонування електроенергетичної системи, ефекти клапанних точок, економічне планування навантаження.**

Introduction. Optimization of dynamic economic dispatch (DED) is a fundamental optimization problem in power system operation, aiming to schedule generating units over a multi-hour horizon while minimizing total operating cost and ensuring compliance with system constraints [1]. Unlike the single-period economic load dispatch (ELD), the DED problem incorporates time-coupled characteristics such as ramp-rate limits, valve-point effects, prohibited operating zones, and transmission losses, making it significantly more complex and highly nonlinear [2]. Accurate and efficient DED scheduling is essential for modern power systems, as it ensures economic efficiency, enhances operational security, accommodates fluctuating load patterns, and supports the integration of renewable energy resources. As power systems evolve toward higher penetration of variable renewable energy and increased demand-side management, the importance of robust DED optimization strategies becomes even more pronounced [3].

Given the nonconvex, multimodal, and dynamic structure of the DED problem, deterministic mathematical programming approaches often struggle to provide globally optimal or computationally feasible solutions. In contrast, metaheuristic algorithms have proven to be powerful tools for solving complex power system optimization problems due to their flexibility, derivative-free search mechanisms, and strong global exploration capabilities [4, 5]. Metaheuristic algorithms are stochastic-based approaches that rely on randomized search processes within the solution space, enabling them to provide high-quality and practically acceptable solutions for complex optimization problems [6–8]. Numerous metaheuristic optimization algorithms – ranging from evolutionary strategies to swarm intelligence and physics-inspired techniques – have been successfully applied to power system applications [9–12]. Recent literature demonstrates the increasing importance of metaheuristic optimization techniques in solving DED problems, particularly due to their strong ability to cope with nonlinearity, nonconvexity, multimodality, and operational constraints. A comprehensive survey of economic and multi-area dispatch confirms the significant expansion of metaheuristic applications in power system optimization and highlights the need for more advanced, adaptive, and robust methods for dispatch problems with dynamic characteristics [13].

Several recent studies have enhanced classical metaheuristics to address the complexities of DED under renewable integration, uncertainty, and practical operating constraints. For instance, an enhanced artificial hummingbird algorithm has been shown to effectively handle DED with uncertain wind power, ramp-rate limits, and valve-point effects, demonstrating strong performance across multiple dynamic test systems [14]. Similarly, the chaotic hippopotamus optimization algorithm (CHOA) has been applied to hybrid renewable power systems involving wind, solar, and electric vehicles, providing improved cost minimization and loss reduction over a 24-hour horizon while satisfying transmission loss and prohibited operating zone constraints [15].

Further improvements have been reported using a cheetah-inspired optimizer, which incorporates demand-side management and pumped-storage operation, achieving measurable cost reductions in renewable-integrated DED environments [16]. Differential evolution (DE) variants have also been adapted for combined heat-and-power DED, introducing migrating variables and constraint-repair mechanisms that significantly enhance feasibility and convergence behavior [17].

Additionally, the improved grey wolf optimizer strengthens exploration–exploitation balance through chaotic initialization and nonlinear convergence mechanisms, achieving superior cost minimization compared with traditional approaches across multi-scale DED systems [18]. Mathematical optimizers have also contributed to DED and ELD improvement; for example, arithmetic optimization algorithm variants using elementary function disturbances provide enhanced global search capability, faster convergence, and improved robustness when addressing nonlinear ELD/DED formulations involving valve-point effects and transmission losses [19].

Despite these advancements, DED remains a challenging problem due to its dynamic constraints, high dimensionality, and susceptibility to premature convergence in existing optimization methods. As highlighted in recent literature, the effectiveness of metaheuristics in solving DED heavily depends on their ability to maintain a proper balance between exploration and exploitation, avoid stagnation in local optima, and adapt their search behavior across the multi-hour dispatch horizon. Consequently, developing novel, robust, and adaptive optimization techniques continues to be an essential research direction in power system studies.

In this context, the present study employs the recently published kakapo optimization algorithm (KOA) to solve the DED problem. KOA is a nature-inspired metaheuristic based on the unique behavioral patterns of the kakapo bird, offering an adaptive, parameter-free, and exploration – exploitation-balanced search mechanism. Its evolutionary dynamics, characterized by probabilistic attraction and fine-tuned local search, make it a promising candidate for addressing the inherent complexities of DED.

The goal of the work is to apply kakapo optimization algorithm for the dynamic economic dispatch problem, aiming to generate economically optimal and operationally feasible generation schedules over a 24-hour dispatch horizon while preserving population diversity and search stability.

The major contributions of this study are summarized as follows. First, a comprehensive DED formulation is considered, incorporating practical system characteristics such as ramp-rate limits, valve-point effects, and time-varying load demands across a 24-hour horizon. Second, the recently developed KOA algorithm is applied to DED for the first time, and its performance is rigorously evaluated. Third, an extensive comparative analysis is performed against nine well-established metaheuristic algorithms to assess robustness, convergence behavior, and cost minimization capability. Fourth, statistical indicators – including mean, best, worst, standard deviation, and rank – are examined to ensure a fair and reliable performance evaluation.

Dynamic economic dispatch problem represents one of the fundamental optimization challenges in modern power system operation, as it extends the traditional single-period dispatch problem into a multi-hour planning horizon. Unlike ELD, where the load demand is assumed to be constant at a single operating point, the DED problem accounts for hourly load variations over a typical 24-hour period. Consequently, its dimensionality becomes significantly higher – specifically, 24 times larger than that of the static ELD – since a separate generation schedule must be determined for each hour of the dispatch interval.

In today's operational environments, system operators face continuously changing demand patterns, technical limitations of generating units, and nonlinearities such as valve-point loading effects. These complexities make the DED problem highly nonconvex and computationally challenging, thereby motivating the use of advanced metaheuristic optimization techniques. The mathematical formulation of the DED problem, including the objective function and its associated operational constraints, is presented in the following subsections.

Objective function. The goal of the DED problem is to minimize the total generation cost over the entire dispatch horizon. The cost of each generator is modeled as a function of its real power output.

The objective function is defined as:

$$\text{Minimize: } F=\sum_{h=1}^{T}\sum_{i=1}^{N_G}F_{ih}\left(P_{ih}\right), \tag{1}$$

where T is the total number of dispatch periods (hours), typically T = 24; N_G is the number of committed (online) generating units; P_{ih} or P_{it} are the real power output (MW) of generator i at hour h (or t); $F_{ih}(P_{it})$ is the fuel cost of generator i during hour h.

For each generator, the fuel cost is approximated by a quadratic function:

$$F_{it}\left(P_{it}\right)=a_i P_{it}^2+b_i P_{it}+c_i\ , \tag{2}$$

where a_i (\$/MW^2), b_i (\$/MW), c_i (\$) are the cost coefficients of generator i;

Valve-point loading effect. To model nonlinear ripples in fuel cost due to valve-point opening, the cost function becomes:

$$F_{it}\left(P_{it}\right)=a_i P_{it}^2+b_i P_{it}+c_i+\left|e_i \sin\left(f_i\left(P_{it}-P_i^{\min}\right)\right)\right|, \tag{3}$$

where e_i, f_i are the valve-point loading coefficients for generator i; $P_i^{\min}$ is the minimum power output (MW) of generator i. The sinusoidal term creates multiple local minima, significantly increasing the difficulty of the optimization process.

DED constraints. A feasible DED schedule must satisfy several operational constraints related to system balance, generator limits and ramping characteristics.

Power balance constraint. At every hour t, the total power generation must match the system demand plus transmission losses:

$$\sum_{i=1}^{N_G} P_{it}=P_{Dt}+P_{Lt}\ , \tag{4}$$

where P_{Dt} is the system load demand (MW) at hour t; P_{Lt} is the transmission loss (MW) at hour t.

Transmission losses are computed using the B-coefficient formula:

$$P_{Lt}=\sum_{i=1}^{N_G}\sum_{j=1}^{N_G} P_{it} B_{ij} P_{jt}\ , \tag{5}$$

where B_{ij} is the loss coefficient (MW^{-1}) relating units i and j.

Generator operating limits. Each generating unit can operate only within its physical minimum and maximum output:

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

where $P_i^{\min}$ is the minimum power output limit of generator i; $P_i^{\max}$ is the maximum power output limit of generator i.

Ramp rate limits. Generating units cannot change their power output instantaneously. Their ramp-up and ramp-down capabilities are modeled as:

Generation increase constraint:

$$P_{it} - P_{i(t-1)} \le UR_i. \tag{7}$$

Generation decrease constraint:

$$P_{i(t-1)} - P_{it} \le DR_i, \tag{8}$$

where UR_i is the ramp-up limit (MW/h) of generator i; DR_i is the ramp-down limit (MW/h) of generator i; $P_{i(t-1)}$ is the output of generator i at the previous hour.

These restrictions create a feasible range for the output during hour t:

$$\max(P_i^{\min}, P_{i(t-1)} - DR_i) \le P_{it} \le \min(P_i^{\max}, P_{i(t-1)} + UR_i). \tag{9}$$

Fitness function and constraint handling. A penalty-based fitness evaluation is used to ensure that all equality and inequality constraints are adequately enforced during the optimization process. The fitness function is expressed as:

$$f=\sum_{t=1}^{n}\sum_{i=1}^{N} F_{it}\left(P_{it}\right)+\lambda_1\left(\sum_{t=1}^{n}\sum_{i=1}^{N} P_{it}-P_{Dt}\right)^2+ \\ +\lambda_r\left(\sum_{t=1}^{n}\sum_{i=1}^{N} P_{it}-P_r^{\lim}\right)^2, \tag{10}$$

where n is the number of hours in the scheduling horizon (n=T); N is the number of generating units (N=N_G); λ_1 is the penalty factor for power balance constraint violation; λ_r is the penalty factor for ramp-limit violation.

The adjusted feasible limit $P_r^{\lim}$ is given by:

$$P_r^{\lim}=\begin{cases} P_{i(t-1)}-DR_i, \text{ if } P_{it}<P_{i(t-1)}-DR_i; \\ P_{i(t-1)}+UR_i, \text{ if } P_{it}>P_{i(t-1)}+UR_i; \\ P_{it}, \text{ else.} \end{cases} \tag{11}$$

This formulation ensures that solutions violating ramp limits incur a penalty rather than being discarded.

Kakapo optimization algorithm. KOA is a recent bio-inspired metaheuristic method developed based on the ecological and behavioral characteristics of the kakapo (Strigops habroptilus), an endangered nocturnal parrot native to New Zealand. The algorithm, originally proposed in [20], captures the kakapo's distinctive survival, mating, and adaptive strategies, translating them into mathematically structured search operators suitable for solving complex optimization problems. In this research, KOA is employed as the core optimizer for minimizing the DED objective function presented in section «Dynamic economic dispatch problem». To enable a rigorous and transparent application of KOA to the DED problem, this section provides a concise yet fully detailed introduction to the theoretical foundations, mathematical modeling, and computational operators of the algorithm. KOA consists of two synergistic phases, exploration and exploitation, each modeling a different biological aspect of kakapo behavior. Exploration is driven by long-range mating calls and lek-based selection, encouraging global diversification. Exploitation, on the other hand, is inspired by freezing and camouflage strategies, promoting localized refinement of promising solutions. Together, these mechanisms establish a balanced search process capable of avoiding premature convergence while efficiently guiding the population toward high-quality regions of the solution space.

Biological motivation and algorithmic concept. Kakapo exhibits several remarkable behaviors that serve as the conceptual basis of KOA:

- **Lek mating and acoustic signaling (exploration).** Male kakapos construct shallow lek depressions that act as acoustic amplifiers, enabling their booming calls to propagate over large distances. Males emitting stronger calls attract more females. In KOA, this is mapped into a mechanism where candidate solutions with superior fitness generate stronger signals, and weaker individuals are probabilistically guided toward these promising regions.
- **Fitness-based female selection.** Females evaluate multiple males and select the one emitting the most dominant call. Algorithmically, each candidate evaluates a set of superior solutions and moves toward the strongest one, providing directional global search.

• **Freezing and camouflage (exploitation).** When threatened, kakapos avoid movement and rely on camouflage rather than escape. KOA converts this behavior into a local search operator that applies small, adaptive adjustments around the current position, gradually shrinking step size as iterations progress.

Exploration phase: global search via lek mating. The exploration phase is inspired by the kakapo's lek mating system, where males attract females with booming calls. In KOA, the relative quality of candidate solutions determines their booming intensity, which guides exploration:

$$F^n = \begin{cases} \dfrac{f_i - f_{worst}}{\sum_{j=1}^{N_{KOA}} f_j - f_{worst}}, \text{ if } \sum_{j=1}^{N_{KOA}} f_j - f_{worst} \neq 0; \\ \dfrac{1}{N_{KOA}}, \text{ else,} \end{cases} \quad (12)$$

where F^n is the normalized of objective function value; f_i is the objective function value of i^{th} member; N_{KOA} is the number of population members; $f_{worst} = \max\{F_1, F_2, ..., F_{NKOA}\}$ is representing the least fit candidate. This normalization ensures that better solutions emit proportionally stronger signals.

The perceived signal by candidate i from candidate j accounts for distance:

$$V_{i,j} = Voice(X_i, X_j) = \frac{F^n}{\sqrt{\sum_{d=1}^{m} (x_{i,d} - x_{j,d})}}, \quad (13)$$

where the denominator represents the Euclidean distance between solutions X_i and X_j, ensuring that influence diminishes with distance and maintaining population diversity.

Each candidate X_i then selects potential mates from the global best solution X_{best} and all superior candidates:

$$Male_i = \{X_{best} \cup X_k \mid F_k < F_i\}. \quad (14)$$

The dominant mate $Male_i$ is chosen as the individual with the highest received signal. Candidate X_i moves probabilistically toward this selected mate:

$$X_i^{P1} = X_i + 2\sin\left(r\frac{\pi}{2}\right) \cdot (Male_i - I \cdot X_i), \quad (15)$$

where X_i^{P1} is the proposed new position for i^{th} member based on exploration phase; $r \sim U(0, 1)$ is a uniform random number; $I \in \{1, 2\}$ is a discrete factor controlling attraction intensity. The new position is accepted if it improves the objective value:

$$X_i = \begin{cases} X_i^{P1}, \text{ if } F_i^{P1} \leq F_i; \\ X_i, \text{ else.} \end{cases} \quad (16)$$

Exploitation phase: local refinement via camouflage. Local exploitation in KOA is motivated by the kakapo's defensive freezing and camouflage behavior. Once a promising solution is identified, the candidate undergoes small, adaptive adjustments to refine its position:

$$X_i^{P2} = X_i + \left(1 - 2\sin\left(r\frac{\pi}{2}\right)\right) \cdot |UB - LB| \cdot e^{-t/T}, \quad (17)$$

where X_i^{P2} is the proposed new position for i^{th} member based on exploitation phase; UB, LB are the decision variable bounds; t is the current iteration; T is the maximum number of iterations. The candidate is updated conditionally:

$$X_i = \begin{cases} X_i^{P2}, \text{ if } F_i^{P2} \leq F_i; \\ X_i, \text{ else.} \end{cases} \quad (18)$$

This mechanism ensures precise local optimization, stabilizes promising candidates, and promotes convergence toward optima.

In the following section, the DED problem – along with its objective function and full set of constraints – is optimized using the KOA. The performance of KOA is then systematically compared with several other state-of-the-art metaheuristic algorithms to demonstrate its effectiveness and robustness in solving complex dynamic dispatch problems.

Simulation studies and performance analysis of KOA on the DED problem. In this section, the recently proposed KOA is applied to the DED problem to evaluate its performance in optimizing generation scheduling over a 24-hour horizon. The primary goal is to minimize the total generation cost while satisfying system operational constraints, including generation limits, ramp rates and network demand requirements.

Case study: 5 unit power system. The DED study considers a standard 5 unit power system operating over 24 h. The hourly load demand profile and generator-specific parameters are provided as follows: number of load hours – 24; number of generators – 5.

Power demand (MW) over 24 h: 410, 435, 475, 530, 558, 608, 626, 654, 690, 704, 720, 740, 704, 690, 654, 580, 558, 608, 654, 704, 680, 605, 527, 463.

Transmission loss coefficients (B-matrix):

$$B = \begin{vmatrix} 4.9 & 1.4 & 1.5 & 1.5 & 2 \\ 1.4 & 4.5 & 1.6 & 2 & 1.8 \\ 1.5 & 1.6 & 3.9 & 1 & 1.2 \\ 1.5 & 2 & 1 & 4 & 1.4 \\ 2 & 1.8 & 1.2 & 1.4 & 3.5 \end{vmatrix} \times 10^{-5}$$

Generators data ($P_{\min}$, $P_{\max}$, cost coefficients and valve-point effects) are presented in Table 1, while ramp rate and operating zone constraints are provided in Table 2.

Table 1

Generators data

Unit	$P_{\min}$, MW	$P_{\max}$ MW	a, \$/MW^2	b, \$/MW	c, \$	e	f
1	10	75	0.008	2	25	100	0.042
2	20	125	0.003	1.8	60	140	0.04
3	30	175	0.0012	2.1	100	160	0.038
4	40	250	0.001	2	120	180	0.037
5	50	300	0.0015	1.8	40	200	0.035

Table 2

Ramp rate and operating zone constraints

Unit	UR, MW/h	DR, MW/h	Zone1 min	Zone1 max	Zone2 min	Zone2 max
1	30	30	10	10	10	10
2	30	30	20	20	20	20
3	40	40	30	30	30	30
4	50	50	40	40	40	40
5	50	50	50	50	50	50

Implementation of KOA on the DED problem. The KOA algorithm was implemented to optimize the hourly generation schedules of the 5 units over the 24 h dispatch period. The hourly generation results obtained from KOA are shown in Table 3, while the convergence behavior of the algorithm is illustrated in Fig. 1.

Table 3
Hourly generation schedule of generators over the 24-hour dispatch horizon

Hours	Gen. 1	Gen. 2	Gen. 3	Gen. 4	Gen. 5	Demand
1	46.11662	83.52216	83.2277	90.9579	169.3697	473.1941
2	21.4801	87.62952	43.90394	139.9543	157.3372	450.3051
3	51.45117	70.03376	68.21506	128.6201	206.9151	525.2352
4	37.86257	53.29862	74.47033	178.3501	192.3671	536.3487
5	50.12573	72.97188	109.0332	164.1918	168.1146	564.4372
6	29.69906	86.06437	119.7154	176.4838	203.91	615.8726
7	51.04515	84.30845	114.7332	176.0769	208.0255	634.1892
8	51.57515	84.69726	140.8388	172.6809	213.9147	663.7069
9	63.70681	79.63767	129.6526	180.9167	245.129	699.0428
10	54.65936	94.41113	129.6619	225.862	209.4364	714.0308
11	52.49315	80.26212	124.6985	183.1834	251.3803	692.0174
12	59.71101	105.8928	137.3994	169.5833	276.8193	749.4059
13	52.1899	109.967	127.5033	186.7113	239.0105	715.382
14	53.20617	81.67361	116.544	236.5096	211.5443	699.4777
15	51.99971	101.9325	119.3569	186.5427	202.7541	662.5859
16	63.73308	76.59892	82.70339	193.765	168.9226	585.723
17	47.08895	90.25797	114.2526	143.979	190.9772	586.5557
18	53.4963	96.00657	120.3826	169.0987	176.6804	615.6646
19	49.33967	79.86549	137.8555	187.8211	208.9346	663.8163
20	53.54952	91.23786	167.7917	197.979	203.6111	714.1692
21	49.37575	105.1834	139.382	149.2361	246.0384	689.2156
22	50.12384	82.59457	104.1344	180.1852	196.0631	613.1011
23	49.42887	63.509	69.39283	170.916	183.0527	536.2994
24	52.14645	72.6833	30	151.2307	160.9773	467.0377

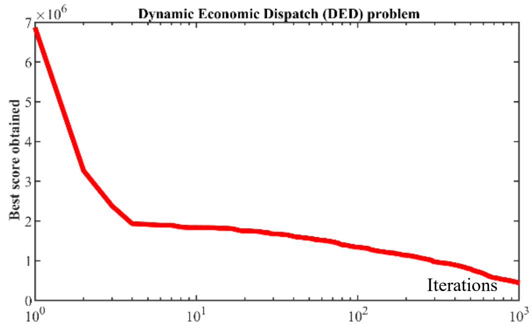

Fig. 1. Convergence curve of KOA performance on the DED problem

The convergence curve in Fig. 1 demonstrates that KOA rapidly approaches near-optimal solutions within the first 100 iterations and gradually refines the total generation cost to a minimal value, confirming the algorithm's stability and efficiency.

Comparative performance analysis. To validate the effectiveness of KOA, its performance was benchmarked against 9 well-known metaheuristic algorithms: genetic algorithm (GA) [21], particle swarm optimization (PSO) [22], gravitational search algorithm (GSA) [23], whale optimization algorithm (WOA) [24], teaching-learning-based optimization (TLBO) [25], multi-verse optimizer (MVO) [26], tunicate swarm algorithm (TSA) [27], grey wolf optimizer (GWO) [28] and marine predators algorithm (MPA) [29].

The statistical results obtained from 30 independent runs of each algorithm are summarized in Table 4, and boxplot distributions of the objective function are depicted in Fig. 2.

The results clearly demonstrate that KOA outperforms all competitor algorithms in terms of mean and best generation cost, achieving the lowest objective value (mean = 437887.2) and securing rank 1 among all tested algorithms. The boxplot analysis in Fig. 2 further highlights the consistency and robustness of KOA, as it exhibits the narrowest interquartile range and minimal variability in solution quality across multiple runs.

Discussion. The superior performance of KOA on the DED problem can be attributed to several factors:

1. **Effective balance between exploration and exploitation.** The lek mating-inspired global search efficiently guides candidate solutions toward promising regions, while the camouflage-driven local refinement ensures precise convergence near optimal solutions.
2. **Preservation of population diversity.** Distance-based signal propagation prevents premature convergence and maintains diverse solution candidates throughout the search process.
3. **Adaptive, stochastic search mechanisms.** Sinusoidal random factors and iteration-based step size reduction provide fine-grained adjustments that enhance solution accuracy.

Overall, the simulation results demonstrate that KOA is highly capable of generating cost-effective and feasible generation schedules for complex, multi-unit DED problems. The algorithm's superior convergence characteristics and robustness compared to GA, PSO, GSA, WOA, TLBO, MVO, TSA, GWO and MPA highlight its potential as a reliable tool for practical power system dispatch applications.

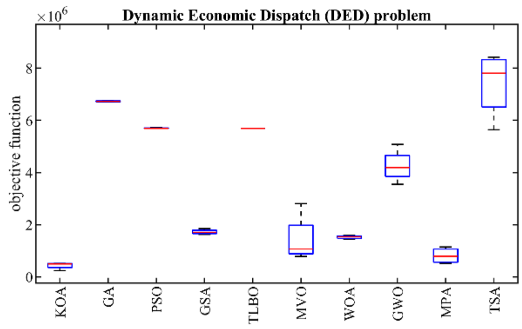

Fig. 2. Boxplot diagrams of KOA and the competitor algorithms on the DED problem

Table 4
Statistical results of KOA and competitor algorithms applied to the DED problem

	KOA	GA	PSO	GSA	TLBO	MVO	WOA	GWO	MPA	TSA
Mean	437887.2	6720657	5698276	1723748	5689705	1434226	1523670	4251127	814578.5	7415002
Best	241032	6697859	5689705	1630110	5689705	783827	1435945	3548498	524603	5636969
Worst	518064.2	6744016	5723987	1852886	5689705	2809419	1592087	5076836	1149721	8413637
Std	132165.5	24865.71	17141.04	94054.47	0	929183.4	65769.13	628895.2	300209.1	1267961
Median	496226.4	6720376	5689705	1705998	5689705	1071828	1533324	4189587	791994.9	7804701
Rank	1	9	8	5	7	3	4	6	2	10

Conclusions. Application of the KOA to the DED problem in a multi-unit power system over a 24 h horizon is investigated. The DED problem, inherently nonconvex and highly nonlinear due to valve-point loading effects, ramp-rate limits, and transmission losses, represents a significant operational challenge for modern power systems. By leveraging KOA's bio-inspired mechanisms, including lek mating-based exploration and camouflage-driven exploitation, the algorithm effectively balances global search diversification with local refinement, enabling the identification of cost-optimal and feasible generation schedules across all dispatch intervals. Simulation results on a standard five-unit system demonstrate that KOA outperforms nine benchmark metaheuristic algorithms in terms of total generation cost, convergence speed, and solution robustness.

The convergence analysis revealed that KOA rapidly reaches near-optimal solutions within the early iterations, while maintaining a stable search process that prevents premature convergence. Statistical performance metrics, including mean, best, worst, standard deviation, and rank, consistently favor KOA, confirming its effectiveness in handling multi-dimensional, multi-modal optimization problems inherent in DED.

The success of KOA in this study can be attributed to three key factors: 1) efficient global exploration through fitness-weighted acoustic signaling and probabilistic attraction, which enables the algorithm to explore diverse solution regions; 2) precise local exploitation inspired by kakapo freezing and camouflage behavior, allowing fine-grained adjustments near promising solutions; 3) adaptive, stochastic search operators that enhance population diversity and robustness against local minima. Collectively, these features render KOA a reliable tool for complex power system dispatch problems, ensuring both economic efficiency and operational feasibility.

For future research, several avenues can be pursued to further enhance the applicability and performance of KOA in DED and related domains:

1. Integration with renewable energy sources such as wind and solar, which introduces additional uncertainty and intermittency in generation profiles.
2. Inclusion of multi-objective criteria, incorporating emission minimization, reliability enhancement, and system security alongside generation cost reduction.
3. Hybridization with other metaheuristics or machine learning techniques to accelerate convergence and improve adaptability to large-scale power systems.
4. Real-time and adaptive implementations, enabling KOA to respond dynamically to sudden load changes or generator outages in practical operational environments.
5. Investigation of scalability and parallelization strategies, to efficiently handle large-scale systems with high-dimensional decision variables and complex network constraints.

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Conflict of interest. The authors declare that they have no conflicts of interest.

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