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Efficient and reliable scheduling of power generating units in the unit commitment problem using the Tardigrade optimization algorithm

Introduction. *The unit commitment (UC) problem is a critical operational task in power systems, involving the optimal scheduling of generating units while meeting demand, satisfying technical constraints, and minimizing operating costs. Due to its combinatorial nature, nonlinear characteristics, and numerous interdependent constraints, UC poses a highly complex optimization challenge. Metaheuristic algorithms have demonstrated strong potential in addressing such large-scale problems; however, many existing methods struggle to maintain a proper exploration–exploitation balance, limiting their performance in dynamic UC environments.* ***Problem.*** *Traditional metaheuristic algorithms often suffer from premature convergence, inadequate local refinement, or dependency on control parameters that require tuning. Such limitations reduce robustness and adaptability when dealing with UC's intricate search landscape. Therefore, there is a need for a parameter-free, self-adaptive optimization algorithm capable of reliably solving UC with high efficiency and convergence stability. The* ***goal*** *of this study is to develop an efficient and reliable scheduling framework for power generating units in the UC problem by employing the tardigrade optimization algorithm (TOA) and to demonstrate its effectiveness compared with established optimization techniques.* ***Methodology.*** *TOA is inspired by the active and cryptobiotic survival behaviors of tardigrades. The exploration phase imitates active adaptive locomotion to broaden global search, while the exploitation phase abstracts cryptobiotic stability to refine solutions locally. These mechanisms are formulated through adaptive state-transition operators that adjust search behavior automatically without external parameters. TOA is applied to a 24-hour UC problem consisting of 10 generating units under realistic load and operational constraints. Its performance is benchmarked against 6 widely used metaheuristic algorithms.* ***Results.*** *The proposed TOA achieves the lowest total operating cost, exhibits strong convergence behavior, and demonstrates high consistency across independent runs, outperforming all comparative methods. The* ***scientific novelty*** *lies in introducing a biologically inspired, parameter-free, self-adaptive metaheuristic algorithm. Its* ***practical value*** *is validated through superior performance in UC scheduling, indicating strong potential for broader power system optimization tasks.* References 21, tables 3, figures 3.

Key words: **tardigrade optimization algorithm, unit commitment problem, metaheuristic algorithm, power system optimization, power generating unit.**

Вступ*. Проблема зобов'язань за потужністю одиниць (UC) є критично важливим операційним завданням в енергетичних системах, що включає оптимальне планування генеруючих блоків з одночасним задоволенням попиту, технічних обмежень та мінімізацією експлуатаційних витрат. Через свою комбінаторну природу, нелінійні характеристики та численні взаємозалежні обмеження, UC створює дуже складну задачу оптимізації. Метаевристичні алгоритми продемонстрували значний потенціал у вирішенні таких масштабних проблем, однак багато існуючих методів мають труднощі з підтримкою належного балансу між розвідкою та експлуатацією, що обмежує їхню продуктивність у динамічних середовищах UC.* ***Проблема****. Традиційні метаевристичні алгоритми часто страждають від передчасної збіжності, недостатнього локального уточнення або залежності від параметрів керування, які потребують налаштування. Такі обмеження знижують стійкість та адаптивність при роботі зі складним ландшафтом пошуку UC. Тому існує потреба в безпараметричному, самоадаптивному алгоритмі оптимізації, здатному надійно вирішувати UC з високою ефективністю та стабільністю збіжності.* ***Метою*** *роботи є розробка ефективної та надійної системи планування роботи енергоблоків у задачі оптимізації енергосистеми з використанням алгоритму оптимізації тихоходок (TOA) та демонстрація її ефективності порівняно з існуючими методами оптимізації.* ***Методика****. TOA натхненний активною та криптобіотичною поведінкою тихоходок, спрямованою на виживання. Фаза дослідження імітує активне адаптивне пересування для розширення глобального пошуку, тоді як фаза експлуатації абстрагує криптобіотичну стабільність для локального уточнення рішень. Ці механізми формулюються за допомогою адаптивних операторів переходу станів, які автоматично коригують поведінку пошуку без зовнішніх параметрів. TOA застосовується до 24-годинної задачі UC, що складається з 10 генеруючих блоків за реальних обмежень навантаження та експлуатації. Його продуктивність порівнюється з 6 широко використовуваними метаевристичними алгоритмами.* ***Результати****. Запропонований TOA досягає найнижчих загальних експлуатаційних витрат, демонструє значну поведінку збіжності та демонструє високу узгодженість у незалежних запусках, перевершуючи всі порівняльні методи.* ***Наукова новизна*** *полягає у впровадженні біологічно натхненного, безпараметричного, самоадаптивного метаевристичного алгоритму. Його* ***практична цінність*** *підтверджена високою продуктивністю у плануванні UC, що вказує на значний потенціал для ширших завдань оптимізації енергосистеми.* Бібл. 21, табл. 3, рис. 3.

Ключові слова: **алгоритм оптимізації тихоходки, завдання планування роботи енергоблоків, метаевристичний алгоритм, оптимізація енергосистеми, енергогенеруюча установка.**

Introduction. The unit commitment (UC) problem is a fundamental optimization task in power system operation, aimed at determining the on/off status of generating units and the optimal allocation of their output power over multiple time intervals [1]. The primary objective is to satisfy system load demand while minimizing the total generation cost, subject to the operational constraints of power units. Due to its economic and operational significance, UC mathematical models play a central role in planning and decision-making for power system operators [2].

The UC problem is inherently combinatorial and nonlinear, as it involves both discrete decision variables (unit status) and continuous variables (generation levels). Efficient solution methods are therefore crucial for achieving optimal system performance while respecting physical and operational constraints [3]. Metaheuristic algorithms have shown effective applications in solving the UC problem, providing near-optimal solutions within reasonable computational effort and successfully handling its nonlinearity and combinatorial complexity [4, 5].

Metaheuristic algorithms are stochastic, population-based optimization techniques inspired by natural, biological, social or physical processes. Their key strength lies in their ability to handle multimodal, nonlinear, high-dimensional and derivative-free problems with reasonable computational effort [6]. Metaheuristics are capable of escaping local optima through probabilistic exploration mechanisms while providing high-quality near-optimal solutions, making them highly suitable for UC scheduling and similar engineering challenges [7–11]. Numerous well-known metaheuristic methods – genetic algorithm (GA) [12], particle swarm optimization (PSO) [13], gravitational search algorithm (GSA) [14], and many recently developed nature-inspired algorithms – have demonstrated notable success in improving UC solution quality compared to deterministic approaches.

However, despite their effectiveness, metaheuristics inherently rely on stochastic operators and therefore can not guarantee convergence to the global optimum [15]. Their performance critically depends on maintaining an appropriate balance between exploration (searching new regions) and exploitation (refining existing promising solutions) [16, 17]. According to the no free lunch theorem [18], no single metaheuristic can outperform all others across every optimization scenario, motivating continuous research into new algorithms capable of offering improved performance, adaptability, and robustness for specific classes of problems such as UC.

In this context, biological systems exhibiting exceptional adaptability and resilience provide a rich source of inspiration for designing new optimization methods. One such organism is the tardigrade (Tardigrada), a microscopic extremophile renowned for its unmatched survival strategies, including cryptobiosis, adaptive locomotion, and reactive environmental exploration. These behaviors naturally align with the fundamental principles of optimization – particularly the dynamic interplay between global exploration and local exploitation.

Motivated by these unique biological characteristics, this study introduces a novel population-based metaheuristic method called the Tardigrade Optimization Algorithm (TOA). In TOA, the exploration mechanism models the tardigrade's adaptive roaming across micro-environments in search of favorable conditions, while the exploitation mechanism mimics its cryptobiotic stability and localized reactivation behavior under improved environmental conditions. This biologically inspired modeling enables TOA to achieve a dynamic and efficient balance between wide-range search and precise local refinement.

The **goal** of this study is to develop an efficient and reliable scheduling framework for power generating units in the UC problem by employing the tardigrade optimization algorithm (TOA) and to demonstrate its effectiveness compared with established optimization techniques.

The major contributions of this study are as follows:

- development of the TOA, inspired by the unique adaptive and cryptobiotic behavior of tardigrades;
- formulation of a mathematical search model capturing both large-scale exploration and small-scale exploitation through biologically inspired mechanisms;
- application of TOA to the UC scheduling problem and comprehensive simulation studies validating its effectiveness;
- comparative performance assessment against modern metaheuristic algorithms, demonstrating superior robustness, convergence ability, and solution accuracy.

Problem definition. UC problem. In this section, the mathematical formulation of the UC problem is presented, which serves as the basis for optimization using the proposed TOA.

Mathematical formulation. The UC problem involves determining the operational schedule of generating units over a predefined time horizon while satisfying demand and operational constraints, with the ultimate objective of minimizing total generation cost. This mathematical representation provides a rigorous framework for modeling the complex interactions between unit statuses, generation levels and system requirements.

Objective function. The primary objective of the UC problem is to minimize the total generation cost across all units and time periods. The cost is typically represented as a quadratic function of the generated power for each unit, reflecting fuel and operational expenditures:

$$\min C_t = \sum_{i=1}^{N_G} \left(a_i + b_i P_{i,t} + c_i P_{i,t}^2 \right), \tag{1}$$

where C_t is the total generation cost at time period t; N_G is the total number of generating units; $P_{i,t}$ is the power output of unit i at time t; a_i, b_i, c_i are the fuel cost coefficients of unit i, capturing the fixed, linear and quadratic components of the generation cost function.

This objective function accurately models the relationship between unit generation levels and operational costs, allowing the evaluation of alternative commitment strategies in a quantitative manner.

Decision variables. The UC problem involves two types of decision variables:

1. Unit status (binary variable). The binary decision variable $u_{i,t}$ is indicating the ON/OFF status of unit i at time t ($u_{i,t} = 1$ if the unit is ON, and $u_{i,t} = 0$ otherwise):

$$u_{i,t} = \begin{cases} 1, \text{ if unit } i \text{ is ON at time } t; \\ 0, \text{ if unit } i \text{ is OFF at time } t. \end{cases} \tag{2}$$

2. Unit generation level (continuous variable):

$$P_{i,t} \geq 0. \tag{3}$$

These two variables are interdependent, as a unit can generate power only when it is switched ON.

Constraints. The UC problem is subject to a set of operational and system constraints, which ensure feasibility, reliability, and safety of power system operation. Each constraint is explained in detail below:

1. Power balance constraint. The total generated power must exactly meet the system load demand at each time interval:

$$\sum_{i=1}^{N_G} u_{i,t} P_{i,t} = P_t^D , \tag{4}$$

where P_t^D is the system load demand at time t. This constraint guarantees that electricity supply matches demand continuously, preventing shortages or surpluses.

2. Generation limits of units. Each unit must operate within its minimum and maximum generation capacities when it is ON:

$$u_{i,t} P_i^{\min} \leq P_{i,t} \leq u_{i,t} P_i^{\max}, \tag{5}$$

where $P_i^{\min}$, $P_i^{\max}$ are the minimum and maximum generation limits of unit i. This constraint ensures operational feasibility by restricting generation to allowable ranges and enforcing that units produce zero output when they are OFF.

Introducing and mathematical modeling of the TOA. This section introduces the proposed TOA, a novel bio-inspired metaheuristic designed to simulate the adaptive, survival-oriented behaviors of Tardigrades (water bears) in natural environments. The algorithm is mathematically modeled to be applicable across a wide variety of optimization problems in engineering, science and artificial intelligence. The TOA models 3 essential biological processes of tardigrades (free aquatic motion, local feeding and survival behavior, and the tun mechanism for revival) each corresponding to exploration, exploitation and adaptive switching between these 2 main phases.

Behavioral analysis of tardigrades and core design concept of TOA. Tardigrades are microscopic invertebrates known for their extraordinary ability to survive under extreme environmental conditions, including desiccation, freezing, radiation and vacuum. Their adaptability originates from a series of behaviors that allow them to explore, exploit, and survive in fluctuating environments. These behaviors are abstracted and mapped into three computational phases in the proposed algorithm:

- **Exploration phase** corresponds to the *free locomotion and foraging behavior* of tardigrades in aquatic environments. In this state, tardigrades move freely to discover new regions containing food or suitable conditions. This inspires wide, randomized search movements across the problem space.
- **Exploitation phase** corresponds to *localized feeding behavior* in nutrient-rich microenvironments. Once a tardigrade identifies a favorable area, it remains locally active with small and precise movements to optimize feeding. This is analogous to local fine-tuning around promising solutions.
- **Switching phase (tun mechanism)** corresponds to *cryptobiosis (tun state)*, a survival response when the environment becomes hostile. The tardigrade dehydrates, halts metabolism, and later revives with renewed energy. In the algorithm, this mechanism controls the transition between exploitation and exploration, allowing the population to escape stagnation and restore diversity.

Through this behavioral mapping, TOA achieves a biologically motivated balance between global exploration, local exploitation, and adaptive restarts, resulting in efficient convergence while preventing premature stagnation.

Initialization process of the TOA. At the beginning of the optimization process, the TOA initializes a population of tardigrades with N member, each representing a candidate solution in the m-dimensional search space. The population matrix X is defined as:

$$X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,d} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ x_{i,1} & \cdots & x_{i,d} & \cdots & x_{i,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,d} & \cdots & x_{N,m} \end{bmatrix}_{N\times m}, \qquad (6)$$

where each element $x_{i,d}$ is the position of tardigrade i in dimension d.

The initial positions are randomly generated within the problem's lower and upper bounds:

$$x_{i,d} = lb_d + r\cdot(ub_d - lb_d), \qquad (7)$$

where lb_d, ub_d are the lower and upper bounds of the d^{th} dimension; $r \sim U(0, 1)$ is the uniformly distributed random number.

The fitness of each tardigrade is evaluated using the objective function F:

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1}. \qquad (8)$$

Exploration phase. The exploration phase models the *free aquatic movement* of tardigrades as they search for new sources of nutrients. This behavior corresponds to global exploration in the search space – large stochastic movements toward promising regions. Each tardigrade identifies potential food locations among members with better fitness values, including the global best position:

$$Food_i = \in \{X_k | F_k < F_i \cup X_{best}\}. \qquad (9)$$

Then, each tardigrade updates its position according to:

$$X_i^{P1} = X_i + I_1\cdot r_1\cdot(Food_i - I_2\cdot X_i) + \Delta X_\varepsilon^{P1}(t), \qquad (10)$$

where $I_i \in \{1, 2\}$ are integer control parameters determining interaction intensity; $r_i \sim U(0, 1)$ is a random coefficient controlling stochastic motion. The perturbation term $\Delta X_\varepsilon^{P1}(t)$ is a random hydrodynamic disturbances:

$$\Delta X_\varepsilon^{P1}(t) = P_\varepsilon \cdot \frac{(1-2r_2)}{(t+1)^{1+r_3}} \cdot |ub - lb|, \qquad (11)$$

where $P_\varepsilon \in \{0, 1\}$ determines the presence of noise, and $r_i \sim U(0, 1)$.

The updated position is accepted if it improves the fitness:

$$X_i = \begin{cases} X_i^{P1}, & \text{if } F_i^{P1} < F_i; \\ X_i, & \text{else.} \end{cases} \qquad (12)$$

This formulation allows each tardigrade to move dynamically toward better regions while maintaining stochastic diversity, thus effectively performing wide exploration.

Exploitation phase. Once a tardigrade finds a resource-rich region, it limits its movement to fine adjustments in the local area. This behavior corresponds to the exploitation phase of optimization.

The local search is expressed as:

$$X_i^{P2} = X_i + \sigma\cdot r_4\cdot(Food_i - I_3\cdot X_i) + \Delta X_\varepsilon^{P2}(t), \qquad (13)$$

The local random perturbation term $\Delta X_\varepsilon^{P2}(t)$ is defined as:

$$\Delta X_\varepsilon^{P2}(t) = P_\varepsilon \cdot \frac{r_5}{(t+1)^{1+r_6}} \cdot (X_{best} - I_4 \cdot X_i), \qquad (14)$$

where $r_i \sim U(0, 1)$ and $I_i \in \{1, 2\}$.

The adaptive coefficient σ controls the intensity of local movement and gradually decreases with iterations, ensuring convergence:

$$\sigma = 1 - (t / T)^{1+r_7}. \qquad (15)$$

Finally, the updated position is accepted if it improves the fitness value:

$$X_i = \begin{cases} X_i^{P2}, & \text{if } F_i^{P2} < F_i; \\ X_i, & \text{else.} \end{cases} \qquad (16)$$

This phase simulates precise micro-movements of tardigrades near favorable food sources, analogous to local refinement around optima.

Tun mechanism: adaptive switching between phases. Tardigrades enter the *tun state* when exposed to unfavorable conditions and later revive once the environment becomes suitable again. In TOA, this phenomenon is abstracted to govern the switching between exploitation and exploration.

If a tardigrade's position does not improve for several consecutive iterations (TS_i), or if the food location becomes less favorable, the algorithm triggers the tun mechanism and reactivates exploration.

The phase update rule is defined as:

Update phase for member i :

$$\begin{cases} \text{switch to exploration, } TS_i > \tau; \\ \text{switch to exploration, } F_i < F_{Food_i}; \\ \text{stay in exploitation, else.} \end{cases} \tag{17}$$

where τ is the maximum allowable stagnation duration.

The counter TS_i is updated in each iteration as:

$$TS_i = 0;$$

$$TS_i = \begin{cases} 0, \text{ if } F_i^{t+1} < F_i^t; \\ TS_i + 1, \text{ else.} \end{cases} \tag{18}$$

When the tun mechanism is activated, the tardigrade regenerates its energy and re-enters the exploration phase from an improved position close to the global best:

$$X_i^{TM} = X_i + r_7 \cdot (X_{best} - I_5 \cdot X_i); \tag{19}$$

$$X_i = \begin{cases} X_i^{TM}, \text{ if } F_i^{TM} < F_i; \\ X_i, \text{ else.} \end{cases} \tag{20}$$

where X_i^{TM} is the newly calculated position for the i-th individual based on the tun mechanism; F_i^{TM} is the corresponding objective function value.

This mechanism helps the algorithm recover diversity, escape local optima and maintain global search ability throughout the optimization process.

Simulation studies and experimental analysis of the UC problem. This section presents a comprehensive analysis of the performance of the proposed TOA in solving the UC problem.

Case study. To evaluate the effectiveness of the proposed TOA in solving the UC problem, a comprehensive case study is designed. The case study considers a power system comprising 10 generating units, with diverse operational characteristics and cost parameters. The detailed specifications of each generating unit including maximum and minimum generation capacities ($P_i^{\max}$ and $P_i^{\min}$) and fuel cost coefficients (a_i, b_i, c_i) are summarized in Table 1. These parameters provide a realistic basis for simulating operational costs and constraints.

The planning horizon for this study is set to 24 hours, representing a typical daily operation schedule. The hourly system load demand (P^D) over the 24-hour period is defined as follows: P^D = (700, 750, 850, 950, 1000, 1100, 1150, 1200, 1300, 1400, 1450, 1500, 1400, 1300, 1200, 1050, 1000, 1100, 1200, 1400, 1300, 1100, 900, 800) MW. This load profile captures variations in electricity demand throughout a typical day, reflecting peak and off-peak periods that challenge the scheduling and dispatch of generating units.

Table 1

Generators data

Unit	$P^{\max}$, MW	$P^{\min}$, MW	a, \$	b, \$/MW	c, \$/MW^2
1	455	150	1000	16.19	0.00048
2	455	150	970	17.26	0.00031
3	130	20	700	16.6	0.002
4	130	20	680	16.5	0.00211
5	162	25	450	19.7	0.00398
6	80	20	370	22.26	0.00712
7	85	25	480	27.74	0.00079
8	55	10	660	25.92	0.00413
9	55	10	665	27.27	0.00222
10	55	10	670	27.79	0.00173

The selected network configuration provides a realistic test bed for evaluating TOA performance, incorporating units with a wide range of generation capacities, fuel costs, and operational constraints. The case study network is modeled as a simplified system with a single-bus load representation, allowing focus on the commitment and dispatch problem without the additional complexity of transmission constraints. Each generating unit is assumed to operate independently, but the total generation must satisfy the system demand in every hour while respecting minimum and maximum generation limits, as well as the binary commitment status of each unit.

By employing this case study, the proposed TOA algorithm is tested under practical operational conditions, enabling assessment of its ability to generate cost-effective, feasible schedules and to balance exploration and exploitation effectively in a real-world power system scenario. This approach provides a robust framework for comparative analysis against other state-of-the-art metaheuristic methods.

Simulation results. The TOA is implemented for the 24-hour planning horizon described in the case study, and the results are summarized in Table 2, which details the hourly generation schedule of each unit alongside the corresponding hourly generation cost.

Table 2 provides the optimal power output for each generating unit across all 24 hours, ensuring that the system demand is met while respecting unit-specific constraints such as minimum and maximum generation limits. The hourly cost of supplying energy is also reported, allowing for an assessment of cost variations throughout the day.

From the results, it is observed that the minimum hourly generation cost occurs at hour 1, with a value of \$13,683.13, while the maximum hourly generation cost is recorded at hour 12, amounting to \$33,932.85. The total generation cost for the entire 24-hour period is calculated to be \$560,497.99, demonstrating the efficiency of TOA in minimizing operational costs under realistic operational conditions.

The generation schedules shown in Table 2 indicate that TOA successfully allocates power outputs in a manner that meets the hourly system demand while maintaining operational feasibility for all units.

Table 2

Results obtained from TOA in optimizing the UC problem

Hour	Cost, $	G1, MW	G2, MW	G3, MW	G4, MW	G5, MW	G6, MW	G7, MW	G8, MW	G9, MW	G10, MW
1	13683.13	455	245	0	0	0	0	0	0	0	0
2	14554.31	455	294.9892	0	0	0	0	0	0	0	0
3	16892.93	454.0284	265.973	0	129.9987	0	0	0	0	0	0
4	19261.7	454.7526	235.2669	129.9902	129.9902	0	0	0	0	0	0
5	20132.57	454.9878	285.0178	129.9972	129.9972	0	0	0	0	0	0
6	22396.72	452.8644	363.8085	125.8501	129.8987	27.57826	0	0	0	0	0
7	23267.58	454.996	423.1044	117.084	129.804	25.01165	0	0	0	0	0
8	24150.11	455	455	130	130	29.98856	0	0	0	0	0
9	27320.34	450.3331	450.3272	127.845	123.1917	100.5967	22.34973	25.35662	0	0	0
10	30154.94	454.3235	454.3237	129.8694	128.3279	136.2574	54.2766	27.12575	15.49565	0	0
11	32042.39	454.9642	454.9642	129.3439	128.417	161.1025	44.04084	25.06252	30.86957	21.2352	0
12	33932.85	454.9856	454.9858	129.9251	129.9251	161.9093	74.2046	38.19795	32.77667	13.07466	10.01527
13	30324.48	453.9498	453.8795	129.5039	129.5039	106.284	65.80941	51.03695	10.03235	0	0
14	27444.02	452.5941	452.5941	129.9926	129.9926	28.77119	79.78389	26.27156	0	0	0
15	24151.93	454.7145	454.7145	130	130	30.569	0	0	0	0	0
16	21005.99	454.0312	335.9734	129.9977	129.9977	0	0	0	0	0	0
17	20132.99	454.4689	285.532	129.9996	129.9996	0	0	0	0	0	0
18	22397.25	454.868	383.3131	106.697	129.9719	25.14999	0	0	0	0	0
19	24147.18	455	455	130	130	29.84141	0	0	0	0	0
20	30232.79	454.9843	454.9886	129.7335	129.9606	105.9667	79.93328	34.41234	10.02059	0	0
21	27277.48	454.8961	454.8964	129.9839	124.2223	90.04006	20.15884	25.80241	0	0	0
22	22400.55	454.1909	381.7471	129.9388	108.2244	25.89879	0	0	0	0	0
23	17765.08	453.8843	316.1406	0	129.9752	0	0	0	0	0	0
24	15428.68	453.5143	346.4857	0	0	0	0	0	0	0	0

The results reflect the algorithm's capability to manage both peak and off-peak demand periods, effectively balancing high-demand hours with cost-efficient generation from multiple units.

Figure 1 shows the hourly load demand versus the total generation output. It can be seen that the scheduled generation closely follows the system demand, ensuring full compliance with the power balance constraint. This confirms that the TOA can generate feasible UC schedules while satisfying demand at all times.

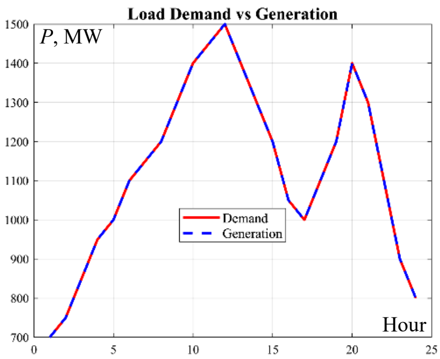

Fig. 1. Hourly generation and demand curves of the power plants over the study period

Figure 2 shows the hourly generation cost curve, highlighting the variation in cost throughout the 24-hour horizon. As observed, the highest hourly generation cost occurs at hour 12, while the lowest cost corresponds to hour 1. This trend is consistent with the system load profile, as periods of higher demand generally lead to increased generation costs due to the dispatch of higher-cost units.

Overall, the simulation results demonstrate that TOA is capable of producing cost-effective and feasible UC schedules across all hours of the day, handling the complexity of multiple units with diverse operational characteristics. The results confirm that TOA is a robust and reliable optimization tool for real-world UC problems.

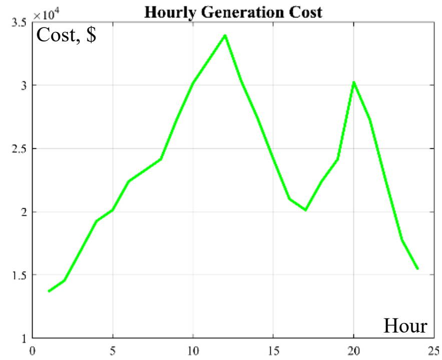

Fig. 2. Hourly generation cost over the study period

Comparison with metaheuristic algorithms. In this subsection, the performance of the proposed TOA is rigorously compared with 6 well-known metaheuristic algorithms, namely: genetic algorithm (GA) [12], particle swarm optimization (PSO) [13], gravitational search algorithm (GSA) [14], whale optimization algorithm (WOA) [19], multi-verse optimizer (MVO) [20] and reptile search algorithm (RSA) [21]. To ensure a fair and statistically significant comparison, TOA and each competitor algorithm were independently executed ten times on the same UC problem instance. The outcomes of these runs were evaluated using 6 statistical indicators: mean, best, worst, median, standard deviation and rank, with results presented in Table 3. The cost metric considered is the average cost per MWh, calculated as:

$$\text{Average cost per MWh} = \text{total cost} / \sum P^D. \qquad (21)$$

Table 3 highlights the statistical performance of all algorithms across multiple runs. The results clearly demonstrate that TOA achieves the lowest mean cost (20.70201 \$/MWh) among all algorithms, reflecting superior economic efficiency in the generation scheduling problem. Furthermore, TOA attains the best recorded cost (20.68258 \$/MWh) and maintains a small standard deviation (0.0118), indicating high solution reliability and robustness against stochastic variations inherent to metaheuristic optimization.

Table 3
Statistical results of the optimization algorithms for the UC problem

Algorithm	Mean	Best	Worst	Median	Std	Rank
TOA	**20.70201**	**20.68258**	**20.71869**	**20.7**	**0.0118**	**1**
GA	20.70768	20.68936	20.72181	20.7	0.01232	2
PSO	20.90376	20.84684	20.93963	20.9	0.03007	3
GSA	21.00885	20.99178	21.02262	21	0.009	7
MVO	20.95189	20.88262	21.02085	20.9	0.04207	5
WOA	20.95449	20.90798	21.0091	21	0.03107	6
RSA	20.95109	20.90124	20.99329	21	0.03373	4

The statistical comparison reveals several key insights:

1. **Superior performance of TOA.** TOA consistently outperforms all other algorithms in terms of both mean and best cost, establishing it as the most effective optimization method for the considered UC problem.
2. **Stability and robustness.** The relatively low standard deviation of TOA indicates high consistency across multiple runs, reducing the likelihood of suboptimal solutions.
3. **Competitor analysis.** GA exhibits competitive performance with slightly higher mean cost and rank 2, while PSO and RSA show moderate performance. The other algorithms (GSA, MVO, WOA) display higher mean costs and greater variability, suggesting less efficient exploration-exploitation balance for this UC instance.

In addition to numerical analysis, Fig. 3 presents boxplots of the cost distributions for TOA and competitor algorithms. The boxplots visually confirm that TOA not only achieves lower median and quartile values but also exhibits a narrower interquartile range, reflecting both high-quality solutions and reduced variability. The boxplots of other algorithms, particularly GSA, WOA, and MVO, indicate larger spread and occasional higher-cost outliers, further emphasizing TOA's superiority in achieving both optimal and reliable solutions.

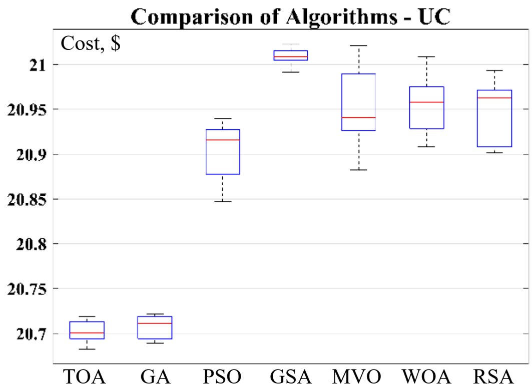

Fig. 3. Boxplot diagrams obtained from TOA and competing algorithms on UC problems

Overall, the comparative analysis demonstrates that TOA provides a robust, cost-effective, and highly reliable optimization framework for the UC problem, outperforming well-established metaheuristic algorithms in both solution quality and stability.

Conclusions. This study presented an efficient and reliable solution framework for the UC problem using the TOA. The UC problem, as a fundamental operational task in power systems, requires optimization methods capable of handling mixed-integer decision variables, nonlinear cost structures, and a wide range of operational constraints. In this work, TOA was employed to schedule ten generating units over a 24-hour horizon while satisfying realistic operating limits and load balance requirements.

The scientific contribution of this study lies in the development and application of a biologically inspired, parameter-free, and self-adaptive optimization mechanism. TOA models the unique survival strategies of tardigrades (active mobility, localized adjustment, and cryptobiotic stabilization) and translates these into adaptive exploration-exploitation operators. This design enables the algorithm to dynamically adjust its search behavior without external parameter tuning, effectively overcoming challenges such as premature convergence and insufficient local refinement that commonly affect traditional metaheuristics in UC applications.

The performance evaluation against six well-established algorithms demonstrated that TOA consistently achieves lower operating costs, stronger convergence stability, and higher robustness across multiple runs. The algorithm maintained feasibility with respect to all UC constraints and produced reliable schedules with minimal variability. These findings validate the practical suitability of TOA for modern power system operations and confirm its superiority in balancing global search efficiency and local optimization accuracy.

Future extensions of this research can further enhance the applicability of TOA. First, TOA may be expanded to large-scale UC systems, multi-area networks, and transmission-constrained environments. Second, integrating renewable energy sources, energy storage systems, and uncertainty modeling would allow TOA to address emerging challenges in future power grids. Third, hybrid TOA variants combining machine learning or local search strategies could improve convergence speed and precision. Additionally, multi-objective UC formulations involving cost, emissions, and reliability merit investigation. Finally, applying TOA to real-time UC, stochastic scheduling, and other energy management problems represents a promising direction for broader power system optimization.

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

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