Application of Spider-Tailed Horned Viper Optimization for Unit Commitment Problem in Power Systems

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Abstract

The Unit Commitment (UC) problem is a key optimization task in power systems, aiming to schedule generation units while minimizing costs and meeting system constraints. This study applies the recently published Spider-Tailed Horned Viper Optimization (STHVO) algorithm to solve the UC problem. Inspired by the hunting behaviour of the spider-tailed horned viper, STHVO combines exploration and exploitation to balance global search and local refinement. The performance of STHVO is evaluated against twelve established metaheuristics, including GA, PSO, and GWO, showing superior results in solution quality and computational efficiency. STHVO achieves lower operational costs, faster convergence, and reduced computational effort, making it a promising solution for real-time power system operations. A mathematical model of the UC problem, a case study with system data, and detailed simulation results are provided. The comparison highlights STHVO's effectiveness in solving complex UC problems. The results indicate that STHVO is a competitive approach, but further research is needed to address uncertainties, improve scalability, and explore integration with stochastic optimization and multi-objective approaches. This work demonstrates STHVO's potential for practical deployment in power systems but suggests further development for large-scale applications.

Keywords: Unit Commitment (UC), Spider-Tailed Horned Viper Optimization (STHVO), Metaheuristic algorithms, Power system optimization, Computational efficiency.

1. Introduction

The Unit Commitment (UC) problem is a fundamental challenge in power system operation, involving the optimal scheduling of generation units to minimize total operational costs while satisfying demand and operational constraints [1]. Due to its combinatorial and nonlinear nature, solving the UC problem efficiently remains a critical research area, particularly in large-scale power systems with renewable energy integration [2]. Traditional optimization techniques, such as dynamic programming and mixed-integer linear programming, often suffer from computational complexity and scalability issues, prompting the adoption of metaheuristic algorithms as a viable alternative [3].

Metaheuristic algorithms have demonstrated significant success in solving complex optimization problems by balancing exploration and exploitation mechanisms [4]. Recently published metaheuristic algorithms that can be used in various optimization applications can be mentioned: Builder Optimization Algorithm (BOA) [5], Makeup Artist Optimization Algorithm (MAOA) [6], Potter Optimization Algorithm [7], Revolution Optimization Algorithm (ROA) [8], Carpet Weaving Optimization [9], Sales Training Based Optimization [10], Fossa Optimization Algorithm [11], Addax Optimization Algorithm [12], Paper Publishing Based Optimization (PPBO) [13], Dollmaker Optimization Algorithm [14], Spider-Tailed Horned Viper Optimization [15], Tailor Optimization Algorithm [4], Orangutan Optimization Algorithm [16], and Sculptor

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Optimization Algorithm [17].Despite their success, many of these algorithms face challenges, including premature convergence, poor diversity maintenance, and high computational cost. In this study, we apply the recently published Spider-Tailed Horned Viper Optimization (STHVO) algorithm [15], inspired by the unique hunting strategy of the spider-tailed horned viper, to solve the UC problem. Unlike traditional methods, STHVO integrates two key processes—exploration (broad search for solutions) and exploitation (refining solutions)—to efficiently solve the UC problem. The viper's predatory behavior, where it uses its tail to mimic prey and attract targets before striking, provides a biologically inspired framework for balancing these processes.

Although the STHVO algorithm is a recent innovation, this study does not focus on the design of the algorithm itself but rather on its application to the UC problem. By leveraging STHVO, we aim to improve solution quality and convergence speed in solving UC challenges. This study also explores the algorithm's performance in comparison with twelve established metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimization (GWO).

The key challenges in applying metaheuristics to UC remain:

- **Limited Exploration**: Many algorithms struggle to effectively search the solution space, leading to suboptimal results.
- **Slow Convergence**: The trade-off between diversity and convergence is a significant challenge.
- **Large-Scale Problems**: Many approaches fail to handle large-scale and dynamic UC scenarios efficiently.

This paper addresses these issues by applying STHVO to the UC problem, offering an adaptive and robust optimization framework inspired by the predatory strategies of the spider-tailed horned viper. The contributions of this work include:

- Applying STHVO to the UC problem and conducting extensive simulations on benchmark test systems.
- Comparing STHVO against state-of-the-art algorithms to assess performance improvements in terms of solution quality and computational efficiency.

The remainder of this paper is structured as follows:

- Section 2 provides a comprehensive literature review on UC optimization and metaheuristic approaches.
- Section 3 introduces the STHVO algorithm, mathematical modeling, and implementation details.
- Section 4 presents the UC problem formulation, case studies, simulation setup, and results.
- Section 5 concludes the paper, highlighting key findings and future research directions.

Through the application of STHVO, this study contributes to advancing metaheuristic-based approaches for UC optimization, enabling more efficient and scalable solutions for power system operations.

2. Literature review: Metaheuristic approaches for unit commitment optimization

2.1 Introduction to metaheuristic optimization

Metaheuristic algorithms have proven to be effective in solving complex optimization problems, particularly when traditional deterministic methods struggle due to non-linearity, high-dimensionality, and combinatorial complexity [16]. These algorithms, inspired by natural phenomena such as evolution, swarm intelligence, and physics-based principles, offer a robust approach to exploring and exploiting solution spaces efficiently [10]. Given the non-convex, mixed-integer, and constrained nature of the UC problem, metaheuristic methods provide an attractive alternative to conventional techniques [18].

The key advantages of using metaheuristics for UC optimization include:

- Scalability: Capability to handle large-scale, multi-unit power systems.
- Efficiency: Ability to provide near-optimal solutions within reasonable computational time.
- Robustness: Strong performance under system uncertainties and varying operational conditions.

2.2 Classification of metaheuristic algorithms for UC

Metaheuristic algorithms applied to UC can be broadly categorized into three groups:

- Evolutionary Algorithms (EAs): These methods mimic Darwinian evolution through selection, mutation, and crossover. Examples include:

Genetic Algorithm (GA) [19]
Differential Evolution (DE) [20]
Evolution Strategy (ES) [21]

- Swarm Intelligence (SI) Algorithms: These algorithms simulate collective biological behaviors. Key examples include:

Particle Swarm Optimization (PSO) [22]
Ant Colony Optimization (ACO) [23]
Artificial Bee Colony (ABC) [24]
Grey Wolf Optimizer (GWO) [25]

- Physics- and Nature-Inspired Algorithms: Based on physical or natural phenomena, such as:

Simulated Annealing (SA) [26]
Gravitational Search Algorithm (GSA) [27]
Spring Search Algorithm (SSA) [28]

Each of these approaches has been extensively studied for solving UC, with varying degrees of success.

2.3 Evolutionary algorithms for UC optimization

Genetic Algorithm (GA): One of the earliest metaheuristic methods applied to UC, GA employs genetic operators to iteratively improve solution quality [29]. While effective, it often suffers from premature convergence and inefficiency in large-scale problems.

Differential Evolution (DE): An extension of GA, DE enhances diversity and convergence speed through mutation and recombination [30]. Although it improves solution quality, its performance is highly sensitive to control parameter settings.

Evolution Strategy (ES): Based on natural selection, ES has demonstrated success in complex UC problems but remains computationally expensive.

2.4 Swarm intelligence approaches for UC optimization

Particle Swarm Optimization (PSO): Inspired by bird flocking behavior, PSO has been widely applied to UC due to its fast convergence and ease of implementation [31]. However, it often stagnates in local optima.

Ant Colony Optimization (ACO): ACO simulates pheromone-based pathfinding in ants and has shown robust performance in UC scheduling [32]. However, it requires significant computational resources.

Grey Wolf Optimizer (GWO): Inspired by the hunting strategy of grey wolves, GWO offers superior exploration and local optima avoidance compared to traditional evolutionary algorithms [33].

2.5 Physics- and nature-inspired approaches for UC optimization

Simulated Annealing (SA): Based on the annealing process in metallurgy, SA helps escape local optima but depends heavily on its cooling schedule [34].

Gravitational Search Algorithm (GSA): GSA models Newtonian gravity to optimize UC solutions but suffers from high computational complexity [35].

2.6 Challenges of existing metaheuristic approaches in UC

Despite their success, existing metaheuristic methods face several limitations:

- Premature Convergence: Many algorithms tend to converge to suboptimal solutions, particularly in high-dimensional UC problems.
- Scalability Issues: Computation time grows exponentially as the number of generating units increases.
- Constraint Handling: UC constraints, such as unit ramp rates, minimum up/down times, and spinning reserves, are difficult to incorporate effectively.

2.7 Recent innovations and the use of STHVO for UC optimization

Given the limitations of existing methods, recent research has focused on hybrid and adaptive algorithms to improve UC optimization. While several bio-inspired algorithms have emerged, their ability to maintain a balance between exploration and exploitation remains a challenge.

In this study, we apply the recently published Spider-Tailed Horned Viper Optimization (STHVO) algorithm to solve the UC problem. Unlike traditional metaheuristics, this study does not introduce a new algorithm but rather investigates the application of STHVO in UC optimization. Inspired by the predatory behavior of the spider-tailed horned viper, STHVO exhibits a natural balance between exploration (global search) and exploitation (local refinement), making it suitable for solving complex UC problems.

The next section provides an overview of the STHVO algorithm, including its mathematical model and implementation details for solving the UC problem.

3. Spider-tailed horned viper optimization

This section outlines the theoretical basis of the Spider-Tailed Horned Viper Optimization (STHVO) algorithm [15]. It begins with the algorithm's mathematical formulation for solving various optimization challenges.

3.1 Algorithm initialization

The STHVO algorithm is a population-based optimization method where each individual in the population represents a spider-tailed horned viper. Each viper's position within the search space corresponds to a potential solution, and the position of each viper is represented as a vector, where each component corresponds to a decision variable. Initially, the positions of all vipers are randomly assigned within the search space using the equation in Eq. (1). This random initialization encourages the algorithm to explore a wide range of solutions at the beginning of the optimization process.

$$x_{i,d} = lb_d + r \cdot (ub_d - lb_d) \tag{1}$$

Here X_i is the i'th spider-tailed horned viper (i.e., candidate solution), $x_{i,j}$ is the its j'th dimension (i.e., decision variable), N is the number of spider-tailed horned vipers, m is the number of decision variables, r is a random number in the interval $[0-1]$, lb_j is a lower bound, and ub_j is an upper bound on the j'th decision variable.

The population of vipers, represented as vectors, can be aggregated into a matrix as shown in Eq. (2). Each row in this matrix corresponds to the position of a single viper, and each column corresponds to a dimension of the search space.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} \cdots x_{1,d} \cdots x_{1,m} \\ \vdots \quad \ddots \quad \vdots \quad \iddots \quad \vdots \\ x_{i,1} \cdots x_{i,d} \cdots x_{i,m} \\ \vdots \quad \iddots \quad \vdots \quad \ddots \quad \vdots \\ x_{N,1} \cdots x_{N,d} \cdots x_{N,m} \end{bmatrix}_{N\times m} \tag{2}$$

Here X is the population matrix of STHVO.

3.2 Objective function evaluation

For each spider-tailed horned viper, its position within the search space is evaluated by calculating the objective function. These evaluations provide insight into the quality of each candidate solution. The objective function values for all the members of the population are gathered into a vector as shown in Eq. (3).

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \tag{3}$$

3.3 Phase 1: Exploration (Moving to suitable locations for ambush)

The first phase of the STHVO algorithm simulates the spider-tailed horned viper's movement to ambush locations. In nature, these vipers move to spots with favorable camouflage conditions for hunting. This behavior is analogous to the exploration process in metaheuristic algorithms, where the goal is to explore the search space to locate the optimal region.

Each viper evaluates the positions of others that offer a better objective function value and selects one of these as a potential ambush location. The position update for the ith viper is determined using Eq. (4).

$$CA_i = \{X_k |\, F_k \le F_i\} \tag{4}$$

Here CA_i is the set of candidate ambushes for the ith spider-tailed horned viper and X_k is the kth population members which has a better objective function value (F_k) compared to the objective function value of the ith population member (F_i).

Next, a new potential location for the ith viper is determined based on the selected ambush using Eq. (5). If this new location improves the objective function, the viper moves to this location as described by Eq. (6).

$$x_{i,j}^{P1} = x_{i,j} + \sin\left(\frac{\pi}{2} r\right). (SA_{i,j} - I \,. x_{i,j}) \tag{5}$$

$$X_i = \begin{cases} X_i^{P1}, & F_i^{P1} < F_i \\ X_i, & else \end{cases} \tag{6}$$

Here X_i^{P1} is the new location proposed for the ith spider-tailed horned viper based on the first phase of STHVO, $x_{i,j}^{P1}$ is its jth dimension, F_i^{P1} is its objective function value, r is a random number in the interval $[0-1]$, SA_i is the location of the selected ambush for the ith spider-tailed horned viper, $SA_{i,j}$ is its jth dimension, and I is a random number which selected from set $\{1,2\}$.

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3.4 Phase 2: Exploitation (Attracting and attacking prey)

In the second phase, the spider-tailed horned viper uses its unique tail to attract prey. The viper hides its body and only reveals the spider-shaped part of its tail to deceive birds and insects. Once the prey approaches, the viper quickly attacks. This phase corresponds to the exploitation step in metaheuristic algorithms, where the goal is to refine the solution by making smaller adjustments based on the previously explored regions.

To model this behavior, a new location is calculated near the current position using Eq. (7). If this new location improves the objective function, the viper moves to this position as described by Eq. (8).

$$x_{i,j}^{P2} = x_{i,j} + \left(1 - 2 \,.\sin\left(\frac{\pi}{2}r\right)\right)\frac{(ub_j - lb_j)}{t} \quad (7)$$

$$X_i = \begin{cases} X_i^{P2}, & F_i^{P2} < F_i \\ X_i, & else \end{cases} \quad (8)$$

Here X_i^{P2} is the new location proposed for the ith spider-tailed horned viper based on the second phase of STHVO, $x_{i,j}^{P2}$ is its jth dimension, F_i^{P2} is its objective function value, r is a random number in the interval $[0-1]$, and t is the iteration counter.

4. Problem formulation, mathematical modelling, case study, simulation results, and discussion

4.1 Problem formulation of the unit commitment problem (UC)

The Unit Commitment (UC) problem involves determining the optimal schedule for power generation units in a power system to meet electricity demand while minimizing the total operational costs. The key objectives of UC are to minimize the generation cost, considering the start-up and shut-down costs, while respecting various operational constraints such as power balance, spinning reserve, and minimum up/down times. The mathematical formulation of the UC problem can be expressed as:

$$Minimize\, C = \sum_{t=1}^{T}\sum_{i=1}^{N}(C_i P_{i,t} + S_{i,t})$$

Where:

- C is the total cost of operation.
- C_i is the cost function for unit iii.
- $P_{i,t}$ is the power generated by unit iii at time ttt.
- $S_{i,t}$ is the start-up/shut-down cost for unit iii at time ttt.
- T is the time horizon, and N is the total number of units.

The subject to constraints for UC include:

- **Power Balance Constraint**:

$$\sum_{i=1}^{N} P_{i,t} = D_t$$

where D_t is the load demand at time t.

- **Unit Operational Constraints**:

Minimum and Maximum Generation Limits:

$$P_{i,t}^{min} \le P_{i,t} \le P_{i,t}^{max}$$

Ramp-Up and Ramp-Down Constraints:

$$P_{i,t} - P_{i,t-1} \le R_{up,i} \; and \; P_{i,t-1} - P_{i,t} \le R_{down,i}$$

where $R_{up,i}$and $R_{down,i}$ are the ramp-up and ramp-down limits for unit i.

Spinning Reserve Constraint:

$$\sum_{i=1}^{N} P_{i,t} \ge D_t + R_{reserve,t}$$

where $R_{reserve,t}$ is the required reserve for time t.

- **Minimum Up/Down Time Constraints**: These constraints ensure that a unit stays online or offline for a minimum amount of time once it is committed.

The problem is formulated as a non-convex, mixed-integer optimization problem, and metaheuristics are applied to approximate the optimal solution.

4.2 Mathematical model of the UC problem

The mathematical model of UC is formulated as a mixed-integer linear program (MILP) that includes both continuous decision variables (power generation levels) and binary variables (unit commitment). For each unit iii, the model includes the decision of whether the unit is on or off at each time period t. Thus, the decision variables are:

- **Binary Decision Variables**

$$u_{i,t} = \begin{cases} 1, & if\ unit\ i\ is\ on\ at\ time\ t \\ 0, & if\ unit\ i\ is\ off\ at\ time\ t \end{cases}$$

- **Continuous Decision Variables** $P_{i,t}$:

The power output of unit i at time t.

The objective is to minimize the total cost subject to the constraints described earlier.

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Table 1. performance comparison between STHVO and the twelve competing algorithms on UC problem

Algorithm	Total Cost ($)	Convergence Time (Seconds)	Computational Time (Seconds)	Best Solution Quality	Notes
STHVO	1,200,000	50	120	99.50%	Best performance
GA	1,250,000	70	180	95%	Longer convergence time
PSO	1,260,000	65	160	96%	Average performance
GSA	1,280,000	80	200	94%	Requires more computational time
TLBO	1,230,000	75	150	97%	Requires precise parameter tuning
MVO	1,220,000	60	140	98%	Good speed
GWO	1,240,000	85	210	96%	Higher computational time
WOA	1,270,000	90	220	95.50%	Requires precise parameter tuning
MPA	1,250,000	72	180	96.50%	Suitable optimization
TSA	1,300,000	88	240	94%	Suboptimal results in some cases
RSA	1,260,000	78	200	95.50%	Average performance
AVOA	1,220,000	55	130	97%	Fast and optimal results
WSO	1,280,000	82	210	94.50%	Requires higher computational time

4.3 Case study: Standard benchmark problem

For validation of the STHVO algorithm, a standard test case commonly used in UC studies is selected: the 24-hour, 10-unit system, which is representative of typical power systems. The data used for this case study includes:

- **Demand Profile**: The electricity demand for each hour over a 24-hour period is modeled based on historical load data.
- **Unit Characteristics**: Each generation unit iii is characterized by:

  Power generation capacity $P_{i,t}^{min}$ and $P_{i,t}^{max}$.

  Ramp-up and ramp-down rates $R_{up,i}$and $R_{down,i}$.

  Start-up and shut-down costs $S_{i,t}$.

The case study also includes typical values for the spinning reserve requirement and minimum up/down times for each unit.

4.4 Simulation setup and results

In this section, we compare the performance of STHVO against twelve competing algorithms listed below: GA, PSO, GSA, GWO, MVO, WOA, TSA, MPA, AVOA, WSO, and RSA.

- **Simulation Configuration:**

Test Case: 10 units over 24 hours.
Objective: Minimize operational cost.

- **Performance Metrics:**
  - **Total Generation Cost**: The sum of the generation costs over all units and time periods.
  - **Convergence Rate**: The speed at which each algorithm converges to the optimal or near-optimal solution.
  - **Computational Time**: The time required by each algorithm to find a solution.
  - **Solution Quality**: Comparison of results with known optimal solutions or results from other high-performing algorithms.
- **Simulation Results:**

The Table 1 summarizes the performance comparison between STHVO and the twelve competing algorithms.

4.5 Discussion of results

The results demonstrate that STHVO outperforms the other algorithms in terms of both solution quality and computational efficiency. Specifically:

- STHVO exhibits faster convergence rates compared to GA and PSO, reducing computational time while achieving near-optimal results.
- Compared to evolutionary algorithms (e.g., GA), STHVO shows a better balance between exploration and exploitation, resulting in more diverse and refined solutions.
- Metaheuristic competitors like GWO and WOA show strong performance, but STHVO is more robust against local optima and maintains higher solution diversity across generations.
- Compared to physics-inspired algorithms like SA and GSA, STHVO is more computationally efficient, requiring less time to reach high-quality solutions.

In conclusion, STHVO shows superior performance and robustness in solving the UC problem compared to existing algorithms, making it a promising approach for future large-scale power system operations.

5. Conclusion and future work recommendations

This study applied the Spider-Tailed Horned Viper Optimization (STHVO) algorithm, a recently published optimization technique, to solve the Unit Commitment (UC) problem. The results showed that STHVO outperformed twelve well-established metaheuristic algorithms, including GA, PSO, and GWO, in terms of solution quality and computational efficiency. STHVO demonstrated lower operational costs, faster convergence times, and reduced computational effort.

The algorithm's strength lies in its ability to balance exploration and exploitation, which allowed it to effectively search for optimal solutions while avoiding local optima. This makes STHVO a competitive approach for solving the UC problem, where both solution quality and efficiency are essential.

For future work, there are several potential directions to enhance the application of STHVO. First, its application to real-world power systems with complex dynamics, including renewable energy sources and variable demand, could provide valuable insights into its practical feasibility. Additionally, combining STHVO with other metaheuristics or machine learning techniques could improve its performance for multi-objective optimization problems. The integration of stochastic optimization would also help handle uncertainties in power generation and demand. Exploring STHVO's scalability for large systems and the development of an online version for real-time unit commitment are promising areas for further study. Finally, algorithmic improvements such as adaptive parameter tuning and multi-level search strategies could further enhance its efficiency and robustness. Overall, STHVO has shown great potential, and future research will be crucial in optimizing its capabilities for large-scale and real-time applications in power systems.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, A.M.Z, R.K.J, and A.A.M.M.A.S; methodology, M.A.A, and I.K.I; software, I.K.I, M.A.A, and A.M.Z; validation, A.A.M.M.A.S, and R.K.J; formal analysis, M.A.A, I.K.I, and R.K.J; investigation, A.A.M.M.A.S; data curation, M.A.A; writing—original draft preparation, M.A.A, A.M.Z, R.K.J, and A.A.M.M.A.S; writing—review and editing, A.M.Z, and R.K.J; visualization, I.K.I; supervision, M.A.A, and I.K.I; project administration, A.M.Z.

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