

Original Article

Efficient Scheduling of Power Generating Units Using Grasshopper Optimization Algorithm

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Abstract - This article introduces a novel method for addressing the unit commitment problem in power systems by utilizing the Grasshopper Optimization Algorithm (GOA). Unit commitment is a crucial technique used in electric power systems for operational planning, aiming to schedule power generating units efficiently to meet load demand while minimizing total operational costs. This involves considering various operational constraints such as power balance, generation capacity, start-up expenses, and minimum durations for both starting up and shutting down. GOA is a mathematical model that accurately replicates the distinct characteristics of grasshopper behavior during both the nymph and adulthood phases, specifically their foraging behavior in search of food sources in the natural environment. The aim of this study is to identify the most efficient unit commitment for producing scheduling, with the goal of minimizing the total operating cost while considering various limitations. The proposed technique is applied to a test system consisting of 5 generating units over a time horizon of 24 hours. The numerical outcomes of the GOA are being compared to those of the Dynamic Programming (DP) technique in terms of the total operating cost. The findings revealed that GOA offers the most economical total operating cost in comparison to DP.

Keywords - Total operational costs, Unit commitment, Generator scheduling, Cost minimization, Dynamic programming.

1. Introduction

Unit Commitment (UC) is known as a popular optimization in electric power systems for operational planning. UC's goal is to determine the scheduling of power generating units that satisfy the load demand while minimizing the total cost operation subjected to a variety of constraints in a specific time horizon. UC must consider many operational constraints such as power balance, generation limit, start-up cost, and minimum up and down time [1].

Integrating unit commitment into planning as a holistic optimization has been acknowledged as a successful method for incorporating flexibility into operational planning. The optimization model incorporates the processes of generator scheduling and economic dispatch. Both the planning and operation processes have been enhanced by transitioning from deterministic to probabilistic optimization in order to tackle the issue of uncertainty. Robust optimization has gained acceptance due to its modest need for uncertainty description [2].

The problem of Unit Commitment (UC) is a highly intricate and non-convex problem that arises in large-scale power systems. Several conventional approaches have been suggested in the past to address the UC problem, including mixed integer linear programming [3], Dynamic

Programming (DP) [4, 5], Priority List (PL) method [6], and Lagrangian Relaxation (LR) [7].

Nevertheless, these solutions are hindered by drawbacks such as the complexity of the issue dimensions, extensive processing time, and the challenge of programming. The Dynamic Programming (DP) method is versatile, but it has drawbacks as it leads to increased mathematical complexity and longer computation times when considering limitations [8].

Lately, numerous academics have suggested metaheuristic optimization techniques as a solution to address the limitations of classical methods in solving the unit commitment problem. Metaheuristics methods have arisen as a potent category of techniques that can surpass the constraints of conventional deterministic methods.

The methods mentioned, such as Genetic Algorithms (GA) [9, 10], Particle Swarm Optimization (PSO) [11], Ant Colony Optimization (ACO) [12], Coyote Optimization Algorithm (COA) [13], Chaotic Arithmetic Optimization Algorithm [14], and Fast Quantum Algorithm [15], are specifically developed to effectively explore and exploit vast and intricate solution spaces. Due to their flexibility, resilience, and ability to produce near-optimal solutions



within realistic processing timeframes, they are well-suited for the UC problem. Recently, Grasshopper Optimization Algorithm (GOA) has been applied to solve many optimization problems. GOA is a precise mathematical model that faithfully reproduces the unique traits of grasshopper behavior throughout their nymph and adulthood stages, particularly their foraging behavior as they look for food sources in their natural surroundings. The grasshopper algorithm is widely acknowledged as an effective computational tool that leverages the behavior of grasshoppers to solve various contemporary technical challenges [16].

GOA approach has proven effective in resolving many power system issues. GOA, as presented in reference [17], is a method used to solve the Optimal Power Flow (OPF) problem by effectively integrating a Center-node Unified Power Flow Controller (C-UPFC). The C-UPFC, a sophisticated, Flexible AC Transmission System (FACTS) device, is installed in the middle of a transmission line to provide power flow control and independent voltage control. The simulation results demonstrate that the suggested algorithm is more efficient and superior in solving OPF compared to other algorithms documented in the literature.

The GOA was employed in [18] to optimize a multistage controller for the autonomous generation control of a power system that incorporates FACTS devices. The robustness of the projected controller is confirmed through sensitivity analysis, which involves testing with multiple load patterns and a wide range of parameterizations.

Many problems have been effectively solved using GOA, including the optimal sizing of Distributed Generation [19], the optimal tuning of PID controllers' gain [20], economic dispatch [21], and optimal load shedding [22]. Due to the effectiveness of GOA in solving many problems in power engineering, this article employs GOA to determine the optimal unit commitment for scheduling production, aiming to minimize the overall operating cost while taking into account different constraints.

2. Problem Formulation

Unit Commitment can be described mathematically with objective functions. The objective of the unit commitment problem is to minimize the total operating cost, which includes the sum of fuel cost and start-up cost of each generating unit in a specific time. The total cost of fossil fuel can be expressed as (1) [23]:

$$C_{i,t}(P_{i,t}) = a_i + b_i P + c_i \cdot P^2_{i,t} \quad (1)$$

Where,

- P_i - Power generated of i^{th} generating unit at time t
- $C_{i,t}$ - Fuel cost of i^{th} generating unit at time t
- a_i, b_i, c_i - Fuel cost coefficients of each corresponding thermal unit

The equation for start-up cost is offered in (2). The primary goal of solving the UC problem is to optimize the allocation of power resources in order to meet the power demand while minimizing the Total Operating Cost (TOC). The Total Operating Cost (TOC) comprises the expenses related to fuel, as well as the costs associated with starting up and shutting down the system.

Typically, the shut-down cost is disregarded and presumed to be negligible. The equation for start-up cost is provided in (2). The main objective of addressing the UC problem is to optimize the allocation of power resources in order to meet the power demand while lowering the Total Operating Cost (TOC).

The Total Operating Cost (TOC) includes the expenditures pertaining to fuel, as well as the expenses linked to initiating and terminating the system. It is calculated based on (3). Usually, the cost of shutting down is ignored and assumed to be insignificant.

$$SU_{i,t} = \begin{cases} SU_{H,i}, & \text{if } MDT_i \leq TOFF_{i,t} \leq MDT_i + T_{cold,i} \\ SU_{C,i}, & \text{if } TOFF_{i,t} > MDT_i + T_{cold,i} \end{cases} \quad (2)$$

Where,

- $SU_{i,t}$ - Start-up cost
- $SU_{C,i}$ - Cold start-up
- MDT_i - Minimum down time
- $SU_{H,i}$ - Hot start-up cost
- $T_{cold,i}$ - Cold start-up hour
- $TOFF_{i,t}$ - Offline time duration of thermal power unit

$$Min TOC = \sum_{t=1}^T \sum_{i=1}^n [C_i(P_{i,t})U_{i,t} + SU_{i,t}(1 - U_{i,t-1})U_{i,t}] \quad (3)$$

Where,

- $u_{i,t}$ - Status of generating units, either ON/OFF
- $C_i(P_{i,t})$ - Fuel cost of power generated of i^{th} generating unit at time t

The stability and reliability of unit commitment scheduling depend on five crucial features of system limitations. The factors encompass power balancing constraint, system reserve requirement constraint, power generating limit constraint, and minimum up and down time restriction.

The power balancing constraint is crucial for efficiently meeting the load demand while minimizing cost and power generation waste. The primary objective of the UC operation is to maintain a specific megawatt capacity as a spinning reserve to provide dependable performance.

In the event of a generator failure, there is a contingency power source available. The spinning reserve in this study is established at 10% of the total load demand for each respective

hour. The term "system" refers to a set of interconnected components or elements that work together to achieve a specific purpose or function.

$$\sum_{i=1}^n P_{i,tmax} U_{i,tmax} \geq P_{demand,t} + R_t \quad (4)$$

Where,

- $P_{i,t}$ - Power output of committed generator unit t
- $U_{i,t}$ - Status of generator units, either ON/OFF
- $P_{demand,t}$ - Status of generator units, either ON/OFF
- $P_{i,t,max}$ - Maximum generating capacity of thermal unit t
- R_t - Spinning reserve at time t

$$P_{i,tmin} \leq P_{i,t} \leq P_{i,tmax} \quad (5)$$

Where,

- $P_{i,t,min}$ - Minimum generating capacity of thermal unit t
- $P_{i,t,max}$ - Maximum generating capacity of thermal unit t

$$T_{i,t}^{on} \geq MUT_i \quad (6)$$

$$T_{i,t}^{off} \geq MDT_i \quad (7)$$

Where,

- $T_{i,t}^{on}$ - Continuous on time of generating unit i
- $T_{i,t}^{off}$ - Continuous on time of generating unit i
- MUT_i - Minimum down time
- MDT_i - Minimum down time

To demonstrate the effectiveness of the unit commitment strategy, the suggested methods are implemented on a system comprising of 5-unit generators. The parameters of a generating system with five generating units are shown in Table 1, along with the variables related to each unit (a, b, and c) and the maximum and minimum power generating capacity.

Table 2 displays the starting state, minimum up and down periods, hot start-up costs, and cold start-up costs. Table 3 displays the load demand associated with each scheduling hour. The unit commitment scheduling takes these load demands into account. The maximum load demand occurs around hour 1400, whereas the minimum demand is observed during the first hour of unit commitment scheduling.

Table 1. Data for 5 unit system

	P_{min} (MW)	P_{max} (MW)	a	b	c
Unit 1	150	455	1000	16.19	0.00048
Unit 2	20	130	700	16.6	0.0002
Unit 3	20	130	680	16.5	0.00211
Unit 4	20	80	370	22.26	0.0072
Unit 5	55	55	660	25.92	0.000413

Table 2. Parameters of the generating system

	Min Up Time (h)	Min Down Time (h)	Hot Start Cost (\$)	Cold Start Cost (\$)	Cold Start Hour (h)
Unit 1	8	8	4500	9000	5
Unit 2	5	5	550	1100	4
Unit 3	5	5	560	1120	4
Unit 4	3	3	170	340	2
Unit 5	1	1	30	60	0

Table 3. Load demand for 24 hours

Hours	Power Demand (MW)	Hours	Power Demand (MW)
1	330	13	810
2	450	14	820
3	480	15	750
4	360	16	800
5	520	17	650
6	590	18	670
7	730	19	790
8	780	20	750
9	620	21	770
10	650	22	610
11	680	23	520
12	630	24	360

3. Development of GWO for Optimal Unit Commitment

The proposed strategy is based on the behavior of grasshoppers. Grasshoppers have long hind legs that allow them to make high jumps before taking flight. Although usually seen alone, grasshoppers can form large swarms that exhibit unique swarming behavior in both their nymph and adult stages. Nymph grasshoppers move like rotating cylinders and consume crops as they migrate. As they mature, they gather in swarms and can migrate long distances in search of food. The larvae phase is characterized by slow movement, while adult grasshoppers move suddenly and cover long distances.

The GOA algorithm, inspired by grasshopper behavior, uses two key tendencies: exploration and exploitation. During exploration, search agents move abruptly to explore new areas, while during exploitation, they converge to specific locations to find optimal solutions [24]. GOA is advantageous due to its fast convergence and ease of implementation.

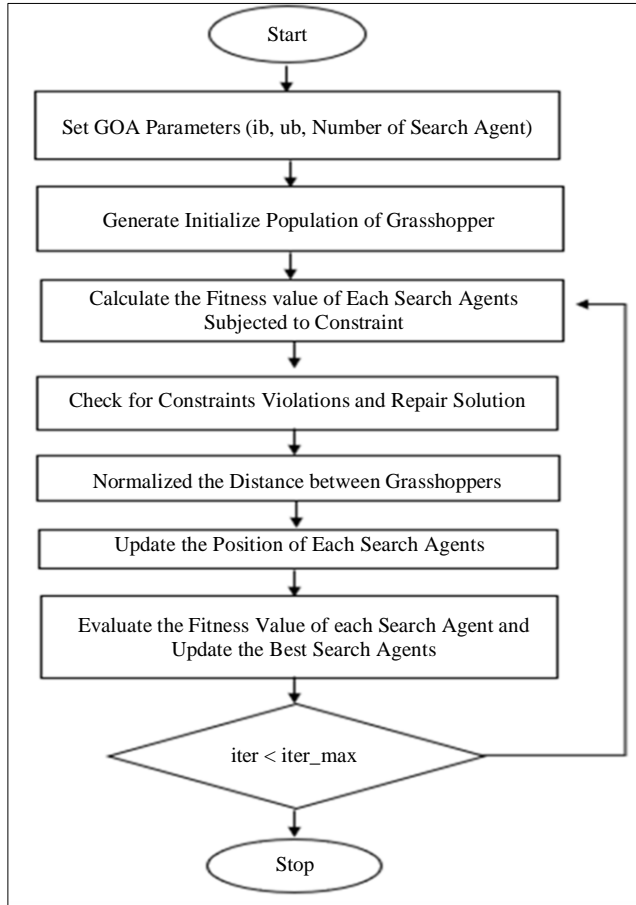


Fig. 1 Flowchart of GOA

Figure 1 presents the flowchart of GOA for determining the unit commitment with minimum cost characteristics. As a beginning, a few parameters need to be set, such as upper boundary, lower boundary, dimension and number of search agents. The upper and lower boundary is represented as the ON/OFF status of the generator.

The dimensions are set according to the number of the generating units used at hours which is from 1 to 5. After that, the population of the grasshopper swarm represented as generator status (G1, G2, G3, G4, G5) and amount of power generated (P1, P2, P3, P4, P5) were generated randomly. Then, the fitness value of each search agent is calculated by considering all the constraints.

The location of the grasshopper was randomly generated in order to gain more random behavior, such as a tendency towards a food source or grasshopper interaction. Again, the constraints violations need to be checked and a repair solution. So, the fitness value is evaluated again, and the current best feasible target can be obtained. The possible feasible was all generated by the random location of the grasshopper. If the possible state is considered in the range, the generation value is generated.

When the value of generation is obtained, the total operating cost is calculated for each hour. The possible feasible outcome must consider generation range and minimum up and down time. For GOA, the total operating cost is fitness. The current best location is updating in order to undergo iteratively until the last outcome is satisfaction. The fitness and location of the best target at the end returned for the global optimum as the best approximation.

4. Results and Discussion

This work addresses the optimal unit commitment problem by employing the GOA. At first, the optimal unit commitment is determined using Dynamic Programming (DP). DP is widely used for solving unit commitment previously and used as the benchmarking to evaluate the effectiveness of GOA.

Table 4. Optimal unit commitment using DP

Hours	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Total Cost (\$/h)
1	330	0	0	0	0	6,395.00
2	450	0	0	0	0	8,382.70
3	455	0	0	0	25	9,836.40
4	360	0	0	0	0	6,890.60
5	455	0	65	0	0	10,787.00
6	455	0	115	20	0	12,229.00
7	455	125	130	20	0	15,501.00
8	455	130	130	65	0	16,066.00
9	455	62	83	20	0	13,085.00
10	455	78	97	20	0	13,591.00
11	455	93	112	20	0	14,099.00
12	455	67	88	20	0	13,253.00
13	455	130	130	80	15	17,525.00
14	455	130	130	80	25	17,726.00
15	455	130	130	35	0	15,376.00
16	455	130	130	75	10	17,248.00
17	455	78	97	20	0	13,591.00
18	455	88	107	20	0	13,930.00
19	455	130	130	75	0	16,298.00
20	455	130	130	35	0	15,376.00
21	455	130	130	55	0	15,834.00
22	455	0	130	25	0	12,257.00
23	455	0	65	0	0	10,227.00
24	360	0	0	0	0	6,890.60

Table 4 displays the power output of each unit (Unit 1 to Unit 5) throughout a 24-hour period, along with the corresponding total cost for each hour determined by DP. Unit 1 continuously maintains high power outputs, ranging from 330 MW to 455 MW. This suggests that Unit 1 is a base unit responsible for supplying most of the power, as it has a lower operational cost compared to other units. Units 2 and 3 are utilized sporadically and usually operate at moderate power levels. These units are used in a more flexible manner, indicating that they are most likely intermediate load units that are activated when the demand surpasses the capacity of the base load unit.

Units 4 and 5, on the other hand, are utilized less frequently and typically operate at lower power levels, often for shorter periods of time. It is quite probable that these units function as peak units, supplying extra power during periods of high demand. The results presented in Table 4 show that the overall cost obtained using DP fluctuates considerably throughout the period of the day, reflecting shifts in demand and the specific combination of units needed to fulfil that demand. The minimum costs are observed when there are fewer units in operation or when the base load unit (Unit 1) can fulfil the demand alone, for example, during hours 4, 6, and 24. The results for the optimal unit commitment obtained using GOA are presented in Table 5.

Table 5 shows that Unit 1 constantly works at high power outputs ranging from 330 MW to 455 MW, indicating that it serves as the base load unit. Units 2 and 3 exhibit greater variability in usage compared to the DP table. They only activate during peak demand hours, although with varying power levels compared to the DP findings. Units 4 and 5 are utilized infrequently, primarily during periods of high demand, to augment the electricity produced by the other units. The hourly cost exhibits variability that is comparable to the DP results, indicating fluctuations in demand and the optimization approach employed by the GOA.

Costs are minimized when the demand can be met with a smaller number of units. Costs increase as more units, especially the ones used during peak times, are added to the system. Several units go operational, each making different power contributions. As an example, the cost for hour 13 is \$17,526, which is influenced by the contributions from Units 1, 2, 3, and 4.

The GOA aims to enhance the unit commitment process by identifying combinations of units that can fulfil the demand at a competitive cost. However, it is important to note that the GOA may yield variations in terms of specific power outputs and costs when compared to the DP approach. The GOA also offers a distinct array of optimal solutions, showing many efficient ways for unit commitment. The unit operation demonstrates adaptability by offering a range of power levels for both intermediate and peak demand units.

Table 5. Optimal unit commitment using GOA

Hours	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Total Cost (\$/h)
1	330	0.0	0.0	0.0	0.0	6,395.00
2	450	0.0	0.0	0.0	0.0	8,382.70
3	426	54.0	0.0	0.0	0.0	9,646.30
4	360	0.0	0.0	0.0	0.0	6,890.60
5	401	118.6	0.0	0.0	0.0	10,273.00
6	455	56.3	78.7	20.0	0.0	12,438.00
7	455	125.0	128.8	21.2	0.0	15,508.00
8	455	130.0	129.6	65.4	0.0	16,068.00
9	455	62.0	95.8	7.2	0.0	13,013.00
10	455	78.0	106.7	10.3	0.0	13,537.00
11	455	93.0	112.3	19.7	0.0	14,098.00
12	455	67.0	89.8	18.2	0.0	13,243.00
13	455	130.0	130.0	79.7	15.3	17,526.00
14	455	130.0	130.0	80.8	24.2	17,724.00
15	455	130.0	128.3	36.7	0.0	15,386.00
16	455	130.0	130.0	79.7	5.3	17,236.00
17	455	78.0	108.2	8.8	0.0	13,529.00
18	455	88.0	121.2	5.8	0.0	13,852.00
19	455	130.0	128.9	76.1	0.0	16,305.00
20	455	130.0	127.3	37.7	0.0	15,391.00
21	455	130.0	129.1	55.9	0.0	15,840.00
22	455	73.2	81.8	0.0	0.0	12,435.00
23	455	21.2	43.8	0.0	0.0	10,253.00
24	360	0.0	0.0	0.0	0.0	6,890.60

Based on the data shown in Table 4 and Table 5, it is evident that both GOA and DP consistently utilized the base load unit (Unit 1) with minimal fluctuations in its operation. The power outputs of intermediate and peak units in GOA display greater fluctuation, indicating the need for a distinct optimization technique. Although the general cost trends are comparable, there are modest variations in the precise hourly prices due to the different optimization strategies employed by GOA and DP. The total cost produced by DP and GOA is summarized in Table 6.

Table 6 presents a detailed comparison of the DP and GOA methods for optimal unit commitment, including hourly power demand and the corresponding total costs calculated by each method. The results reveal that for many hours, the costs between the two methods are very close, often differing by only a few dollars. However, specific hours show more pronounced cost differences, such as at hour 3, where GOA

achieves a significant cost reduction of approximately \$190 compared to DP. Similarly, GOA costs \$72 less than DP at hour 9 and \$78 less at hour 18.

Table 6. Comparison of the total cost using GOA and DP

Hours	Power Demand (MW)	Total Cost (\$/h)	
		DP	GOA
1	330	6,395.00	6,395.00
2	450	8,382.70	8,382.70
3	480	9,836.40	9,646.30
4	360	6,890.60	6,890.60
5	520	10,787.00	10,273.00
6	590	12,229.00	12,438.00
7	730	15,501.00	15,508.00
8	780	16,066.00	16,068.00
9	620	13,085.00	13,013.00
10	650	13,591.00	13,537.00
11	680	14,099.00	14,098.00
12	630	13,253.00	13,243.00
13	810	17,525.00	17,526.00
14	820	17,726.00	17,724.00
15	750	15,376.00	15,386.00
16	800	17,248.00	17,236.00
17	650	13,591.00	13,529.00
18	670	13,930.00	13,852.00
19	790	16,298.00	16,305.00
20	750	15,376.00	15,391.00
21	770	15,834.00	15,840.00
22	610	12,257.00	12,435.00
23	520	10,227.00	10,253.00
24	360	6,890.60	6,890.60
Total Cost (\$/h)		312,394.00	311,860.00

The total cost over the 24-hour period is \$312,394.00 for DP and \$311,860.00 for GOA, giving GOA a total cost advantage of \$534. This indicates that GOA achieves slightly

lower total costs and demonstrates marginally more efficient optimization. The flexibility and adaptability of GOA, employing bio-inspired optimization techniques to find near-optimal solutions more efficiently, contributes to these cost savings. In contrast, DP's systematic approach, while robust, can be computationally expensive.

5. Conclusion

This study conducted a comprehensive comparison between the Dynamic Programming (DP) and Grasshopper Optimization Algorithm (GOA) methods for optimal unit commitment in power generation systems over a 24-hour period, evaluating the power generated by five units and the associated costs for each hour. The results demonstrate that both DP and GOA effectively optimize unit commitment, ensuring reliable power supply while minimizing operational costs.

Notably, GOA achieved a slightly lower total cost of \$311,860.00 compared to DP's \$312,394.00, indicating marginally higher efficiency. GOA consistently matched or outperformed DP in hourly costs, resulting in a total cost reduction of \$534.00 over the period. Both methods provided near-optimal solutions, but GOA exhibited greater flexibility and adaptability to varying demand levels, often yielding lower costs in specific hours. Additionally, GOA's bio-inspired optimization techniques efficiently find near-optimal solutions with reduced computational effort, while DP, despite its robustness and systematic exploration of all combinations, is computationally intensive.

In conclusion, the Grasshopper Optimization Algorithm presents a viable and potentially superior alternative to Dynamic Programming for optimal unit commitment in power systems. Its ability to deliver cost-effective solutions with enhanced computational efficiency makes it an attractive option for real-world applications. Future research could explore the scalability of GOA and its performance in larger and more complex power systems, as well as investigate hybrid approaches that combine the strengths of both methods for even greater optimization performance.

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References

- [1] Ce Shang et. al., "Robust Planning Upon Unit Commitment," *International Journal of Electrical Power & Energy Systems*, vol. 157, pp. 1-4, 2024. [\[CrossRef\]](#) [\[Google Scholar\]](#) [\[Publisher Link\]](#)
- [2] Soraphon Kigsirisin, and Hajime Miyauchi, "Short-Term Operation Scheduling of Unit Commitment Using Binary Alternative Moth-Flame Optimization," *IEEE Access*, vol. 9, pp. 12267-12281, 2021. [\[CrossRef\]](#) [\[Google Scholar\]](#) [\[Publisher Link\]](#)
- [3] G.W. Chang et al., "A Practical Mixed Integer Linear Programming Based Approach for Unit Commitment," *IEEE Power Engineering Society General Meeting*, vol. 1, pp. 221-225, 2004. [\[CrossRef\]](#) [\[Google Scholar\]](#) [\[Publisher Link\]](#)

- [4] Neha Thakur, and L.S. Titare, "Determination of Unit Commitment Problem Using Dynamic Programming," *International Journal of Novel Research in Electrical and Mechanical Engineering*, vol. 3, no. 1, pp. 24-28, 2016. [[Google Scholar](#)] [[Publisher Link](#)]
- [5] Prateek Kumar Singhal, and R. Naresh Sharma, "Dynamic Programming Approach for Solving Power Generating Unit Commitment Problem," *2nd International Conference on Computer and Communication Technology*, pp. 298-303, 2011. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [6] Tomonobu Senjyu et al., "Emerging Solution of Large-Scale Unit Commitment Problem by Stochastic Priority List," *Electric Power Systems Research*, vol. 76, no. 5, pp. 283-292, 2006. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [7] Xiang Yu, and Xueqing Zhang, "Unit Commitment Using Lagrangian Relaxation and Particle Swarm Optimization," *International Journal of Electrical Power & Energy Systems*, vol. 61, pp. 510-522, 2014. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [8] C.C.A. Rajan, "An Evolutionary Programming Based Tabu Search Method for Solving the Unit Commitment Problem in Utility System," *IEEE Region 10 Conference TENCON 2004*, vol. 3, no. 1, pp. 472-475, 2004. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [9] V. Senthil Kumar, and M.R. Mohan, "Solution to Security Constrained Unit Commitment Problem Using Genetic Algorithm," *International Journal of Electrical Power Energy System*, vol. 32, no. 2, pp. 117-125, 2010. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [10] Tolga Karabas, and Sedef Meral, "An Exact Solution Method and a Genetic Algorithm-Based Approach for the Unit Commitment Problem in Conventional Power Generation Systems," *Computers & Industrial Engineering*, vol. 176, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [11] I. Jacob Raglend et al., "Solution to Profit Based Unit Commitment Problem Using Particle Swarm Optimization," *Applied Soft Computing*, vol. 10, no. 4, pp. 1247-1256, 2010. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [12] K. Vaisakh, and L.R. Srinivas, "Evolving Ant Colony Optimization Based Unit Commitment," *Applied Soft Computing*, vol. 11, no. 2, pp. 2863-2870, 2011. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [13] E.S. Ali, S.M. Abd Elazim, and A.S. Balobaid, "Implementation of Coyote Optimization Algorithm for Solving Unit Commitment Problem in Power Systems," *Energy*, vol. 263, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [14] Pravin G. Dhawale et al., "Chaotic Arithmetic Optimization Algorithm for Optimal Sizing of Security Constrained Unit Commitment Problem in Integrated Power System," *IEEE 11th Region 10 Humanitarian Technology Conference (R10-HTC)*, pp. 366-371, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [15] Xiaodong Zheng, Jianhui Wang, and Meng Yue, "A Fast Quantum Algorithm for Searching the Quasi-Optimal Solutions of Unit Commitment," *IEEE Transactions on Power Systems*, vol. 39, no. 2, pp. 4755-4758, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [16] Paulos Bekana, Archana Sarangi, and Shubhendu Kumar Sarangi, "Analysis of Crossover Techniques in Modification of Grasshopper Optimization Algorithm," *International Conference in Advances in Power, Signal, and Information Technology (APSIT)*, pp. 1-5, 2021. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [17] Ayman Alhejji et al., "Optimal Power Flow Solution with an Embedded Center-Node Unified Power Flow Controller Using an Adaptive Grasshopper Optimization Algorithm," *IEEE Access*, vol. 8, pp. 119020-119037, 2020. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [18] Pratap Chandra Nayak, Ramesh Chandra Prusty, and Sidhartha Panda, "Grasshopper Optimization Algorithm Optimized Multistage Controller for Automatic Generation Control of a Power System with FACTS Devices," *Protection and Control of Modern Power Systems*, vol. 6, no. 1, pp. 1-15, 2021. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [19] Suresh Velamuri et al., "Combined Approach for Power Loss Minimization in Distribution Networks in the Presence of Gridable Electric Vehicles and Dispersed Generation," *IEEE Systems Journal*, vol. 16, no. 2, pp. 3284-3295, 2022. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [20] Ahmed Hussain Elmetwaly, Azza Ahmed Eldesouky, and Abdelhay Ahmed Sallam, "An Adaptive D-FACTS for Power Quality Enhancement in an Isolated Microgrid," *IEEE Access*, vol. 8, pp. 57923-57942, 2020. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [21] Yeganeh Sharifian, and Hamdi Abdi, "Solving Multi-Area Economic Dispatch Problem Using Hybrid Exchange Market Algorithm with Grasshopper Optimization Algorithm," *Energy*, vol. 267, pp. 1-12, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [22] Masoud Ahmadipour et al., "Optimal Load Shedding Scheme Using Grasshopper Optimization Algorithm for Islanded Power System with Distributed Energy Resources," *Ain Shams Engineering Journal*, vol. 14, pp. 1-12, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [23] A. Turgeon, "Optimal Unit Commitment," *IEEE Transaction on Automatic Control*, vol. 22, no. 2, pp. 223-227, 1977. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [24] Shahrzad Saremi, Seyedali Mirjalili, and Andrew Lewis, "Grasshopper Optimisation Algorithm: Theory and Application," *Advances in Engineering Software*, vol. 105, pp. 30-47, 2017. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]