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Research Article

CO_2 Emission-Constrained Short-Term Unit Commitment Problem Using Shuffled Frog Leaping Algorithm

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The increasing concerns about greenhouse gas emissions have made it necessary to incorporate environmental constraints in the operation of power systems. The CO_2 emission-constrained short-term unit commitment problem (CSCUCP) is a multiobjective optimization problem that involves minimizing both the cost of operation and the CO_2 emissions. This paper proposes an integer-coded shuffled frog-leaping algorithm (SFLA) to minimize both total CO_2 emissions and operating costs for the unit commitment problem (UCP) over a one-day scheduling period. The SFLA is inspired by the natural food-searching behavior of frogs. The proposed method aims to determine the optimal start-up and shut-down times for generating units to meet fluctuating loads while minimizing operating costs and CO_2 emissions. The method takes into account fuel costs, start-up and shut-down costs, and maintenance costs while satisfying various constraints. The study uses the IEEE 39 bus with a 10-unit test system, and the results are related to conventional methods. The proposed method consistently produces lower CO_2 emissions and total operating costs compared to the existing methods.

1. Introduction

In an electric power system, there will be a continuous variation in load from time to time and during day time and early evening, the total load on the system will be higher due to industrial loads and lights, and most of the population will be asleep during the late evening and early morning making the total load lower. So, the commitment of units assumes importance to dispatch the thermal generating units determining their operating output to meet demand and reserve requirements at lower cost [1].

Management strategies of complex energy systems composed of different technologies are mandatory to exploit optimally the characteristics of each power generator, to reduce the cost of energy and the impact of greenhouse gas emissions, and to increase the penetration of mini- and microgrids into energy systems [2]. In today's world, it is crucial to schedule generators while limiting emissions. Temperature inversion is a phenomenon where the atmospheric temperature increases with altitude. This effect, along with pollution concentration, can have a significant impact [3].

The excessive emissions of greenhouse gases have caused an ecological crisis, leading to the global consensus on reducing greenhouse gas emissions in the Tokyo Protocol [4]. In response to corporate environmental responsibility, businesses are increasingly engaging in collaborations with members of their supply chains to mitigate emissions. The pressing issue of climate change, primarily driven by greenhouse gas emissions, has evolved into a global concern [5–7]. The United Nations Framework Convention on Climate Change (UNFCCC) was established to address the challenges posed by climate change, largely stemming from greenhouse gas emissions. This international framework is dedicated to achieving efficient and cost-effective reductions in greenhouse gas emissions. The Kyoto Protocol, a legally binding treaty operating under the UNFCCC, outlines specific emission reduction targets for developed nations, encompassing six greenhouse gases, notably carbon dioxide, methane, and nitrous oxide. The overarching goal of these endeavors under the UNFCCC is to mitigate the adverse impacts of climate change on both the environment and human society [8].

The UNFCCC framework, subsequently adopted, introduced the Kyoto Protocol as a binding agreement compelling industrialized countries to pursue cost-effective reductions in greenhouse gas emissions. The Kyoto Protocol focuses on reducing the emissions of six greenhouse gases, namely carbon dioxide, methane, nitrous oxide, hydrofluorocarbons, perfluorocarbons, and sulfur hexafluoride. Among these gases, carbon dioxide emissions are particularly environmentally detrimental [9]. Within the UNFCCC, industrialized countries have committed to mandated reductions in their emissions of the six greenhouse gases over two commitment periods: the first spanning from 2008 to 2012 and the second from 2013 to 2020 [10].

The scheduling problem varied depending on the boundaries that have been taken for that particular problem. Many solution methods have been suggested to solve the generation scheduling problem, such as exhaustive enumeration, priority list (PL), dynamic programming (DP), Lagrangian relaxation (LR), and branch and bound methods [11].

For large-size utilities, the exhaustive enumeration method is not suitable as it does not give an accurate solution. Due to high relative production costs, the PL method is not suitable. Dynamic programming may take more computational time and mathematical complexity [12]. One disadvantage of the Lagrangian relaxation method is its inherent suboptimality. In the branch and bound method, if the lower bound exceeds the upper bound in a minimization problem, it means that the optimal decision variable cannot lie within the subset being considered [13].

Recently, the increase in the growth of power system structure demands the use of artificial intelligence techniques. The popularly used artificial intelligence techniques used in power systems are genetic algorithm (GA), artificial neural network (ANN), Tabu search, simulated annealing (SA), and particle swarm optimization (PSO). Long execution time and no guarantee of convergence to an optimal solution are the limitations of the genetic algorithm. The use of artificial neural networks (ANN) can increase the speed of operation in certain applications, but it may lead to unreliable scheduling of units when employing an active search approach [14]. To prevent being stuck in local minima and to incorporate a flexible memory system, Tabu search is utilized [15]. Simulated annealing has some mathematical complexity [16]. Particle swarm optimization has the capability of generating quality solutions and efficiently exploring the search space [17].

At the outset, research primarily centered on enhancing only optimization algorithms. Consequently, various real-world constraints underwent in-depth examination to expedite resolution processes. While these constraints offer computational advantages, their incorporation introduces complexities such as implementation challenges and oscillations during iterative convergence to optimal solutions.

The primary contribution of this paper lies in the proposal of employing the shuffled frog leaping (SFL) algorithm to optimize power system generation in the context of CO_2 emission-constrained unit commitment. The utilization of binary variables to represent the on/off status and start-up/shut-down status of specific generators results in smaller changes in emissions and fuel costs, reduces the number of iterations, and enhances the computational efficiency of the unit commitment problem.

The frog leaping algorithm has recently gained popularity for solving the unit commitment problem with fuel cost reduction as the objective function. However, the algorithm has not considered the emission limitation constraint in its solutions. This paper introduces an enhanced version of the shuffled frog leaping algorithm that has previously been used for solving unit commitment problems in deregulated power systems, but without considering constraints on CO_2 emissions. The proposed algorithm includes CO_2 emission constraints, thus improving the optimization process for unit commitment problems. This study validates the new algorithm using the IEEE 39 bus with a 10-unit system and compares the results with existing methods. This contribution is the primary novelty of this research paper.

2. Mathematical UC Problem Formulation

The goal of the unit commitment (UC) problem is to minimize the overall cost of the power system, encompassing both operational expenses and start-up costs. In this study, we take into account two primary objectives. The first objective aims to minimize the total production cost throughout the scheduling horizon, which can be represented as the combination of start-up costs and fuel expenses. The UC problem can be mathematically formulated by the following equation:

$$\begin{gathered}\min \mathrm{TC} = \sum_{t=1}^{T}\sum_{i=1}^{N} \mathrm{FC}_i\left(P_{i,t}\right).U_{i,t} + \mathrm{ST}_{i,t}.U_{i,t}\left(1 - U_{i,t-1}\right),\\ \mathrm{FC}_i\left(p_{i,t}\right) = A_i + B_i.P_{i,t} + \left(P_{i,t}\right)^2,\\ \mathrm{ST}_i = \sigma_i + \delta_i\left(1 - \exp\left(\frac{-T_i^{\mathrm{OFF}}}{\tau_i}\right)\right).\end{gathered} \tag{1}$$

The second objective focuses on minimizing CO_2 emissions, which can be mathematically expressed as a quadratic function. CO_2 emissions are closely tied to fuel consumption and are calculated using the unit fuel input-output relationship in conjunction with an emission factor. Therefore, in this paper, we employ a second-order emission function to derive the equation for CO_2 emission costs.

$$\min EC_i\left(P_{i,t}\right) = \alpha_i + \beta_i.P_{i,t} + \gamma_i.\left(P_{i,t}\right)^2. \tag{2}$$

The objective function is subjected to the following constraints.

2.1. Equality Constraints

2.1.1. Power Balance Constraint

$$\sum_{i=1}^{N} P_{i,t}.U_{i,t} = \mathrm{PD}_t \quad (t = 1, 2 \ldots, T). \tag{3}$$

2.2. Inequality Constraints

2.2.1. Generation Limit Constraint

$$P_{i,\min} \leq P_{i,t} \leq P_{i,\max}, \quad 0 \leq R_{i,t} \leq P_{i,\max} - P_{i,\min}. \tag{4}$$

2.2.2. Minimum-Up Time Constraint

$$T_i^{\mathrm{ON}} \geq \mathrm{MU}_i. \tag{5}$$

2.2.3. Minimum-Down Time Constraint

$$T_i^{\mathrm{OFF}} \geq \mathrm{MD}_i. \tag{6}$$

2.2.4. Spinning Reserve Constraints

$$\sum_{i=1}^{N} P_{i,t}.U_{i,t} \geq \mathrm{PD}_t + \mathrm{SR}_t. \tag{7}$$

2.2.5. Ramp-Up Constraint. Maximum ramp-up constraint is the maximum generation output in a minute that unit is able to increase in an hour.

$$P_{i,t} - P_{i,t-1} \leq K.\mathrm{UR}_i. \tag{8}$$

2.2.6. Ramp-Down Constraint. Maximum ramp-down constraint is the maximum generation output in a minute that unit is able to decrease in an hour.

$$P_{i,t-1} - P_{i,t} \leq K.\mathrm{DR}_i, \tag{9}$$

where $K = 60$ min is the UC scheduling time step.

3. Shuffled Frog-Leaping Algorithm (SFLA)

The shuffled frog-leaping algorithm (SFLA) draws inspiration from the foraging behavior of frogs and combines elements of meme diffusion for global exploration with search mechanisms akin to particle swarm optimization (PSO) for local exploitation. In SFLA, a group of frogs emulates the collective behavior observed in a swamp, where they leap from stone to stone in search of the stone with the most abundant food resources. Each stone in the swamp represents a potential solution, and the frogs aim to locate the stone with the highest food quantity. Frogs can communicate and exchange information, facilitating the propagation of effective strategies or "memes" among them. This meme improvement process leads to adjustments in each frog's leaping step size [18, 19].

The simplicity and efficiency of SFLA have made it a valuable tool for addressing various real-world optimization problems. These applications include solving the traveling salesman problem (TSP) [20], vehicle routing problem [21], economic dispatch problem [22], profit-based generation scheduling problem [23], 0/1 knapsack problem [24], resource-constrained project scheduling problem [25], flow shop scheduling problem [26], and grid task scheduling problem [27].

The frog leaping algorithm begins by dividing the initial population of frogs into several subsets, known as memeplexes, with an equal number of frogs in each subset. The algorithm utilizes a concept of memeplexes where the frogs interact with each other and exchange ideas, resulting in a combination of local search and global information exchange techniques. The frogs within each memeplex use local search to improve their positions by shuffling to obtain more food. Meanwhile, the information obtained by each memeplex is compared globally to other memeplexes.

If a frog's position is incorrect, the algorithm updates it according to the original frog leaping rule as shown in Figure 1.

$$D_i = \mathrm{rand.}\left(X_b - X_w\right), \quad X_w^{\mathrm{new}} = X_w^{\mathrm{current}} + D_i, \left(D_{i,\min} < D_i < D_{i,\max}\right). \tag{10}$$

3.1. Initialization. To begin the first cycle of scheduling, the duration of the operation for unit "i" is determined while ensuring that the minimum-up and down-time constraints are satisfied [28]. The unit will maintain the same operating mode (ON/OFF) as the last cycle of the previous scheduling day for at least the required number of hours to meet these constraints [29].

$$T_i^1 = \begin{cases} +\mathrm{Rand}\left(\max\left(0, \mathrm{MU}_i - T_i^0\right), T\right), & \text{if } T_i^0 > 0, \\ -\mathrm{Rand}\left(\max\left(0, \mathrm{MD}_i + T_i^0\right), T\right), & \text{if } T_i^0 < 0. \end{cases} \tag{11}$$

If $T_i^{c-1} < 0$, cycle "c" represents ON status with duration.

$$T_i^c = \begin{cases} +\mathrm{Rand}\left(\mathrm{MU}_i, \mathrm{RT}_i^{c-1}\right), & \text{if } \left(\mathrm{RT}_i^{c-1} > \mathrm{MU}_i\right), \\ +\mathrm{RT}_i^{c-1}, & \text{otherwise.} \end{cases} \tag{12}$$

If $T_i^{c-1} > 0$, cycle "c" represents OFF status with duration.

$$T_i^c = \begin{cases} -\mathrm{Rand}\left(\mathrm{MD}_i, \mathrm{RT}_i^{c-1}(c-1)\right), & \text{if } \left(\mathrm{RT}_i^{c-1} > \mathrm{MD}_i\right), \\ -\mathrm{RT}_i^{c-1}, & \text{otherwise,} \end{cases} \tag{13}$$

where RT_i^{c-1} is the scheduling time after the allocation of first $(c-1)$ cycles.

$$\mathrm{RT}_i^{c-1} = T - \sum_{P=1}^{c-1} \left|T_i^P\right|. \tag{14}$$

3.2. Fitness Function Calculation. The overall objective of SFLA is to minimize the following fitness function subjected to a number of system and unit constraints:

$$\text{fitness} = \begin{cases} \max \text{Profit}, \\ \min \text{Emission}. \end{cases} \tag{15}$$

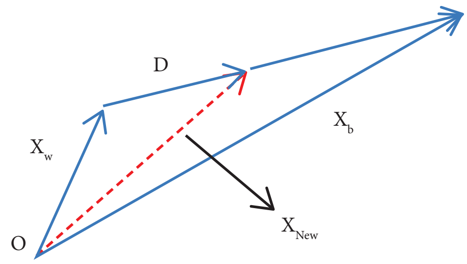

Figure 1: Frog leaping rule.

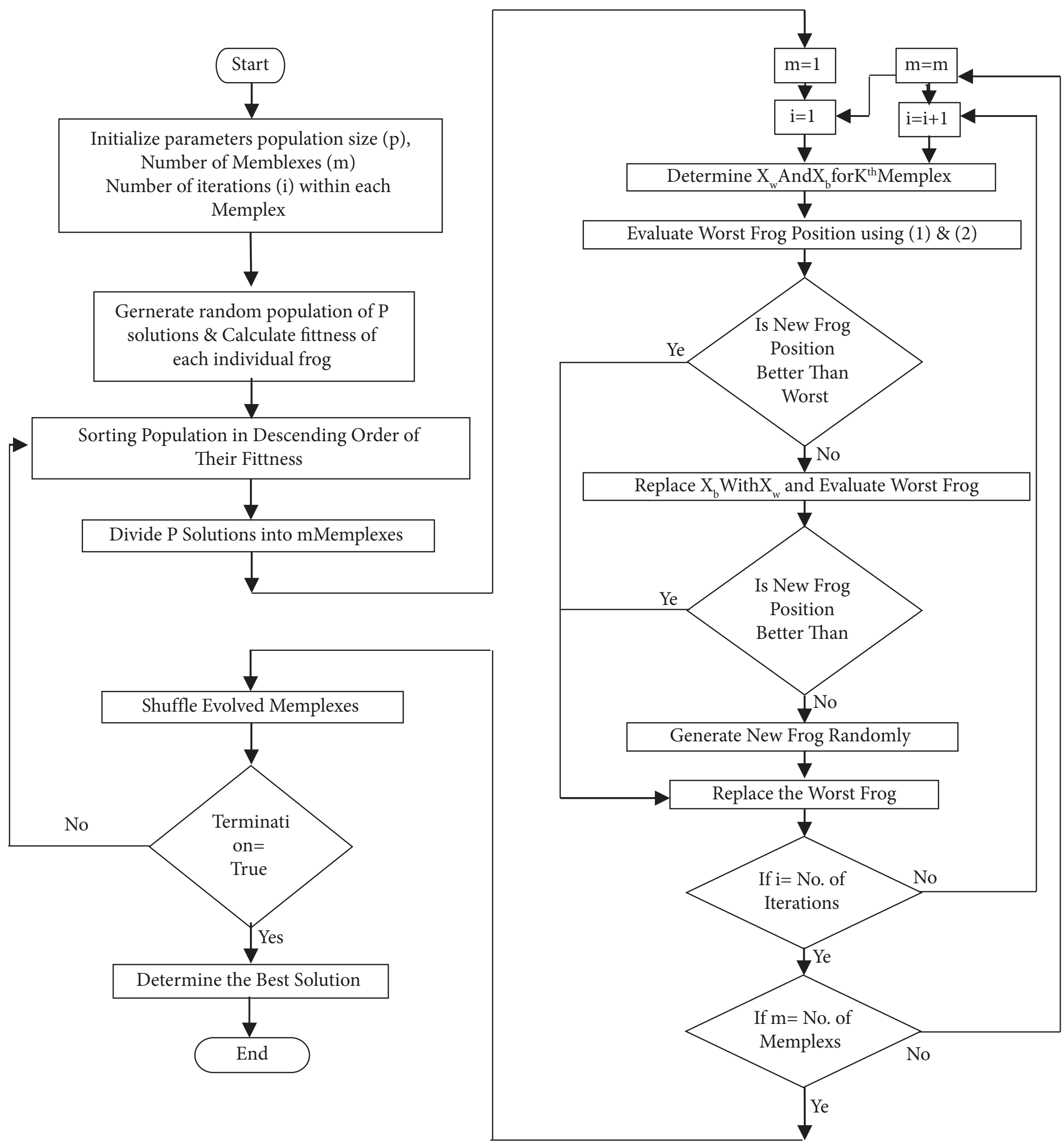

Figure 2: Proposed method flowchart.

4. Input Parameters

The proposed integer-coded shuffled frog-leaping algorithm (SFLA) method was utilized to solve the unit commitment problem for an IEEE 39 bus system consisting of ten generators over a 24-hour horizon. Figure 2 depicts the flowchart of the proposed SFLA method. The load demand curve for the 24-hour scheduling horizon is shown in Figure 3 and is used to determine the on/off cycles of the thermal generating unit. Table 1 provides the generator CO_2

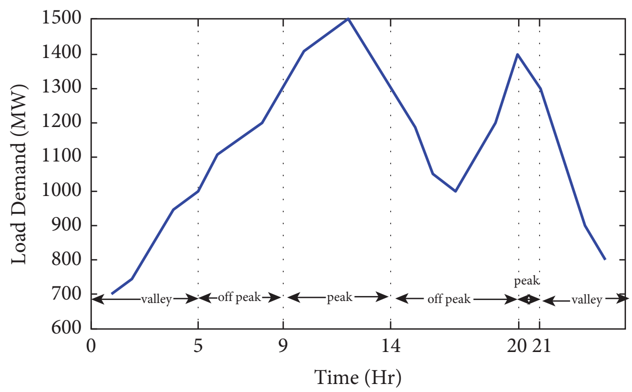

Figure 3: Operating cycle.

Table 1: Generator CO_2 emission coefficient.

Units	α_i (ton-CO_2/MW^{2}h)	β_i (ton-CO_2/MWh)	γ_i (ton-CO_2/h)	Start-up CO_2 (ton-CO_2)
U–1	$2.240E-05$	0.7557	46.677	210.0
U–2	$1.446E-05$	0.8056	45.276	233.3
U–3	$9.335E-05$	0.7748	32.674	25.67
U–4	$9.848E-05$	0.7701	31.740	26.13
U–5	$3.1\ 97E-05$	0.1582	3.6157	7.231
U–6	$5.720E-05$	0.1788	2.9729	1.365
U–7	$7.282E-06$	0.2557	4.4248	2.396
U–8	$3.807E-05$	0.2389	6.0841	0.2765
U–9	$2.046E-05$	0.2513	6.1302	0.2765
U–10	$1.594E-05$	0.2561	6.1763	0.2765

emission coefficient and start-up CO_2 emission information. The study considers a 10% spinning reserve and initializes the frog population with 200 individuals divided into 20 memeplexes, each containing 10 frogs. The proposed work employs 20 shuffling iterations to obtain optimal solutions.

5. Simulation Results

The MATLAB 7.10 software is used to implement the proposed algorithm. The personal computer with a core i3 (2.10 GHZ) processor with 4 GB RAM is used. The paper presents a proposed method that does not consider spinning reserve with 10% and the shut-down cost of generating units. It is tested in two cases and compared to the existing dynamic programming (DP) method [30]. The problem investigated involves a multiobjective function that seeks to minimize both fuel cost and CO_2 emission. The Pareto front solution for the multiobjective problem is obtained using the weighted sum average method, and the formula is also presented in the following equation:

$$\text{EntireCost} = W_1.\text{FC}_i\left(P_{i,t}\right) + W_2.\text{EC}_i\left(P_{i,t}\right). \tag{16}$$

5.1. Case 1. In this case, the weightage value for the minimizing cost function W_1 is taken as one whereas the weightage value for minimizing CO_2 emission function W_2 is taken as zero. This leads to a single objective cost-minimizing problem. The results for 24 hrs short-term thermal generation scheduling with CO_2 emission limitation using the proposed method are tabulated in Table 2. Table 2 shows the unit scheduling, total operating cost, and total CO_2 emission level during each time period of generation, and in this schedule, the minimum-up and down-time constraints are not violated. Figure 4 shows the convergence graph for this case in the proposed method.

5.2. Case 2. In this case, the weightage value for the minimizing cost function W_1 is taken as zero, and the weightage value for the minimizing CO_2 emission function W_2 is taken as one. This leads to the single objective CO_2 emission minimizing problem. Table 3 presents the hourly unit commitment schedule, total operating cost, and CO_2 emission output levels for 24 hours. The convergence of the CO_2 emission output level is shown in Figure 5. The proposed method is effective in generating a schedule that considers banked units and ensures optimal CO_2 emission and total operating cost. Figures 6 and 7 compare the operating costs and CO_2 emissions for two cases. The comparison of computational time with existing methods is shown in Figure 8.

The results obtained for variation in w using the proposed method, as described by equation (16), are shown in Table 4. From the results obtained, to achieve a reduction in total operating cost and CO_2 emission value simultaneously, W_1 and W_2 values must persist between 0.3 and 0.7. The effects of weighting factor variations on total operating cost and CO_2 emission value units are shown in Figure 8. The comparisons of computational time with existing methods are shown in Figure 9.

Table 2: $W_1 = 1$ and $W_2 = 0$ conditions.

Hours	Unit commitment schedule 1	2	3	4	5	6	7	8	9	10	Fuel cost ($)	Start-up cost ($)	Emission (t-CO_2)	Start-up emission (t-CO_2)	Total operating cost ($)	Total CO_2 emission (t-CO_2)
1	1	1	0	0	0	0	0	0	0	0	13683.13	0.00	638.67	0.00	13683.13	638.67
2	1	1	0	0	0	0	0	0	0	0	14554.50	0.00	679.34	0.00	14554.50	679.34
3	1	1	0	0	1	0	0	0	0	0	16809.45	1783.52	748.08	7.23	18592.96	755.31
4	1	1	0	0	1	0	0	0	0	0	18597.67	0.00	819.97	0.00	18597.67	819.97
5	1	1	0	1	1	0	0	0	0	0	20020.02	1113.78	897.93	26.13	21133.80	924.06
6	1	1	1	1	1	0	0	0	0	0	22387.04	1096.29	1006.96	25.67	23483.34	1032.63
7	1	1	1	1	1	0	0	0	0	0	23261.98	0.00	1047.80	0.00	23261.98	1047.80
8	1	1	1	1	1	0	0	0	0	0	24150.34	0.00	1085.41	0.00	24150.34	1085.41
9	1	1	1	1	1	1	1	0	0	0	27251.06	858.24	1111.71	3.76	28109.30	1115.47
10	1	1	1	1	1	1	1	1	0	0	30057.55	60.00	1135.34	0.28	30117.55	1135.62
11	1	1	1	1	1	1	1	1	0	0	30978.14	0.00	1142.73	0.00	30978.14	1142.73
12	1	1	1	1	1	1	1	1	1	1	33944.76	120.00	1123.94	0.55	34064.76	1124.49
13	1	1	1	1	1	1	1	1	0	0	30057.55	0.00	1135.34	0.00	30057.55	1135.34
14	1	1	1	1	1	1	1	0	0	0	27251.06	0.00	1111.71	0.00	27251.06	1111.71
15	1	1	1	1	1	0	0	0	0	0	24150.34	0.00	1085.41	0.00	24150.34	1085.41
16	1	1	1	1	1	0	0	0	0	0	21513.66	0.00	966.20	0.00	21513.66	966.20
17	1	1	1	1	1	0	0	0	0	0	20641.82	0.00	925.50	0.00	20641.82	925.50
18	1	1	1	1	1	0	0	0	0	0	22387.04	0.00	1006.96	0.00	22387.04	1006.96
19	1	1	1	1	1	0	0	0	0	0	24150.34	0.00	1085.41	0.00	24150.34	1085.41
20	1	1	1	1	1	1	1	1	0	0	29137.94	824.70	1126.86	4.04	29962.64	1130.90
21	1	1	1	1	1	1	1	0	0	0	27251.06	0.00	1111.71	0.00	27251.06	1111.71
22	1	1	0	1	1	1	0	0	0	0	22655.35	0.00	894.83	0.00	22655.35	894.83
23	1	1	0	1	0	0	0	0	0	0	17838.16	0.00	832.61	0.00	17838.16	832.61
24	1	1	0	0	0	0	0	0	0	0	15427.42	0.00	720.09	0.00	15427.42	720.09
Total cost ($)											559057.3	5856.53	23440.51	67.66	564913.8	23508.17

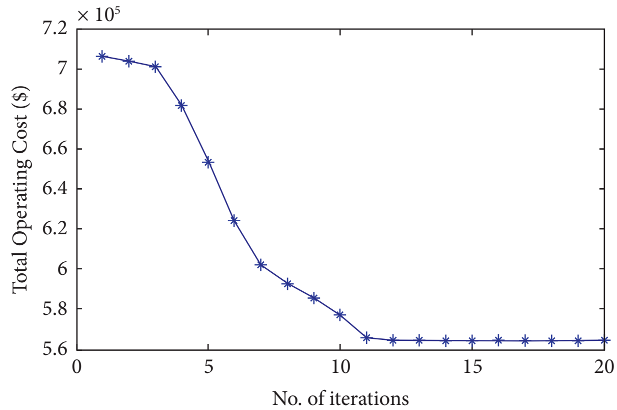

FIGURE 4: Convergence graph for total operating cost ($).

TABLE 3: $W_1 = 0$ and $W_2 = 1$ conditions.

Hours	Unit commitment schedule										Fuel cost ($)	Start-up cost ($)	Emission (t-CO_2)	Start-up emission (t-CO_2)	Total operating cost ($)	Total CO_2 emission (t-CO_2)
	1	2	3	4	5	6	7	8	9	10						
1	0	1	0	1	1	1	1	1	1	1	20469.74	3740.17	376.78	37.95	24209.91	414.73
2	0	1	0	1	1	1	1	1	1	1	21312.25	0.00	416.10	0.00	21312.25	416.10
3	0	1	0	1	1	1	1	1	1	1	23050.65	0.00	497.24	0.00	23050.65	497.24
4	0	1	0	1	1	1	1	1	1	1	24784.95	0.00	578.19	0.00	24784.95	578.19
5	0	1	0	1	1	1	1	1	1	1	25658.90	0.00	618.98	0.00	25658.90	618.98
6	0	1	1	1	1	1	1	1	1	1	28026.15	1096.29	728.02	25.67	29122.44	753.69
7	0	1	1	1	1	1	1	1	1	1	28900.71	0.00	768.84	0.00	28900.71	768.84
8	0	1	1	1	1	1	1	1	1	1	29776.82	0.00	809.73	0.00	29776.82	809.73
9	1	1	1	1	1	1	1	1	1	1	32340.01	8390.99	929.38	210.00	40731.00	1139.38
10	1	1	1	1	1	1	1	1	1	1	34042.15	0.00	1008.83	0.00	34042.15	1008.83
11	1	1	1	1	1	1	1	1	1	1	34862.11	0.00	1047.10	0.00	34862.11	1047.10
12	1	1	1	1	1	1	1	1	1	1	35684.48	0.00	1085.48	0.00	35684.48	1085.48
13	1	1	1	1	1	1	1	1	1	1	34042.15	0.00	1008.83	0.00	34042.15	1008.83
14	1	1	1	1	1	1	1	1	1	1	32340.01	0.00	929.38	0.00	32340.01	929.38
15	1	1	1	1	1	1	1	1	1	1	30592.43	0.00	847.81	0.00	30592.43	847.81
16	1	1	1	1	1	1	1	1	1	1	27983.17	0.00	726.07	0.00	27983.17	726.07
17	1	1	1	1	1	1	1	1	1	1	27132.57	0.00	687.25	0.00	27132.57	687.25
18	1	1	1	1	1	1	1	1	1	1	28851.06	0.00	766.53	0.00	28851.06	766.53
19	1	1	1	1	1	1	1	1	1	1	30592.43	0.00	847.81	0.00	30592.43	847.81
20	1	1	1	1	1	1	1	1	1	1	34042.15	0.00	1008.83	0.00	34042.15	1008.83
21	1	1	1	1	1	1	1	1	1	1	32340.01	0.00	929.38	0.00	32340.01	929.38
22	0	1	1	1	1	1	1	1	1	1	28026.15	0.00	728.02	0.00	28026.15	728.02
23	0	1	1	1	1	1	1	1	1	1	24543.87	0.00	565.53	0.00	24543.87	565.53
24	0	1	1	1	1	1	1	1	1	1	22846.11	0.00	487.18	0.00	22846.11	487.18
Total cost ($)											692241	13227.45	18397.29	273.62	705468.5	18670.91

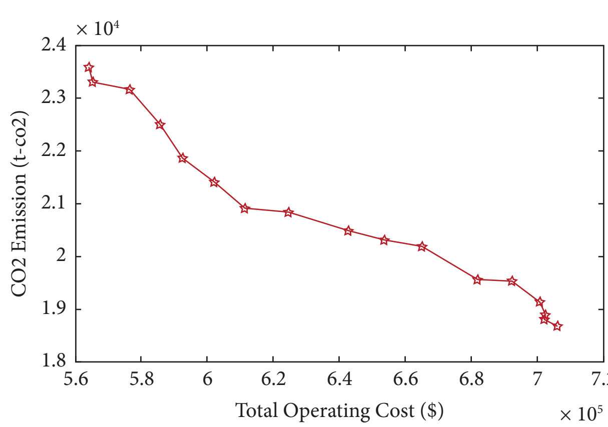

FIGURE 5: Convergence graph for CO_2 emission (t-CO_2).

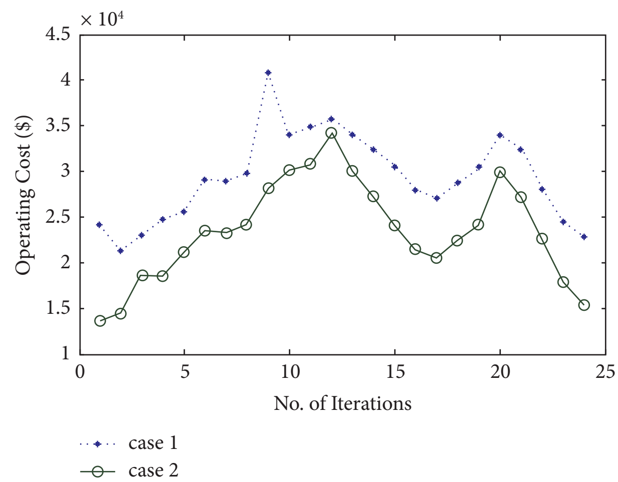

Figure 6: Comparison of operating cost between proposed method case 1 and case 2 for 10-unit test system.

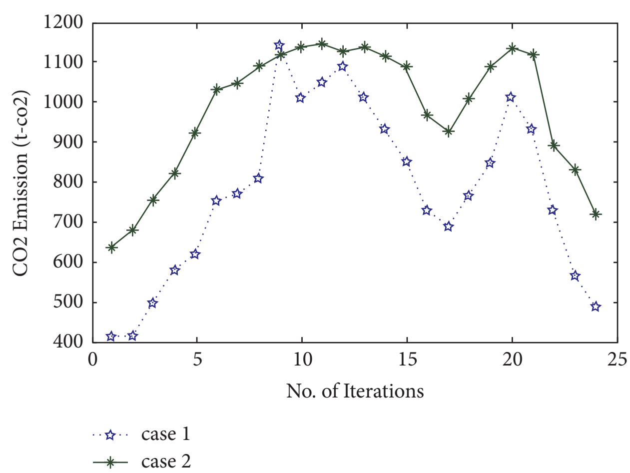

Figure 7: Comparison of CO_2 emission between proposed method case 1 and case 2 for 10-unit test system.

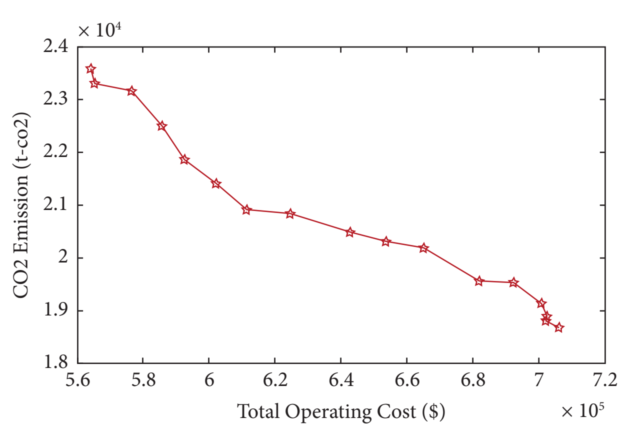

Figure 8: Pareto front.

Table 4: Comparison of simulation results.

Methods	Constraints taken	Total operating cost ($/day)	Total operating cost ($/year)	Total emission (tons/day)	Total emission (tons/year)
Traditional UC [31]	Minimum cost ($)	762802.98	278423087.7	23517	8583705
PSO [32]	Minimum cost ($)	725260	264719900	23028	8405220
DP [17]	Minimum cost ($)	701700	256120500	23517	8583705
	Minimum CO_2 emission (t-CO_2)	772200	281853000	19026	6944490
Proposed method	Minimum cost ($)	564913.8	206193537	23508.17	8580482
	Minimum CO_2 emission (t-CO_2)	705468.5	257495987	18670.91	6814882

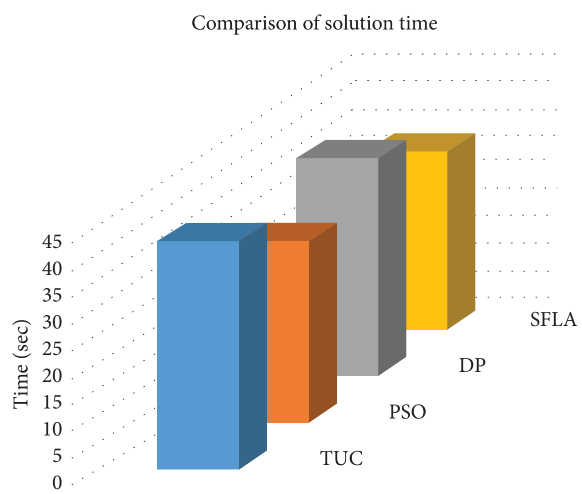

Figure 9: Comparison of computational time with existing methods.

6. Conclusion

In this study, we suggested an integer-coded shuffled frog-leaping algorithm (SFLA) to reduce the unit commitment problem's (UCP) operating costs and overall CO_2 emissions over a one-day scheduling period. The SFLA is inspired by the natural food-searching behavior of frogs. The suggested approach aims to identify the ideal generating unit start-up and shut-down times to meet fluctuating loads while reducing operating costs and CO_2 emissions. The approach satisfies a number of constraints while accounting for fuel costs, start-up and shut-down costs, and maintenance costs. The study makes use of a test system for the IEEE 39 bus with 10 units, and the outcomes are consistent with dynamic programming approaches. The proposed work also suggests a new multiobjective optimization algorithm that improves on some of the drawbacks of the weighting sum approach. Numerous simulations have demonstrated the effectiveness of the new algorithm. In comparison to the currently used methods, the proposed method consistently results in lower CO_2 emissions and overall operating costs. According to the findings of this study, the suggested SFLA method is a viable strategy for resolving the CO_2 emission-constrained short-term unit commitment problem (CSCUCP). The approach can identify options that considerably lower CO_2 emissions and operating expenses. The approach can also adhere to a number of restrictions, including minimum ramp rates, minimum generation levels, and up-and-down times. The suggested approach can be used to lower operating costs while also enhancing the environmental performance of power systems. Power system managers can use this technique to schedule generating units in a way that reduces CO_2 emissions and operating costs. Researchers can use the technique to create brand-new optimization algorithms for handling the CSCUCP.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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