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RESEARCH ARTICLE

Application of Binary Slime Mould Algorithm for Solving Unit Commitment Problem

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ABSTRACT A challenging engineering optimization problem in electrical power generation is the unit commitment problem (UCP). Determining the scheduling for the economic consumption of production assets over a specific period is the premier objective of UCP. This paper presents a take on solving UCP with Binary Slime Mould Algorithm (BSMA). SMA is a recently created optimization method that draws inspiration from nature and mimics the vegetative growth of slime mould. A binarized SMA with constraint handling is proposed and implemented to UCP to generate optimal scheduling for available power resources. To test BSMA as a UCP optimizer, IEEE standard generating systems ranging from 10 to 100 units along with IEEE 118-bus system are used, and the results are then compared with existing approaches. The comparison reveals the superiority of BSMA over all the classical and evolutionary approaches and most of the hybridized methods considered in this paper in terms of total cost and convergence characteristics.

INDEX TERMS Binary slime mould algorithm (BSMA), heuristic optimization algorithm, unit commitment problem (UCP), economic load dispatch (ELD), power system optimization.

I. INTRODUCTION

Conventional power generation and supply systems at present handle dynamic load demand with multiple generating units. The load demand is dynamic because it fluctuates over time as per user-end consumption. When the user-end consumption or load demand is at its highest, all the available generating units must be kept running. On the other hand, when the user-end consumption or load demand is less, it is unnecessary to keep all the available generating units turned on and running. It is economically disadvantageous to keep all the generating units running and some generating units are required to be turned off. To ensure the power station's cost-effective and efficient operation, it is essential to schedule which units are to be turned on and turned off. Besides satisfying the varying load demand, proper scheduling results in a cost-effective power generation, which generates more profit and ensures efficient usage of generation utilities. The process of determining the schedule of multiple generating units for a specific period is called Unit Commitment (UC). The UC Problem is an optimization problem whose objective is to reduce the cost of electrical energy generation by fulfilling various constraints regarding system and production units. The UCP is a large-scale, mixed-integer, non-linear optimization problem with complicated constraint requirements.

Over the last few decades, researchers have designed, developed, and applied numerous classical, evolutionary heuristic/metaheuristic, and hybridized optimization techniques to solve the UCP. Classical optimization techniques are standard numerical/mathematical methods to solve an optimization problem. Some of the classical optimization techniques that were used to solve UCP are Priority List [1], Dynamic Programming [2], Lagrangian Relaxation and its different variants [3], Benders Decomposition [4], Mixed

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Integer Linear Programming [5], Second Order Cone Programming [6], Semi-definite Programming [7], Branch and Bound methods [8], etc. Researchers used these classical optimization techniques as some of the early attempts in solving UCL. Classical optimization techniques are advantageous because they follow a straightforward approach to a solution. Furthermore, their convergence process is iteration-less and swift. Finally, their output is integer-type. However, several limitations were seen while implementing these classical optimization techniques. For instance, due to its process, Priority List [1] eliminates some potentially optimal solutions, leading to a sub-optimal solution. On the other hand, the rest of the classical optimization techniques like Dynamic Programming [2], Lagrangian Relaxation [3], and Mixed Integer Linear Programming [5] suffer from excessive computational time and resources to find the optimal solution. All of these shortcomings resulted in costlier solutions and motivated researchers to try and implement newer optimization approaches. Consequently, throughout the years, researchers attempted to hybridize classical optimization techniques and apply those techniques to solve UCP. Some examples of hybridized classical optimization techniques are Quantum Surrogate Lagrangian Relaxation [9] and Fuzzy Mixed Integer Linear Programming [10]. However, like their predecessors, these hybridized methods fall short of providing an efficient convergence to the solution as the complexity of the generation system increases.

In recent years, many evolutionary heuristic/metaheuristic algorithms have been developed by different researchers. Most of them were influenced by various natural occurrences and preying behavior of animals. These algorithms were later implemented to solve UCP. Some of the nature-inspired evolutionary metaheuristic techniques that were applied to solve UCP are Genetic Algorithm [11], Binary Particle Swarm Optimization [12], Ant Colony Optimization [13], Binary Grey Wolf Optimizer [14], Imperialistic Competition Algorithm [15], Enhanced PSO [16], Shuffled Leaping Frog Algorithm [17], Enhanced Simulated Annealing [18], Binary Gravitational Search Algorithm [19], Evolutionary Programming [20], Binary Fish Migration Optimization [21], Chaotic Gorilla Troops Optimizer [22], Binary Alternative Moth-Flame Optimization [23], etc. Applying these metaheuristic algorithms for solving UCP offered an advanced, smooth, and swift convergence to the global solution compared to the classical optimization techniques. These metaheuristic algorithms also offered greater handling capability of complex UCP constraints. It is to be noted that, all of these nature-inspired algorithms are very diverse. Some of them show significant improvement over others in exploring the most optimal solution due to the nature-inspired process it follows. Earlier nature-inspired meta-heuristics like Genetic Algorithm [11] and Particle Swarm Optimization [12] provide premature convergence [24] and limited explorability. Additionally, their solution was largely dependent on the selection of weighting parameters. Later, these problems were solved in algorithms like Grey Wolf Optimizer [14], Whale Optimization Algorithm [43], and other newer nature-inspired meta-heuristics. Researchers are continuously working to overcome the still prevalent shortcomings like uncertain convergence, entrapment to local minima, the requirement of excessive iteration, and longer simulation time. An extensive review of the implementation of classical, metaheuristic, and hybridized optimization techniques for solving UCP is performed in [24].

Hybridized methods combine both classical optimization techniques and evolutionary metaheuristic algorithms to solve UCP. Well-known hybridized techniques are hybrid PSO-GWO [25], Lagrangian Relaxation and Genetic Algorithm [26], LRPSO [27], a Solution Modification Process [28], Hybrid Genetic ICA [29], Hybrid Harmony Random Search [30], Improved Pre-prepared Power Demand Table and Muller Method [31], local convergence average BPSO [32]. Quantum-inspired hybridization is another noteworthy attempt to hybridize classical and evolutionary techniques. QEA [33], QIBGSA [34], QBPSO [35], and QIBGWO [36] are some of the examples of that. Hybridized solution techniques solve the shortcomings of classical optimization techniques (handling system dimensionality, lack of convergence) and evolutionary algorithms (uncertainty of convergence, limited explorability). Complex sequential procedure is the most common drawback of hybridized techniques, resulting in longer iteration time and slower convergence. For instance, due to the sequential calculation of PSO and GWO [25], hybrid PSO-GWO convergence is substantially slower than NPSO. On the other hand, some of these metaheuristic and hybridized methods are quite good in terms of solution quality. But the search for a more efficient, cost-effective, modern, and adoptive optimization approach is still going on as the power generation optimization problem domain broadened in recent years with the inclusion of similar complex optimization problems to UCP.

Newer optimization algorithms like Binary Harris Hawk Optimizer [37], Binary Horse Herd Optimization [38], Runge Kutta Method [39], Colony Predation Algorithm [40], Weighted Mean of Vectors (INFO) [41], Rime Optimization Algorithm [42], and Slime Mould Algorithm (SMA) have shown competitive performance compared to the existing algorithms like GWO, WOA, MFA, SSA, etc. for different universal benchmark functions and engineering design problems [44], [45], [46]. So the potential of these algorithms as a UCP solver should be explored.

A recently developed, nature-inspired stochastic optimization approach was presented by Li et al. [46] to simulate the behavior and morphological changes of the acellular slime mould *Physarum polycephalum*. Most notably, Physarum polycephalum can make multi-objective foraging decisions [47]. It can also figure out the quickest route through a maze and solve challenging puzzles. The SMA assimilates continuous updating of the slime mould position to locate the optimal food source, which is translated as optimal cost in the case of UCP. However, the continuous-natured decision-making process of the original SMA should be transformed into binary decision-making, as the on/off scheduling of UCP is represented with binary values (0, 1). So, sigmoid transformation [48] is used to binarize the continuous-natured SMA. Furthermore, heuristic adjustment of [33] is used with SMA for handling the UCP constraints. A modified binarized SMA is formed and proposed by applying the above-mentioned modifications. The novel contributions of this study can be enlisted as follows:

1) Binarizing the original SMA to match the binary solution space of UCP, hence proposing a BSMA.
2) Modeling the proposed BSMA to be compatible with UCP objective functions and regulatory constraints.
3) Testing the proposed BSMA for UCP in aspects of an economical solution, convergence process, and time required to reach the optimum solution.
4) Establishing BSMA as a UCP optimizer based on the simulation results and comparative studies.

The remainder of the paper follows the following structure. Unit commitment problem formulation, its constraint, and its boundaries are described in Section II, SMA, and its working phases are discussed in Section III. The application of BSMA to solve UCP is described in Section IV. Performance tests for different test systems, comparisons, convergence, and deviation characteristics are explored in Section V. A discussion section detailing the summary of the proposed work along with limitations and insightful implications is provided in Section VI. Lastly, the paper is concluded with a conclusion and future prospects of this topic in Section VII.

II. PROBLEM FORMULATION OF UNIT COMMITMENT

The main goal of unit commitment is to determine the best generating schedule for the available units that will result in the lowest operating cost and, consequently, the most profit. A generating unit's entire running cost is made up of three components: fuel cost, starting cost, and shutdown cost.

A. FUEL COST

Fuel costs are determined using unit heat rate data and fuel price information. It is a second-order quadratic function of the power output of each generator at each hour defined by Economic Dispatch (ED) [49]. Fuel cost can be expressed as:

$$F^i_{cost} = a^i + b^i P^i_G + c^i P^{i2}_G \tag{1}$$

where F^i_{cost} is the fuel cost function of i^{th} unit, P^i_G is the power generated by the i^{th} unit and, a^i, b^i, c^i are the fuel cost coefficients of i^{th} unit. A sinusoidal term is added with Equation (1) for valve point loading [50] in multi-valve steam turbines [51]. So fuel cost function with valve-point loading effect can be expressed as:

$$F^i_{cost} = a^i + b^i P^i_G + c^i P^{i2}_G + \left| d^i sin\left(e^i * \left(P^i_{G\_min} - P^i_G\right)\right)\right| \tag{2}$$

where d^i and e^i are the valve-point coefficients of i^{th} unit and $P^i_{G\_min}$ is the minimum generation limit of i^{th} unit. The total fuel cost of overall generation can be expressed as:

$$Total\ Fuel\ Cost = \sum\nolimits_{t=1}^{H} \sum\nolimits_{i=1}^{N} F^i_{cost} P^i_G * \delta^i_t \times \forall t \in H; \quad i \in N; \ \delta^i_t \in \{0, 1\} \tag{3}$$

where H is the total period of load demand considered for unit commitment, i.e., total scheduling hours, N is the total number of generating units and δ^i_t is the generating status bit of i^{th} unit at t^{th} hour.

B. COSTS OF START-UP AND SHUTDOWN

The start-up cost is required to bring a de-committed thermal generating unit back to a committed state. The start-up cost is warmth dependent [25], and, therefore, can vary depending upon the de-committed period of the inactive generating unit. Start-up cost can be expressed as:

$$SU_{cost_t}{}^i = \begin{cases} SU^i_{cost\_hot}, & for\ T^i_{mu} \le T^i_{off} \le \left(T^i_{md} + T^i_{cold}\right) \\ SU^t_{cost\_cold}, & for\ T^i_{off} \ge \left(T^i_{md} + T^i_{cold}\right) \end{cases} \tag{4}$$

where $SU_{cost_t}{}^i$ is the start-up cost of i^{th} unit at t^{th} hour, $SU^i_{cost\_hot}$ and $SU^i_{cost\_cold}$ are the hot and cold start-up costs of i^{th} unit respectively, T^i_{off} is the consecutive hours of de-committed state of i^{th} unit, T^i_{mu} and T^i_{md} are the minimum up and down times of i^{th} unit, respectively. And lastly, T^i_{cold} is the cold start hours of i^{th} unit.

Shutdown costs refer to a fixed amount of cost to maintain a de-committed generating unit, and it is independent of the de-committed period. Shutdown costs are neglected in this study following the other approaches in [11], [12], [14].

So the total cost of overall generation can be represented as:

$$Total\ Cost = \sum\nolimits_{t=1}^{H} \sum\nolimits_{i=1}^{N} F^i_{cost} P^i_G * \delta^i_t + SU_{cost_t}{}^i * \left(1 - \delta^i_t\right) \delta^i_t \tag{5}$$

C. GENERATION REGULATING CONSTRAINTS

In practical cases, plant operators face numerous generation regulating constraints. For instance, a generating unit's minimum and maximum generation limitations vary with time. Also, the time required to bring a de-committed unit online is considered. The implication of such constraints to UCP is stated below:

1) LIMITS ON MAXIMUM AND MINIMUM GENERATION

A committed unit's power generation should remain within its maximum and minimum limits.

$$P^i_{G\_min} \delta^i_t \le P^i_G \delta^i_t \le P^i_{G\_max} \delta^i_t \tag{6}$$

where $P^i_{G\_min}$ and $P^i_{G\_max}$ are the minimum and maximum generation limits of i^{th} unit.

2) POWER SUPPLY AND BALANCING LOAD DEMAND

As per load demand and power supply balance constraint, the summation of power generation of all committed units must be greater than or equal to the load demand at time t.

$$\sum_{i}^{N} P_{G_t}^{i} * \delta_t^i \geq P_{D_t} \tag{7}$$

where P_{D_t} is the load demand at t^{th} hour.

3) SPINNING RESERVE

An extra generation capacity should be reserved to continue satisfying load demand in the cases of a sudden excessive load or any generation failure. It makes the system more reliable and immune to failures. This excess reserve capacity is known as the spinning reserve. Spinning reserve is added with the load demand and the summation is considered as the generation requirement. So Equation (7) be re-written as:

$$\sum_{i}^{N} P_{G_t}^{i} * \delta_t^i \geq P_{D_t} + SR_t \tag{8}$$

where at t^{th} hour, the required spinning reserve is SR_t.

4) MINIMUM TIME FOR UP/DOWN

A generating unit should be brought online after a certain time interval from a de-committed status based on its thermal cooling characteristics. Similarly, the unit must run for a certain time before being shut down. These limitations—known as the Minimum Up and Minimum Down Time—can be stated as follows:

$$\delta_t^i = \begin{cases} 1, & for\ 1 \leq T_{on_{t-1}}^{\ i} \leq T_{mu}^{i} \\ 0, & for\ 1 \leq T_{off_{t-1}}^{\ i} \leq T_{md}^{i} \end{cases} \tag{9}$$

5) INITIAL STATUS

The terminal status of every unit from the previous scheduling period should be assessed to avoid disrupting the minimum time for the up/down cycle of the generating units.

To summarize the unit commitment problem formulation, the objective function of Equations (6), (8), and (9) are inequality constraints. This constrained minimization problem of unit commitment will be solved using BSMA.

III. OVERVIEW OF SMA

SMA is a recently developed nature-based optimization algorithm [46] that has been applied to solve several engineering optimization problems. The working principle of SMA mimics the food-searching phenomenon of slime mould. A slime mould may explore several food sources simultaneously, preferring a higher concentration of food. Feedback-dependent propagation wave from bio-oscillator controls the cytoplasmic flow, hence the thickness of the vein towards a food source. Figure 1 and Figure 2 of [52] show a good visualization of the process.

The exploration phase of SMA involves locating the food and approaching the location in the search area. This process

FIGURE 1. Slime mould exploits the nutrient source (oat flakes) exploiting oat flakes by a network of cytoplasmic veins [52].

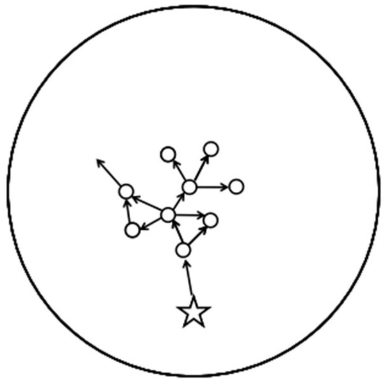

FIGURE 2. Scheme of the cytoplasmic propagation, circles are the nutrient source (oat flakes), star mark is the primary slime mould position and arrows are cytoplasmic veins [52].

as in [46], can mathematically be expressed as such:

$$\vec{X}(k+1) = \begin{cases} \vec{X_b}(k) + \vec{vb} * \left(\vec{W}\vec{X_A}(k) - \vec{X_B}(k)\right), & for\ r < p \\ \vec{vc} * \vec{X}(k), & for\ r \geq p \end{cases} \times \forall \vec{vb} \in [-a, a]; \quad \vec{vc} \in [-1, 1]; \ r \in \{0, 1\} \tag{10}$$

where k represents the current iteration, and r is a random number between $\{0, 1\}$. $\vec{X}\,(k)$ represents the current slime mould location and $\vec{X}\,(k+1)$ refers to the next location. $\vec{X_b}\,(k)$ is the best location with the most potent odor found. $\vec{X_A}\,(k)$ and $\vec{X_B}\,(k)$ are two randomly selected slime mould positions. $\vec{vb}$ and $\vec{vc}$ oscillates in-between their limits and refers to the decision-making of slime mould, whether to reach the food source or search for other higher quality sources (Figure 3). Both the variables reach zero as the number of iterations increases because, by then, the slime mould finds its optimal food source. The limits of $\vec{vb}$ can be expressed as:

$$a = arctanh\left(-\left(\frac{k}{max\_k}\right) + 1\right) \tag{11}$$

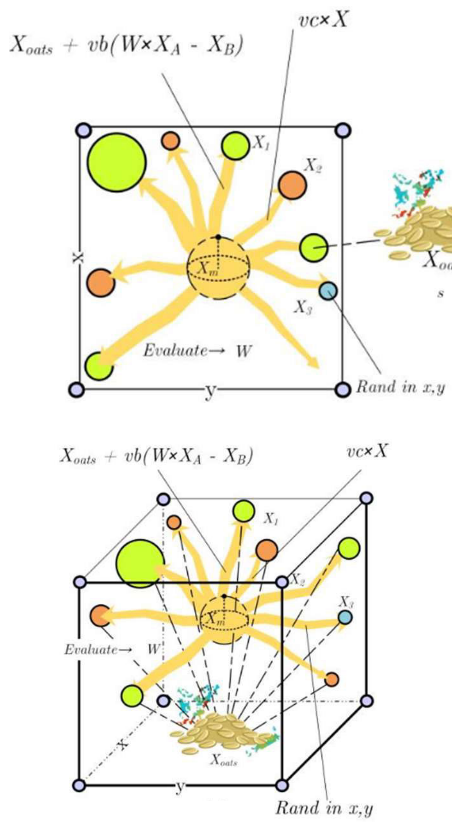

FIGURE 3. Exploration phase of slime mould with possible locations in 2-dimension and 3-dimension [46].

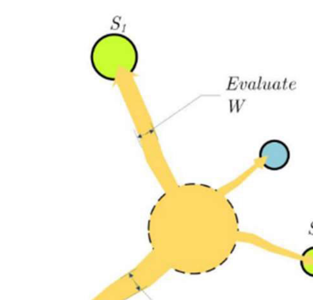

FIGURE 4. Assessment of fitness [46].

where max_k is the number of iterations that can be performed at most.

p is a function formulated as:

$$p = tanh(|S(v) - DF|) \quad \forall v \in \{1, 2, 3, \ldots\ldots n\} \tag{12}$$

where v is the number of slime mould veins, $S(v)$ is the current fitness value of $\vec{X}$, and DF is the best fitness among all the iterations. And lastly, $\vec{W}$ represents the frequency of oscillation which determines the thickness of the veins.

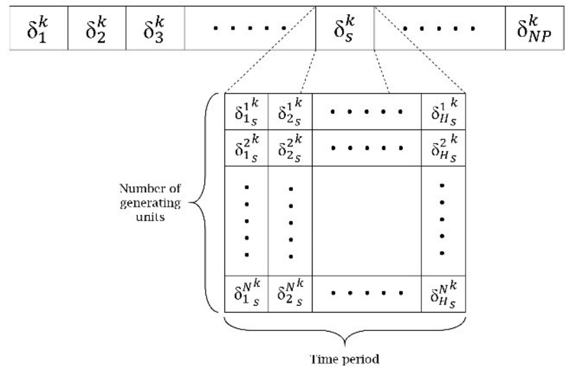

FIGURE 5. Population structure of unit commitment with BSMA.

In simpler terms, $\vec{W}$ is the weight of the slime mould. $\vec{W}$ is mathematically expressed as:

$$\vec{W}(SmellIdx(v)) = \begin{cases} 1 + rlog\left(\dfrac{bF - S(v)}{bF - wF} + 1\right), & for\ condition \\ 1 - rlog\left(\dfrac{bF - S(v)}{bF - wF} + 1\right), & for\ others \end{cases} \tag{13}$$

where *condition* indicates that $S(v)$ ranks first 50% of the population, bF & wF are the best and worst fitness of the ongoing iteration routine, respectively (Figure 4), and *SmellIdx(v)* refers to a sequence of fitness value sorted in ascending order.

In the exploitation phase, the SMA optimizer continuously updates the slime mould position depending on the feedback from the exploration phase. As in [46], this can be expressed as follows:

$$\vec{X}^* = \begin{cases} rand * (UB - LB) + LB, & for\ rand < z \\ \overrightarrow{X_b}(k) + \overrightarrow{vb} * \left(W * \overrightarrow{X_A}(k) - \overrightarrow{X_B}(k)\right), & for\ r < p \\ \overrightarrow{vc} * \vec{X}(k), & for\ r \geq p \end{cases} \times \forall\ rand \in [0, 1]; \quad r \in [0, 1] \tag{14}$$

where LB and UB are the lower and upper bounds of the search area, respectively. *rand* and r are random values between 0 and 1, and lastly, the value of parameter z is taken as 0.03, as the probability maintains a proper balance between exploration and exploitation at this constant z value [46].

IV. APPLICATION OF BSMA TO SOLVE UCP

This section discusses the SMA binarization method, priority list of units, solving Economic Load Dispatch (ELD) with the lambda iteration method, and constraint handling processes. Then the use of BSMA to solve the constraint minimization problem of unit commitment is described in detail with necessary diagrams.

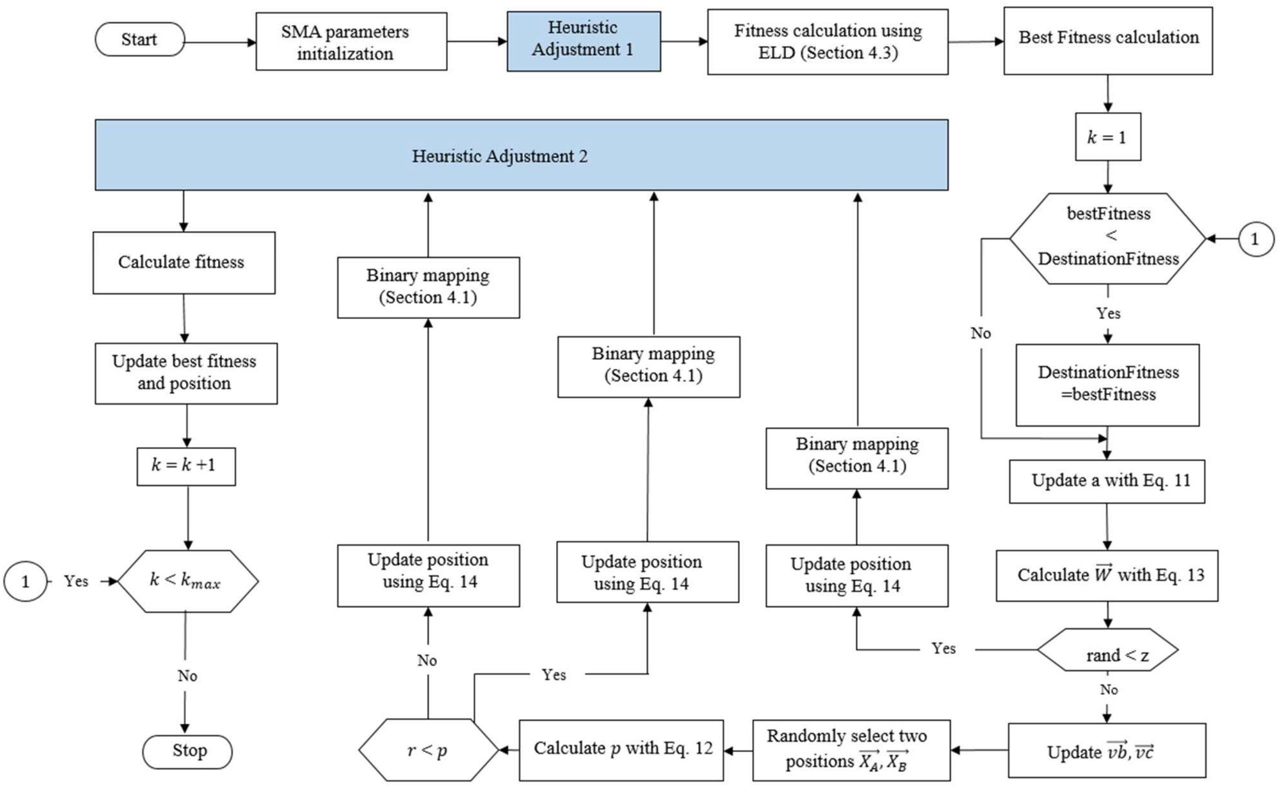

FIGURE 6. Flowchart of UCP with BSMA.

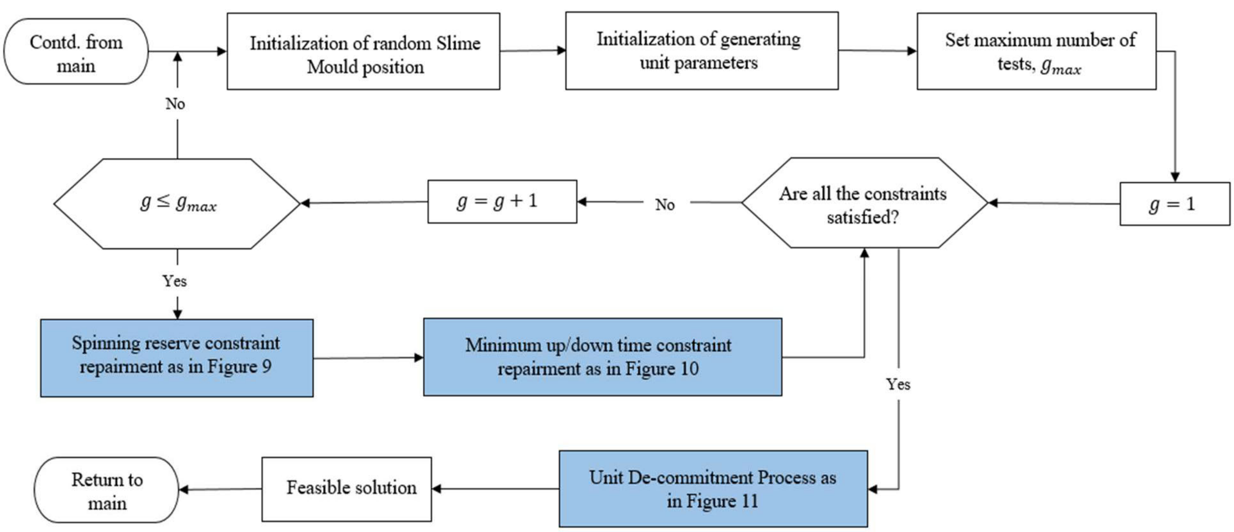

FIGURE 7. Flowchart of Heuristic adjustment 1.

A. POPULATION STRUCTURE AND BINARY MAPPING

An illustration of the BSMA population structure is shown in Figure 5. In Figure 5, the commitment status of i^{th} unit of s^{th} slime mould at k^{th} iteration and t^{th} hour is represented as $\delta_{t_s}^{ik}$ However, SMA itself is non-discrete in nature, meaning a particular slime mould of the population can be assigned continuous values. Sigmoid transform inspired by BPSO [48] is used to limit $\delta_{t_s}^{ik}$ to only binary values. Sigmoid transform

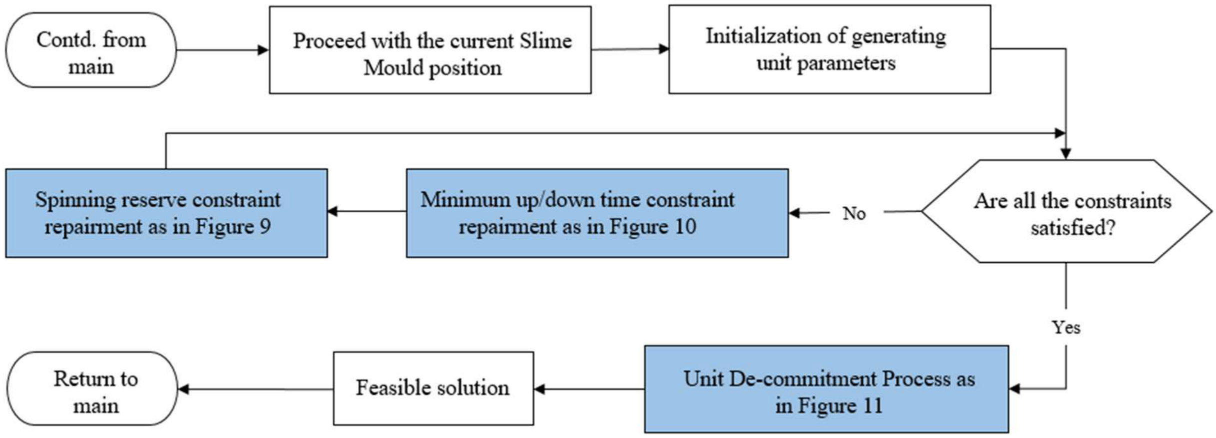

FIGURE 8. Flowchart of Heuristic adjustment 2.

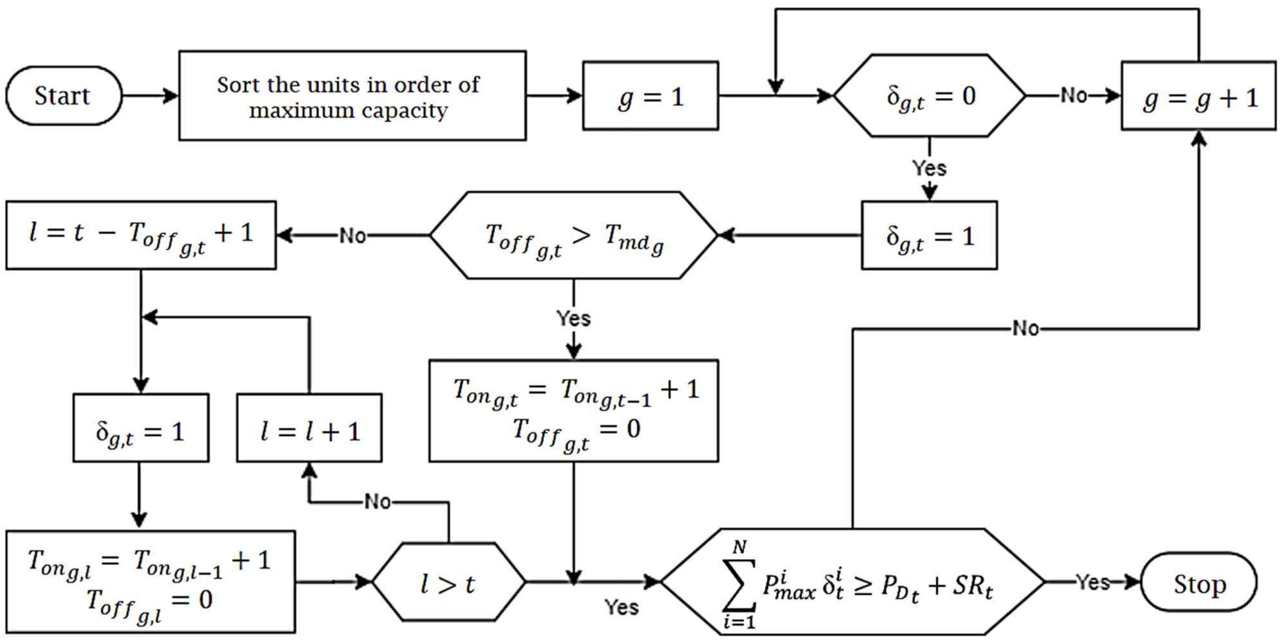

FIGURE 9. Flowchart of spinning reserve constraint handling for constraint repairment.

equation is expressed as:

$$S_f\left(X_S^k\right) = \frac{1}{1 + e^{-X_S^k}} \tag{15}$$

$$X_s^{k+1} = \begin{cases} 1, & for\ S_f\left(X_s^k\right) > r \\ 0, & otherwise \end{cases} \tag{16}$$

where S_f denotes the transfer function, $\left(X_s^k\right)$ is the position for s^{th} slime mould at k^{th} iteration, and finally, r is a random number in [0,1].

Value "1" is assigned to $\delta_{t_s}^{i^k}$ if i^{th} unit is committed at t^{th} hour, and vice versa for a de-committed unit. An N × H matrix is assigned to each δ_s^k where N is the maximum number of units, and $i \epsilon \{1, 2, 3, \ldots, \mathrm{N}\}$ and H represents the total time horizon and $t \epsilon \{1, 2, 3, \ldots, H\}$. NP denotes the overall population of slime mould and $S \epsilon \{1, 2, 3, \ldots, \mathrm{NP}\}$.

B. THE PRIORITY LIST OF GENERATING UNITS

Not all the units have the same running cost, as the cost parameters of a generator change to a great extent over its lifetime. A priority list is formed according to the objective function of fuel cost in Equation (1). Fuel cost, F_{cost}^i of i^{th} unit depends greatly on it's fuel co-efficients a^i, b^i and c^i. The lesser the value of F_{cost}^i of a generating unit, the higher it is placed on the priority list and, consequently, kept committed for a more extended period.

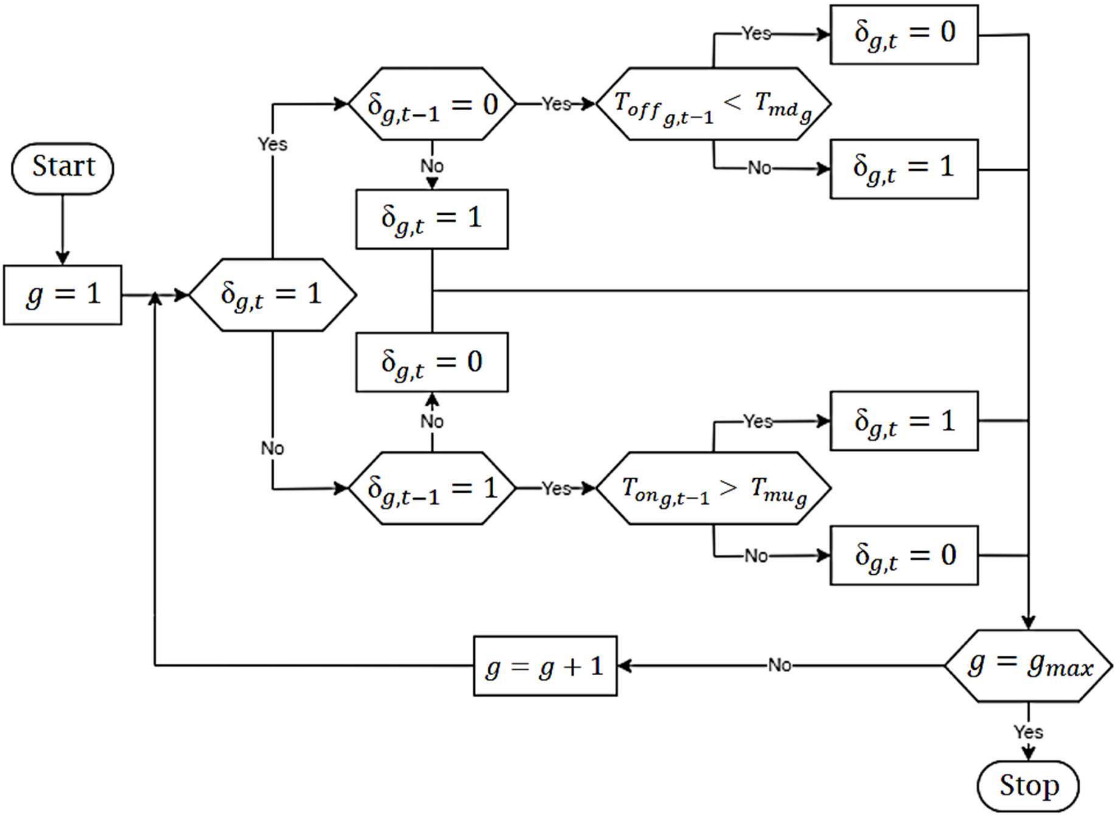

FIGURE 10. Flow of minimum up time, minimum down time constraint repairment.

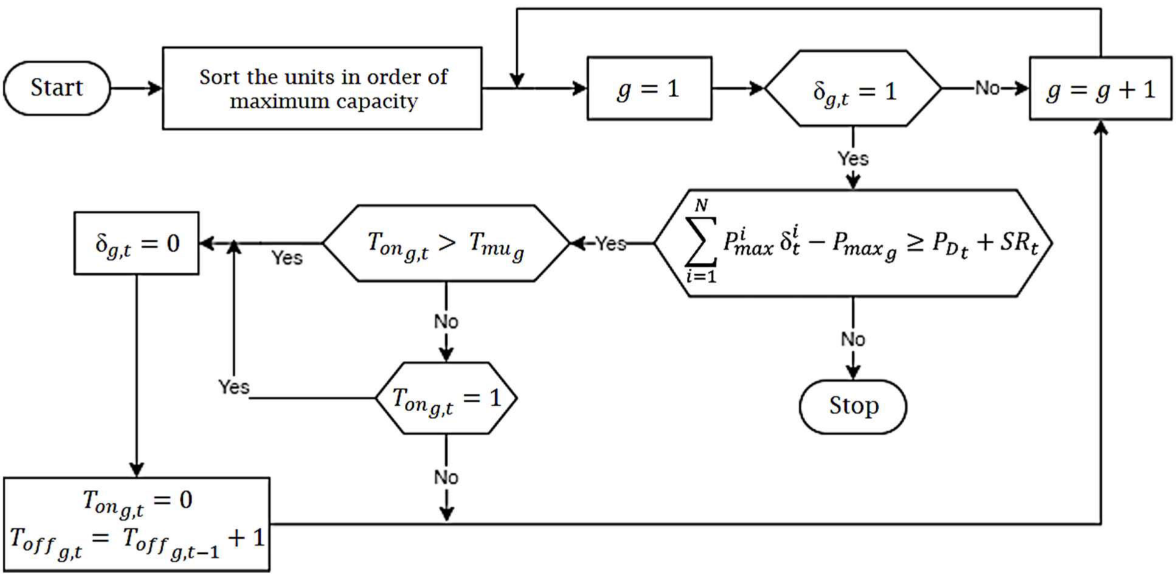

FIGURE 11. De-commitment process to avoid excess spinning reserve.

C. ECONOMIC LOAD DISPATCH USING LAMBDA ITERATION METHOD

Economic load dispatch (ELD) is a technique for distributing generation demand among available units to reduce overall generation and operation costs while maintaining all system operating constraints. After determining a feasible unit schedule, the generation schedule is obtained on a tolerance basis. The margin specifies the difference between the generation and load demand to a specified limited value. After finding the optimal value, conventional cost calculation takes place.

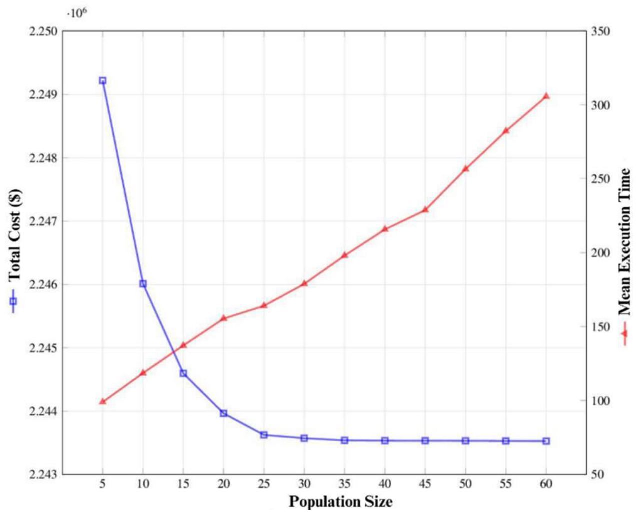

FIGURE 12. Variation of total cost and mean execution time against population size (for the 40-unit system, 100 iterations).

ELD using piecewise quadratic cost functions cannot be easily solved by traditional numerical methods [53]. Therefore, an enhanced lambda iteration method [54] is used to execute economic load dispatch.

D. CONSTRAINT HANDLING AND REPAIRMENT

In order to eliminate the infeasible solutions from the search space, a heuristic approach by Han and Kim [33] is adopted in this paper. Handling constraints like minimum up/down time improves the solution quality and significantly reduces the possibility of failure. On the other hand, extra reserve capacity and unnecessary committed units can increase the running cost by a wide margin. Therefore, the constraint handling heuristic approach is used for every slime mould of the population.

1) REPAIR OF SPINNING RESERVE CONSTRAINT

For system reliability, the spinning reserve constraint must be met. The solution is not feasible as long as the spinning reserve constraint is violated, so the required number of units are committed until the requisite spinning reserve capacity and load demand are satisfied.

Figure 9 provides a detailed illustration of the spinning reserve constraint repair.

2) REPAIR OF MINIMUM UP/DOWN TIME CONSTRAINT

Before being committed or de-committed, all units must follow the minimum up/down time. The heuristic adjustment process for any minimum up/down time constraint violation is shown in Figure 10.

3) UNIT DE-COMMITMENT PROCESS

While satisfying the spinning reserve constraint and minimum up/down time constraint, some extra thermal units might be committed, resulting in an unnecessary increase in operational cost. The de-commitment process described in Figure 11 is applied to de-commit those inessential units.

TABLE 1. Hourly load demand for the 10-unit system.

Time (h)	1	2	3	4	5	6	7	8
Load (MW)	700	750	850	950	1000	1100	1150	1200
Time (h)	9	10	11	12	13	14	15	16
Load (MW)	1300	1400	1450	1500	1400	1300	1200	1050
Time (h)	17	18	19	20	21	22	23	24
Load (MW)	1000	1100	1200	1400	1300	1100	900	800

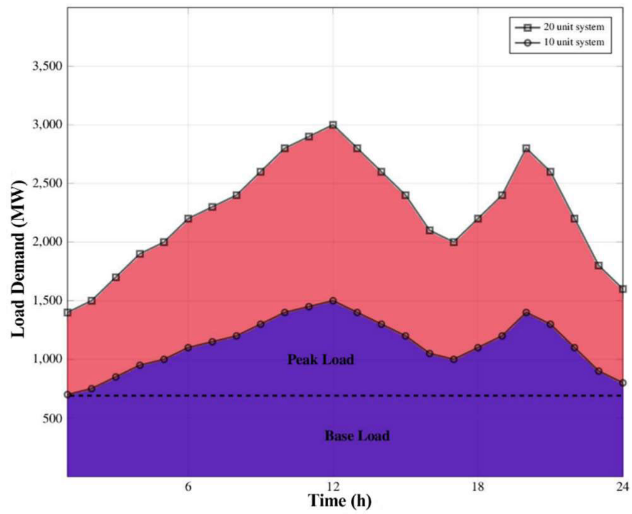

FIGURE 13. Hourly load demand curve for 10 and 20-unit systems.

E. FUNDAMENTAL STEPS OF UCP WITH BSMA

A detailed illustration of UCP with BSMA is represented as flowcharts in Figure 6, Figure 7, and Figure 8. The fundamental steps are described below:

- Step 1: Initialize the search agent population according to Section IV-A.
- Step 2: Formation of priority list discussed in Section IV-B.
- Step 3: Adjust the unit status of each search agent to meet the spinning reserve constraint as specified in Section IV-D1 and Figure 9.
- Step 4: Modify the search agents to meet the minimum up/down time constraint as in Section IV-D2 and Figure 10.
- Step 5: De-commit the unnecessary units following the procedure explained in Section IV-D3 and Figure 11.
- Step 6: Solve ELD with the lambda iteration method as in Section IV-C.
- Step 7: Initialization of the BSMA parameters.

TABLE 2. Unit data for 10-unit system.

Unit No.	$P^i_{G\_max}$	$P^i_{G\_min}$	a^i	b^i	c^i	T^i_{mu}	T^i_{md}	$SU^i_{cost\_hot}$	$SU^i_{cost\_cold}$	T^i_{cold}	Initial Status
Unit 1	455	150	1000	16.19	0.00048	8	8	4500	9000	5	8
Unit 2	455	150	970	17.26	0.00031	8	8	5000	10000	5	8
Unit 3	130	20	700	16.60	0.00200	5	5	550	1100	4	-5
Unit 4	130	20	680	16.50	0.00211	5	5	560	1120	4	-5
Unit 5	162	25	450	19.70	0.00398	6	6	900	1800	4	-6
Unit 6	80	20	370	22.26	0.00712	3	3	170	340	2	-3
Unit 7	85	25	480	27.74	0.00079	3	3	260	520	2	-3
Unit 8	55	10	660	25.92	0.00413	1	1	30	60	0	-1
Unit 9	55	10	665	27.27	0.00222	1	1	30	60	0	-1
Unit 10	55	10	670	27.79	0.00179	1	1	30	60	0	-1

TABLE 3. Commitment status and hour wise generation target for 10-unit system (without any added valve point loading).

Time (h)		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Commitment Status	U1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	U2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	U3	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
	U4	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
	U5	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
	U6	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	1	1	1	0	0
	U7	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	1	1	1	0	0
	U8	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0
	U9	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0
	U10	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
Generation Target (in MW)	U1	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455
	U2	245	295	265	235	285	360	410	455	455	455	455	455	455	455	455	310	260	360	455	455	455	455	420	345
	U3	0	0	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	0	0	0
	U4	0	0	0	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	0	0	0
	U5	0	0	0	0	0	25	25	30	100	162	162	162	162	100	30	25	25	25	30	162	85	145	25	0
	U6	0	0	0	0	0	0	0	0	20	33	73	80	33	20	0	0	0	0	0	33	20	20	0	0
	U7	0	0	0	0	0	0	0	0	0	25	25	25	25	0	0	0	0	0	0	25	25	25	0	0
	U8	0	0	0	0	0	0	0	0	10	0	10	43	0	0	0	0	0	0	0	10	0	0	0	0
	U9	0	0	0	0	0	0	0	0	0	0	0	10	0	10	0	0	0	0	0	0	0	0	0	0
	U10	0	0	0	0	0	0	0	0	0	10	10	10	10	0	0	0	0	0	0	0	0	0	0	0

Step 8: Calculate the fitness value of each feasible search agent with the UCP objective function based on Equation (5).

Step 9: Determine the *bestFitness* among the search agents by comparing individual fitness values.

Step 10: Evaluate the weight of the slime mould using Equation (13).

Step 11: Update the values of p, $\overrightarrow{vb}$ and $\overrightarrow{vc}$ for each search agent.

Step 12: Reform the slime mould positions with Equation (14).

Step 13: Perform sigmoid transform for updated positions found in V according to Equations (15) and (16).

Step 14: If the current iteration does not exceed the maximum number of iterations, go to Step 3. Otherwise, continue.

Step 15: Obtain the values of the search agent with *bestFitness* as the optimal solution.

V. PERFORMANCE ASSESSMENT OF BSMA

In order to test its effectiveness in solving UCP, BSMA is modeled for three different test cases. The first test case considers test systems consisting of 10, 20, 40, 60, 80, and 100 generating units. The cost function mentioned in equation (1) is applied for all the test systems of the first test case. The second test case considers a test system consisting of 10 generating units. For this case, the cost function with added valve-point loading effect mentioned in equation (2) is applied. The third test case is a standard IEEE 118-bus 54-unit system. The cost function of equation (1) is used for this test case. A MATLAB 2016b environment with INTEL core i3, 4 GB RAM, and Windows 10 operating

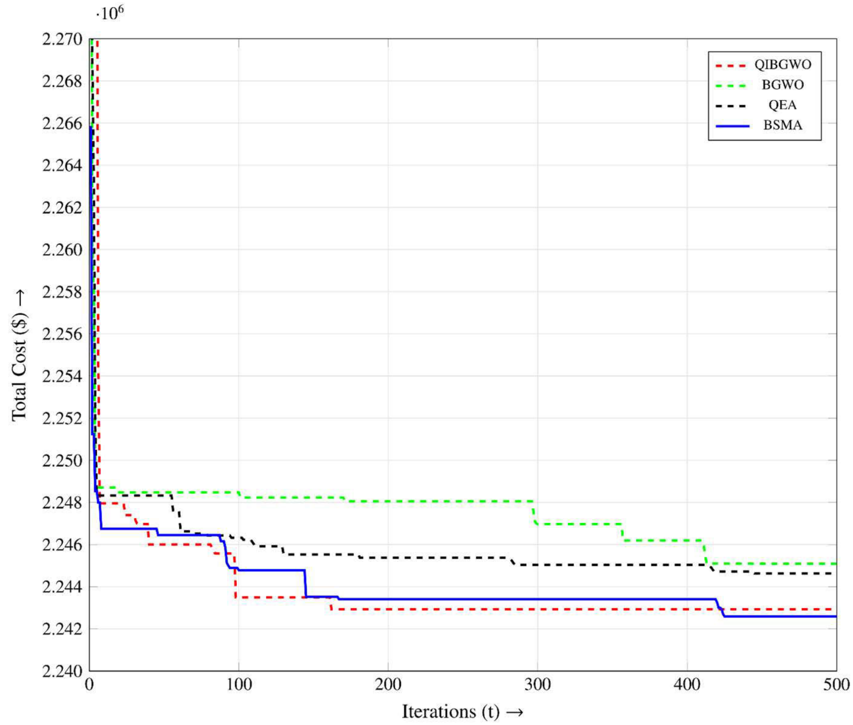

FIGURE 14. Convergence comparison of BSMA with other optimization techniques for a 40-unit system.

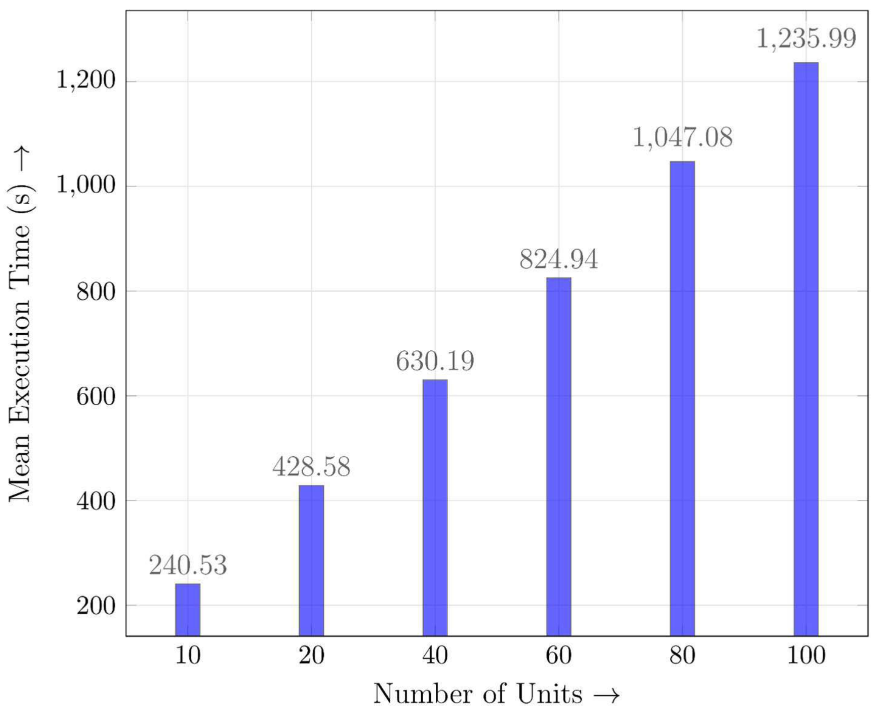

FIGURE 15. Mean execution time of test systems for applied BSMA (500 iterations).

system simulates the performance tests. The effectiveness of BSMA in solving the UCP is demonstrated by comparing the simulation results with numerical test results from prior research works. The comparison is conducted using the numerical test results obtained directly from the published works.

TABLE 4. Comparative study of generation cost for 10 and 20-unit systems (without any added valve point loading).

Optimization Technique	10-generating unit system			20-generating unit system		
	Best ($/day)	Average ($/day)	Worst ($/day)	Best ($/day)	Average ($/day)	Worst ($/day)
GA [11]	563977	-	566606	1126243	-	1132059
EP [20]	564551	565352	566231	1126494	1127257	1129793
QEA [33]	563938	563969	564672	1123607	1124689	1125715
LR [3]	566107	566493	566817	1128362	1128395	1128444
ESA [18]	565828	565988	566260	1126254	1127955	1129112
PSO [64]	564212	565783	565103	1125983	-	1131054
IPSO [64]	563954	564579	564162	1125279	-	1127643
BDE [65]	563997	563997	563997	1126998	1127374	1127927
BPSO [12]	563977	563977	563977	1128192	1128213	1128403
QBPSO [35]	563977	563977	563977	1123297	1123981	1124294
IQEA [67]	563977	563977	563977	1123890	1124320	1124504
BFWA [69]	563977	564018	564855	1124658	1124941	1125087
HGICA [29]	563935.31	563937	563938	1124565	1124933	1125147
HHSRSA [30]	563937.60	563965.31	563995.33	1124889	1124912.8	1124951.5
RCGA [55]	563937	564019	564219	1123297	1123851	1124537
QIBGWO [36]	563936.30	563936.3	563936.3	1123294	1123459	1123526
BFMO [21]	-	564864	-	-	1131958	-
ABFMO [21]	-	565136	-	-	1131551	-
BGWA [14]	563976	564378	565518	1125546	1126126	1127393
CGTO [22]	563427.8	564297	565017	1123449	1125435	1126660
BAMFO [23]	563938	563974	563977	1123825	1124759	1125495
Proposed BSMA	**563662**	**563937**	**564254**	**1123205**	**1123701**	**1124294**

The population parameter for simulation is determined after studying the effect it has on the results. The impact of population size on total cost and execution time is depicted in Figure 12. This study is conducted for a 40-unit system and 100 iterations. The 40-unit system is considered a trade-off test system between small, medium, and large-scale systems [14]. The study suggests population greater than 25 produces similar results with greater execution time. Hence, 25 is selected as the slime mould population size for the performance tests carried out in this paper.

A. CASE-I: 10–100 UNIT SYSTEMS WITHOUT VALVE-POINT LOADING EFFECT

These benchmark unit systems are further classified into three categories, Small Scale, Medium Scale, and Large Scale Systems. A 10% spinning reserve is considered in all three cases. Transmission losses are neglected.

1) SMALL SCALE TEST SYSTEMS

Two test systems, 10 and 20-unit systems are studied as small-scale generation systems for performance testing. 24-hour load demand data for the 10-unit system is shown in Table 1 and illustrated in Figure 13. Generating unit data for a 10-unit system are shown in Table 2. The commitment status and hourly generation target obtained from the simulation is shown in Table 3. As per Table 3, the generation cost is $559866.23/day, and the start-up cost is $4070/day. Performance comparison with 21 other renowned approaches is shown in Table 4. Table 4 shows the best, average, and worst cost in $/day from the results of 50 independent trials. The table shows that the average cost of BSMA is on par with hybridized approach QIBGWO [36], both with $563936, better than the Binary Grey Wolf Algorithm [14], Hybrid harmony search/random search algorithm [30], Hybrid genetic imperialistic competitive algorithm [29] and all the other classical, evolutionary and hybridized methods. The best cost found for BSMA is $563662, which is significantly better than any other approach. Convergence and deviation characteristics for 1000 iterations and 50 trials are shown in Figure 16(a) and 17(b) respectively. The standard deviation (σ) is 0.0293% for the 10-unit system, which is significantly better than other optimization techniques. The mean execution time for this performance test is shown in Figure 15.

A 20-unit system comprises two 10-unit systems, each having characteristics mentioned in Table 2. The hourly load demand for a 20-unit system is twice that of a 10-unit system, as illustrated in Figure 13. A similar approach is followed for creating a 20-unit system and an hourly load demand for a 20-unit system in the other research works [14], [35], and [36]. The commitment status and hour-wise generation target for a random trial as illustrated in Table 5. From Table 5, the total generation cost is $1115010.63, and the start-up cost for this load demand is $8690. The standard deviation (σ) is 0.0283%. Convergence and deviation attributes for 1000 iterations and 50 trials are illustrated in Figure 16 (b) and Figure 17 (b) respectively. The mean execution time is shown in Figure 15. Table 4 compares the performance of BSMA with other optimization techniques. In this case, the best cost recorded for 50 trials is $1123205, and it is marginally better than QIBGWO [36], Ring Crossover Genetic Algorithm [55], and Quantum Inspired Binary PSO [35]. However, the average cost of $1123701 is better than all the other optimization techniques except QIBGWO [36].

2) MEDIUM SCALE TEST SYSTEMS

40 and 60-unit systems are studied as medium-scale test systems. Unit characteristics and hourly load demand were replicated for forming a 20-unit system in the previous section.

TABLE 5. **Commitment status and hour wise generation target for 20-unit system (without any added valve point loading).**

Time (h)		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Commitment Status	U1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	U2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	U3	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
	U4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1
	U5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
	U6	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1	1
	U7	1	1	1	0	0	0	0	0	0	1	1	1	0	0	0	0	1	1	1	1	0	0	0	1
	U8	1	1	0	0	1	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	0	1	0
	U9	0	1	1	0	0	0	0	0	1	0	1	1	1	0	1	0	0	0	1	1	1	0	0	0
	U10	1	0	1	0	1	1	0	0	1	1	0	1	1	1	1	1	1	0	0	1	1	0	0	1
Generation Target (in MW)	U1	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455
	U2	150	195	295	417.5	455	432.5	455	455	455	455	455	455	455	455	455	435	362.5	455	455	455	455	397.5	287.5	375
	U3	0	0	0	0	0	0	0	0	0	130	130	130	130	130	130	130	130	130	130	130	130	0	0	0
	U4	120	130	130	130	130	130	130	130	130	130	130	130	130	130	0	0	0	0	0	130	130	130	130	130
	U5	25	25	25	25	30	25	35	125	157.5	162	162	162	162	110	135	25	25	37.5	122.5	162	82.5	25	0	0
	U6	0	0	0	0	0	0	20	20	20	33	73	80	43	0	0	0	20	20	20	33	20	20	20	20
	U7	25	25	25	0	0	0	0	0	0	25	25	25	0	0	0	0	25	25	25	25	0	0	0	25
	U8	10	10	0	0	10	0	10	10	10	10	10	43	10	10	10	0	0	0	0	0	10	0	10	0
	U9	0	10	10	0	0	0	0	0	10	0	10	10	10	0	10	0	0	0	10	10	10	0	0	0
	U10	10	0	10	0	10	10	0	0	10	10	0	10	10	10	10	10	10	0	0	10	10	0	0	10
Time (h)		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Commitment Status	U1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	U2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
	U3	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
	U4	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1
	U5	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
	U6	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	1	1	1	0	0	0
	U7	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	1	0	0
	U8	0	0	0	0	0	0	0	1	0	0	1	1	0	1	1	0	0	0	0	0	0	1	0	0
	U9	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0
	U10	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
Generation Target (in MW)	U1	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455
	U2	150	195	295	417.5	455	432.5	455	432.5	455	455	455	455	455	455	455	435	362.5	455	455	455	455	397.5	287.5	0
	U3	0	0	0	0	0	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	0	0
	U4	0	0	0	0	0	130	130	130	130	130	130	130	130	130	0	0	0	0	0	130	130	130	130	130
	U5	0	0	0	0	0	0	0	0	157.5	162	162	162	162	110	135	25	25	37.5	122.5	162	82.5	25	25	0
	U6	0	0	0	0	0	0	0	0	0	33	73	80	43	0	0	0	0	0	20	33	20	0	0	0
	U7	0	0	0	0	0	0	25	25	25	25	25	25	0	0	0	0	0	0	0	25	25	25	0	0
	U8	0	0	0	0	0	0	0	10	0	0	10	43	0	10	10	0	0	0	0	0	0	10	0	0
	U9	0	0	0	0	0	0	0	0	0	0	10	10	10	10	10	0	0	0	0	0	0	0	0	0
	U10	0	0	0	0	0	0	0	0	0	0	0	10	10	0	0	0	0	0	0	0	0	0	0	0

A similar approach is followed to produce 40 and 60-unit test systems. As previously mentioned, the 40-unit system can be considered a trade-off test system between small, medium, and large-scale systems [14]. Therefore, the convergence curve found in a 40-unit system trial is illustrated in Figure 14. Figure 14 also depicts the nature of convergence of QEA [33], BGWO [14], and QIBGWO [36] for a 40-unit system trial. The comparison of convergence curves reveals that the convergence process of BSMA is competitive with QIBGWO. Both BSMA and QIBGWO converge more quickly than the other two optimization techniques. The cost comparison shown in Table 6 reveals the superiority of BSMA for 40 and 60-unit systems over most optimization techniques. The best, average, and worst cases of convergence found during the simulation are shown in Figure 16(c) and Figure 16(d) for 40 and 60-unit systems, respectively. Deviation characteristics are shown in Figure 17(c) and Figure 17(d). The declining value of standard deviation (σ) suggests that BSMA is more effective for larger systems. Lastly, the mean execution time for both units is shown in Figure 15.

3) LARGE SCALE TEST SYSTEMS

80 and 100-unit systems are studied as large-scale test systems. In these occasions, the standard deviation is significantly less compared to smaller systems, and BSMA converges in lesser iterations. A comparison of the total cost with other optimization techniques is tabulated in Table 7. For the 80-unit test system, BSMA has shown the most optimal cost of \$4483602, where QIBGWA [36] being the second best and RCGA [46] next on the list. Similarly, for the 100-unit system, BSMA is leading with an average cost of \$5602705.

TABLE 6. Comparative study of generation cost for 40 and 60-unit systems (without any added valve point loading).

Optimization Technique	40-generating unit system			60-generating unit system		
	Best ($/day)	Average ($/day)	Worst ($/day)	Best ($/day)	Average ($/day)	Worst ($/day)
GA [11]	2252909	-	2269282	3376625	-	3384252
EP [20]	2249093	2252612	2256085	3371611	3376255	3381012
QEA [33]	2245557	2246728	2248296	3366676	3368220	3372007
LR [3]	2258503	2258503	2258503	3394066	3394066	3394066
ESA [18]	2250012	2252125	2254539	-	-	-
PSO [64]	2250012	-	2257146	3374174	-	3382921
IPSO [64]	2248163	-	2252117	3370979	-	3379125
BDE [65]	2245700	2246600	2247284	3367066	3367405	3367783
BPSO [12]	2243210	2244634	2245982	3363649	3365301	3367171
QBPSO [35]	2242957	2244657	2245941	3361980	3367550	3367755
IQEA [67]	2245151	2246026	2246701	3365003	3365667	3366223
BFWA [69]	2248228	2248572	2248645	3367445	3367828	3367974
HGICA [29]	2239186	2242612	2246085	-	-	-
HHSRSA [30]	2248508	2248652.7	2248757	-	-	-
RCGA [55]	2242887	2243569	2244117	3365337	3366052	3366873
QIBGWO [36]	2242947	2244071	2244279	3361766	3364280	3364873
BFMO [21]	-	2267669	-	-	3399860	-
ABFMO [21]	-	2265867	-	-	3397162	-
BGWA [14]	2252475	2257866	2263333	3367276	3367550	3367755
CGTO [22]	2245648	2249802	2252392	3366104	3370803	3374159
BAMFO [23]	2247165	2249309	2251438	3369731	3373302	3376174
Proposed BSMA	**2242303**	**2243302**	**2244683**	**3363492**	**3364888**	**3366098**

TABLE 7. Comparative study of generation cost for 80 and 100-unit systems (without any added valve point loading).

Optimization Technique	80-generating unit system			100-generating unit system		
	Best ($/day)	Average ($/day)	Worst ($/day)	Best ($/day)	Average ($/day)	Worst ($/day)
GA [11]	4507692	-	4552982	5626361	-	5690086
EP [20]	4498479	4505536	4512739	5626885	5633800	5639148
QEA [33]	4488470	4490128	4492839	5609550	5611797	5613220
LR [3]	4526022	4526022	4526022	5657277	5657277	5657277
ESA [18]	4498076	4501156	4503987	5617876	5624301	5628506
PSO [64]	4501538	-	4513725	5625376	-	5641378
IPSO [64]	4495032	-	4508943	5619284	-	5633021
BDE [65]	4489022	4490456	4491262	5609341	5609984	5610608
BPSO [12]	4491083	4491681	4492686	5610293	5611181	5612265
QBPSO [35]	4482085	4485410	4487168	5602486	5604275	5606178
IQEA [67]	4486963	4487985	4489286	5606022	5607561	5608525
BFWA [69]	4491284	4492550	4493036	5610954	5612422	5612790
HGICA [29]	4485936	4487958	4489282	5604022	5608561	5613260
RCGA [55]	4486991	4487476	4487949	5606663	5607088	5607850
QIBGWO [36]	4481925	4486761	4487935	5602365	5605773	5606974
BFMO [21]	-	4533861	-	-	5664875	-
ABFMO [21]	-	4531605	-	-	5660087	-
BGWA [14]	4495173	4506362	4513026	5628975	5637699	5643899
CGTO [22]	4488147	4493483	4494937	5605708	5606095	5705756
BAMFO [23]	4493825	4499720	4503106	5618038	5624372	5628197
Proposed BSMA	**4482619**	**4483602**	**4485743**	**5601253**	**5602705**	**5604741**

The average cost found for 100-unit system better than all the other optimization techniques including QBPSO [35]. Table 6 and Table 7 indicate that the BSMA proposed in this paper has shown better performance for the larger test systems than the smaller ones. The convergence and deviation characteristics of these two large-scale test systems are shown in Figure 16(e), Figure 16(f), Figure 17 (e), and Figure 17(f) respectively. Figure 15 shows the mean execution time of 80 and 100-unit systems.

B. CASE-II: EFFECT OF VALVE POINT LOADING ON THE 10-UNIT SYSTEM

A single set of a 10-unit system is considered in this second test case. The fuel cost function includes the sinusoidal term of the valve-point loading effect as mentioned in equation (2). Generating unit data and load demand are obtained from [54]. The spinning reserve is set at 6% of the load demand. The transmission losses are ignored. The generation schedule is tabulated in Table 8. Table 9 shows that the average total generating cost of BSMA is better than BRABC [51] and TLBO [56]. Only QTLBO [56] has shown a better cost than the proposed BSMA in this test case.

C. CASE-III: TEST SYSTEM FOR IEEE 118 BUS

In the third test case of BSMA performance testing, an IEEE 118-bus 54-unit test system is considered. The quadratic cost function of equation (1) is used in this test case. The spinning reserve is set at 10% of the load demand and the transmission losses are ignored. Appendices A.11 and A.12 show load demand & generating unit data. Comparison is shown in

TABLE 8. Generation plan for 10-unit System (including valve point loading).

	Generation Target (in MW) and Cost of Generation (in $/h)											
Time (h)	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10	$F_{cost}(\$/h)$	$SU_{cost}(\$/h)$
1	456.5	395.5	184.0	0	0	0	0	0	0	0	25181.2	550
2	379.9	395.5	334.5	0	0	0	0	0	0	0	26912.0	0
3	379.9	395.5	308.5	0	174.1	0	0	0	0	0	30457.9	900
4	456.5	308.2	297.1	120.4	223.9	0	0	0	0	0	34379.0	560
5	456.5	395.5	296.6	107.6	223.9	0	0	0	0	0	36100.5	0
6	456.5	395.5	310.8	241.3	223.9	0	0	0	0	0	39580.5	0
7	456.5	395.5	326.1	300.0	223.9	0	0	0	0	0	41461.7	0
8	456.5	395.5	298.8	241.4	222.6	159.9	0	0	0	0	43000.3	340
9	456.5	395.7	296.2	299.7	222.5	122.4	130.9	0	0	0	46092.1	520
10	456.5	395.5	321.1	299.8	222.8	160.0	131.0	85.4	0	0	50444.9	60
11	456.5	395.7	307.5	299.9	223.4	159.9	131.0	120.0	52.0	0	52793.3	60
12	456.5	458.6	300.7	299.9	222.6	160.0	130.9	85.3	52.0	53.4	55354.8	60
13	456.5	395.4	321.6	299.9	222.6	159.7	131.0	85.3	0	0	50446.3	0
14	456.5	395.5	296.6	299.5	222.6	122.4	130.9	0	0	0	46086.8	0
15	456.5	395.6	298.8	241.3	224.0	159.9	0	0	0	0	43000.1	0
16	456.5	395.5	297.3	180.8	224.0	0	0	0	0	0	37714.4	0
17	456.5	395.5	284.7	119.4	224.0	0	0	0	0	0	36092.6	0
18	456.5	395.5	302.1	120.4	222.6	0	130.9	0	0	0	39077.9	260
19	456.5	395.5	315.5	180.8	172.8	123.9	130.9	0	0	0	42687.3	170
20	456.5	395.5	339.8	299.8	222.5	159.9	130.9	47.0	20.1	0	50904.3	120
21	456.5	458.6	340.0	185.3	222.7	129.9	130.9	0	0	0	46628.0	0
22	456.5	395.5	325.0	299.8	0	0	130.9	0	20.0	0	39671.6	30
23	456.5	395.5	302.1	0	0	0	130.9	0	47.0	0	32131.4	0
24	456.5	395.5	331.9	0	0	0	0	0	0	0	28525.3	0

TABLE 9. Comparative study of generation cost for 10-unit system (including valve point loading).

Optimization Technique	Average Cost ($)
Binary/Real Coded Artificial Bee Colony [51]	982949.55
Teaching-learning Based Algorithm [56]	978426.82
Quasi-oppositional Teaching Learning Based Algorithm [56]	976827.17
Proposed BSMA	978354.24

TABLE 10. Comparative study of generation cost for IEEE 118-bus 54-unit system (without any added valve point loading).

Approach	Average Cost ($)
Semi-definite Programming [57]	1645444.98
Binary/Real Coded Artificial Bee Colony [51]	1644269.71
Binary/Real Coded Firefly Algorithm [58]	1644141
Firefly Algorithm with Multiple Workers [59]	1644134
Proposed BSMA	1644122.68

TABLE 11. Load demand for 54-unit system 118-bus system.

Time (h)	1	2	3	4	5	6	7	8	9	10	11	12
Load (MW)	4200	3960	3480	2400	3000	3600	4200	4680	4920	5280	5340	5040
Time (h)	13	14	15	16	17	18	19	20	21	22	23	24
Load (MW)	4800	4560	5280	5400	5100	5340	5640	5880	6000	5400	5220	4920

Table 10 with SDP [57], BRABC [51], BRCFF [58], and FFA with multiple workers [59]. The comparison shows the superiority of BSMA, as it has shown the least cost for IEEE 118-bus 54-unit system compared to the other 4 techniques.

VI. DISCUSSION

The UCP is a complex optimization problem that requires finding the optimal scheduling of power generation units to meet the forecasted power demand while satisfying the operational constraints of the power system. The BSMA is a new optimization technique that has been proposed for solving the UCP. To ensure compatibility with UCP objective functions and regulatory constraints, the proposed BSMA is modeled accordingly. Through simulation results and comparative studies, BSMA is established as an effective UCP optimizer. Furthermore, performance assessment tests have

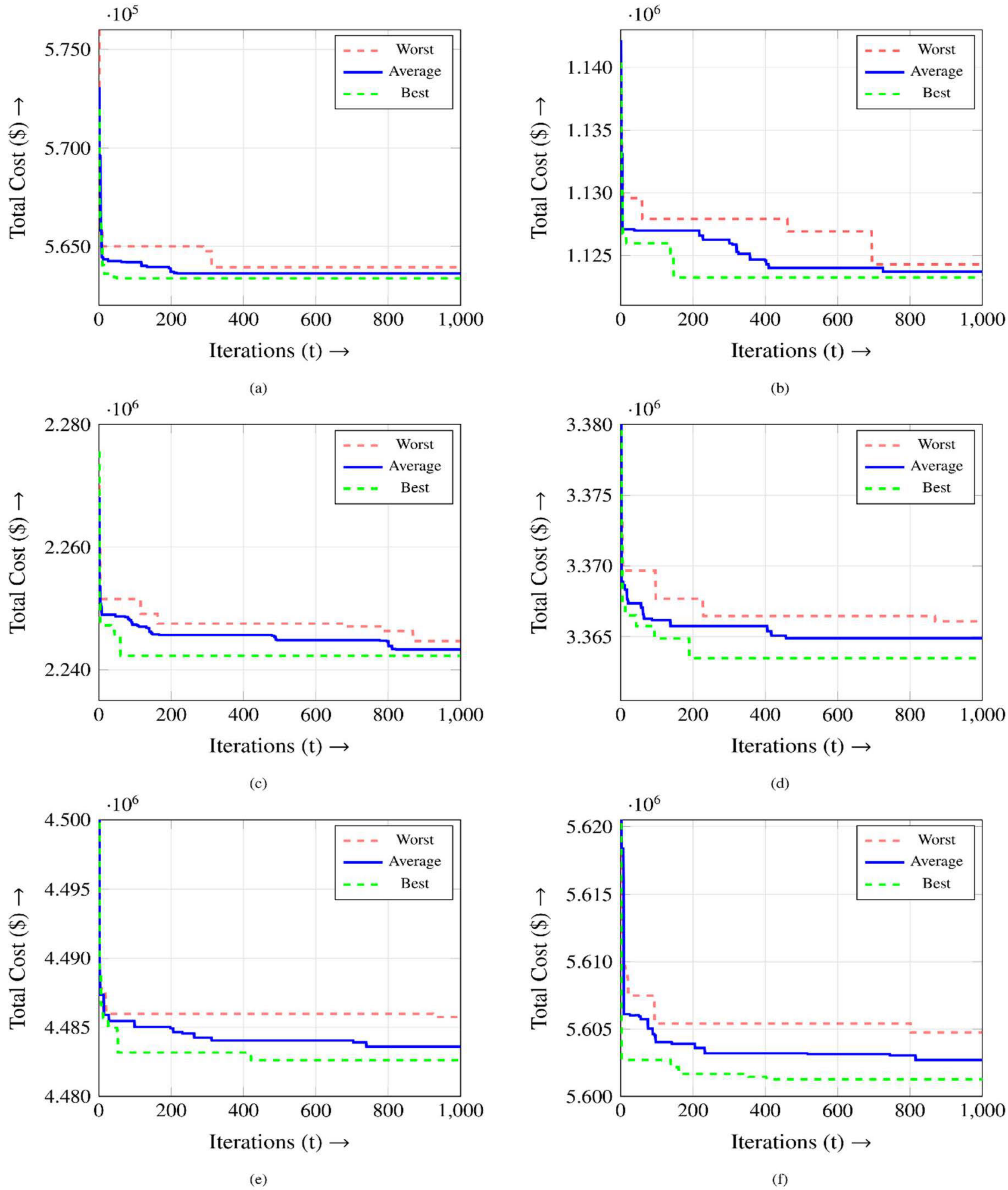

FIGURE 16. Convergence curves of different test systems for applied BSMA: (a) 10 units, (b) 20 units, (c) 40 units, (d) 60 units, (e) 80 units, (f) 100 units.

shown that the BSMA algorithm achieved the least production cost in a reasonable computational time compared to the other approaches for benchmark test systems.

The BSMA may have certain limitations when applied to solve UCP. One such limitation is that the BSMA is tailored for short-term operational scheduling of unit systems that have a limited size, ranging from 10 to 100 units, and may not be suitable for larger systems. Although the BSMA has a faster convergence rate compared to other benchmark test systems, this rate may not be optimal for all applications, and other optimization techniques may be necessary to achieve the desired performance. In addition, the sigmoid transfer

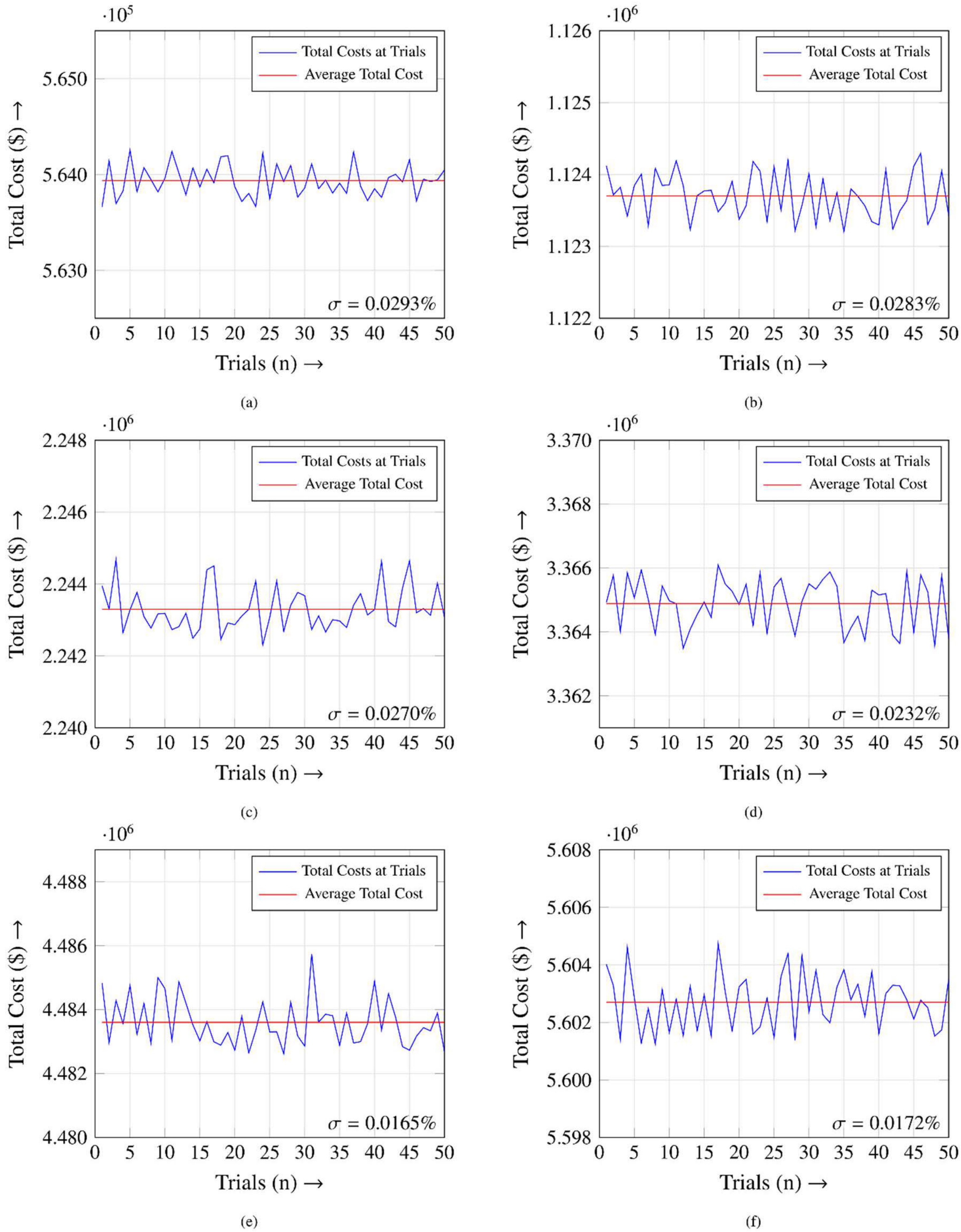

FIGURE 17. Deviation of results of different test systems for applied BSMA: (a) 10 units, (b) 20 units, (c) 40 units, (d) 60 units, (e) 80 units, (f) 100 units.

function employed in the BSMA may not accurately represent the behavior of real-world power systems, and fine-tuning the algorithm's parameter values may require a significant amount of experimentation.

To achieve better results in the future, researchers can explore various ways of improving the proposed algorithm, such as implementing different pheromone update rules or stochastic operators. Additionally, combining the BSMA

TABLE 12. Parameter settings used by other optimization algorithms.

Method	Parameter	Explanation
PSO	$c_1 = 2$ $c_2 = 2$ $m = 1$	Cognitive experience factor. Social experience factor. Neighboring index
IPSO	$c_{max} = 0.8$, $c_{min} = 0.5$ $c_1 = 2$ $c_1 = 2$	Inertia weight calculation constant. Cognitive experience factor. Social experience factor.
HGICA	$X, Y, E = [0\ 100]$	Control parameters
GA	Swap window operator =0.3 Swap window hill-climb operator =0.3 The crossover probability = [0.4, 0.9] The mutation probability = [0.004, 0.024]	
EP	$c = \frac{1}{10}$ of the population	Competitions numbers
BPSO, QBPSO	ω (The reference lacks specific numerical information) c_1,c_2 (The reference lacks specific numerical information) rn1,rn2	Factor of inertia weight. Acceleration coefficients. Random numbers generated between 0 and 1.
LR	(The reference contains no information regarding parameter configurations)	
BAMFO	$b = 1$ $t = [-1\ 1]$	A fixed value for the spiral pattern. A random number in the range [-1, 1].
BFMO, ABFMO	δ $(Reduces\ in\ linear\ manner\ from\ 0.7\ to\ 0.3)$	Distance parameter
BDE	Mutation Factor, $MF = [0,1]$	MF is a constant and real factor
QEA, IQEA	$\lambda = 0.2,0.4$	The variation scope of two Qbit $Qb_g(1)$ and $Qb_g(0)$.
ESA	$\alpha = 0.95$ (Constant value slightly below 1)	By tuning the parameter α, it is simple to regulate the rate of cooling schedule.

algorithm with other optimization techniques like genetic algorithms or particle swarm optimization can enhance the overall optimization process by leveraging the strengths of each approach and reducing their weaknesses. The flexibility and robustness of the BSMA make it suitable for different optimization problems in power system engineering and other fields, including load forecasting, energy storage optimization, and renewable energy integration. To evaluate its effectiveness and performance, the BSMA can be applied to real-world UCP scenarios, which will enable power system operators to make informed decisions regarding the scheduling of power-generating units and ensure a stable and reliable electricity supply.

VII. CONCLUSION AND FUTURE PROSPECT

A binarized SMA is presented in this paper to solve the single-objective thermal Unit Commitment Problem. The foraging behavior of slime mould and its searching procedure for nutrition sources are mimicked in SMA. SMA is then transformed into BSMA and made compatible with UCP parameters. Original SMA is confined to discrete values with sigmoid transformation, fitness values are determined with lambda iteration based on Economic Load Dispatch, and heuristic adjustments handle complex UCP constraints for all the search agents. BSMA is tested for 10, 20, 40, 60, 80, and 100-unit test systems and then compared with 20 renowned classical, heuristic-metaheuristic,

TABLE 13. Generating unit data for 54-unit 118-bus system.

Unit No.	$P^i_{G\_max}$	$P^i_{G\_min}$	a^i	b^i	c^i	T^i_{mu}	T^i_{md}	$SUT^i_{cost\_hot}$	$SUT^i_{cost\_cold}$	T^i_{cold}	Initial Status
U1	30	5	31.67	26.24	0.0697	1	1	40	120	2	1
U2	30	5	31.67	26.24	0.0697	1	1	40	120	2	1
U3	30	5	31.67	26.24	0.0697	1	1	40	120	2	1
U4	300	150	6.78	12.89	0.0109	8	8	440	1320	7	8
U5	300	100	6.78	12.89	0.0109	8	8	110	330	7	8
U6	30	10	31.67	26.24	0.0697	1	1	40	120	2	1
U7	100	25	10.15	17.82	0.0128	5	5	50	150	4	5
U8	30	5	31.67	26.24	0.0697	1	1	40	120	2	1
U9	30	5	31.67	26.24	0.0697	1	1	40	120	2	1
U10	300	100	6.78	12.89	0.0109	8	8	100	300	7	8
U11	350	100	32.96	10.76	0.003	8	8	100	300	7	8
U12	30	8	31.67	26.24	0.0697	1	1	40	120	2	1
U13	30	8	31.67	26.24	0.0697	1	1	40	120	2	1
U14	100	25	10.15	17.82	0.0128	5	5	50	150	4	5
U15	30	8	31.67	26.24	0.0697	1	1	40	120	2	1
U16	100	25	10.15	17.82	0.0128	5	5	50	150	4	5
U17	30	8	31.67	26.24	0.0697	1	1	40	120	2	1
U18	30	8	31.67	26.24	0.0697	1	1	40	120	2	1
U19	100	25	10.15	17.82	0.0128	5	5	59	177	4	5
U20	250	50	28	12.33	0.0024	8	8	100	300	7	8
U21	250	50	28	12.33	0.0024	8	8	100	300	7	8
U22	100	25	10.15	17.82	0.0128	5	5	50	150	4	5
U23	100	25	10.15	17.82	0.0128	5	5	50	150	4	5
U24	200	50	39	13.29	0.0044	8	8	100	300	7	10
U25	200	50	39	13.29	0.0044	8	8	100	300	7	10
U26	100	25	10.15	17.82	0.0128	5	5	50	150	4	5
U27	420	100	64.16	8.34	0.0106	10	10	250	750	8	10
U28	420	100	64.16	8.34	0.0106	10	10	250	750	8	10
U29	300	80	6.78	12.89	0.0109	8	8	100	300	7	10
U30	80	30	74.33	15.47	0.0459	4	4	45	135	4	4
U31	30	10	31.67	26.24	0.0697	1	1	40	120	2	1
U32	30	5	31.67	26.24	0.0697	1	1	40	120	2	1
U33	20	5	17.95	37.70	0.0283	1	1	30	90	2	1
U34	100	25	10.15	17.82	0.0128	5	5	50	150	4	5
U35	100	25	10.15	17.82	0.0128	5	5	50	150	4	5
U36	300	150	6.78	12.89	0.0109	8	8	440	1320	7	10
U37	100	25	10.15	17.82	0.0128	5	5	50	150	4	5
U38	30	10	31.67	26.24	0.0697	1	1	40	120	2	1
U39	300	100	32.96	10.76	0.003	8	8	440	1320	7	10
U40	200	50	6.78	12.89	0.0109	8	8	400	1200	7	10
U41	20	8	17.95	37.70	0.0283	1	1	30	90	2	1
U42	50	20	58.81	22.94	0.0098	1	1	45	135	2	1
U43	300	100	6.78	12.89	0.0109	8	8	100	300	7	8
U44	300	100	6.78	12.89	0.0109	8	8	100	300	7	8
U45	300	100	6.78	12.89	0.0109	8	8	110	330	7	8
U46	20	8	17.95	37.70	0.0283	1	1	30	90	2	1
U47	100	25	10.15	17.82	0.0128	5	5	50	150	4	5
U48	100	25	10.15	17.82	0.0128	5	5	50	150	4	5
U49	20	8	17.95	37.70	0.0283	1	1	30	90	2	1
U50	50	25	58.81	22.94	0.0098	2	2	45	135	2	2
U51	100	25	10.15	17.82	0.0128	5	5	50	150	4	5
U52	100	25	10.15	17.82	0.0128	5	5	50	150	4	5
U53	100	25	10.15	17.82	0.0128	5	5	50	150	4	5
U54	50	25	58.81	22.94	0.0098	2	2	45	135	2	2

and hybridized approaches. Performance assessment tests have shown that BSMA achieved the least production cost in a reasonable computational time compared to the other approaches for benchmark test systems. The convergence is found to be much quicker as the optimizer reaches its final solution in lesser iterations. Comparatively, a lesser standard deviation for large and medium-sized test systems shows the potential of BSMA as a suitable optimizer for larger systems. For IEEE 118-bus system, BSMA outperforms the competing algorithms with its most cost-effective solution.

The proposed BSMA can be further developed to address profit-driven and multi-objective UCP challenges, optimize the scheduling of clean energy sources while adhering to security constraints, and address optimization problems in micro grids. The IEEE 123 node test feeder is an ideal platform for implementing this algorithm due to its compatibility and proven effectiveness. The application of this algorithm on the IEEE 123 node test feeder holds tremendous potential as a promising prospect. BSMA has the potential to bring about a significant transformation in the way we manage and optimize our energy systems. By leveraging the power of BSMA, we can improve the efficiency and effectiveness of our energy systems, which can lead to numerous benefits such as reduced costs, increased reliability, and a more sustainable future. Therefore, it is imperative that we continue to explore and invest in this area of research to fully realize the potential of BSMA and unlock the benefits it can bring to our energy systems.

NOMENCLATURE

Unit Commitment Problem Symbols:

N	Number of generating units overall.
i	Index of thermal units ($i = 1, 2, 3, \ldots, N$).
H	Total number of scheduling hours.
t	Index of operational hours ($t = 1, 2, 3, \ldots, H$).
F^i_{cost}	i^{th} Unit's fuel cost function.
a^i, b^i, c^i	i^{th} Unit's fuel cost coefficients.
d^i, e^i	Coefficients of the i^{th} unit's valve-point loading effect.
P^i_G	Power generated by i^{th} unit.
δ^i_t	Generating status bit of i^{th} unit at t^{th} hour.
$SU_{cost_t}{}^i$	Startup cost of i^{th} unit at t^{th} hour.
$SU^i_{cost\_hot}$	i^{th} Unit's hot startup cost.
$SU^i_{cost\_cold}$	i^{th} Unit's cold startup cost.
T^i_{mu}	i^{th} Unit's minimum up time.
T^i_{md}	i^{th} Unit's minimum down time.
$T_{on^i_t}$	Consecutive hours of committed state of i^{th} unit going into t^{th} hour.
$T_{off^i_t}$	Consecutive hours of de-committed state of i^{th} unit going into t^{th} hour.
T^i_{hot}	Hot start hours of i^{th} unit Hot start hours.
T^i_{cold}	i^{th} Unit's cold start hours.
$P^i_{G\_max}$	i^{th} Unit's maximum power generation.
$P^i_{G\_min}$	i^{th} Unit's minimum power generation.
P_{Dt}	Load demand at t^{th} hour.
SR_t	Spinning reserve required at t^{th} hour.

Binary Slime Mould Algorithm Symbols:

K	Current iteration number.
max_k	No. of iterations allowed maximum.
$\vec{X}$	Slime mould location at current iteration.
$\vec{vb}, \vec{vc}$	Decision making variables of slime mould.
$\vec{X_b}$	Best slime mould location found from previous iterations.
$\vec{W}$	Weight of the slime mould.
$\vec{X_A}, \vec{X_B}$	Slime mould locations selected at random for the current iteration.
S	Fitness value at current location $\vec{X}$.
DF	Best fitness among all the iterations.
bF, wF	Best and worst fitness of the ongoing iteration routine respectively.
$\vec{X}*$	Updated Slime mould location for current iteration.
UB, LB	Upper and lower bounds of slime mould search area respectively.
S_f	Sigmoid transformation function.
NP	Overall population of slime mould.
s	Slime mould index ($s = 1, 2, 3, \ldots, NP$).
z	Balance parameter for Exploration and Exploitation.

DECLARATIONS OF INTEREST

None

APPENDIX A
TEST DATA FOR 54-UNIT 118-BUS SYSTEM

See Tables 11–13.

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