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A Cost-Effective Solution for Non-Convex Economic Load Dispatch Problems in Power Systems Using Slime Mould Algorithm

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Abstract: Slime Mould Algorithm (SMA) is a newly designed meat-heuristic search that mimics the nature of slime mould during the oscillation phase. This is demonstrated in a unique mathematical formulation that utilizes adjustable weights to influence the sequence of both negative and positive propagation waves to develop a method to link food supply with intensive exploration capacity and exploitation affinity. The study shows the usage of the SM algorithm to solve a non-convex and cost-effective Load Dispatch Problem (ELD) in an electric power system. The effectiveness of SMA is investigated for single area economic load dispatch on large-, medium-, and small-scale power systems, with 3-, 5-, 6-, 10-, 13-, 15-, 20-, 38-, and 40-unit test systems, and the results are substantiated by finding the difference between other well-known meta-heuristic algorithms. The SMA is more efficient than other standard, heuristic, and meta-heuristic search strategies in granting extremely ambitious outputs according to the comparison records.

Keywords: economic load dispatch; non-convex; slime mould algorithm; with and without valve-point effect

1. Introduction

In the actual functioning of power systems, Economic Load Dispatch (ELD) is a crucial problem to solve. The role of the power system is to deliver continuous power to the consumers at affordable price which is its main important feature [1,2]. The objective is to reduce energy-generating costs while fulfilling load needs and ensuring equality and inequality constraints. This fact results in a higher degree of pollution awareness in thermal plants, as well as a lower cost of diagnosing the problem. Because they operate in conjunction with a collection of viable alternatives, evolutionary methods are now perfectly suited for discovering answers to optimization problems. All optimization approaches, including evolutionary ones, are known to be influenced by constraints [3], since the traditional procedure of an evolutionary approach by employing operators for individuals in a population may violate the constraints rules. The way evolutionary approaches deal with constraint rules of challenges is a significant aspect that is directly connected to the quality of solutions created for such problems. By converting the present solution that opposes the constraints into a viable one, a redesigned method eliminates unattainable solutions. In every step of the evolutionary method, the number of better individuals grows as a result.

Wind, solar, thermal, nuclear, renewable, hydro, and other power producing facilities are used in most power generation systems. It is known that nuclear power plants are controlled at stable power outputs. In the case of renewable energy systems, the operational cost will not change as much as the production. In thermal systems, however, the running cost varies with the total power output. As a result, the economic load dispatch issue, which includes the use of thermal systems as generators, is considered a critical optimization issue in electric power systems. Maintaining an economical operation is a difficult challenge for both traditional and smart grid systems. When power systems are exposed to operational and transmission imperatives, the economic load dispatch limit the optimal outcome for an electric power generation to sustain the load demand with minimum generation price. The economic load dispatch problem is usually solved by sophisticated computerized approaches that meet the operational and power system imperatives via minute-to-minute monitoring. A little increase in economic load dispatch demonstrates its long-term reaction to the declining price of total power output. As a result, a variety of optimization methods have been developed to address cost-effective load dispatch issues while producing high-quality results. Traditional optimization approaches were the sole option to address economic load dispatch concerns for many years. Because of the limitations of conventional methods, system operators have a chance to fail to notice the realistic and technological imperatives of the system's units. There are two types of simplifications in this category. First, combined with the accuracy of the generating unit's pricing model, particularly for different types of fuels or taking the valve-point loading impact into account [4], multi-valve steam turbines are widely seen in real-world generating units. The valve point of the generating unit is drawn when the steam turbine's intake valve opens abruptly, pushing the energy consumption curve upward. This phenomenon is known as the "valve-point effect". The sine term must be overlaid on the fuel cost function due to the valve-point effects' discontinuity and high-order nonlinearity of input and output characteristics. Therefore, it is necessary to analyze the fuel curve and cost function for power generation with the valve-point effect. The other is related to network topology and is only concerned with reducing transmission system loss [5].

The main contributions of this work are as follows:

- The slime mould algorithm is implemented as it has great global search capability.
- The SM algorithm is used to solve a non-convex and cost-effective load dispatch problem (ELD) in an electric power system.
- The efficiency of the algorithm is tested on standard IEEE test systems.
- The method is evaluated on nine different test systems with and without valve-point loading effects.

The remaining sections of this article are structured as follows: Section 2 consists of the literature survey; mathematical formulation for single area economic load dispatch is provided in Section 3; concepts of the slime mould algorithm and its economic load dispatch flow chart are provided in Sections 4 and 5, respectively. Section 6 contains results and discussions, and the conclusion is given in Section 7.

2. Literature Survey

The economic load dispatch problem is a major concern for the cost-effective operation of electric power systems, as it concentrates on basically assembling the power outputs of the units by establishing time intervals in order to decrease generating costs while still meeting other system requirements. In general, the traditional economic load dispatch problem is reduced in order to solve the convex quadratic programming problem [6], which may now be handled effectively using MOSEK [7]. Furthermore, the system becomes non-smooth, non-convex, and non-continuous when the valve-point loading effect, transmission loss, and prohibited operating zones are taken into account. The objective function arises as multiples of the local minimum as a result of these features, making global minima exceedingly difficult to attain. Aside from that, the non-smooth nature of the function makes the derivate-based mathematical programming technique challenging to apply directly.

Traditional optimization techniques often look at linear, piecewise linear, and price functions of generators in quadratic functions, with only network loss being considered. These classic techniques include Lambda Iteration [8], Gradient Descent Method [9], Linear Programming [10], Newton's Technique [11], Dynamic Programming [12], Gradient search [13], and the Lagrangian Relaxation Algorithm [14]. Because of the persistence of severe nonlinear characteristics in real-world practical networks, such as the use of more fuel, nonlinearity in power flow, prohibited operating zones, and valve-point loading effects, traditional techniques are being harmed by oscillatory issues which lengthen the solution time for large systems [15]. As a result, while dealing with high-dimensional economic dispatch difficulties, these suffer from disadvantages such as failure to meet imperatives and lengthy time calculations.

This time-consuming calculation in optimization methods prompted researchers to develop meta-heuristic optimization strategies to solve large-scale problems. The meta-heuristics method in [16] takes into consideration non-convex pricing functions and non-smooth operating functions as well as other imperatives. This includes techniques such as Synergic Predator-Prey Optimization (SPPO) [17], Seeker Optimization Algorithm (SOA) [18], Genetic Algorithm (GA) [19,20], Evolutionary Programming (EP) [21], Firefly Algorithm (FA) [22], Particle Swarm Optimization (PSO) [23–25], Artificial Bee Colony (ABC) [26], Colonial Competitive Differential Algorithm (CCDE) [27], Bacterial Foraging Algorithm (BFA) [28], Improved Tabu Search Algorithm (ITS) [29], Ant Colony Optimization (ACO) [30], Group Search Optimizer (GSO) [31], Harmony Search Algorithm (HAS) [32], Biogeography Based Optimization (BBO) [33], and Differential Evolution (DE) [34].

Heuristic techniques, which are known for their adaptability and flexibility, have received a lot of attention in recent years for solving a range of real-time economic load dispatch issues. Such techniques include Orthogonal Learning Competitive Swarm Optimizer(OLCSO) [35], Water Cycle Algorithm (WCA) [36], Moth Flame Optimizer (MFO) [37], Opposition-Based Krill Herd Algorithm (OKHA) [38], Two-Stage Artificial Bee Colony (TSABC) [39], Modified Crow Search Algorithm (MCS) [40], Chaotic Improved Harmony Search Algorithm (CIHSA) [41], Improved Fireworks Algorithm with Chaotic Sequence Operator (IFWA-CSO) [42], Exchange Market Algorithm (EMA) [43], Distance-Based Firefly Algorithm (DFA) [44], Root Tree Optimization Algorithm (RTO) [45], Backtracking Search Algorithm (BSA) [46], Adaptive Charged System Search Algorithm (ACSS), Ant Lion optimizer (ALO) [47], Grey Wolf Optimization (GWO) [48], Improved Differential Evolution (IDE) [49], Improved Bird Swarm Algorithm (IBSA) [50], Chaotic Bat Algorithm (CBA) [51], Particle Swarm Optimization (PSO) [52,53], Island Bat Algorithm (IBA) [54], Dual-Population Adaptive Differential Evolution (DPADE) [55], and Chaotic Teaching-Learning-Based Optimization (CTLBO) [56], which are used to solve economic load dispatch problems. To summarize, the Artificial Cooperative Search Algorithm (ACS) [57] was recently proposed on the basis of a co-evolution method that may find an optimal solution for the problematical economic load dispatch issue with a high degree of probability. Offering economic load dispatch with valve-point loading impact [58] evolves the requisite condition for the local minimum. A Traverse Search Method (TSM) was presented for addressing economic load dispatch with valve-point loading effect by taking into account such an important state. A method called Dimensional Steepest Decline Technique (DSD), which employs the decline rate series of fuel cost, was proposed in [58] to search efficiently for optimum solutions based on prior local minima data. Few articles have focused on combining two or more ways to solve the issue of economic load dispatch in order to improve the strategies' performance.

Furthermore, to meet the greater complexity of economic dispatch problems in practice, two or more techniques have been pooled to produce a hybrid methodology. This technique combines two or more traditional methods with any meta-heuristic optimizer. The newly designed hybrid optimizers include Bee Colony Optimization joined with Sequential Quadratic Programming (BCO-SQP) [59], Interior Point Method (IPM) integrated with Differential Evolution (DE) [60], mixed Differential Evolution with Biogeography-Based Optimization (DE-BBO) [61], Particle Swarm Optimizer-Sequential Quadratic Programming (PSO-SQP) [62], combined Active Power Optimization with Genetic Algorithm (GA-APO) [63], Chaotic Self-adaptive Particle Swarm Optimization [64], and Modified Sub-Gradient integrated with Harmony Search (MSG-HS) [65].

Their stochastic character, on the other hand, leads to a few drawbacks that many heuristics-based approaches suffer from. The choice of parameters, for example, is crucial for these techniques to function, and they need a lot of individual research to get an acceptable result.

The optimization approaches, on the other hand, are difficult to master, and the solutions obtained in each run are similar. As a result, unlike stochastic searching approaches, these strategies must be conducted just once. As a result, these approaches have recently received a lot of attention. Mixed Integer Quadratic Programming (MIQP) was developed to linearize the cost function induced by valve-point effects, according to [66]. Three approaches to find a solution for dynamic economic dispatch (DED) were incorporated in [11] based on this MIQP method: Multistep Method, Warm Start Method, and Range Restriction Format. The complete generating price function was recovered by its linear nearness to solve Dynamic Economic Load Dispatch (DED), and then a combination approach was included with Mixed Integer Linear Programming and Interior Point Technique in [67]. In [68], the economic dispatch problem was rebuilt using the Quadratically Constrained Quadratic Programming (QCQP) form, resulting in the Semi-Definite Programming (SDP) technique. This problem may be addressed iteratively using the Convex Iteration Method and the Branch and Bound approach. To address the economic dispatch issue, which included transmission loss and prohibited operating zones, [69] suggested a method called A Bi-level Branch and Bound approach (BB) in combination with Mixed Integer Quadratically Constrained Quadratic Programming. A fresh Big-M approach based on the MIQP strategy was proposed in the publication [70]. In [71], R.A. Jabr proposed the Semi definite Programming (SDP) technique.

In the paper [72], the authors focused on solving economic dispatch problems with penetration of wind energy sources. Peng et al. in [73] discussed the combined scheduling problem with due consideration of other renewable energy sources. The paper [74] provided a comprehensive review on different optimization methods available to find solutions for a combined economic emission dispatch problem. Liaquat et al. [75] made a comprehensive literature review on several developed optimization techniques and discussed the nature of the objective functions engaged in various dispatch problems. Tapas et al. [76] listed different techniques which were suggested by various authors for combined economic operation and environmental impact. B. Y. Qu et al. [77] in his literature survey covered the topics of typical MOEAs, classical EED problems, Dynamic EED problems which incorporated wind power, EED problems which incorporated electric vehicles, and EED problems within microgrids. Liaquat et al. [78] suggested the firefly method which succeeded fruitfully in solving a highly non-linear and multi-modal dispatch problem by assigning the optimum power sharing for every energy source in different scheduling time limits. Nazari-Heris et al. [79] explained the interconnection of gas, water, and power generation systems initially and then presented the mathematical formulation in a later stage and listed its advantages.

When utilizing these various meta-heuristic approaches, the primary faults at an idle are particularly aware for the initial value of the control parameters. While combining optimizers yields acceptable results, identifying the optimal point of inclusion between two meta-heuristics is challenging. Furthermore, hybrid systems' intrinsic complexity demands a non-eligible rise in the amount of work necessary to appropriately manage the control parameters.

To address the issue of economic load dispatch, the following are the primary contributions of this article which are based on a few limitations pointed in this section: firstly, it analyses the objective functions implicated in each problem and considers different types of constraints and goal functions. Secondly, it goes through the nature of the objective function that each dispatch problem involves and highlights the most important decision variables and suggests ways to update the situation. Lastly, it provides suggestions on how to enhance the present forms of common ED issues. Thus, this study proposes a new meta-heuristic method called the Slime Mould Optimization (SMA). Slime mould behavior is replicated using a unique meta-heuristics Slime mould method [80–82]. This approach includes a number of techniques that may be used to effectively balance the exploration and exploitation stages. This method deals with engineering design optimization and real-world issues. In this work, SMA is used to identify solutions to economic load dispatch problems on a variety of test systems. Other new and popular approach outcomes are compared to analyze the results.

3. Mathematical Formulation for Single-Area Economic Load Dispatch

The goal of the economic load dispatch problem is to lower the entire fuel cost of the power system by finding the optimum combination of power outputs from all generating units while congregating load demand and operational constraints.

3.1. Single-Area Economic Load Dispatch

The fuel cost for unit generation is represented as a quadratic function, with the assumption that the collective cost curves of the generating units develop as linear functions over time. The math for the single-area economic load dispatch for an hour is as follows in Equation (1):

$$fc(P^g) = \sum_{n=1}^{ng} [a_n \left(P_n^g\right)^2 + b_n P_n^g + c_n] \tag{1}$$

here, $n \in ng$

The dispatching of power generating units for 'Hr' Hours can be represented as:

$$fc(P^g) = \sum_{hr=1}^{Hr} (\sum_{n=1}^{ng} [a_n \left(P_n^g\right)^2 + b_n P_n^g + c_n]) \tag{2}$$

here $n \in ng; hr \in Hr$

The right mathematics for ED is Equation (2). Because load demand changes over time, 'hr' is changed from a single hour to 'Hr' hours.

The above objective functions are subjected to the following equality and inequality constraints:

3.1.1. Power Balance Constraint

Total power generation is equal to total power demand plus system power loss.

$$\sum_{n=1}^{ng} P_n^g = P^d + P^l \tag{3}$$

here, P^d indicates requirement of power

here, the power loss, P^l, might be written as:

$$P^l = \sum_{n=1}^{ng} \sum_{m=1}^{ng} P_n^g B_{nm} P_m^g \tag{4}$$

In presence of loss coefficients B_{i0} and B_{00} matrices, the Equation (4) can be written as:

$$P^l = P_n^g B_{nm} P_m^g + \sum_{n=1}^{ng} P_n^g \times B_{i0} + B_{00} \tag{5}$$

The extension of Equation (5) is as follows:

$$P^l = \begin{bmatrix} P_1 & P_2 \ldots & P_{ng} \end{bmatrix} \begin{bmatrix} B_{11} & B_{12} & B_{1n} \\ B_{21} & B_{22} & B_{2n} \\ B_{n1} & B_{n2} & B_{nn} \end{bmatrix} \begin{bmatrix} P_1 \\ P_2 \\ P_{ng} \end{bmatrix} + \begin{bmatrix} P_1 & P_2 & P_{ng} \end{bmatrix} \begin{bmatrix} B_{01} \\ B_{02} \\ B_{0ng} \end{bmatrix} + B \tag{6}$$

3.1.2. Generator Limit Constraint

The true power output of each generator is controlled by the upper and lower operational limits.

$$P^g_{n(minimum)} \leq P_n^g \leq P^g_{n(maximum)} \quad n = 1, 2, 3, \ldots, ng \tag{7}$$

where $P^g_{n(minimum)}$ implies the lowest real power allocated at unit n and $P^g_{n(maximum)}$ implies the highest real power allotted at unit n.

3.1.3. Ramp Rate Limits

The output power of the generating unit is boosted between the lower and higher limits of active power generation. Figure 1 depicts ramp rate limits.

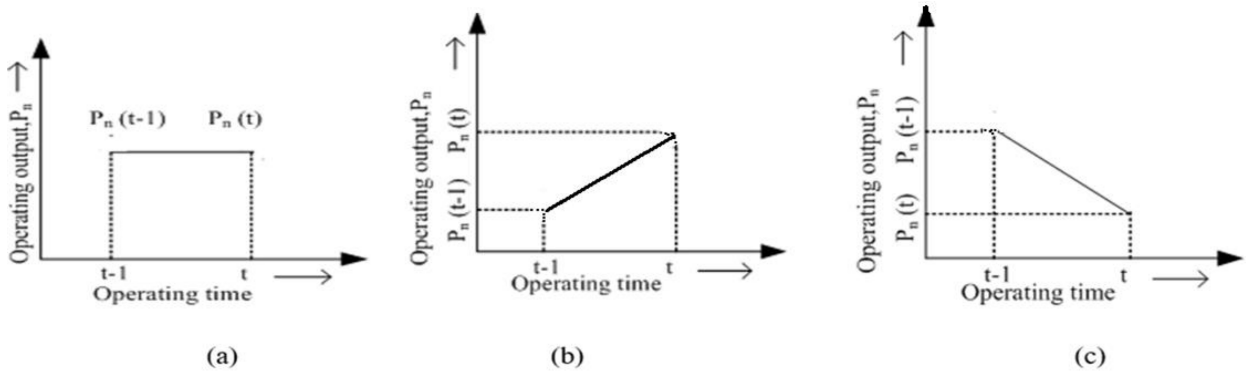


Figure 1. Ramp rate limits (**a**) Increasing generator power (**b**) Reducing generator power (**c**) Generated power within upper and lower limits.

(a) By increasing generated power,

$$P_n^g - P_0^{g0} \leq ur_n \quad n = 1, 2, 3, \ldots, ng \tag{8}$$

(b) By reducing the amount of generated power,

$$P_n^{g0} - P_n^g \leq dr_n \quad n = 1, 2, 3, \ldots, ng \tag{9}$$

As a consequence, the generator ramp rate is shown in the following equation.

$$maximum[P^g_{n(maximum)}, \left(ur_n - P_n^g \right)] \leq minimum[P^g_{n(minimum)}, \left(P_n^{g0} - dr_n \right) \tag{10}$$

where $n = 1, 2, 3, \ldots, ng$, P_n^{g0} is the current active power of the nth generation unit, P_n^g is the previous result of the active power of the nth generation unit, dr_n and ur_n are the lower and upper range for nth generation unit ramp rate limits.

Figure 1 [65] depicts the ramp limitations requirement.

3.1.4. Prohibited Operating Zones

Prohibited Operating Zones (POZ) are allocated to the graph for input–output powers in the generating unit, which may discontinue due to functional constraints of the generator produced by a defective mistake in the machine parts or the machine itself. As tracing genuine performance curves becomes increasingly difficult, the competent economy is calculated by disregarding performance curves in these areas. Figure 2 [46] depicts curves of prohibited operating zones. The discontinuous input–output power limitations are as follows in Equation (11):

$$\begin{cases} P_{n(minimum)} \leq P_n \leq P^{POZ}_{n(minimum),1} \\ P^{POZ}_{n(maximum),m-1} \leq P_n \leq P^{POZ}_{(minimum),m} \\ P^{POZ}_{n(maximum),m} \leq n_i \leq P_{n(maximum)};\ \ m = n_{poz} \end{cases} ;\ \ m = 2, 3, \ldots n_{poz} \tag{11}$$

where m denotes overall operating zones of nth generator,
$P^{POZ}_{n(maximum),m-1}$ indicates upper limit of $(m-1)$thpoz of nth generator
$P^{POZ}_{(minimum),m}$ shows the lower limit of mthpoz of nth generator
n_{poz} stands for overall operating zones.

Figure 2 [46] shows a sketch of the prohibited operating zones.

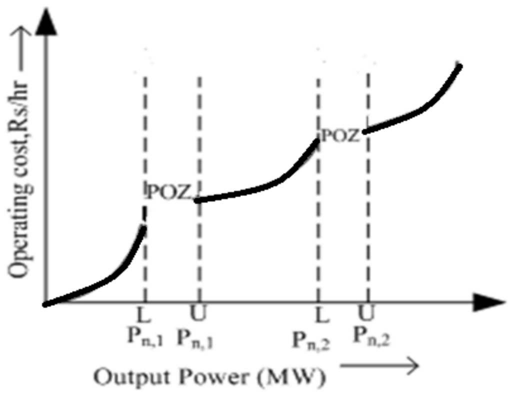


Figure 2. Curves of POZ.

4. Slime Mould Algorithm

There are numerous species in nature, each with their own distinctive behavior; however, only a handful of these characteristics draw attention and may be easily adopted and statistically molded to confront non-convex models. Many analysts aspire to emulate the working process for computational and algorithm evolution because of this flexibility. Slime moulds have been approved for the past few years based on this concept. The living style, characteristic behaviour of moulding structure based on the conditions, physical nature adjustments in food by estimating the distance, future plans for safeguarding by shifting to new regions of food sources before foraging based on the available information for moving towards rich food centres, and having the capability of stretching its biomass to various places to reach rich food are the key features to adopt in a SMA technique. Because of tremendous global search capabilities, SMA provides superior results.

It is known that the behavior of the organism can be imitated and molded to tackle the mathematics of unconstrained and non-convex characteristics. Researchers have tried to imitate the guiding principles to develop computations and algorithms. The slime moulds have received considerable attention over the past few years. Scientifically, the slime mould is titled Physarum polycephalum [83]. The slime mould undergoes a few changes in its structure, i.e., it repositions its front position into a fan shape model and its interconnected venous network allows the cytoplasm to flow inside at some level in a relocation series. This stretchable venous network helps in searching for food in multiple places and grabs the food from food points. The slime mould has the ability to creep up to 900 sq. meters if it finds rich food points in the environment.

If there is no food, the slime mould creeps brilliantly. This natural behavior of slime moulds explains how it searches, travels, and reaches the food point according to environmental changes [84]. When the slime mould is approaching the target, it has the ability to judge its positive and negative wave propagation to discover a faster route to grab the food. This indicates that the slime mould can build a perfect path to reach the food point. It always selects a rich food area [85]. Based on the food availability and environmental changes, it changes speed and reaches a new location from an old location before foraging. The slime mould gathers the information about available food on empirical rules and plans to start the new search. Though the current region is rich in food, it divides its biomass to search for other resources which have high-quality food. According to the availability of the food point, the slime mould adjusts its search patterns. Figure 3 [86] displays slime mould moving towards food source.

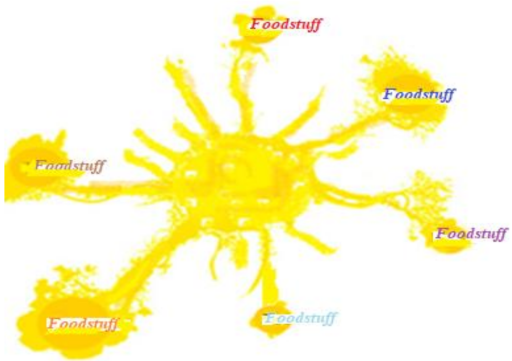


Figure 3. Slime mould creeping towards food.

4.1. Mathematical Modeling of SMA

The mathematical modeling of SMA is discussed in three stages, namely approaching food, wrapping food, and food grabble.

4.1.1. Technique of Approaching Food

Step1: Slime mould identifies the food based on the smell present in the air. The mathematics to explicate contraction phase and update its position during food search process are presented in the below expression which depends on x and p.

$$\overrightarrow{Y(\tau+1)} = \overrightarrow{Y_b(\tau)} + \vec{vb} \times (\vec{W} \times \overrightarrow{Y_A(\tau)} - \overrightarrow{Y_B(\tau)}), x > p \tag{12}$$

$$\overrightarrow{Y(\tau+1)} = \vec{vc} \times \overrightarrow{Y(\tau)}, x > p \tag{13}$$

where $\vec{vb}$ is the parameter which ranges from $[-d, d]$, $\vec{vc}$ is the parameter which reaches zero linearly. τ is the current iteration, $\vec{Y_b}$ is the position of every particle in that area where aroma is maximum, $\vec{Y}$ is the position of slime mould, randomly picked variables are $\vec{Y_A}$, $\vec{Y_b}$, and $\vec{W}$ is the weight.

The maximum limit p is as follows:

$$p = tanh|F(t) - bf| \tag{14}$$

where $t = 1, 2, \ldots, n$, $F(t)$ is the fitness of slime mould's location, bf is the fitness value from all the steps. Equation (4) describes the range of the parameter $\vec{vb}$.

$$\vec{vb} = [-d, d] \tag{15}$$

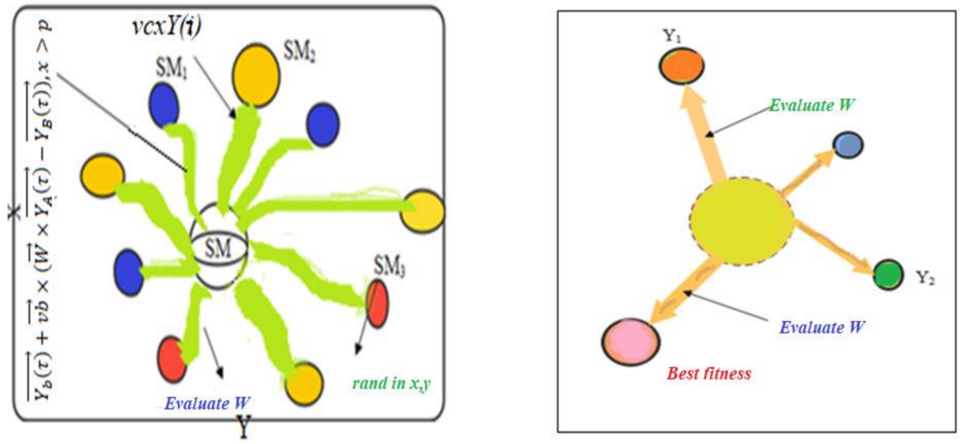
$$d = arctanh\left[-\left(\frac{\tau}{max_\tau}\right) + 1\right] \tag{16}$$

The equation $\vec{W}$ is expressed as follows:

$$\overrightarrow{W[StenchIndex(\tau)]} = \begin{cases} 1 + xlog\left(\frac{OpF-F(t)}{OpF-lF} + 1\right) \\ 1 - xlog\left(\frac{OpF-F(t)}{OpF-lF} + 1\right) \end{cases} \tag{17}$$

$$StenchIndex = sort(F) \tag{18}$$

Here, $F(t)$ ranks the first half of the population, random value x lies in the interval $[0,1]$, optimal fitness value and least fitness value of the present iteration is given by OpF and lF, sorting the fitness value is done by $sort(F)$. Figure 4a,b [86] depicts the outcomes of the Equations (12) and (13) and the possible positions of the slime mould in 2D and 3D view.



(**a**) (**b**)

Figure 4. (**a**): 2D view of possible position; (**b**) assessment of fitness.

4.1.2. Technique of Wrapping Food

The slime mould's updated location is numerically given as:

$$\vec{Y^I} = \begin{cases} rand \times (U_{ub} - U_{lb}) + U_{lb}, rand < z \\ \overrightarrow{Y_b(\tau)} + \vec{vb} \times (\vec{W} \times \overrightarrow{Y_A(\tau)} - \overrightarrow{Y_B(\tau)}), x > p \\ \vec{vc} \times \overrightarrow{Y(\tau)}, x > p \end{cases} \tag{19}$$

The upper and lower bounds of search ranges are given as U_{ub}, U_{lb}, $rand$, and x indicates the random value in the interval [0,1]. Figure 5a,b [86] depicts the slime mould's fitness value assessment process.

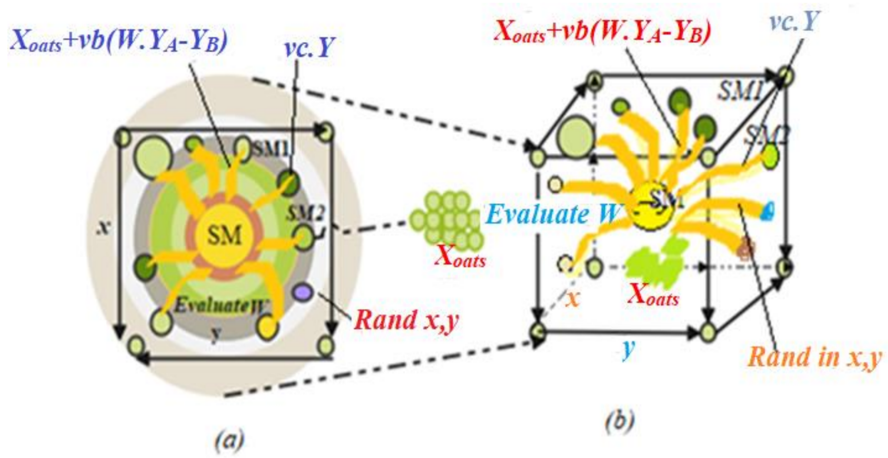


Figure 5. (**a**) Slime mould fitness assessment in 2D view and (**b**) Slime mould fitness assessment in 3D view.

4.1.3. Technique of Food Grabble

The slime mould's location gets upgraded in the search process and the value of $\vec{vb}$ varies within the limits $[-d, d]$, and $\vec{vc}$ fluctuates between $[-1, 1]$ and falls to zero.

The PSEUDO code for the proposed SM algorithm is exposed in Algorithm 1 and Figure 6 [86] presents the flow chart.

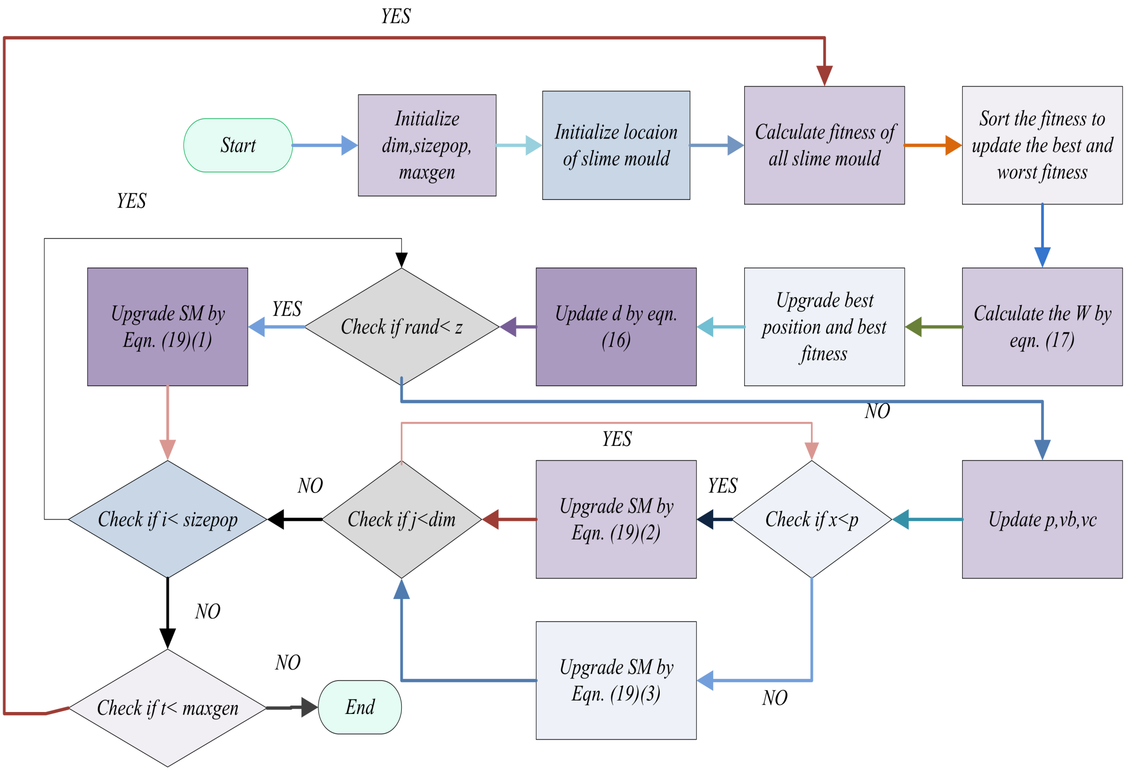


Figure 6. Flow Chart of SMA Algorithm.

Algorithm 1 PSEUDO Code for Slime Mould Algorithm.

Initialize the parameter popsize, Max_iteration;
Initialize the positions of slime mould $\overrightarrow{Y^I}$ (I = 1,2,3, ... ,n)
While $(\tau \leq Max_{iteration})$
Calculate the fitness of all slime mould;
update bestfitness, ***OpF***
Calculate the W by ***Equation*** *(17);*
For each search portion
Update p, $\overrightarrow{vc}$, $\overrightarrow{vb}$;
Update positions by ***Equation*** *(19);*
End For
$\tau = \tau + 1$;
End while
Return Bestfitness, OpF;

5. Economic Load Dispatch Flow Chart Using Slime Mould Optimizer

Next, load the slime mould algorithm's input factors. The number of generations in which the system optimizes to achieve a lower price by meeting all of the constraints is based on the initial data loaded. Every objective function's fitness value is established by fulfilling the search space's bounds. Using Equation (19), the performance of the economic load dispatch issue is evaluated until the best price is found. SMA chooses the values within boundaries, especially for inequality constraints if the results generated in any iteration go out of range, and it adds a penalty factor for equality constraints, exactly like any other method. This procedure is continued until the last iteration has been finished and the best outcomes have been achieved. The algorithm steps are:

Step 1: Initiate by loading the system parameters and SMA factors; Step 2: Place the preliminary data at random to equal the entire number of generators present; Step 3: Optimize for the random point of every search agent and deliver back when diverging from the search space; Step 4: Verify each main function's fitness value; Step 5: Set t determined fitness in an array; Step 6: Adapt the best and worst fitness values; Step 7: Regulate for slime mould's flexible weight; Step 8: Revise the locations of search agents; Step 9: Evaluate slime mould's weight in the phases of wrapping and grabbling food; Step 10: Search agents find two locations randomly in the phase of food approach; Step 11: Return to exploring fitness; Step 12: Find the optimum cost-effective fuel price; Step 13: Put an end to the program.

Figure 6 [86] depicts the slime mould algorithm flow chart.

The flowchart in Figure 6 describes the functioning of slime mould algorithm in which the position of slime mould is initialized. The fitness is calculated and sorted to update the best and worst fitness. The slime mould is actually based on the propagation wave generated by the biological oscillator to alter the cytoplasm flow in veins in order to reach the better location of food. To show the venous width variations in the slime mould, $\overrightarrow{W}$, $\overrightarrow{vb}$, $\overrightarrow{vc}$ are used which recognize the variations. The value of $\overrightarrow{W}$ is calculated to upgrade the best position and best-fitness values. $\overrightarrow{vb}$ lies between [−d,d] and reaches zero as the iteration increases. $\overrightarrow{vc}$ remains in the interval [−1,1] and tends to zero. $\overrightarrow{vb}$ plays a key role in deciding to reach a food source. Thus, finally the slime mould reaches the best location of food point by the iterative process.

6. Test System Results and Discussion

In this section of the paper, the IEEE bus systems in small-, medium-, and large-size test systems are considered, and comparisons are done with other methods to see how well the slime mould optimization algorithm performed on the economic load dispatch issue. The goal of implementing this approach was to lower the cost of fuel. The recommended method was implemented in MATALB R2016a on a laptop with an Intel Core i3 CPU, 7th generation, and 8GB RAM in order to discover a solution for the economic load dispatch issue. Search agents considered 50 and 500 iterations, and 30 maximum runs while implementing SMA. The effectiveness of the proposed approach was tested on a variety of test systems, including constraints such as with and without valve-point loading effects, which are addressed in Section 6.

To validate the efficacy of the proposed SMA technique, it was implemented on 3-, 5-, 6-, 10-, 13-, 15-, 20-, 38-, and 40- unit systems to find solution for the economic load dispatch issue. Overall, the obtained fuel cost results of SMA were compared with other already existing economic load dispatch solution methods from standard papers. The conditions considered for the analysis to solve economic load dispatch by SMA include: (a) without valve-point effect; (b) with valve-point effect; (c) with transmission losses; and (d) without transmission losses. The following are the test cases discussed.

6.1. Test System-I (Small-Scale Power System)

This section covers six different cases without valve-point loading and two different cases with valve-point loading:

I—Case Study

The input test data, as well as loss coefficient matrices, were obtained from [87]. A three-generator test system with a power requirement of 150 MW was assessed, which is given in Appendix A in Table A1. In this case, the ELD issue was cracked without the valve-point effect. Table 1 indicates that the slime Mould algorithm's fuel price was 1590.627083 Rs./h, which was the lowest of all the algorithms while still satisfying the system constraints. Figure 7a depicts the convergence curve of SMA obtained by simulation which was stable.

Table 1. (Case-I) Slime mould algorithm results for economic dispatch of a 3-unit system (without valve-point effect).

	Transfer of Power Generating Units					
Method	**Fuel Price (Rs./h)**	**Required Power in Demand (MW)**	**G1**	**G2**	**G3**	**Loss in Power, P_{Loss} (MW)**
Grey Wolf Optimizer [88]	1597.4815	150	30.4998	64.6208	54.8994	2.3444
Quadratic Programming [89]	1596	150	32.8116	64.5973	54.9329	2.3419
Lambda Method [87]	1599.98	150	33.4701	64.0974	55.1011	2.6686
Particle Swarm Optimization [87]	1597.48	150	32.8101	64.595	54.9369	2.342
Genetic Algorithm [87]	1600	150	34.4895	64.0299	54.1534	2.6728
Slime Mould Algorithm	**1590.627083**	150	10	76.42812	64.24508	0.336600019

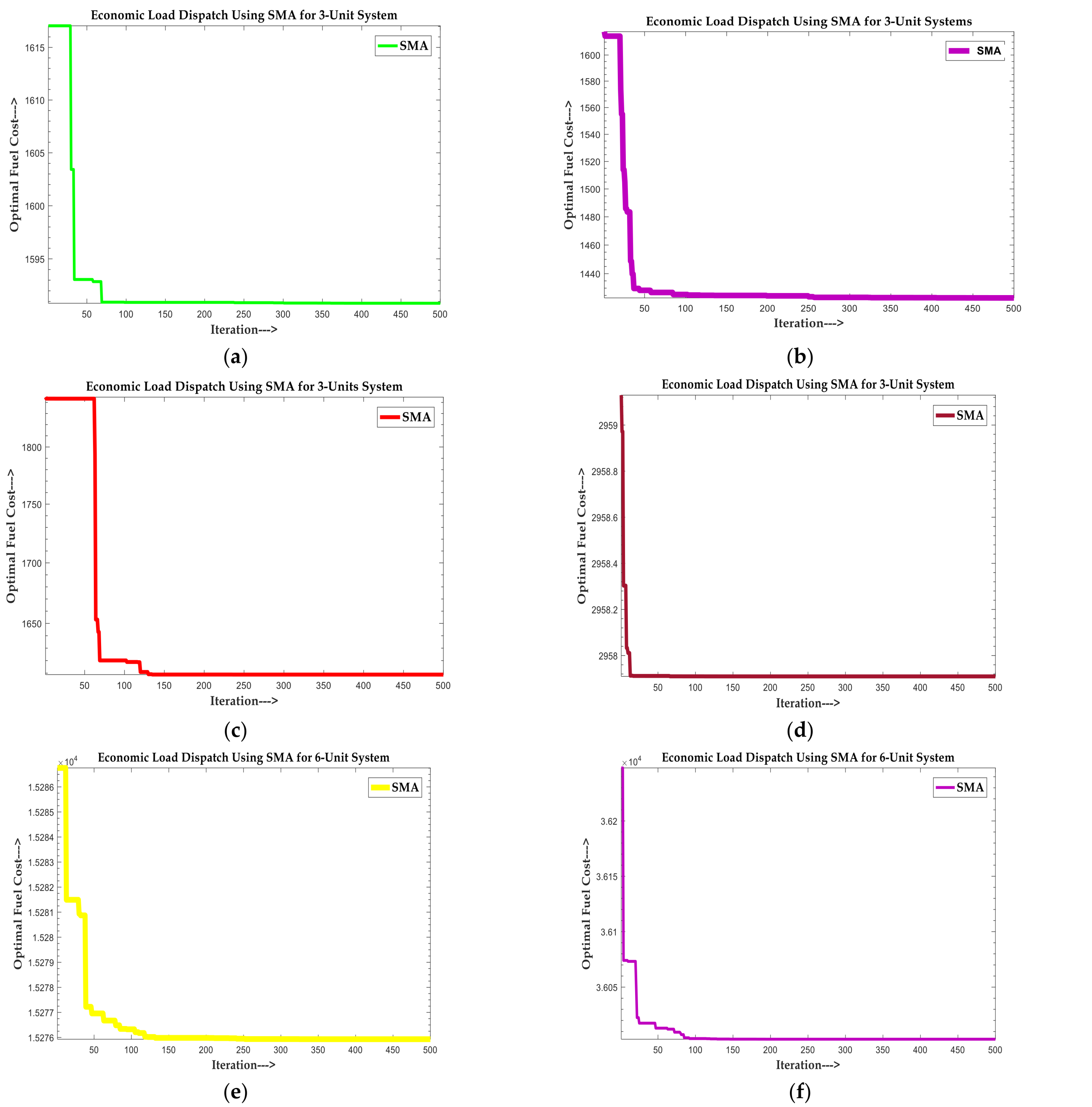


Figure 7. Convergence curve of slime mould algorithm for economic load dispatch for small-scale power systems (3-generating unit systems and 6-generating unit systems) without valve-point loading effect; (**a**) Case-I (3-unit system) convergence curve, (**b**) Case-II (3-unit system) convergence curve.,(**c**) Case-III (3-unit system) convergence curve, (**d**) Case-IV (3-unit system) convergence curve, (**e**) Case-V (6-unit system) convergence curve, (**f**) Case-VI (6-unit system) convergence curve.

II—Case Study

The input data for this system were drawn from [90] and loss coefficient matrices. A three-generator test system with a power requirement of 125 MW was used which was needed to assess the comparable transmission given in Table A2. In this case, the ELD issue was cracked without the valve-point effect. Table 2 indicates that the slime mould algorithm's fuel price was 1413.990605 Rs./h, which was the best of all algorithms while still satisfying the system constraints. Figure 7b depicts the convergence curve of SMA obtained by simulation which was stable.

Table 2. (Case-II) Slime Mould algorithm results for economic dispatch of a 3-unit system (without valve-point effect).

	Transfer of Power Generating Units					
Method	**Fuel Price (Rs./h)**	**Required Power in Demand (MW)**	**G1**	**G2**	**G3**	**Loss in Power, P_{Loss} (MW)**
Lambda Algorithm [90]	1422.159458	125	-	-	-	2.084005739
Firefly Algorithm [90]	1421.561972	125	-	-	-	1.964774407
Slime Mould Algorithm	**1413.990605**	125	10	70.21971	45.41896	0.319332527

III—Case Study

The input data for this system were drawn from [90] and loss coefficient matrices. A three-generator test system with a power requirement of 150 MW was assessed which is given in Table A3. In this case, the ELD issue was cracked without the valve-point effect. Table 3 indicates that the slime mould algorithm's fuel price was 1608.866334 Rs./h, which was the best of all algorithms while still satisfying the system constraints. Figure 7c depicts the convergence curve of SMA obtained by simulation which was stable.

Table 3. (Case-III) Slime mould algorithm results for economic dispatch of a 3-unit system (without valve-point effect).

	Transfer of Power Generating Units					
Method	**Fuel Price (Rs./hr)**	**Required Power in Demand (MW)**	**G1**	**G2**	**G3**	**Loss in Power, P_{Loss} (MW)**
Lambda Algorithm [90]	1625.4586	150	-	-	-	2.813864755
Firefly Algorithm [90]	1616.921725	150	32.729	63.843	56.151	2.721760653
Slime Mould Algorithm	**1608.866334**	150	10	80	60.74528	0.372641

IV—Case Study

The input data for a three-unit test system were drawn from [91], with 250 MW power need, as well as loss coefficient matrices which were required to assess comparable transmission and are displayed in Table A4. Table 4 indicates that the slime mould technique yielded a fuel price of 2957.909554 Rs./h, which was the best fuel price among all known algorithms while still satisfying all the constraints. Figure 7d depicts the convergence curve of SMA obtained by simulation which was stable.

Table 4. (Case-IV) Slime mould algorithm results for economic dispatch of a 3-unit system (without valve-point effect).

	Transfer of Power Generating Units					
Method	**Fuel Price (Rs./h)**	**Required Power in Demand (MW)**	**G1**	**G2**	**G3**	**Loss in Power, P_{Loss} (MW)**
Particle Swarm Optimization [91]	2959.98	250	151.09	42.04	56.87	0
Slime Mould Algorithm	**2957.909554**	250	165.7781	29.85793	54.36396	0

V—Case Study

With a power demand of 1263 MW, a six-unit test system without valve-point load effect was taken from [92], which is given in Table A5. The loss coefficients matrix was zero.

Table 5 shows that the slime mould algorithm obtained a best fuel price of 15,275.9304 Rs./h, beating already existing algorithms by satisfying all the constraints. The convergence curve of SMA obtained by simulation which was stable is shown in Figure 7e.

Table 5. (Case-V) Slime mould algorithm results for economic dispatch of a 6-unit system (without valve-point effect).

			Transfer of Power Generating Units						
Method	**Fuel Price (Rs./h)**	**Required Power in Demand (MW)**	**G1**	**G2**	**G3**	**G4**	**G5**	**G6**	**Loss in Power, P_{Loss} (MW)**
New Particle Swarm Optimization-local random search [93]	15,450	1263	446.96	173.3944	262.3436	139.5120	164.7089	89.0162	12.9361
Differential Evaluation [94]	15,445.90	1263	400.00	186.55	289.00	150.00	200.00	50.00	12.52
New Particle Swarm Optimization [93]	15,450	1263	447.4734	173.1012	262.6804	139.4156	165.3002	87.9761	12.9470
Simulated Annealing Algorithm [92]	15,466.00	1263	447.08	173.18	263.92	139.06	165.58	86.63	12.47
Classical Particle Swarm Optimization 2(CPSO2) [24]	15,446	1263	434.4295	173.3231	274.4735	128.0598	179.4759	85.9281	12.9582
Particle Swarm Optimization [95]	15,450	1263	447.50	173.32	263.47	139.06	165.48	87.13	12.958
Genetic Algorithm [96]	15,459	1263	474.81	178.64	262.21	134.28	151.90	74.18	13.022
New Modified Particle Swarm Optimization [97]	15,447	1263	446.71	173.01	265.00	139.00	165.23	86.78	12.733
Particle Swarm Optimization –local random search [93]	15,450	1263	47.4440	173.3430	263.3646	139.1279	165.5076	87.1698	12.9571
Firefly Algorithm [92]	15,443	1263	445.08	173.08	264.42	139.59	166.02	87.21	12.4
Classical Particle Swarm Optimization 1(CPSO1) [24]	15,447	1263	434.4236	173.4385	274.2247	128.0183	179.7042	85.9082	12.9583
Biogeography-Based Optimization [98]	15,443.0963	1263	447.3997	173.2392	263.3163	138.0006	165.4104	87.07979	12.464
Iteration Particle Swarm Optimization (IPSO) [24]	15,444	1263	440.5711	179.8365	261.3798	131.9134	170.9823	90.8241	12.548
Artificial Bee Colony Optimization [99]	15,445.90	1263	438.65	167.90	262.82	136.77	171.76	97.67	12.52
Self-Organizing Hierarchical Particle Swarm Optimization [100]	15,446.02	1263	438.21	172.58	257.42	141.09	179.37	86.88	12.55
Slime Mould Algorithm	**15,275.9304**	1263	446.6889	171.254	264.1159	125.2018495	172.1444773	83.59471703	0

VI—Case Study

This system was comprised of a six-unit test system with a total power requirement of 700 MW, as well as loss coefficient matrices which were needed to assess comparable transmission, and the input data were drawn from [91], which is given in Table A6. Table 6 indicates that the fuel cost using the slime mould algorithm was 36,003.12394 Rs./h, which was the best of all methods satisfying the constraints. Figure 7f depicts the convergence curve of SMA obtained by simulation which was stable.

Table 6. (Case-VI) Slime mould algorithm results for economic dispatch of a 6-unit system (without valve-point effect).

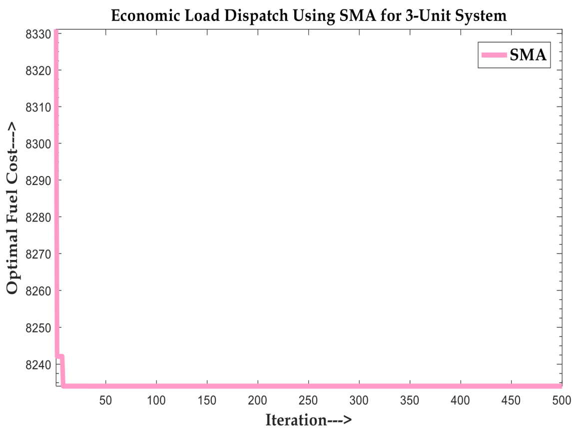
			Transfer of Power Generating Units						
Method	**Fuel Price (Rs./h)**	**Required Power in Demand (MW)**	**G1**	**G2**	**G3**	**G4**	**G5**	**G6**	**Loss in Power, P_{Loss} (MW)**
Conventional Method [91]	36,914.01	700	28.33	10	118.95	118.67	230.75	212.80	19.50
Particle Swarm Optimization [91]	36,912.16	700	28.28	10	119.02	118.79	230.78	212.56	19.43
Slime Mould Algorithm	**36,003.12394**	700	24.9763	10	102.6661	110.6311238	232.6778302	219.0486296	0

VII—Case Study

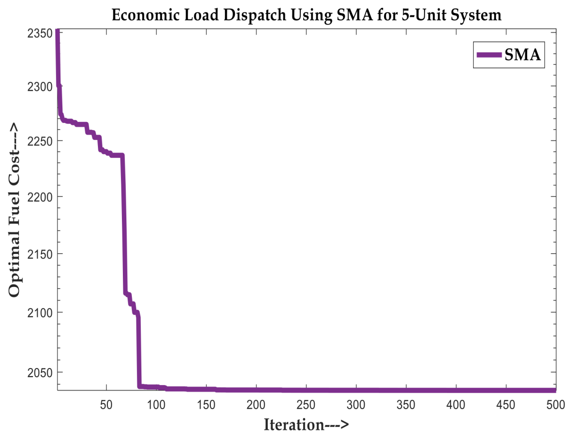
A three-generator test system with valve-point loading effect was utilized with a 850 MW power demand, and the input test information is given in Table A7 which was acquired from [4] with the loss coefficient matrix set to zero. Table 7 indicates that the best fuel price across all algorithms was 8234.07173 Rs./h when utilizing the slime mould algorithm that satisfied all the constraints. Figure 8a depicts the convergence curve of SMA obtained by simulation which was stable.

Table 7. (Case-VII) Slime mould algorithm results for economic dispatch of a 3-unit system (with valve-point effect).

			Transfer of Power Generating Units			
Method	**Fuel Price (Rs./h)**	**Required Power in Demand (MW)**	**G1**	**G2**	**G3**	**Loss in Power, P_{Loss}(MW)**
CPSO [4]	8234.07	850	300.267	400	149.733	NR
GA [101]	8575.64	850	382.2552	340.3202	127.4184	NR
EP-SQP [4]	8234.07	850	300.264	400	149.733	NR
DE [49]	8234.07173	850	300.2668999	400	149.7331001	NR
PSO [4]	8234.07	850	300.267	400	149.733	NR
ABC [101]	8253.10	850	300.266	400	149.733	NR
PSO-SQP [4]	8234.07	850	300.268	400	149.733	NR
EP [4]	8234.07	850	300.264	400	149.736	NR
Lambda [101]	8575.68	850	382.258	340.323	127.419	NR
CPSO–SQP [4]	8234.07	850	300.266	400	149.734	NR
Slime Mould Algorithm	**8234.07173**	850	300.2668998	400	149.7331002	0



(**a**)



(**b**)

Figure 8. Convergence curve of slime old algorithm for economic load dispatch for small-scale power systems (3-generating unit system and 5-generating unit system) with valve-point loading effect, (**a**) Convergence curve for Case-VII (3-unit system), (**b**)Convergence curve for Case-VIII (5-unit system).

VIII—Case Study

With a power demand of 730 MW, a five-unit test system with valve-point loading effect was used, and its input test information was taken from [101] with the loss coefficient matrix set to zero, which is given in Table A8. Table 8 shows that the slime mould algorithm obtained a fuel price of 2034.972427 Rs./h, satisfying all the constraints and was the best fuel price among all algorithms. The convergence curve of SMA obtained by simulation which was stable is shown in Figure 8b.

Table 8. (Case-VIII) Slime mould algorithm results for economic dispatch of a 6-unit system (with valve-point effect).

			Transfer of Power Generating Units					
Method	**Fuel Price (Rs./h)**	**Required Power in Demand (MW)**	**G1**	**G2**	**G3**	**G4**	**G5**	**Loss in Power, P_{Loss} (MW)**
Genetic Algorithm [101]	2412.538	730	218.0184	109.0092	147.5229	28.37844	227.0275	NR
Particle Swarm Optimization [101]	2252.572	730	229.5195	125	175	75	125.4804	NR
Lambda [101]	2412.709	730	218.028	109.014	147.535	28.380	272.042	NR
APSO [101]	2140.97	730	225.3845	113.020	109.4146	73.11176	209.0692	NR
Slime Mould Algorithm	**2034.972427**	730	229.5195832	102.9830227	112.6813882	74.9999977	209.816008	0

6.2. Test System-II (Medium-Scale Power System)

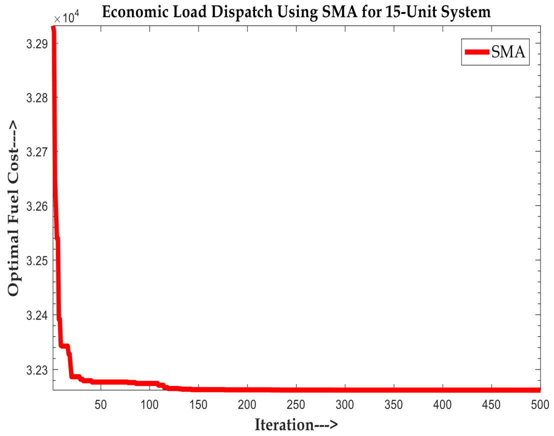
Under medium-size power systems, four distinct test systems were tested. Two of the cases were examined without the effect of valve-point loading, whereas the other two were tested with the influence of valve-point loading.

I—Case Study

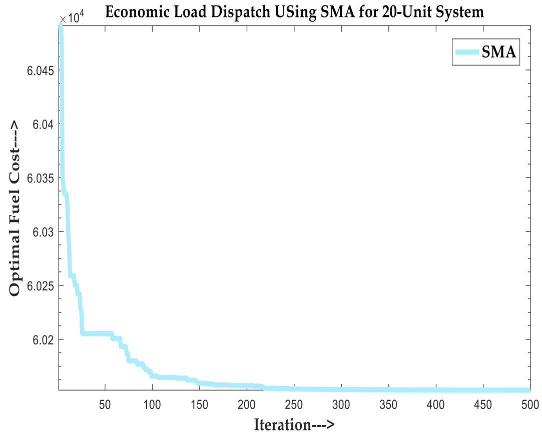
For a 15-unit test system with a power demand of 2630 MW, the input test information was obtained from [102], coupled with loss coefficient matrices which were essential to predict comparable transmission and are given in Table A9. In this case, the ELD issue was cracked without valve-point effect. Table 9 indicates that the best fuel price across all algorithms was 32,259.69352 Rs./h when utilizing the slime mould algorithm which satisfied all the constraints. Figure 9a depicts the convergence curve of SMA obtained by simulation which was stable.

Table 9. (Case-I) Slime mould algorithm results for economic dispatch of a 15-unit system (without valve-point effect).

Method	**CPSO1 [24]**	**ETQ [102]**	**PSO [102]**	**ESO [102]**	**SOH_PSO [24]**	**PSO(4) [102]**	**CPSO2 [24]**	**IPSO [24]**	**ABC [103]**	**ES [102]**	**Hybrid GAPSO [24]**	**GA [102]**	**Slime Mould Algorithm**
Fuel price (Rs. /h)	32,835	32,507.5	32,858	32,506.6	32,751.39	32,508.12	32,834	32,709	32,707.85	32,568.54	32,724	33,113	**32,259.69325**
Required Power in Demand (MW)	2630	2630	2630	2630	2630	2630	2630	2630	2630	2630	2630	2630	2630
G1	450.05	450	439.12	456	455	440.499	450.02	455	455	455	436.8482	415.31	455
G2	454.04	450	407.97	456	380	179.5947	454.06	380	380	380	409.6974	359.72	454.7336
G3	124.82	130	119.63	130	130	21.0524	124.81	129.97	130	130	117.0074	104.42	130
G4	124.82	130	129.99	130	130	87.1376	124.81	130	130	150	128.2705	74.98	129.9999991
G5	151.03	335	151.07	304.24	170	360.7675	151.06	169.93	169.9997	168.92	153.3361	380.28	288.3104957
G6	460	455	459.99	460	459.96	395.833	460	459.88	460	459.34	457.4078	426.79	459.9767033
G7	434.53	465	425.56	465	430	432.0085	434.57	429.25	430	430	424.4400	341.32	465
G8	148.41	60	98.56	60	117.53	168.9198	148.46	60.43	71.9698	97.42	101.1949	124.79	60.19352401
G9	63.61	25	113.49	25	77.90	162	63.59	74.78	59.1798	30.61	116.1186	133.14	25
G10	101.13	20	101.11	20	119.54	138.4343	101.12	158.02	159.8004	142.56	102.2243	89.26	25.24209
G11	28.656	20	33.91	29.15	54.50	52.6294	28.655	80	80	80	35.0317	60.06	20.04263
G12	20.912	55	79.96	59.24	80	66.8875	20.914	78.57	80	85	78.8482	50	61.37133
G13	25.001	25	25.	25	25	62.7471	25.002	25	25.0024	15	27.1292	38.77	25.00313
G14	54.418	15	41.41	17.28	17.86	47.5574	54.414	15	15.0056	15	37.1594	41.94	15.09977
G15	20.625	15	35.61	15	15	27.6065	20.624	15	15.0014	15	37.0390	22.64	15.04694
Loss in Power, P_{Loss} (MW)	32.1302	15.8	32.42	13.79	32.28	13.6745	32.1303	30.858	13	23.85	31.75	38.28	0.010082332



(a)



(b)

Figure 9. Convergence curve of slime mould algorithm for economic load dispatch for medium-scale power systems (15-generating unit system and 20-generating unit system) without valve-point loading effect, (**a**) Convergence curve for Case-I (15-unit system), (**b**) Convergence curve for Case-II (20-unit system).

II—Case Study

For a twenty generator test system with a power requirement of 2500 MW, the input test data were obtained from [102], which is shown in Table A10 along with loss coefficient matrices which are essential to predict comparable transmission. In this case, the ELD issue was cracked without valve-point effect. Table 10 indicates that the slime mould algorithm yielded a fuel price of 60,152.72915 Rs./h, which was the lowest of all methods. Figure 9b depicts the convergence curve of SMA obtained by simulation which was stable.

Table 10. (Case-II) Slime mould algorithm results for economic dispatch of a 20-unit system (without valve-point effect).

Method	Hopfield Neural Network [104]	Lambda-Iteration Method [102]	Slime Mould Algorithm
Fuel Price (Rs./h)	62,456.6341	62,456.6391	**60,152.72915**
Required Power in Demand (MW)	2500	2500	2500
G1	512.7804	512.7805	599.9962
G2	169.1035	169.1033	127.2091
G3	126.8897	126.8898	50.01089
G4	102.8656	102.8657	50
G5	113.6836	113.6836	92.80191
G6	73.5709	73.5710	20.00047
G7	115.2876	115.2878	124.9982
G8	116.3994	116.3994	50
G9	100.4063	100.4062	112.1931
G10	106.0267	106.0267	43.44606
G11	150.2395	150.2394	289.1196
G12	292.7647	292.7648	433.1905
G13	119.1155	119.1154	122.9385
G14	30.8342	30.8340	72.39983
G15	115.8056	115.8057	95.40311
G16	36.2545	36.2545	36.15509
G17	66.8590	66.8590	30.01615
G18	87.9720	87.9720	39.79051
G19	100.8033	100.8033	80.33078
G20	54.3050	54.3050	30
Loss in Power, P_{Loss}(MW)	91.9669	91.9670	0

III—Case Study

The input test information was obtained from [105] with the loss coefficient matrix set to zero, and a ten generator test system with valve-point loading effect was used with a power demand of 2000 MW, which is shown in Table A11. Table 11 shows that when utilizing the slime mould algorithm, the fuel price was 106170.418 Rs./h, which was the best fuel price among all algorithms. The convergence curve of SMA obtained by simulation which was stable is shown in Figure 10a.

Table 11. (Case-III) Slime mould algorithm results for economic dispatch of a 10-unit system (with valve-point effect).

Method	PDE [106]	FPA [106]	MODE [106]	PSO [105]	NSGAII [106]	GSA [106]	PSO-TVAC [107]	ABC_PSO [106]	EMOCA [106]	MSCO [106]	SPEA-2 [106]	Slime Mould Algorithm
Fuel Price (Rs./h)	113,510	113,370	113,484	107,620	113,539	113,490	107,620	113,420	113,445	110,870	113,520	**106,170.418**
Power in Demand (MW)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
G1	54.9853	53.188	54.9487	53.1000	51.9515	54.9992	53.8	55	55	52.8995	52.9761	54.99996
G2	79.3803	79.975	74.5821	79.2000	67.2584	79.9586	78.9	80	80	74.9428	72.813	79.9999
G3	83.9842	78.105	79.4294	112	73.6879	79.4341	109	81.14	83.5594	97.4068	78.1128	89.30891
G4	86.5942	97.119	80.6875	121	91.3554	85.0000	125	84.216	84.6031	95.9554	83.6088	79.87863
G5	144.4386	152.74	136.8551	98.8000	134.0522	142.1063	98.8	138.3377	146.5632	131.8702	137.2432	66.48786
G6	165.7756	163.08	172.6393	100	174.9504	166.5670	90.4	167.5086	169.2481	200.5119	172.9188	70.00002
G7	283.2122	258.61	283.8233	299	289.4350	292.8749	298	296.8338	300	227.9224	287.2033	290.7383
G8	312.7709	302.22	316.3407	320	314.0556	313.2387	330	311.5824	317.3496	303.6511	326.4023	328.5865
G9	440.1135	433.21	448.5923	467	455.6978	441.1775	468	420.3363	412.9183	366.3189	448.8814	470
G10	432.6783	466.07	436.4287	356	431.8054	428.6306	351	449.1598	434.3133	470.0000	423.9025	470
Loss in Power, P_{Loss} (MW)	83.9	84.3	84.33	NR	84.25	83.9869	NR	84.1736	83.56	21.4789	84.1	0

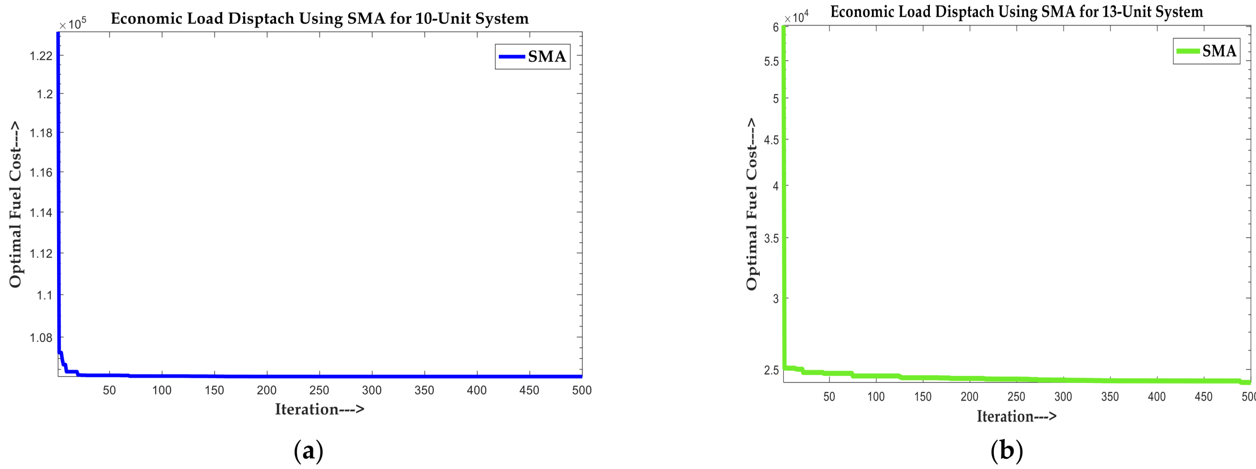


Figure 10. Convergence curve of slime mould algorithm for economic load dispatch for medium-scale power systems (10-generating unit system and 13-generating unit system) with valve-point loading effect, (**a**) Convergence curve for Case-III (10-unit system), (**b**) Convergence curve for Case-IV (13-unit system).

IV—Case Study

With a power demand of 2520 MW, a thirteen generator test system with valve-point loading effect was used and the input test data were obtained from [62], with the loss coefficient matrix set to zero and shown in Table A12. Table 12 shows that when utilizing the slime mould algorithm, the fuel price was 24,177.23727 Rs./h, which was the best fuel price among all known algorithms. The convergence curve of SMA obtained by simulation which was stable is shown in Figure 10b.

Table 12. (Case-IV) Slime mould algorithm results for economic dispatch of a 13-unit system (with valve-point effect).

Method	GWO [108]	JAYA [108]	NGWO [108]	EP-SQP [62]	SA [62]	GA [62]	PSO-SQP [62]	CJAYA [62]	GWOII [108]	GWOI [108]	GA-SA [62]	CPSO [4]	Slime Mould Algorithm
Fuel Price (Rs./h)	24,231.18	24,220.7529	24,185.45	24,266.44	24,970.91	24,418.99	24,261.05	24,178.8040	24,198.47	24,244.69	24,275.71	24,211.56	**24,177.23727**
Required Power in Demand (MW)	2520	2520	2520	2520	2520	2520	2520	2520	2520	2520	2520	2520	2520
G1	647.3842	628.3185	630.9951	628.3136	668.40	627.05	628.3205	628.3185	630.9811	645.5569	628.23	682.32	628.3184973
G2	306.3995	299.2009	297.9355	299.1715	359.78	359.40	299.0524	299.1992	300.8038	306.9539	299.22	299.83	298.0415722
G3	309.6117	306.9105	299.9253	299.0474	358.20	358.95	298.9681	299.1993	302.7475	306.5356	299.17	299.17	298.9244776
G4	175.1400	159.7339	157.9267	159.6399	104.28	158.93	159.4680	159.7330	160.1702	169.6878	159.12	159.70	159.7225373
G5	66.8791	159.7337	159.6433	159.6560	60.36	159.73	159.1429	159.7331	161.0252	168.4922	159.95	159.64	159.6885214
G6	162.7466	159.7338	159.2335	158.4831	110.64	159.68	159.2724	159.7331	160.9845	174.9721	158.85	159.67	159.72331
G7	174.3111	109.8673	159.7630	159.6749	162.12	159.53	159.5371	159.7330	159.1231	167.1394	157.26	159.64	159.4163763
G8	61.2250	159.7342	159.6615	159.7265	163.03	158.89	158.8522	159.7330	110.4278	116.8800	159.93	159.65	159.6905
G9	175.1400	159.7340	159.4265	159.6653	161.52	110.15	159.7845	159.7331	159.7720	116.8800	159.86	159.78	159.7157
G10	116.7600	114.8012	76.8790	114.0334	117.09	77.27	110.9618	110.0403	116.8577	116.8800	110.78	112.46	76.2922
G11	116.7600	114.8001	79.5038	75	75	75	75	114.7994	77.0418	109.9096	75	74	114.166
G12	99.9167	92.4018	86.8040	60	60	60	60	55	91.4990	59.0347	60	56.50	55.00003
G13	108.5598	55.0027	94.1941	87.5884	119.58	55.41	91.6401	55	88.6915	66.5129	92.62	91.64	91.30029
P_{Loss} (MW)	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	0

6.3. Test System-III (Large-Scale Power System)

Two test systems were examined in this section, one without valve-point loading and the other with valve-point loading.

I—Case Study

The input test information was taken from [88] with the loss coefficient matrix set to zero, and a thirty-eight generator test system with a power demand of 6000 MW was evaluated. The input test data are given in Table A13. Table 13 shows that the fuel price using the slime mould algorithm was 9402608.045 Rs./h, which was the best fuel price among all algorithms. The convergence curve of SMA obtained by simulation which was stable is depicted in Figure 11.

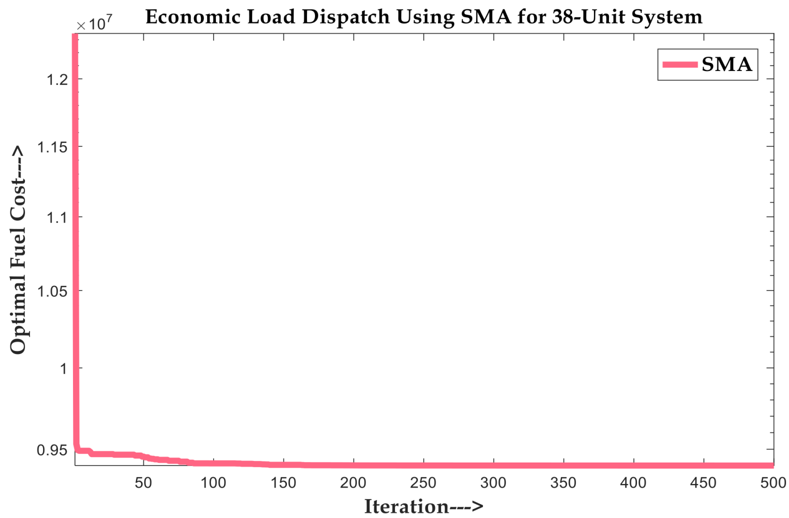


Figure 11. Convergence curve of slime mould algorithm for economic load dispatch for large-scale power systems (38-generating unit system) without valve-point loading effect.

Table 13. (Case-I) Slime mould algorithm results for economic dispatch of a 38-unit system (without valve-point effect).

Method	Grey Wolf Optimizer (GWO) [88]	Pattern Search (PS) [88]	Biogeography Based Optimization (BBO) [88]	SPSO [109]	PSO_Crazy [109]	λ-Logic-Based Method [88]	PSO_TVAC [109]	New PSO [109]	Slime Mould Algorithm
Fuel Price (Rs./h)	9,417,226	9,543,984.8	9,417,633.6	9,543,984.777	9,520,024.601	9,417,235.8	9,500,448.307	9,516,448.312	**9,402,608.045**
Required Power in Demand (MW)	6000	6000	6000	6000	6000	6000	6000	6000	6000
G1	429.7056	258.3397	550	519.097	366.631	426.6061	443.659	550.000	550
G2	416.2439	258.3397	550	437.920	550.000	426.6061	342.956	512.263	324.723
G3	408.4052	238.3397	500	374.789	467.129	429.6633	433.117	485.733	326.8208
G4	412.4527	238.3397	500	394.877	370.471	429.6633	500.000	391.083	327.2394159
G5	433.6422	238.3397	375.6216	356.603	425.712	429.6633	410.539	443.846	326.6712585
G6	425.6522	238.3397	200	380.358	415.226	429.6633	482.864	358.398	326.5721853
G7	435.6207	238.3397	200	300.234	339.872	429.6633	409.483	415.729	327.0354
G8	437.6536	238.3397	200	335.871	289.777	429.6633	446.079	320.816	327.5622428
G9	115.2751	196.2345	114	238.171	195.965	114	119.566	115.347	114
G10	116.883	196.2345	114.6486	218.563	170.608	114	137.274	204.422	114
G11	130.7939	196.2345	162.1622	196.630	138.984	119.7681	138.933	114.000	114
G12	153.2393	196.2345	114	234.500	262.350	127.0729	155.401	249.197	114
G13	110	196.2345	129.2432	111.529	114.008	110	121.719	118.886	110
G14	90.028	196.2345	90	100.731	92.393	90	90.924	102.802	90
G15	82.0111	196.2345	153.2432	122.464	89.044	82	97.941	89.039	82.00004
G16	120	196.2345	120	125.310	130.555	120	128.106	120.000	120.0000328
G17	157.1682	196.2345	204.3243	155.981	167.850	159.5981	189.108	156.562	147.205372
G18	65	196.2345	65	65.000	65.754	65	65.000	84.265	65.00016196
G19	65.0326	196.2345	65	70.071	65.000	65	65.000	65.041	65
G20	271.9524	196.2345	120	263.950	199.594	272	267.422	151.104	272
G21	271.959	196.2345	182.4324	245.065	272.000	272	221.383	226.344	272
G22	259.81	196.2345	110	191.702	130.379	160	130.804	209.298	260
G23	120.8832	190	187.2973	99.123	173.544	130.6487	124.269	85.719	96.81893
G24	12.3567	150	27.027	15.058	13.263	10	11.535	10.000	10.00006
G25	107.634	125	125	60.060	112.161	113.3051	77.103	60.000	84.92456
G26	92.4117	110	110	91.140	105.898	88.0669	55.018	90.489	72.26642
G27	39.6668	75	75	41.006	35.995	37.5051	75.000	39.670	35.00027
G28	20.005	70	70	20.399	22.335	20	21.682	20.000	20
G29	20.0014	70	70	34.650	30.045	20	29.829	20.995	20.00028
G30	20.0302	70	70	20.957	24.112	20	20.326	22.810	20
G31	20.013	70	70	20.219	20.494	20	20.000	20.000	20.00006
G32	20.007	60	60	25.424	20.011	20	21.840	20.416	20
G33	25.0032	60	60	26.517	27.440	35	25.620	25.000	25.00003
G34	18.008	60	60	18.822	18.000	18	24.261	21.319	18
G35	8.006	60	60	9.173	8.024	8	9.667	9.122	8.000021
G36	25.002	60	60	26.507	25.000	25	25.000	25.184	25
G37	22.4379	38	38	24.344	20.000	21	31.642	20.000	20
G38	20.0048	38	38	27.181	24.371	21	29.935	25.104	20.00002
Loss in power, P_{Loss} (MW)	NR	NA	NR	NA	NA	NR	NA	NA	0

II—Case Study

With a power demand of 10,500 MW, a forty generator test system with valve-point loading effect was used and the input test information was taken from [108] with the loss coefficient matrix set to zero, which is shown in Table A14. Table 14 shows that when utilizing the slime mould algorithm, the fuel price was 121,658.6656 Rs./h, which was the best fuel price among other known algorithms. The convergence curve of SMA obtained by simulation which was stable is seen in Figure 12.

Table 14. (Case-II) Slime mould algorithm results for economic dispatch of a 40-unit system (with valve-point effect).

Method	MPSO [108]	GWO [108]	NGWO [108]	PSO-LRS [108]	IGA [108]	NPSO [108]	GWOII [108]	CJAYA [108]	GWOI [108]	Slime Mould Algorithm
Fuel Price (Rs./h)	122,252.265	122,602.37	121,881.81	122,035.7946	121,915.93	121,704.7391	122,430.74	122,581.85	122,678.91	**121,658.6656**
Required Power in Demand (MW)	10,500	10,500	10,500	10,500	10,500	10,500	10,500	10,500	10,500	10,500
G1	114	109.0947	111.3177	111.9858	110.97	113.9891	107.6544	114	109.7268	112.3525188
G2	114	112.0471	112.7551	110.5273	110.88	113.6334	109.2161	111.6651	111.7342	112.4688984
G3	120	115.4584	118.6377	98.5560	98.17	97.5500	94.7874	119.9876	119.2197	97.49149956
G4	182.222	179.8333	183.3649	182.9622	178.85	180.0059	182.3441	188.2606	181.6041	179.7415579
G5	97	46.1649	91.8097	87.7254	87.78	97	86.9731	96.9763	89.8836	93.71705917
G6	140	83.1571	104.3697	139.9933	140	140	109.1907	139.9488	125.1816	139.99945
G7	300	261.6345	297.6533	259.6628	260.37	300	259.4910	264.0949	265.0775	260.4361978
G8	299.021	292.4025	289.4349	297.7912	286.83	300	284.1803	299.9814	290.2216	289.743
G9	300	284.7149	298.4044	284.8459	285.14	284.5797	285.1526	284.9042	285.2586	296.0535
G10	130	132.9049	129.35	130	204.86	130.0517	129.3500	130.0908	134.9231	130.0189
G11	94	101.6726	241.9702	94.6741	165.98	243.7131	317.4787	94.0011	167.9983	168.7887
G12	94	319.8174	166.9113	94.3734	167.75	169.0104	157.3563	94	183.6314	168.7212
G13	125	215.0746	214.849	214.7369	214.31	125	300.6095	125.1028	219.5396	125.0003
G14	304.485	394.9259	215.669	394.1370	305.65	393.9662	305.0848	394.2529	394.9259	394.2872
G15	394.607	398.1829	305.69	483.1816	393.66	304.7586	395.3099	484.1262	212.7154	304.5919405
G16	305.323	304.1546	394.6479	304.5381	394.60	304.5120	203.9544	304.5950	484.5572	394.3118
G17	490.272	490.0842	494.7618	489.2139	489.22	489.6024	489.6721	490.8265	494.3478	489.2914608
G18	500	493.2515	493.1559	489.6154	489.25	489.6087	492.3490	489.3438	491.2367	489.881
G19	511.404	511.4229	512.7416	511.1782	511.23	511.7903	514.3882	51.3775	514.3755	511.2385
G20	512.174	511.9422	520.8929	511.7336	510.69	511.2624	511.7323	512.1395	514.3755	511.2866
G21	550	532.3762	526.1137	523.4072	524.74	523.3274	532.2046	523.6621	522.6016	523.3004
G22	523.655	532.2484	532.1443	523.4599	525.52	523.2196	527.3193	523.3534	523.6988	523.2929
G23	534.661	530.7732	536.8421	523.4756	522.98	523.4707	527.3193	524.9677	523.6988	523.3215
G24	550	526.1112	524.4669	523.7032	522.22	523.0661	539.9336	524.2850	536.1385	523.2599
G25	525.057	524.4545	525.2461	523.7854	523.26	523.3978	526.6306	522.9279	523.5451	523.3046
G26	549.155	523.4934	529.3289	523.2757	523.32	523.2897	524.8658	523.2298	524.0780	523.2675
G27	10	11.5028	9.95	10	10	10.0208	9.95	10	14.8568	10.00489
G28	10	9.9541	9.95	10.6251	10	10.0927	9.95	10.0047	21.0962	10
G29	10	10.3272	9.95	10.0727	10	10.0621	9.95	10	13.1286	10.00001
G30	97	91.6019	88.4106	51.3321	88.86	88.9456	90.3385	97	88.5089	92.73674
G31	190	188.8475	188.9088	189.8048	162.30	189.9951	159.6875	190	188.0180	189.9981
G32	190	165.2531	188.8126	189.7386	177.94	190	188.9923	189.9503	166.2968	190
G33	190	188.9197	186.9624	189.9122	160.18	190	173.1974	190	182.0808	190
G34	200	189.2968	195.0897	199.3258	166.54	165.9825	189.6808	169.8860	164.9636	195.8292
G35	200	180.4605	171.5047	199.3065	164.80	172.4153	192.1671	199.8549	172.6948	200
G36	200	184.2698	176.1085	192.8977	170.68	191.2978	157.5027	199.9896	191.0765	200
G37	110	89.6748	89.5297	110	108.17	109.9893	104.4095	109.9712	108.8942	89.89076
G38	110	90.1485	89.3589	109.8628	100.68	109.9521	86.74132	109.9977	100.8804	91.73751
G39	110	57.0464	109.3222	92.8751	109.34	109.8733	100.2970	109.9871	27.8744	109.9905
G40	512.964	514.3622	512.5412	511.6883	511.28	511.5671	512.43873	511.2250	511.7717	511.2371
Loss in Power, P_{Loss} (MW)	NR	NR	NR	NR	NR	NR	NR	NR	NR	0

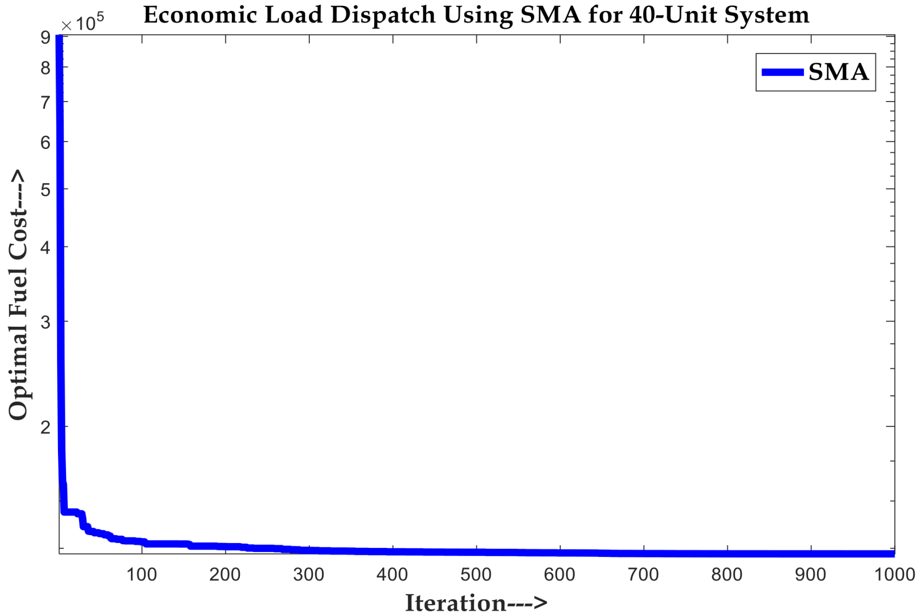


Figure 12. Convergence curve of slime mould algorithm for economic load dispatch for large-scale power systems (40-generating unit system) with valve-point loading effect.

It can be observed that the SMA technique reported minimum fuel cost when compared with other methods. Thus, the proposed SMA method presented an excellent performance compared to the competition. As per the condition considered in solving the ED problem, it has been proven that the SMA technique was best suited for all cases and situations in this paper.

In order to intuitively analyze the location and fitness changes of the slime mould during foraging, the qualitative analysis findings of SMA in lowering the fuel cost in economic load dispatch are provided in Figures 7–12. During the iteration phase, the convergence curve reveals the ideal fitness value in the slime mould. The convergence curve shows how the average fitness of the slime mould's ideal fitness value changes over time. We can see the slime mould's convergence rate and the moment when it transitions between exploration and exploration gradation by looking at the decline of the curve.

On an Intel Core i3, 7th Gen, with 8GB RAM, the suggested SMA method was tested. The capacity of the search agents to get closer to the origin determines the search procedure for the best position. During the search process by various agents, there is a chance of being entrapped far or near, which is characterized in terms of exploration and exploitation. The suggested algorithm's stochastic nature was justified and studied by running it for 30 maximum runs and 500 iterations. The approach was tested on typical benchmark functions, and it was shown that it increases the rate of convergence and has a high capacity to escape from local minima. The convergence rate was higher than that of other globally certified systems, and the system outperformed them. A comparison of SMA and other approaches is shown in Figure 13, and it was observed that the convergence curves of unimodal benchmark functions show that the proposed approach reaches the optimal state substantially sooner.

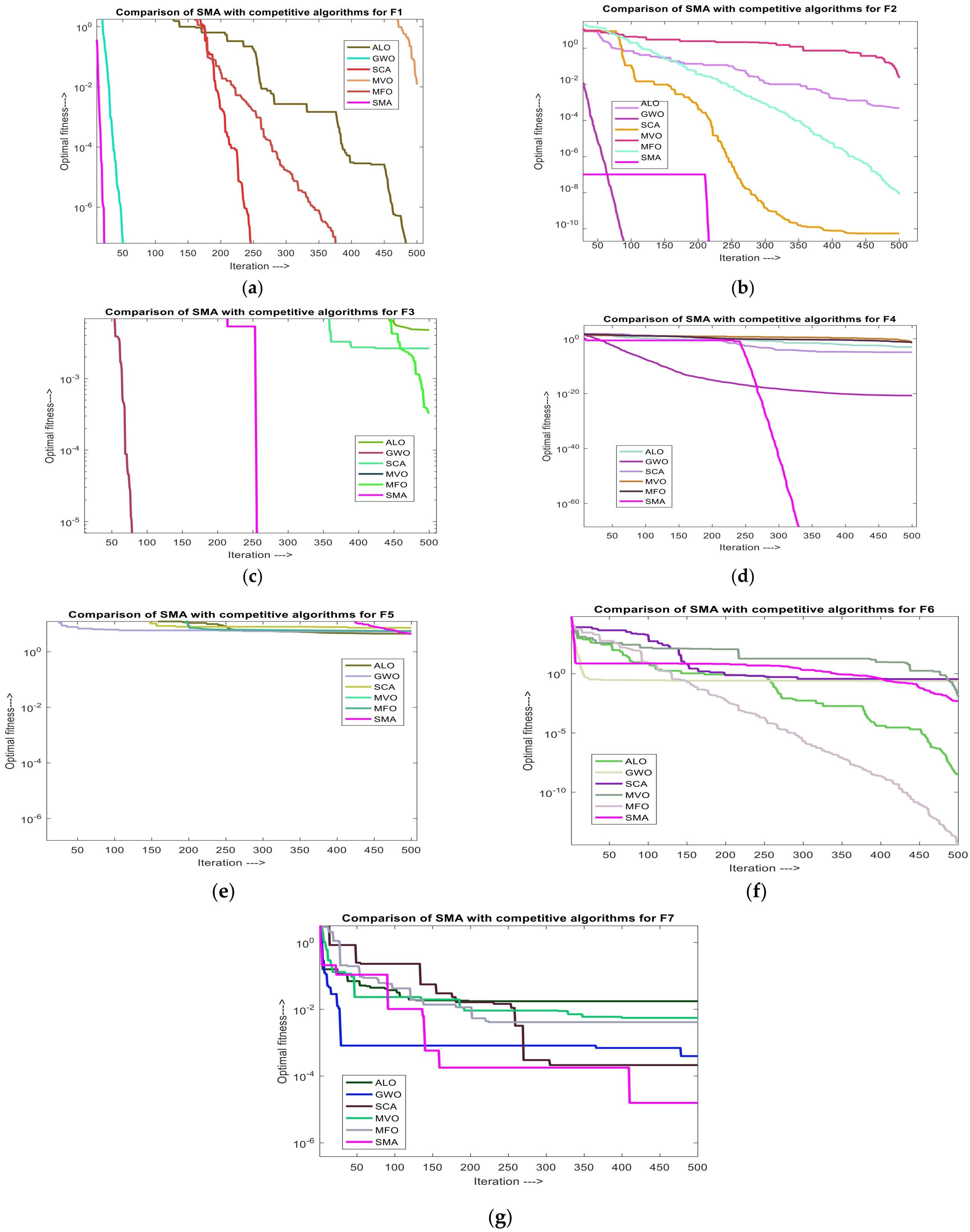


Figure 13. Convergence curve for unimodal functions showing comparison of slime mouldalgorithm) with other existing algorithms, (**a**) Convergence curve for F1 function, (**b**) Convergence curve for F2 function, (**c**) Convergence curve for F3 function, (**d**) Convergence curve for F4 function, (**e**) Convergence curve for F5 function, (**f**) Convergence curve for F6 function, (**g**) Convergence curve for F7 function.

7. Conclusions

The slime mould optimization technique was utilized in this paper to tackle economic load dispatch problems in electric power networks. The proficiency of this method was studied on standard IEEE bus systems of 3-, 5-, 6-, 10-, 13-, 15-, 20-, 38-, and 40-generating unit systems under small-, medium-, and large-sized power systems. According to the data, the slime mould optimizer is obviously best appropriate to handle economic load dispatch problems due to its lower fuel costs and minimal transmission loss. Its convergence rate was greater than that of other well-known optimizers. The slime mould optimizer achieves maximum avoidance in the local optimum by striking a balance between exploration and exploitation. As a result, this algorithm delivers better solutions for economic load dispatch issues. It has the potential to be utilized in the future to solve economic load dispatch problems in multiple areas and in a variety of sectors.

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Abbreviations

$\boldsymbol{P^g}$ = Generating units' output power; $\boldsymbol{P_n^g}$ = the active power of the nth generator; $\boldsymbol{ng}$ = number of generators in total; $\boldsymbol{a_n}$, $\boldsymbol{b_n}$, $\boldsymbol{c_n}$ are the fuel coefficients for power producing units; $\boldsymbol{fc(P^g)}$ = the total cost of fuel for all power plants; $\boldsymbol{P^d}$, $\boldsymbol{P^l}$ are total power demand and system power loss; $\boldsymbol{dr_n}$, $\boldsymbol{ur_n}$ are the lower and upper ranges of nth generator unit ramp rate limitations; $\boldsymbol{B_{i0}}$, $\boldsymbol{B_{00}}$ are the loss coefficient matrices; $\boldsymbol{P_n^{g_0}}$ is the current active power of the nth generation unit.

Appendix A

Table A1. Data for the 3-unit generator test system.

Total Units	P_{min} (MW)	c ($/h)	b ($/MWh)	a ($/(MW)^{2}h)	P_{max} (MW)
1	10	200	7.00	0.008	85
2	10	180	6.3	0.009	80
3	10	140	6.8	0.007	70

Matrix of Transmission loss coefficient for three-unit system:

$$B_0 = \begin{bmatrix} 0.0003 & 0.0031 & 0.0015 \end{bmatrix}; B_{00} = [0.00030523]; B = 10^{-3}\begin{bmatrix} 0.0218 & 0.0093 & 0.0028 \\ 0.0093 & 0.0228 & 0.0017 \\ 0.0028 & 0.0017 & 0.0179 \end{bmatrix}$$

Table A2. Data for the 3-unit generator test system.

Total Units	P_{min} (MW)	c ($/h)	b ($/MWh)	a ($/(MW)^{2}h)	P_{max} (MW)
1	10	200	7.02	0.00816	85
2	10	180	6.35	0.00900	80
3	10	140	6.97	0.00782	70

Matrix of Transmission loss coefficient for 3-unit system:

$$B_0 = \begin{bmatrix} 0.0003 & 0.0031 & 0.0015 \end{bmatrix}; B_{00} = [0.00030523]; B = 10^{-3}\begin{bmatrix} 0.0218 & 0.0093 & 0.0028 \\ 0.0093 & 0.0228 & 0.0017 \\ 0.0028 & 0.0017 & 0.0179 \end{bmatrix}$$

Table A3. Data for the 3-unit generator test system.

Total Units	P_{min} (MW)	c ($/h)	b ($/MWh)	a ($/(MW)^{2}h)	P_{max} (MW)
1	10	200	7.02	0.00816	85
2	10	180	6.35	0.00900	80
3	10	140	6.97	0.00782	70

Matrix of Transmission loss coefficient for 3-unit system:

$$B_0 = \begin{bmatrix} 0.0003 & 0.0031 & 0.0015 \end{bmatrix}; B_{00} = [0.00030523]; B = 10^{-3}\begin{bmatrix} 0.0218 & 0.0093 & 0.0028 \\ 0.0093 & 0.0228 & 0.0017 \\ 0.0028 & 0.0017 & 0.0179 \end{bmatrix}$$

Table A4. Data for the 3-unit generator test system.

Total Units	P_{min} (MW)	c ($/h)	b ($/MWh)	a ($/(MW)^{2}h)	P_{max} (MW)
1	50	328.13	8.663	0.00525	250
2	5	136.91	10.04	0.00609	150
3	15	59.16	9.76	0.00592	100

Matrix of Transmission loss coefficient for 3-unit system:

$$B_0 = \begin{bmatrix} 0 & 0 & 0 \end{bmatrix}; B_{00} = [0]; B = \begin{bmatrix} 0.000136 & 0.0000175 & 0.000184 \\ 0.000175 & 0.0001540 & 0.000283 \\ 0.000184 & 0.0002830 & 0.001610 \end{bmatrix}$$

Table A5. Data for the 6-unit generator test system.

Total Units	P_{min} (MW)	c ($/h)	b ($/MWh)	a ($/(MW)^{2}h)	P_{max} (MW)
1	100	240	7.0	0.0070	500
2	50	200	10.0	0.0095	200
3	80	220	8.5	0.0090	300
4	50	200	11.0	0.0090	150
5	50	220	10.5	0.0080	200
6	50	190	12.0	0.0075	120

Table A6. Data for the 6-unit generator test system.

Total Units	P_{min} (MW)	c ($/h)	b ($/MWh)	a ($/(MW)^{2}h)	P_{max} (MW)
1	10	756.79886	38.53973	0.15240	125
2	10	451.32513	46.15916	0.10587	150
3	35	1049.9977	40.39655	0.02803	225
4	35	1243.5311	38.30553	0.03546	210
5	130	1658.5596	36.32782	0.02111	325
6	125	1356.6592	38.27041	0.01799	315

Matrix of Transmission loss coefficient for 6-unit system:

$$B_0 = \begin{bmatrix} 0 & 0 & 0 \end{bmatrix}; B_{00} = [0]; B = \begin{bmatrix} 0.000140 & 0.000017 & 0.000015 & 0.000019 & 0.000026 & 0.000022 \\ 0.000017 & 0.000060 & 0.000013 & 0.000016 & 0.000015 & 0.000020 \\ 0.000015 & 0.000013 & 0.000065 & 0.000017 & 0.000024 & 0.000019 \\ 0.000019 & 0.000016 & 0.000017 & 0.000071 & 0.000030 & 0.000025 \\ 0.000026 & 0.000015 & 0.000024 & 0.000030 & 0.000069 & 0.000032 \\ 0.000022 & 0.000020 & 0.000019 & 0.000025 & 0.000032 & 0.000085 \end{bmatrix}$$

Table A7. Data for the 3-unit generator test system.

Total Units	P_{min} (MW)	e (1/MW)	d ($/h)	c ($/hr)	b ($/MWh)	a ($/(MW)^{2}h)	P_{max} (MW)
1	100	0.0315	300	561	7.92	0.001562	600
2	100	0.042	200	310	7.85	0.00194	400
3	50	0.063	150	78	7.97	0.00482	200

Table A8. Data for the 5-unit generator test system.

Total Units	P_{min} (MW)	e (1/MW)	d ($/h)	c ($/hr)	b ($/MWh)	a ($/(MW)^{2}h)	P_{max} (MW)
1	50	0.035	200.0	40.0	1.8	0.0015	300
2	20	0.040	140.0	60.0	1.8	0.0035	125
3	30	0.038	160.0	100.0	2.1	0.0012	175
4	10	0.042	100.0	25.0	2.0	0.0080	75
5	40	0.037	180.0	120.0	2.0	0.0010	250

Matrix of Transmission loss coefficient for 15-unit system:

$$B_{00} = [0.0055]; B = 10^{-3}\begin{bmatrix} 1.4 & 1.2 & 0.7 & -0.1 & -0.3 & -0.1 & -0.1 & -0.1 & -0.3 & -0.5 & -0.3 & -0.2 & 0.4 & 0.3 & -0.1 \\ 1.2 & 1.5 & 1.3 & 0.0 & -0.5 & -0.2 & 0.0 & 0.1 & -0.2 & -0.4 & -0.4 & 0.0 & 0.4 & 1.0 & -0.2 \\ 0.7 & 1.3 & 7.6 & -0.1 & -1.3 & -0.9 & -0.1 & 0.0 & -0.8 & -1.2 & -1.7 & 0.0 & -2.6 & 11.1 & -2.8 \\ -0.1 & 0.0 & -0.1 & 3.4 & -0.7 & -0.4 & 1.1 & 5.0 & 2.9 & 3.2 & -1.1 & 0.0 & 0.1 & 0.1 & -2.6 \\ -0.3 & -0.5 & -1.3 & -0.7 & 9.0 & 1.4 & -0.3 & -1.2 & -1.0 & -1.3 & 0.7 & -0.2 & -0.2 & -2.4 & -0.3 \\ -0.1 & -0.2 & -0.9 & -0.4 & 1.4 & 1.6 & 0.0 & -0.6 & -0.5 & -0.8 & 1.1 & -0.1 & -0.2 & -1.7 & 0.3 \\ -0.1 & 0.0 & -0.1 & 1.1 & -0.3 & 0.0 & 1.5 & 1.7 & 1.5 & 0.9 & -0.5 & 0.7 & 0.0 & -0.2 & -0.8 \\ -0.1 & 0.1 & 0.0 & 5.0 & -1.2 & -0.6 & 1.7 & 16.8 & 8.2 & 7.9 & -2.3 & -3.6 & 0.0 & 0.5 & -7.8 \\ -0.3 & -0.2 & -0.8 & 2.9 & -1.0 & -0.5 & 1.5 & 8.2 & 12.9 & 11.6 & -2.1 & -2.5 & 0.7 & -1.2 & -7.2 \\ -0.5 & -0.4 & -1.2 & 3.2 & -1.3 & -0.8 & 0.9 & 7.9 & 11.6 & 20.0 & -2.7 & -3.4 & 0.9 & -1.1 & -8.8 \\ -0.3 & -0.4 & -1.7 & -1.1 & 0.1 & 1.1 & -0.5 & -2.3 & -2.1 & -2.7 & 14.0 & 0.1 & 0.4 & -3.8 & 16.8 \\ -0.2 & 0.0 & 0.0 & 0.0 & -0.2 & -0.1 & 0.7 & -3.6 & -2.5 & -3.4 & 0.1 & 5.4 & -0.1 & -0.4 & 2.8 \\ 0.4 & 0.4 & -2.6 & 0.1 & -0.2 & -0.2 & 0.0 & 0.0 & 0.7 & 0.9 & 0.4 & -0.1 & 10.3 & -10.1 & 2.8 \\ 0.3 & 1.0 & 11.1 & 0.1 & -2.4 & -1.7 & -0.2 & 0.5 & -1.2 & -1.1 & -3.8 & -0.4 & -10.1 & 57.8 & -9.4 \\ -0.1 & -0.2 & -2.8 & -2.6 & -0.3 & 0.3 & -0.8 & -7.8 & -7.2 & -8.8 & 16.8 & 2.8 & 2.8 & -9.4 & 128.3 \end{bmatrix}$$

$$B_0 = 10^{-3}\begin{bmatrix} -0.1 & -0.2 & 2.8 & -0.1 & 0.1 & -0.3 & -0.2 & -0.2 & 0.6 & 3.9 & -1.7 & 0.0 & -3.2 & 6.7 & -6.4 \end{bmatrix}$$

Table A9. Data for the 15-unit generator test system.

Total Units	P_{min} (MW)	c ($/h)	b ($/MWh)	a ($/(MW)^{2}h)	P_{max} (MW)
1	150	671	10.1	0.000299	455
2	150	574	10.2	0.000183	455
3	20	374	8.8	0.001126	130
4	20	374	8.8	0.001126	130
5	150	461	10.4	0.000205	470
6	135	630	10.1	0.000301	460
7	135	548	9.8	0.000364	465
8	60	227	11.2	0.000338	300
9	25	173	11.2	0.000807	162
10	25	175	10.7	0.001203	160
11	20	186	10.2	0.003586	80
12	20	230	9.9	0.005513	80
13	25	225	13.1	0.000371	85
14	15	309	12.1	0.001929	55
15	15	323	12.4	0.004447	55

Matrix of Transmission loss coefficient for 20-unit system:

$$B = 10^{-3}\begin{bmatrix}
8.70 & 0.43 & -4.61 & 0.36 & 0.32 & -0.66 & 0.96 & -1.60 & 0.80 & -0.10 & 3.60 & 0.64 & 0.79 & 2.10 & 1.70 & 0.80 & -3.20 & 0.70 & 0.48 & -0.70 \\
0.43 & 8.30 & -0.97 & 0.22 & 0.75 & -0.28 & 5.04 & 1.70 & 0.54 & 7.20 & -0.28 & 0.98 & -0.46 & 1.30 & 0.80 & -0.20 & 0.52 & -1.70 & 0.80 & 0.20 \\
-4.61 & -0.97 & 9.00 & -2.00 & 0.63 & 3.00 & 1.70 & -4.30 & 3.10 & -2.00 & 0.70 & -0.77 & 0.93 & 4.60 & -0.30 & 4.20 & 0.38 & 0.70 & -2.00 & 3.60 \\
0.36 & 0.22 & -2.00 & 5.30 & 0.47 & 2.62 & -1.96 & 2.10 & 0.67 & 1.80 & -0.45 & 0.92 & 2.40 & 7.60 & -0.20 & 0.70 & -1.00 & 0.86 & 1.60 & 0.87 \\
0.32 & 0.75 & 0.63 & 0.47 & 8.60 & -0.80 & 0.37 & 0.72 & -0.90 & 0.69 & 1.80 & 4.30 & -2.80 & -0.70 & 2.30 & 3.60 & 0.80 & 0.20 & -3.00 & 0.50 \\
-0.66 & -0.28 & 3.00 & 2.62 & -0.80 & 11.8 & -4.90 & 0.30 & 3.00 & -3.00 & 0.40 & 0.78 & 6.40 & 2.60 & -0.20 & 2.10 & -0.40 & 2.30 & 1.60 & -2.10 \\
0.96 & 5.04 & 1.70 & -1.96 & 0.37 & -4.90 & 8.24 & -0.90 & 5.90 & -0.60 & 8.50 & -0.83 & 7.20 & 4.80 & -0.90 & -0.10 & 1.30 & 0.76 & 1.90 & 1.30 \\
-1.60 & 1.70 & -4.30 & 2.10 & 0.72 & 0.30 & -0.90 & 1.20 & -0.96 & 0.56 & 1.60 & 0.80 & -0.40 & 0.23 & 0.75 & -0.56 & 0.80 & -0.30 & 5.30 & 0.80 \\
0.80 & 0.54 & 3.10 & 0.67 & -0.90 & 3.00 & 5.90 & -0.96 & 0.93 & -0.30 & 6.50 & 2.30 & 2.60 & 0.58 & -0.10 & 0.23 & -0.30 & 1.50 & 0.74 & 0.70 \\
-0.10 & 7.20 & -2.00 & 1.80 & 0.69 & -3.00 & -0.60 & 0.56 & -0.30 & 0.99 & -6.60 & 3.90 & 2.30 & -0.30 & 2.80 & -0.80 & 0.38 & 1.90 & 0.47 & -0.26 \\
3.60 & -0.28 & 0.70 & -0.45 & 1.80 & 0.40 & 8.50 & 1.60 & 6.50 & -6.60 & 10.7 & 5.30 & -0.60 & 0.70 & 1.90 & -2.60 & 0.93 & -0.60 & 3.80 & -1.50 \\
0.64 & 0.98 & -0.77 & 0.92 & 4.30 & 0.78 & -0.83 & 0.80 & 2.30 & 3.90 & 5.30 & 8.00 & 0.90 & 2.10 & -0.70 & 5.70 & 5.40 & 1.50 & 0.70 & 0.10 \\
0.79 & -0.46 & 0.93 & 2.40 & -2.80 & 6.40 & 7.20 & -0.40 & 2.60 & 2.30 & -0.60 & 0.90 & 11.0 & 0.87 & -1.00 & 3.60 & 0.46 & -0.90 & 0.60 & 1.50 \\
2.10 & 1.30 & 4.60 & 7.60 & -0.70 & 2.60 & 4.80 & 0.23 & 0.58 & -0.30 & 0.70 & 2.10 & 0.87 & 3.80 & 0.50 & -0.70 & 1.90 & 2.30 & -0.97 & 0.90 \\
1.70 & 0.80 & -0.30 & -0.20 & 2.30 & -0.20 & -0.90 & 0.75 & -0.10 & 2.80 & 1.90 & -0.70 & -1.00 & 0.50 & 11.0 & 1.90 & -0.80 & 2.60 & 2.30 & -0.10 \\
0.80 & -0.20 & 4.20 & 0.70 & 3.60 & 2.10 & -0.10 & -0.56 & 0.23 & -0.80 & -2.60 & 5.70 & 3.60 & -0.70 & 1.90 & 10.8 & 2.50 & -1.80 & 0.90 & -2.60 \\
-3.20 & 0.52 & 0.38 & -1.00 & 0.80 & -0.40 & 1.30 & 0.80 & -0.30 & 0.38 & 0.93 & 5.40 & 0.46 & 1.90 & -0.80 & 2.50 & 8.70 & 4.20 & -0.30 & 0.68 \\
0.70 & -1.70 & 0.70 & 0.86 & 0.20 & 2.30 & 0.76 & -0.30 & 1.50 & 1.90 & -0.60 & 1.50 & -0.90 & 2.30 & 2.60 & -1.80 & 4.20 & 2.20 & 0.16 & -0.30 \\
0.48 & 0.80 & -2.00 & 1.60 & -3.00 & 1.60 & 1.90 & 5.30 & 0.74 & 0.47 & 3.80 & 0.70 & 0.60 & -0.97 & 2.30 & 0.90 & -0.30 & 0.16 & 7.60 & 0.69 \\
-0.70 & 0.20 & 3.60 & 0.87 & 0.50 & -2.10 & 1.30 & 0.80 & 0.70 & -0.26 & -1.50 & 0.10 & 1.50 & 0.90 & -0.10 & -2.60 & 0.68 & -0.30 & 0.69 & 7.00
\end{bmatrix}$$

$$B_0 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix},\ B_{00} = 0$$

Table A10. Data for the 20-unit generator test system.

Total Units	P_{min} (MW)	c (\$/h)	b (\$/MWh)	a (\$/(MW)^{2}h)	P_{max}(MW)
1	150	1000	18.19	0.00068	600
2	50	970	19.26	0.00071	200
3	50	600	19.80	0.00650	200
4	50	700	19.10	0.00500	200
5	50	420	18.10	0.00738	160
6	20	360	19.26	0.00612	100
7	25	490	17.14	0.00790	125
8	50	660	18.92	0.00813	150
9	50	765	18.27	0.00522	200
10	30	770	18.92	0.00573	150
11	100	800	16.69	0.00480	300
12	150	970	16.76	0.00310	500
13	40	900	17.36	0.00850	160
14	20	700	18.70	0.00511	130
15	25	450	18.70	0.00398	185
16	20	370	14.26	0.07120	80
17	30	480	19.14	0.00890	85
18	30	680	18.92	0.00713	120
19	40	700	18.47	0.00622	120
20	30	850	19.79	0.00773	100

Table A11. Data for the 10-unit generator test system.

Total Units	P_{min} (MW)	e (1/MW)	d ($/h)	c ($/hr)	b ($/MWh)	a ($/(MW)^{2}h)	P_{max} (MW)
1	10	0.0174	33	1000.403	40.5407	0.12951	55
2	20	0.0178	25	950.606	39.5804	0.10908	80
3	47	0.0162	32	900.705	36.5104	0.12511	120
4	20	0.0168	30	800.705	39.5104	0.12111	130
5	50	0.0148	30	756.799	38.539	0.15247	160
6	70	0.0163	20	451.325	46.1592	0.10587	240
7	60	0.0152	20	1243.531	38.3055	0.03546	300
8	70	0.0128	30	1049.998	40.3965	0.02803	340
9	135	0.0136	60	1658.569	36.3278	0.02111	470
10	150	0.0141	40	1356.659	38.2704	0.01799	470

Table A12. Data for the 13-unit generator test system.

Total Units	P_{min} (MW)	e (1/MW)	d ($/h)	c ($/hr)	b ($/MWh)	a ($/(MW)^{2}h)	P_{max} (MW)
1	0	0.035	300	550	8.10	0.00028	680
2	0	0.042	200	309	8.10	0.00056	360
3	0	0.042	200	307	8.10	0.00056	360
4	60	0.063	150	240	7.74	0.00324	180
5	60	0.063	150	240	7.74	0.00324	180
6	60	0.063	150	240	7.74	0.00324	180
7	60	0.063	150	240	7.74	0.00324	180
8	60	0.063	150	240	7.74	0.00324	180
9	60	0.063	150	240	7.74	0.00324	180
10	40	0.084	100	126	8.6	0.00284	120
11	40	0.084	100	126	8.6	0.00284	120
12	55	0.084	100	126	8.6	0.00284	120
13	55	0.084	100	126	8.6	0.00284	120

Table A13. Data for the 38-unit generator test system.

Total Units	P_{min} (MW)	c ($/h)	b ($/MWh)	a ($/(MW)^{2}h)	P_{max} (MW)
1	220	64,782	796.9	0.3133	550
2	220	64,782	796.9	0.3133	550
3	220	64,670	795.5	0.3127	550
4	220	64,670	795.5	0.3127	550
5	220	64,670	795.5	0.3127	550
6	220	64,670	795.5	0.3127	550
7	220	64,670	795.5	0.3127	550
8	220	64,670	795.5	0.3127	550
9	114	172,832	915.7	0.7075	500
10	114	172,832	915.7	0.7075	500
11	114	176,003	884.2	0.7515	500
12	114	173,028	884.2	0.7083	500
13	110	91,340	1250.1	0.4211	500
14	90	63,440	1298.6	0.5145	365
15	82	65,468	1298.6	0.5691	365
16	120	77,282	1290.8	0.5691	325
17	65	190,928	238.1	2.5881	315
18	65	285,372	1149.5	3.8734	315
19	65	271,676	1269.1	3.6842	315
20	120	39,197	696.1	0.4921	272
21	120	45,576	660.2	0.5728	272
22	110	28,770	803.2	0.3572	260
23	80	36,902	818.2	0.9415	190
24	10	105,510	33.5	52.123	150
25	60	22,233	805.4	1.1421	125
26	55	30,953	707.1	2.0275	110
27	35	17,044	833.6	3.0744	75
28	20	81,079	2188.7	16.765	70
29	20	124,767	1024.4	26.355	70
30	20	121,915	837.1	30.575	70
31	20	120,780	1305.2	25.098	70
32	20	104,441	716.6	33.722	60
33	25	83,224	1633.9	23.915	60
34	18	111,281	969.6	32.562	60
35	8	64,142	2625.8	18.360	60
36	25	103,519	1633.9	23.915	60
37	20	13,547	694.7	8.482	38
38	20	13,518	655.9	9.693	38

Table A14. Data for the 40-unit generator test system.

Total Units	P_{min} (MW)	e (1/MW)	d ($/h)	c ($/hr)	b ($/MWh)	a ($/(MW)^{2}h)	P_{max} (MW)
1	36	0.084	100	94.705	6.73	0.00690	114
2	36	0.084	100	94.705	6.73	0.00690	114
3	60	0.084	100	309.54	7.07	0.02028	120
4	80	0.063	150	369.03	8.18	0.00942	190
5	46	0.077	120	148.89	5.35	0.01140	97
6	68	0.084	100	222.33	8.05	0.01142	140
7	110	0.042	200	287.71	8.03	0.00357	300
8	135	0.042	200	391.98	6.99	0.00492	300
9	135	0.042	200	455.76	6.60	0.00573	300
10	130	0.042	200	722.82	12.9	0.00606	300
11	94	0.042	200	635.20	12.9	0.00515	375
12	94	0.042	200	654.69	12.8	0.00569	375
13	125	0.035	300	913.40	12.5	0.00421	500
14	125	0.035	300	1760.4	8.84	0.00752	500
15	125	0.035	300	1728.3	9.15	0.00708	500
16	125	0.035	300	1728.3	9.15	0.00708	500
17	220	0.035	300	647.85	7.97	0.00313	500
18	220	0.035	300	649.69	7.95	0.00313	500
19	242	0.035	300	647.83	7.97	0.00313	550
20	242	0.035	300	647.81	7.97	0.00313	550
21	254	0.035	300	785.96	6.63	0.00298	550
22	254	0.035	300	785.96	6.63	0.00298	550
23	254	0.035	300	794.53	6.66	0.00284	550
24	254	0.035	300	794.53	6.66	0.00284	550
25	254	0.035	300	801.32	7.10	0.00277	550
26	254	0.035	300	801.32	7.10	0.00277	550
27	10	0.077	120	1055.1	3.33	0.52124	150
28	10	0.077	120	1055.1	3.33	0.52124	150
29	10	0.077	120	1055.1	3.33	0.52124	150
30	47	0.077	120	148.89	5.35	0.01140	97
31	60	0.063	150	222.92	6.43	0.00160	190
32	60	0.063	150	222.92	6.43	0.00160	190
33	60	0.063	150	222.92	6.43	0.00160	190
34	90	0.042	200	107.87	8.95	0.0001	200
35	90	0.042	200	116.58	8.62	0.0001	200
36	90	0.042	200	116.58	8.62	0.0001	200
37	25	0.098	80	307.45	5.88	0.0161	110
38	25	0.098	80	307.45	5.88	0.0161	110
39	25	0.098	80	307.45	5.88	0.0161	110
40	242	0.035	300	647.83	7.97	0.00313	550

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