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Optimal Power Flow Control Variables using Slime Mould Algorithm for Generator Fuel Cost and Loss Minimization with Voltage Profile Enhancement Solution

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ABSTRACT

This paper presents a new nature-inspired metaheuristic technique namely Slime Mould Algorithm (SMA) which is inspired from the swarming behavior and morphology of slime mould in nature to solve a practical optimal power flow (OPF) problem. OPF is a highly non-linear complex optimization problem in the power system. SLM algorithm is used to determine the best values of control variables of which a selected objective function is minimized such as costs of conventional power generation minimization, active power loss reduction and improvement of the voltage profile. In the presented paper three case studies of IEEE 30-bus, IEEE 57-bus systems and large Algerian electrical test system DZ114 to show the effectiveness of this novel technique. The results of this research prove that SMA outperforms other techniques in terms of fuel cost minimization, reduction of active power losses and voltage deviation improvement.

Key words: Metaheuristic technique, optimal power flow, slime mould algorithm, power system.

1.INTRODUCTION

The optimal power flow (OPF) is currently considered as one of the most essential tools for inefficient planning and controlling the operation of power systems. The OPF is a well-studied problem of optimization in control systems. This problem has been introduced by Carpentier in 1962 [1]. In general, the OPF is a nonlinear problem that involves the procedure of determining the optimal values of the control variables of the system to minimize the objective function, subject to various equality and inequality constraints [2]. The optimal power flow has been formulated and successfully applied for several years to various objective functions related to the electrical power system, such as in [3]–[6]. In OPF optimization, the problem may have a single objective function or multi-objective function**.**

Several different mathematical techniques were developed and applied in the power system for solving the OPF problem. These optimization techniques can be divided into two groups; Classical (or conventional) optimization algorithms and modern optimization algorithms. Compared to classical algorithms, modern optimization algorithms converge rapidly into the optimal solution. The modern optimization algorithms may be classified into three classes, metaheuristic optimization algorithms (MAs), artificial-intelligence-based optimization algorithms (AI), and a hybrid of two or more modern optimization algorithms. In the power system, these modern algorithms have been developed and proposed to find the optimal solution of the OPF problem in small and large-scale systems, particularly nonlinear or non-convex complex optimization problems.

The metaheuristic term was introduced in 1986 by Glover [7]. The principle of the metaheuristic algorithms (MAs) is to minimize or maximize one or multi-objective functions to find the best solutions for difficult and complex optimization problems [8]. The MAs represent a major revolution in the field of optimization and are therefore widely used to solve the optimization problems related to the power system.MAs can be categorized into four main categories according to their nature-inspired or some of their characteristics such as evolution-based algorithms (EAs), physics-based algorithms (PAs), human-based algorithms (HAs) and swarm-based algorithms (SAs) [9]. Several metaheuristic algorithms are implemented in electrical power system for solving the OPF problem with different objective functions such as salp swarm optimizer [10], Moth Swarm Algorithm [11], differential evolution [12], moth-flame optimizer [13], glowworm swarm optimization [14], Sine-Cosine algorithm (SCA) [15], Differential search algorithm [16], stud krill herd algorithm [17], Artificial bee colony algorithm [18], Symbiotic organisms search algorithm [19], improved colliding bodies optimization algorithm [20], Firefly Algorithm [21], multi-verse optimizer [22]. Ant lion optimizer [23].

The present work aims to apply a new stochastic optimization technique, namely slime mould algorithm (SMA) to solve our problem and satisfy our imposed conditions. The SMA is based on mode of oscillation in nature and simulates the swarming behavior and morphology of slime mould in foraging. In this work, SMA algorithm has been used to solve the OPF problem for the IEEE 30-bus, IEEE 57-bus systems and large Algerian electrical power system DZ114 with different objective functions considered that have to be optimized, such as the total fuel cost(TFC), reduction of active power losses and improvement of the voltage deviation.

2.FORMULATION OF THE OPF PROBLEM

2.1 Formulation Problem

The OPF solution gives the optimal value of the control variables by minimizing an objective function while satisfying various equality and inequality constraints. Generally, the mathematical expression of the optimization problem may be represented as follows:

$$\text{Min} \quad F(x,u) \quad (1)$$

$$\text{Subjected to} \quad g(x,u)=0 \quad (2)$$

$$h(x,u)\le 0 \quad (3)$$

where x and u represent respectively the vectors of the state variables (dependent variables) and control variables(independent variables), $F(x,u)$ denotes the objective function or optimization goalto be optimized.

2.2Control variables

The control variables or independent variables should be adjusted to satisfy the load flow equations. The set of control variables in the OPF can be expressed by vector u as:

$$u=\left[P_{G_2}\dots P_{G_{NG}},V_{G_1}\dots V_{G_{NG}},Q_{C_1}\dots Q_{C_{NC}},T_1\dots T_{NT}\right] \quad (4)$$

where: P_G is the generator active power, V_G is the generator voltage, Q_{C1} is the reactive power injected by the shunts compensator, T is the tap setting of transformers, NG is the number of generators,NC is the number of shunts compensators units and NT is the number of regulating transformers.

2.3State variables

The set of variables which describe the electrical power state can be expressed by vector x as follows:

$$x=\left[P_{Gslack},Q_{G_1}\dots Q_{G_{NG}},V_{L_1}\dots V_{L_{NL}},S_{l_1}\dots S_{l_{nl}}\right] \quad (5)$$

where, P_{Gslack} is the active power output from the slack bus generator, Q_G is the reactive power produce by the generators, V_L is the voltage profile at the load busses and S_l is the apparent power flow, N_G is the total number of generators buses, N_L is the total number of load buses or PQ buses, and N_l is the total number of transmission lines.

2.4Constraints OPF

In OPF, constraints can be classified into equality and inequality constraints.

2.4.1 Equality constraints

The equality constraints reflect the power-system physics which represents the balanced power load flow equations. These constraints can be represented as follows:

$$P_{G_i}+P_{W_i}-P_{d_i}=V_i\sum_{j=1}^{N}V_j\left(g_{ij}\cos\delta_{ij}+z_{ij}\sin\delta_{ij}\right) \quad (6)$$

$$Q_{G_i}+Q_{W_i}-Q_{d_i}=V_i\sum_{j=1}^{N}V_j\left(g_{ij}\sin\delta_{ij}+z_{ij}\cos\delta_{ij}\right) \quad (7)$$

2.4.2 Inequality constraints

The inequality constraints reflect the limiting of the power system operation. These inequality constraints are as follows:

$$\begin{cases} P_{Gi}^{min}\le P_{Gi}\le P_{Gi}^{max} \\ Q_{Gi}^{min}\le Q_{Gi}\le Q_{Gi}^{max} \\ V_{Gi}^{min}\le V_{Gi}\le V_{Gi}^{max} \\ T_{NTi}^{min}\le T_{NTi}\le T_{NTi}^{max} \\ \left|S_{Li}\right|\le S_{Li}^{max} \end{cases} \quad (8)$$

3.SLIME MOULD ALGORITHM

A Slime Mould Algorithm (SMA) is a new technique nature-inspired proposed by Shimin Li *et. al* in 2020[24], this algorithm simulates the swarming behavior and morphology of slime mould in foraging, and is based on mode of oscillation in nature. One of the most interesting characteristic in the slime mould is the unique pattern based on the multiple food sources to create a venous network connecting them at the same time. This scheme gives the high capability of escaping from local optima solutions. The algorithm is aroused by slime mold diffusion and foraging behavior. Slime mould can approach food, depending on the smell in the air. In the SMA algorithm, the proposed mathematical model uses the adaptive weight to simulate the combination of positive and negative feedback from the bio-oscillator-based propagation wave that was inspired by slime mould to form the optimal pathway to connect food. The slime mold morphology varies, with three different forms of contraction [24]. Figure 1 shows the morphology of slime mould during foraging.

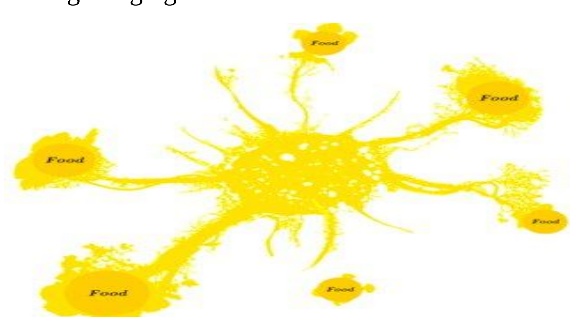

Figure 1: Foraging morphology of slime mould[24]

3.1 Approach food

The following formulas for imitating the contraction mode is proposed to model the behavior of slime mould to approaching food according to the odor in the air as a mathematical formula:

$$\overrightarrow{X(t+1)} = \begin{cases} \overrightarrow{X_b(t)} + \overrightarrow{vb}\left(\vec{W} * \overrightarrow{X_A(t)} - \overrightarrow{X_B(t)}\right), r < p \\ \overrightarrow{vc} * \overrightarrow{X(t)}, r \geq p \end{cases}$$

where $\vec{X}$denotes the slime mould location,$\overrightarrow{X_b}$is the individual emplacement with the highest odor concentration currently found, $\overrightarrow{X_A}$ and $\overrightarrow{X_B}$ are indicated two randomly selected individuals from the swarm,$\overrightarrow{vb}$is a parameter with distributed in the range of $[-a, a]$, $\overrightarrow{vc}$ decreases linearly from 1 to 0,t shows the current iteration and $\vec{W}$ represents the slime mould weight and given in the Eq (12). p is the parameter given by Eq.(10) as follows:

$$p = \tanh\left|S(i) - DF\right| \quad (10)$$

where$S(i)$ shows the fitness of $\vec{X}$, $i \in 1, 2, \ldots, n$, DF is the optimum fitness obtained in all iterations.
The parameter of a is given as follows:

$$a = \operatorname{arctanh}\left(-\left(\frac{t}{\max\_t}\right) + 1\right) \quad (11)$$

The expression of $\vec{W}$ define the location of slime mould and is given as follows:

$$\overrightarrow{W(SmellIndex(i))} = \begin{cases} 1 + r * \log\left(\frac{bF - S(i)}{bF - wF} + 1\right), condition \\ 1 - r * \log\left(\frac{bF - S(i)}{bF - wF} + 1\right), others \end{cases}$$

where $condition$ denotes that $S(i)$ is ranked first half of the population, r represents the random value distributed in the range of $[0,1]$, bF and wF are represent the optimal and worst fitness value obtained in the current iterative process, respectively, $SmellIndex$ represents the sequence of fitness values sorted as follows:

$$SmellIndex = Sort(S) \quad (13)$$

3.2Wrap food

This portion mathematically simulates the mode of contraction in the venous tissue structure of slime mould while searching. The higher the food concentration reached by the vein, the stronger the bio-oscillator-generated wave, the quicker the cytoplasm flows and the thicker the vein. The following mathematical formula represents updating the emplacement of slime mould:

$$\overrightarrow{X^*} = \begin{cases} rand * (ub - lb) + lb, rand < z \\ \overrightarrow{X_b(t)} + \overrightarrow{vb} * \left(W * \overrightarrow{X_A(t)} - \overrightarrow{X_B(t)}\right), r < p \\ \overrightarrow{vc} * \overrightarrow{X(t)}, r \geq p \end{cases} \quad (14)$$

wherelb and ub denote, respectively, the lower and upper boundaries of the search range, $rand$denote the random valuedistributed in the range(9)of in [0,1].

3.3 Grabble food

Slime mould depends primarily on the propagation wave to change the cytoplasmic flow in the veins, so that they appear to be in a better food concentration location. Slime mould can approach food more quickly food when the concentration and quality of food are high, while if the food concentration is lower, approach it more slowly, thus increasing the efficiency of slime mould in selecting the optimal source of food.

In the SMA process, the value of $\overrightarrow{vb}$parameter oscillates randomly in the interval between $[-a, a]$ and progressively approaches zero as the iterations increase. The value of $\overrightarrow{vc}$ oscillates randomly in the interval between [-1, 1] and finally tends to be zero. The flowchart of the implementation of the proposed algorithm for solving the OPF problem is shown in figure 2.

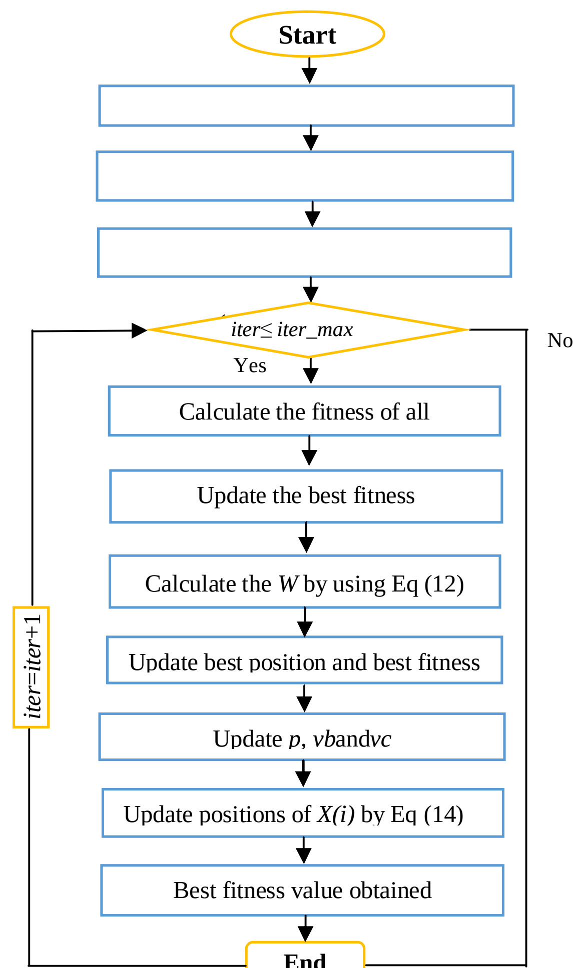

Figure 2: Flowchart of the SMA Algorithm

4.RESULTS AND DISCUSSIONS

The proposed SMA is implemented to solve the OPF problem for the IEEE 30-bus, IEEE 57-bus and Algerian 114-bus systems with different case studies are investigated. In this section, dissimilar objective functions have been considered to verify the efficiency and performance of the SMA according to the optimal adjustment of control variables. All the simulations cases are carried out by using MATLAB version 2009b, and computed with specification Intel® Core™ i5 CPU@1.80 GHz and 8Go RAM. In this work, the SMA population size and the number of iterations maximal are 40 and 500 respectively.

4.1 IEEE 30-bus power system

The first test is dedicated on the standard IEEE 30-bus power system. This system consists of 6 generators, 41 transmission lines of which 4 transformers with off-nominal taps ratio located on lines 6–9, 4–12, 9–12 and 27–28. In addition, nine reactive power sources were installed at buses 10, 12, 15, 17, 20, 21, 23, 24, and 29. The total load is (2.834 +j0.735) p.u. in this test system, the control variables transformers as present in Eq. (4).

Case 1: Minimization of generation fuel cost

In the first case, the quadratic equation of generation fuel cost of thermal generators is formulated as the objective function with satisfying all system constraints:

$$\boldsymbol{FC} = \Big(\sum_{i=1}^{N} \boldsymbol{a}_i + \boldsymbol{b}_i \boldsymbol{P}_{G_i} + \boldsymbol{c}_i \boldsymbol{P}_{G_i}^2\Big) + Penalty(\$/\text{h}) \quad (15)$$

whereFC denotes the fuel cost of the ith generator, P_{Gi} is the active power generated by the thermal generators, a_i, b_i and c_i are the cost coefficients of ith generator.

In this case, the proposed method is tested to find the optimal fuel cost according to the optimal power distribution of the production units.Table 2 summarizes the optimal settings values of control variables, optimum fuel cost, active power loss reduction and deviation voltage for SMA as well as those obtained by using the Grasshopper Optimization Algorithm (GOA). From this table, it can be seen that the power generated, the generator voltage, the ratios of the four transformers and the reactive power injected by the reactive power sources are all within their permissible limits. Furthermore, we can also see that the fuel cost and the active power losses obtained by using the SMA are to up 798.9709 $/h and 8.5752 MW respectively, and are better compared to those found by GOA algorithm. Also, the fuel cost obtained via SMA compared to some other methods available in the literature as show in Table 1.The results achieved show that SMA gives better value to minimize the fuel cost compared to some other methods that prove the effectiveness of the proposed algorithm.The convergence characteristics of the fuel cost with SMA and GOA over iterations are shown in figure 3. It can be seen that the SMA algorithm outperforms the GOA algorithm in terms of convergence rate towards the global optimum solution.

Table 1: Comparison of solutions for fuel cost minimization using SMA and different methods: Case 1.

Method		Fuel cost ($/h)	Method description
SMA		798.9709	Slime mould algorithm
GOA		799.1541	Grasshopper optimization algorithm
MFO	[13]	799.072	Moth-Flame Optimizer
GSO	[14]	799.06	Glowworm Swarm Optimization
MSCA	[15]	799.31	Modified Sine-Cosine algorithm
BHBO	[25]	799.921	Black-hole-based optimization
MSA	[11]	800.5099	Moth swarm algorithm

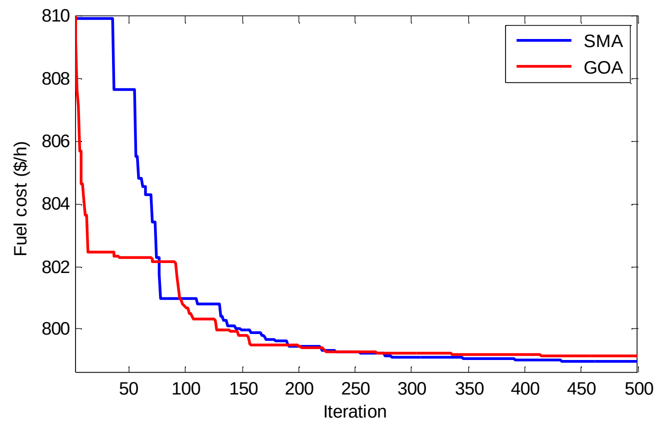

Figure 3: Convergence characteristics of fuel cost minimization via SMA and GOA for case 1

Case 2: Minimization of active power transmission losses.

In this study, the second case investigated consists of minimizing the active power losses, which is formulated as follows:

$$PL = \sum_{i=1}^{N} P_{loss_i} = \Big(\sum_{i=1}^{N} P_{G_i} - \sum_{i=1}^{N} P_{D_i}\Big) + Penalty(MW)$$

whereP_{loss} denotes the active power transmission losses, P_{Gi} is the active power generated by the thermal generators, P_D is the active power demand**.**

In this case, the SMA has been applied on the IEEE-30 bus system to minimize the active power losses (PL), and the results obtained are presented in Table 3 (case 2). For this table, it can be seen that the active power losses is reduced from 8.5752 MW to 2.8612 MW which is lowered by 33.36 %. Furthermore, the total fuel cost has increased from 798.9709 $/h to 967.0437 $/h (21.04 % of increase). In Table 2, the active power losses achieved via SMA are compared to other algorithms in the literature which made sense that SMA's results give best values compared to those found by GOA, MSA, FPA, MSCA and BHBO.

Table 2: Comparison of solutions for active power loss minimization using SMA and different methods: Case 2.

Method		Real power losses (MW)	Method description
SMA		2.8612	Slime mould algorithm
GOA		2.8761	Grasshopper optimization algorithm
MSA	[11]	3.1005	Moth swarm algorithm
FPA	[13]	3.115	Flower Pollination Algorithm
MSCA	[16]	2.9334	Modified moth swarm algorithm
BHBO	[25]	3.503	Black-Hole-BasedOptimization

Table 3: Comparative results of the OPF solution for three first cases via SMA and GOA (IEEE 30-bus system)

Control Variables	Limits		Case 1		Case 2		Case 3	
	Min	Max	SMA	GOA	SMA	GOA	SMA	GOA
$P_{G1}(MW)$	50	200	177.5784	176.9284	51.2614	51.2761	176.6000	175.8887
$P_{G2}(MW)$	20	80	48.6770	48.6125	80.0000	80.0000	48.7151	48.5933
$P_{G5}(MW)$	15	50	21.2668	21.2930	50.0000	50.0000	20.6913	21.3365
$P_{G8}(MW)$	10	35	21.2316	21.4706	34.9999	35.0000	24.0425	22.1339
$P_{G11}(MW)$	10	30	12.0890	11.7344	30.0000	30.0000	11.1974	13.2896
$P_{G13}(MW)$	12	40	12.0000	12.0000	40.0000	40.0000	12.0000	12.0132
$V_{G1}(p.u)$	0.95	1.1	1.1000	1.10000	1.1000	1.1000	1.0386	1.0360
$V_{G2}(p.u)$	0.9	1.1	1.0879	1.08731	1.0979	1.0977	1.0215	1.0211
$V_{G5}(p.u)$	0.9	1.1	1.0618	1.06018	1.0793	1.0806	1.0120	1.0096
$V_{G8}(p.u)$	0.9	1.1	1.0701	1.06820	1.0876	1.0874	1.0012	1.0078
$V_{G11}(p.u)$	0.9	1.1	1.1000	1.08632	1.1000	1.1000	1.0743	0.9994
$V_{G13}(p.u)$	0.9	1.1	1.1000	1.10000	1.1000	1.1000	0.9967	1.0039
$T_{11}(p.u)$	0.9	1.1	1.0259	1.02124	1.0331	0.9528	1.0922	0.9701
$T_{12}(p.u)$	0.9	1.1	0.9010	0.92514	0.9193	1.0650	0.9000	0.9637
$T_{15}(p.u)$	0.9	1.1	0.9803	1.03081	0.9870	1.0019	0.9533	0.9597
$T_{36}(p.u)$	0.9	1.1	0.9568	0.98510	0.9834	0.9989	0.9716	0.9748
Q_{C10}	0	5	4.3806	0.46076	1.0281	2.8301	1.1213	4.8940
Q_{C12}	0	5	4.7790	0.65000	0.2155	4.9053	0.1221	0.0000
Q_{C15}	0	5	4.8272	0.00973	4.7108	0.8276	5.0000	3.7480
Q_{C17}	0	5	4.9942	3.95461	2.4109	4.9996	2.8105	2.8491
Q_{C20}	0	5	2.5651	0.47622	4.9982	4.1987	5.0000	4.9998
Q_{C21}	0	5	2.8396	4.98415	4.9042	4.8385	4.9967	4.9998
Q_{C23}	0	5	3.4609	5.00000	0.3454	4.0771	4.9518	4.9996
Q_{C24}	0	5	4.9957	4.77304	4.9181	4.9993	4.5074	4.8556
Q_{C29}	0	5	1.1562	3.81110	2.8276	4.6776	3.3481	4.9913
Fuel cost ($/h)			798.9709	799.1541	967.0437	967.0793	803.6474	803.8743
Power losses (MW)			8.5752	8.6389	2.8612	2.8761	9.8464	9.8552
Voltage deviation (p.u.)			1.4494	1.5172	1.9139	1.8681	0.1045	0.1160

The convergence characteristics of the active power losses with SMA and GOA are shown in figure 4. This figure show that active power losses are reduced with a few numbers of iterations using SMA compared with the GOA.

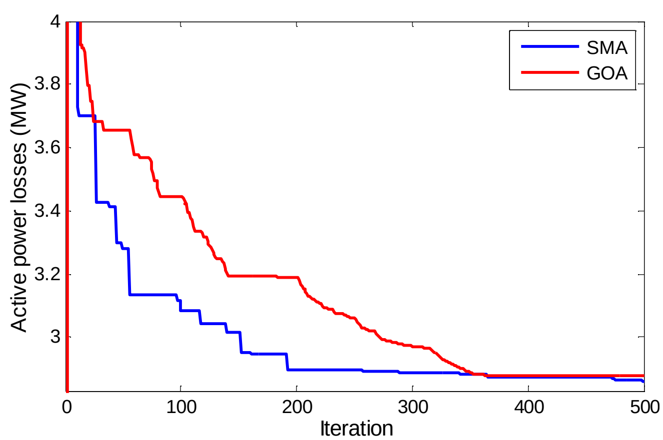

Figure 4: Convergence characteristics of active power loss minimization via SMA and GOA for case 2

Case 3: Voltage profile improvement

In the third case, the objective function is to improve the voltage profile by reducing the cumulative voltage deviation (TVD) of load buses (PQ) from the nominal value of 1.0 p.u.Bus voltage is known as the most significant and important safety and service quality indices [26].The expression of the cumulative VD is presented as follows:

$$TVD = \sum_{i=1}^{N} |V_i - 1.0| \qquad (17)$$

Thus, the objective function which represents the sum of the total fuel cost and improves the total TVD can be given as follows:

$$FCTVD = \left(\sum_{i=1}^{N} \boldsymbol{a}_i + \boldsymbol{b}_i \boldsymbol{P}_{G_i} + \boldsymbol{c}_i \boldsymbol{P}_{G_i}^2 \right) + \boldsymbol{w}_{VD} * \boldsymbol{TVD}$$

wherew_{VD} is a suitable weighting factor for balancing target function values and preventing the dominance of an objective over another. In this study w_{VD} is selected as 100.

For case 3 of minimizing the fuel cost and improve voltage profile, SMA and GOA algorithms lead to VD of 0.1045 p.u and 0.1160 p.u, respectively as shown in Table 2. Moreover, the comparison of voltage deviation achieved by SMA and different algorithms is shown in Table 4 which displays that the results achieved by SMA are better than GOA, MSA, MFO, PSO, FPA, and BHBO.

Table 4: Comparison of solutions for voltage deviation minimization using SMA and different methods: Case 3.

Method		TVD (p.u.)	Method description
SMA		0.1045	Slime mould algorithm
GOA		0.1160	Grasshopper optimization algorithm
MSA	[11]	0.1084	Moth swarm algorithm
MFO	[14]	0.1065	Moth-Flame Optimizer
PSO	[13]	0.1506	Particle Swarm Optimization
FPA	[13]	0.1845	Flower Pollination Algorithm
BHBO	[25]	0.1262	Black-Hole-BasedOptimization

The convergence characteristics of the voltage deviation with SMA and GOA over iterations are shown in figure 5. It allows us to notethat the algorithm SMA converges towards the optimum value at the iteration 250.

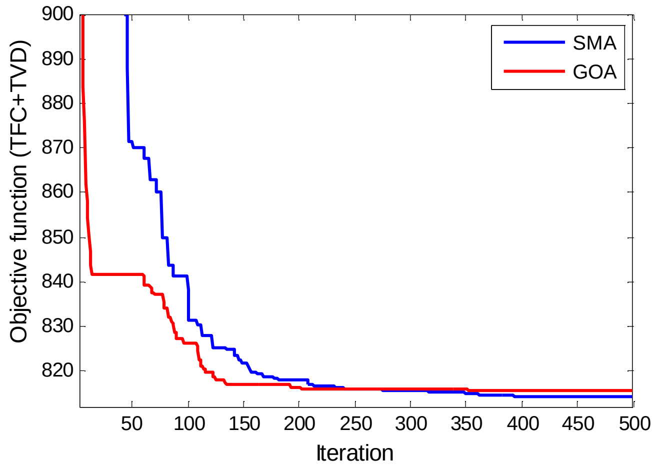

Figure 5: Convergence characteristics of voltage deviation minimization via SMA and GOA for case 3

4.2IEEE 57-bus power system

The second scenario is carried out on an IEEE-57 bus power system, involves the following characteristics, 7 generators at the buses 1, 2, 3, 6, 8, 9 and 13, 80 transmission lines, 15 transformer under off-nominal taps ratio and 3 reactive compensators are installed on buses 18, 25 and 53. The total load demand of this system is 1250.8 MW +j 336.4 MVar The system data and variable limits are given in ref [27].

Case 4: Minimization of generation fuel cost

In this case, the objective function is to optimize the total fuel cost in the IEEE-57 bus system and is described by Eq. (16). Table 6 lists the optimal values of control variables considering fuel cost by the proposed algorithm. From this results obtained, the best value of fuel cost and active power losses by the proposed method are 41612.2484 \$/h and 13.6737 MW respectively.

Table 5 show that the best fuel cost is obtained by SMA and to some different algorithms in literature. Therefore, the results show the ability of the proposed algorithm to reach the global optimum better for IEEE 57-bus system than the other algorithms previously reported in this table.

Table 5: Comparison of solutions for fuel cost minimization using SMA and different methods: case 4.

Method		Fuel cost (\$/h)	Method description
SMA		41612.2484	Slime mould algorithm
IHDE	[28]	41667.9900	Improved Hybrid Differential Evolution Algorithm
DSA	[16]	41686.8200	Differential search algorithm
MSA	[11]	41673.7231	Mothswarmalgorithm

The convergence characteristics of the fuel cost with SMA over iterations are shown in Figure 6. It can be seen that the SMA algorithm convergence rate towards the global optimum solution with few iteration.

Table 6: Comparative results of the OPF solution for cases four and five via SMA (IEEE 57-bus system)

Control Variables	Case 4 SMA	Case 5 SMA	Control Variables	Case 4 SMA	Case 5 SMA
P_{G1}	142.970	160.146	T_{24-25}	1.0378	1.0378
P_{G2}	85.4620	56.9513	T_{24-25}	0.9156	0.9156
P_{G3}	43.6867	122.634	T_{24-26}	1.0643	1.0643
P_{G6}	87.4800	94.2250	T_{7-29}	0.9756	0.9756
P_{G8}	461.251	315.843	T_{34-36}	0.9309	0.9309
P_{G9}	83.8414	99.9517	T_{11-41}	0.9162	0.9162
P_{G12}	360.611	409.995	T_{15-45}	0.9001	0.9001
V_{G1}	1.0927	1.0999	T_{14-46}	0.9000	0.9000
V_{G2}	1.0909	1.0982	T_{10-51}	0.9000	0.9000
V_{G3}	1.0857	1.0996	T_{13-49}	0.9000	0.9000
V_{G6}	1.0981	1.0985	T_{11-43}	0.9382	0.9382
V_{G8}	1.1000	1.0988	T_{40-56}	1.0619	1.0619
V_{G9}	1.0787	1.0831	T_{39-57}	1.0268	1.0268
V_{G12}	1.0822	1.0887	T_{9-55}	0.9681	0.9681
T_{4-18}	0.9398	0.9650	Q_{C18}	21.239	21.239
T_{4-18}	1.0495	0.9173	Q_{C25}	14.328	14.328
T_{21-20}	1.0508	0.9978	Q_{53}	15.444	15.444

	Case 4	Case 5
Fuel cost (\$/h)	41612.2484	43827.00
Power losses (MW)	13.6737	8.9471
Voltage deviation (p.u.)	6.2852	6.9302

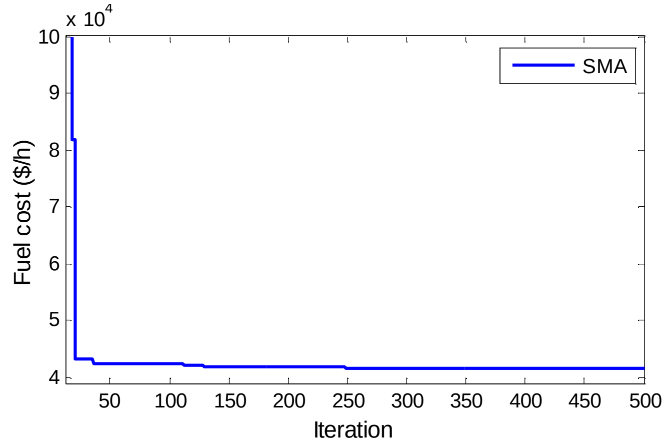

Figure 6: Convergence characteristics of fuel cost minimization via SMA for case 4

Case 5: Minimization of active power transmission losses.

This objective function of this case is to minimize the active power transmission losses for the IEEE 57-bus system. The simulation result obtained by SMA is presented in Table 6. The active power losses obtained by SMA is decreased from 13.6737 MW to 8.9471 MW which is lowered by 34.57 %. In Table 7, SMA can get less active PL than other methods reported in the literature.

Table 7: Comparison of solutions for active power loss minimization using SMA and different methods: case 5.

Method		Real power losses (MW)	Method description
SMA		8.9471	Slime mould algorithm
AMO	[29]	10.51031	Animal Migration Optimization
ABC	[30]	12.63	Artificial bee colony algorithm
IABC	[30]	11.16	Improved artificial bee colony
TSA	[31]	12.473	Tree-seedalgorithm

The convergence characteristics of the active power losses with SMA over iterations are shown in figure 7. This figure illustrates that active power losses are reduced with a few numbers of iterations using SMA.

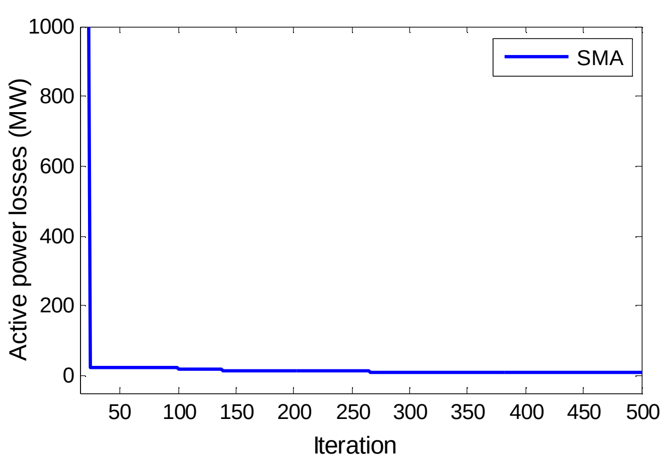

Figure 7: Convergence characteristics of active power loss minimization via SMA for case 5

4.3Algerian 114-bus power system

In this scenario aims to test proposed MSA on the large-scale power system Algerian 114-bus. This system consists of 15 generators, 175 transmission lines of which 16 transformers with off-nominal taps ratio are located from line 160 to line 175, and 99 load bus. The total load demand of this system is 3,727 MW +j 2070 MVar.

Case 6: Minimization of generation fuel cost

In the last case, the objective function is to optimize the total fuel cost given by Eq. (16).The values of fifteen generator cost coefficients are taken from Ref. [32]. To illustrate the performance and effectiveness of the SMA algorithm, results obtained by SMA are compared to GOA. The optimal value of control variables for the SMA and GOA of case 6 are given in Table 8. The total fuel cost and active power losses by the proposed method are 19170.205 $/h and 74.9442 MW respectively, these optimal solutions are better than GOA solution.

Table 8 : Comparative results of the OPF solution for case six via SMA and GOA (ALG 114-bus system)

Control Variables	Limits		Case 4	
	Min	Max	SMA	GOA
$P_{G4}(MW)$	135	1350	453.8747	448.1932
$P_{G5}(MW)$	135	1350	453.5975	447.9109
$P_{G11}(MW)$	10	100	100.0000	99.9885
$P_{G15}(MW)$	30	300	193.4539	212.7919
$P_{G17}(MW)$	135	1350	450.2094	448.1112
$P_{G19}(MW)$	34.5	345	197.3511	200.2757
$P_{G22}(MW)$	34.5	345	193.5089	193.6903
$P_{G52}(MW)$	34.5	345	191.6327	192.1776
$P_{G80}(MW)$	34.5	345	190.8255	188.3100
$P_{G83}(MW)$	30	300	188.2240	185.3476
$P_{G98}(MW)$	30	300	189.2664	185.2582
$P_{G100}(MW)$	60	600	600.0000	600.0000
$P_{G101}(MW)$	20	200	200.0000	200.0000
$P_{G109}(MW)$	10	100	100.0000	100.0000
$P_{G111}(MW)$	10	100	99.9999	100.0000
Fuel cost ($/h)			19170.205	19178.818
Power losses (MW)			74.9442	75.0552

SMA stands competitively regarding total fuel cost minimization to several algorithms as presented in Table 9. This archive's results by the proposed algorithm show the ability of SMA to find a better solution for large scale power systems.

Table 9: Comparison of solutions for fuel cost minimization using SMA and different methods: case 6.

Method		Fuel cost ($/h)	Method description
SMA		19170.205	Slime mould algorithm
GOA		19178.818	Grasshopper optimization algorithm
DE	[32]	19203.340	Differential evolution
GWO	[33]	19171.958	Grey wolfoptimizer
GA-ED-PS	[34]	19199.444	Hybrid GA-DE-PS
MOALO	[35]	19355.859	Multiobjectiveant lion algorithm

The convergence characteristics of SMA and the GOA for case 6 which minimize the TFC are shown in Figure 8. In the first place, the SMA algorithm converges towards the optimum value at the iteration 80 compared to GOA, that the convergence towards the optimal value is reached at the iteration 160. From this figure, SMA superior and robust to get the best solution in the few iterations compared to GOA.

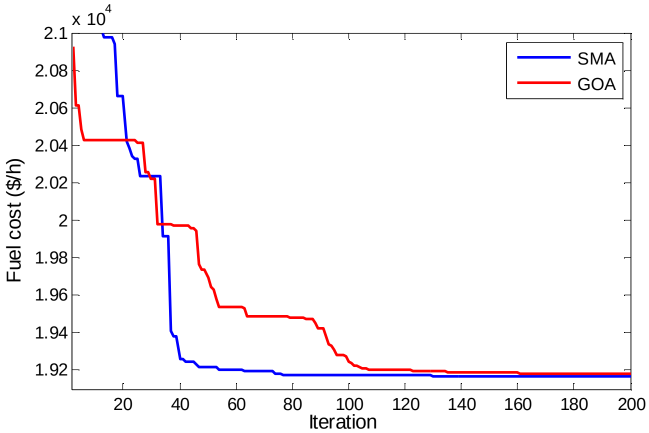

Figure 8: Convergence characteristics of fuel cost minimization via SMA and GOA for case 6

5. CONCLUSION

A new metaheuristic technique, called a slime mould algorithm (SMA) has been proposed in this paper to solve the OPF problem. The SMA has been successfully implemented and applied to the IEEE 30-bus, IEEE 57-bus systems and validated on large scale 114-bus Algerian power system under various test cases in order to minimize the fuel cost, reduce the active power losses and improve the voltage profile. In order to verify the effectiveness and performance of the SMA algorithm, the obtained results via SMA are compared with grasshopper optimization algorithm (GOA) and to some methods reported in the literature. The optimization results achieved by using the SMA algorithm given the best values in the all cases study based on the optimal setting values of control variables. Based on the results for all cases studies, it can be concluded that the SMA algorithm is capable to solve the OPF problem for a small system and large-scale power system.

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