Application of the Slime Mould Algorithm on the Bi-Objective Environmental Economic Dispatch Problem

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ABSTRACT

This paper investigates the performance of one of the latest metaheuristic swarm-based approaches called Slime Mould Algorithm (SMA). SMA is used here to solve the static bi-objective constrained Economic Emission Dispatch (EED) problem in the presence of renewable energy sources while considering the Valve-Point Effects (VPE). The SMA approach is applied to indicate the adequate optimal solutions for operating the committed thermal units under different operational constraints. The sought optimal solutions are the midpoint between cost saving and pollutant gas emission reduction. This study also examines the influence of integrating renewable energy sources (wind and solar) into the conventional power production network. SMA technique is applied on 3- and 6-unit IEEE test systems in several case studies. The simulation numerical results indicate that SMA has a high efficiency and a better performance compared to known state-of-the-art algorithms. The proposed approach was programmed and simulated in MATLAB.

Keywords-economic emission dispatch; renewable energy sources; slime mould algorithm; valve-point effects

I. INTRODUCTION

For fuel-based power systems, the Economic Dispatch (ED) remains a major optimization problem that can be tackled by tracking the electrical consumption which helps anticipate the required power production that should be satisfied with existing operating production units while preserving the minimum possible cost. This task aims at finding the adequate to-be-produced power per operating generator that meets the power demand and operational constraints. Traditionally, an ED problem is formulated to seek for the optimum fuel cost regardless of the pollutant gas emitted in the air by thermal units. But due to the high consciousness of environmental protection, the harmful produced emissions lead to the formulation of the bi-objective Emission Economic Dispatch (EED) problem in which fuel cost and pollutant emissions are considered simultaneously to be optimized whereas these two objectives are incompatible in a way that any decrease in the emissions tends to increase fuel costs and vice-versa [1], so, optimization tools tend to find the proper allocation of generating units in order to acquire the best compromise between reducing the quantity of emission and cost in the same time. On the other hand, studies have revealed that the integration of renewable energy into the conventional power production system plays a significant role in the reduction of both fuel cost and pollutant emissions due to its cheaper production cost and lower environmental impact. Nevertheless, renewable energy sources present some disadvantages such as their intermittent nature [2].

Nowadays, several meta-heuristic algorithms have been utilized in a wide range of engineering problems. Such techniques are usually inspired from real-life aspects such as physical, biological, or environmental processes [3]. Some of the meta-heuristic techniques have been used to solve EED problems. In [4], the EED with Valve Point Effect (VPE) consideration was solved using the genetic algorithm. Particle swarm optimization was applied in [5] to solve the EED problem in the presence of wind power. Grey wolf optimizer was applied in [6] to the EED with the integration of a wind farm. The bi-objective problem was solved in [7] with the use of cuckoo search. Teaching learning based optimization was developed in [8] to solve the EED taking VPE into account. These methods yield high-quality solutions for the EED problem with non-linear and non-convex cost functions by reaching global or near-global optimal solutions [9]. Among the numerous existing meta-heuristic optimization approaches, in this work we propose adapting and evaluating a swarm-based approach to the EED problem in the presence of the most popular renewable energy sources, solar and wind. The Slime Mould Algorithm (SMA), initially introduced in 2020 [10], is inspired by a natural behavior based on the phenomenon of slime oscillation.

II. ENVIRONMENTAL ECONOMIC DISPATCH WITH WIND AND SOLAR PENETRATION

The EED problem is defined as a constrained multi-objective optimization problem that aims to minimize simultaneously the total power cost and the emissions of pollutant gases while satisfying the power balance and operational constraints.

A. Objective Functions

1) Cost Function

One of the bi-objectives of the EED problem is to minimize the total fuel generation cost which can be formulated as follows:

$$\text{Minimize}(F_T = \sum_{i=1}^{N_G} C(P_{Gi})) \tag{1}$$

where F_T is the total generation cost function in \$/h. $C(P_{Gi})$ is the cost of the i^{th} generation unit, P_{Gi} is the real output power of the i^{th} generation unit, and i is the number of committed generation units.

For conventional economic dispatch problem, the fuel cost function of the thermal generation unit is approximated by a smooth quadratic function as follows:

$$C(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2 \tag{2}$$

where a_i, b_i, and c_i, are the cost coefficients of the i^{th} generation unit.

However, in reality, a multiple steam valves exist in large turbines whose role is to maintain the power balance in fuel generation units. These valves open and close with the objective of reaching a certain load. Due to this practice, a non-convexity appears in fuel cost function, called valve-point loading. This non-convexity is modelled as [11]:

$$C(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left| d_i \sin\left[e_i (P_{Gi}^{\min} - P_{Gi}) \right] \right| \tag{3}$$

where d_i and e_i are the valve-point coefficients of the fuel cost for the i^{th} generating unit.

2) Emission Function

The other objective of EED problem is to minimize the production of atmospheric emissions such as SO_x, NO_x, and CO_2 caused by the operation of fossil fuel power units. Among the various harmful gases emitted by each generation unit, NO_x is particularly considered in this study due to its globally-recognized high risk. The emission function is a quadratic function which is described as [12]:

$$\text{Minimize}(E_T = \sum_{i=1}^{N_G} E_{NOx}(P_{Gi})) \tag{4}$$

where:

$$E_{NOx}(P_{Gi}) = \alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2 \tag{5}$$

where E_T is the total emission function measured in kg/h, E_{NOx} is the NOx emission of the i^{th} generating unit, α_i, β_i and γ_i are the NO_x emission coefficients of the i^{th} generating unit.

3) Total Objective Function

The above non-linear combined EED represents a bi-objective optimization problem that could be converted into a single-objective function by the use of the price penalty factor. The weighted objective function is represented as follows:

$$FO = \omega F_T(P_{Gi}) + h(1-\omega) E_T(P_{Gi}) \tag{6}$$

where ω is the weight factor in a range [0, 1] and h is the price penalty factor. h is the ratio between the maximum fuel cost and the maximum emissions of the corresponding generator:

$$h_i = \frac{C(P_{Gi}^{\max})}{E_{NOx}(P_{Gi}^{\max})} \tag{7}$$

B. Wind and Solar Power Modeling

Environmental concerns surrounding the operation of fuel-based production power systems comprise the contribution to the global warming, the exhaustion of fossil fuels, and the emission of different forms of harmful gazes in the air. These concerns provide the stimulus to increase the utilization of renewable energy sources for its numerous advantages. In our study we choose to deploy the two most popular green energy sources, solar and wind power.

1) Solar Power

Solar power has an intermittent form due to its dependency on two climate parameters which are solar radiation and temperature. Thereby the simplified model that allows predicting the maximum power provided by a solar panel is written in terms of climate parameters [13]:

$$P_s = k_1 E_c [1 + K_2 (T_j - T_{jref})] \quad (8)$$

where E_c is solar radiation, T_j is the cell junction temperature, T_{jref} is the reference temperature of the panel at 25°C, k_l represents the dispersion characteristic of the panels where the value for one panel with a range of [0.095, 0.105], and the parameter $K_2 = 0.47\% / °C$ is the drift in panels temperature.

This mathematical model is improved with the addition of a third parameter:

$$P_s = K_1 [1 + K_2 (T_j - T_{jref})](K_3 + E_c) \quad (9)$$

2) Wind Power

Wind power is a clean and cheap renewable energy resource. However, the stochastic availability of the wind poses challenges in terms of operation and control that is why wind turbines should be built with mechanical adjustment to develop minimal power from a minimal wind speed in a way to avoid mechanical overload. The maximum wind power provided by a wind turbine can be predicted by [2]:

$$P_w = \frac{1}{2} \rho C_p A v^3 10^{-3} \quad (10)$$

where A is the traversed area by the wind (m²), is the air density (1.225kg/m^3), v is the wind speed (m/s), and C is the efficiency factor which depends on the wind speed and the architecture of the system.

C. Constraints

The objective function is minimized under the operational following constraints.

1) Power Balance Constraint

The total generation power must satisfy the demand and the transmission losses.

$$\sum_{i=1}^{N_G} P_{Gi} - P_D - P_L = 0 \quad (11)$$

where P_D and P_L are respectively the power demand and the transmission lines power losses in MW.

In the presence of renewable energy power the power balance constraint would be updated to the following form:

$$\sum_{i=1}^{N_G} P_{Gi} - P_D - P_L - P_{Ren} = 0 \quad (12)$$

where P_{ren} is the total renewable energy power in MW.

The system power loss is approximated by the use of the following relation:

$$P_L = \sum_{i=1}^{N_G} \sum_{j}^{N_G} P_{Gi} B_{ij} + \sum_{i=1}^{N_G} B_{0i} P_{Gi} + B_{00} \quad (13)$$

where B and B_0 are the loss coefficients matrix and B_{00} is the loss coefficient constant.

III. SLIME MOULD ALGORITHM

Slime moulds have fascinated scientists with their ability to navigate by finding the quickest way that lead to their target, which is the source of food. Although they are brainless creatures, they manage to build an intelligent network that is able to calculate the best trajectory. Slime moulds exhibit swarm intelligence. In the Slime Mould Algorithm (SMA) [10], slimes' movements are imitated in order to obtain a problem's optimal solution.

A. Mathematical Model

The mathematical modelling of SMA [10] is based on three phases of the slime moulds movement which are: approach, wrap, and grabble food.

1) Approach Food

Slime moulds approach food according to its odor in the air. The equation that imitates the contraction mode is:

$$\overrightarrow{X(t+1)} = \begin{cases} \overrightarrow{X_b(t)} + \overrightarrow{vb}.(\overrightarrow{W}.\overrightarrow{X_A(t)} - \overrightarrow{X_B(t)}, r < p \\ \overrightarrow{vc}.\overrightarrow{X(t)}, r \geq p \end{cases} \quad (15)$$

where $\overrightarrow{X}$ represents the slime mould location, t refers to the current iteration, $\overrightarrow{X_b}$ represents the best individual location currently found, i.e. the position with the highest odour concentration, $\overrightarrow{X_A}$ and $\overrightarrow{X_B}$ are two individuals randomly selected from the swarm, $\overrightarrow{vc}$ is a parameter that decreases linearly from 1 to 0, $\overrightarrow{vb}$ is a parameter in the range of [-*a*, *a*], where *a* and is calculated by:

$$a = \operatorname{arctanh}(-(\frac{t}{\max\_t}) + 1) \quad (16)$$

The formula of p is:

$$\overrightarrow{W(SmellIndex(i))} = \begin{cases} 1 + r.\log(\frac{bF - S(i)}{bF - wF} + 1), \text{condition} \\ 1 - r.\log(\frac{bF - S(i)}{bF - wF} + 1), \text{others} \end{cases} \quad (17)$$

$$SmellIndex = sort(S) \quad (18)$$

where condition indicates that $S(i)$ ranks the first half of the population, r denotes a random value in the interval [0, 1], and bF and wF signify the optimal and the worst fitness obtained in the current iteration respectively. *SmellIndex* is the sorted sequence of fitness values.

2) Wrap Food

The mathematical model for updating the slime mould location is:

$$\overrightarrow{X^*} = \begin{cases} rand.(UB - LB) + LB, rand < z \\ \overrightarrow{X_b(t)} + \overrightarrow{vb}.(W.\overrightarrow{X_A(t)} - \overrightarrow{X_B(t)}), r < p \\ \overrightarrow{vc}.\overrightarrow{X(t)}, r \geq p \end{cases} \quad (19)$$

where *LB* and *UB* are the lower and the upper boundaries of the search agents respectively, *rand* and *r* denote random values in [0, 1], and z is a parameter within [0, 0.1].

3) Grabble Food

This phase mimics the propagation wave produced by the biological oscillator of slime moulds that changes the cytoplasmic flow in their veins in order to get better food sources. $\overrightarrow{vb}$, $\overrightarrow{vc}$, and $\overrightarrow{W}$ are used to simulate the variations of the venous width of the slime moulds. $\overrightarrow{vb}$ is a vector of random values between [-*a*, *a*] that approaches zero as the repartitions progress, $\overrightarrow{vc}$ values oscillate in the range [-1, 1], and tend eventually to zero. $\overrightarrow{W}$ mathematically simulates the oscillation frequency of a slime mould based on the food concentration.

B. SMA Pseudo-Code

The general procedure of SMA algorithm is described as follows [10]:

- Initialize the parameters population size, dim, *LB* ,*UB*, z and $\max\_t$.
- Initialize the set of random slime mould positions.
- **While** ($t < \max\_t$)

  Calculate and sort the fitness of all slime moulds.

  Update bF, wF and X_b.

  Calculate W using (17).

  For each search agent update p , vb, vc.

  Update positions of search agents using (19).

  End **For.**

  End **While.**
- Return bF and X_b.

SMA is adapted to our problem in order to search for the best compromise solution between reducing cost and emissions. The parameter dim represents the dimension of the problem, in the EED problem denotes the number of generating units of the network. The fitness function is the objective function of the EED problem. *LB* and *UB* are the limits of each generation unit. The parameter z is set to 0.03.

IV. RESULTS AND DISCUSSIONS

In order to prove the effectiveness of SMA we present the simulation results of applying the proposed algorithm on the IEEE 9-bus and 30-bus systems, under different scenarios. The cost and NO_x coefficients for the IEEE 9-bus and 30-bus systems are taken from [14, 15]. Simulations were programmed using MATLAB and were carried out for the three following case studies:

- Case study 1: EED problem without VPE consideration.
- Case study 2: EED problem with VPE consideration.
- Case study 3: EED with VPE consideration in the presence of renewable energy.

We note that in all the studied cases, the transmissions lines power losses are taken into consideration and calculated with the use of (13) where the loss coefficients matrix of the IEEE 9-bus and 30-bus systems are given in (20) and (21).

$$B_{ij} = \begin{bmatrix} 0.00003 & 0 & 0 \\ 0 & 0.00009 & 0 \\ 0 & 0 & 0.00012 \end{bmatrix}$$
$$B_{0i} = [0 \quad 0 \quad 0] \quad (20)$$
$$B_{00} = 0$$

$$B_{ij} = \begin{bmatrix} 0.000218 & 0.000103 & 0.000009 & -0.00001 & 0.000002 & 0.000027 \\ 0.000103 & 0.000181 & 0.000004 & -0.000015 & 0.000002 & 0.00003 \\ 0.000009 & 0.000004 & 0.000417 & -0.000131 & -0.000153 & -0.000107 \\ -0.000010 & -0.000015 & -0.000131 & 0.000221 & 0.000094 & 0.000050 \\ 0.000002 & 0.000002 & -0.000153 & 0.000094 & 0.000243 & -0.000001 \\ 0.000027 & 0.00003 & -0.000107 & 0.000050 & -0.000001 & 0.000358 \end{bmatrix}$$
$$B_0 = [-0.000003 \quad 0.000021 \quad -0.000056 \quad 0.000034 \quad 0.000015 \quad 0.000078] \quad (21)$$
$$B00 = 0.000014$$

A. Case Study 1

1) 9-Bus System

In this case study the SMA was applied to solve the bi-objective EED problem without VPE consideration. The power demand to be satisfied by the 3 generating units is 850MW. In order to find the best compromise that provides the minimum cost and the minimum emissions in the same time, the SMA program was run several times for all the possible values of weight factor in the range of [0, 1] with a step of 0.1. The simulations results are compared to NSGA II [16] and CSA [17] and are represented in Table I.

TABLE I. IEEE 9-BUS RESULTS COMPARISON FOR CASE STUDY 1

Unit	Method		
	NSGAII	**CSA**	**SMA**
P_{G1}(MW)	470.9502	470.9570	448.2615
P_{G2}(MW)	280.7243	280.6630	350.9556
P_{G3}(MW)	113.6211	113.6750	111.7446
P_L(MW)	15.2950	15.2940	15.9507
Cost ($)	8149.7220	8349.7200	**8346.7192**
NO_x emission (kg/h)	0.09654	0.09654	**0.0894**
Convergence time (s)	-	0.09	14.851

The convergence curve of the SMA for this case study is presented in Figure 1. We notice that SMA provides lower cost than NSGA II and CSA with a profit of 0.035%. Furthermore, SMA yields a better solution of NO_x emissions with an important profit of 7%.

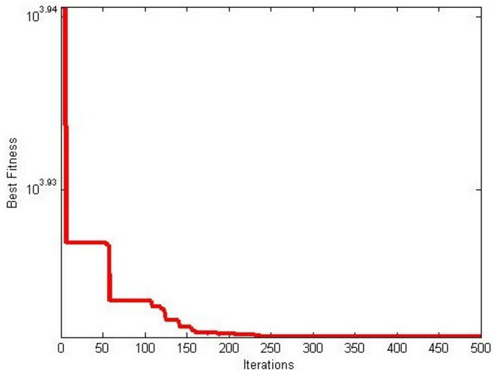

Fig. 1. IEEE 9-bus SMA simulation results for case study 1.

2) 30-Bus System

For this case study ,the total fuel cost and the emission index are simultaneously optimized. SMA was run for the following values of weight factor: 0, 0.25, 0.5, 0.75, and 1. The population size was chosen as 1000 generations, and the iteration number as 500. The performance of SMA is compared to the metaheuristic method HSABC [18]. Table II gives the comparison results of the two previously mentioned approaches for the different weight factor values for a power demand of 283.4 MW. The convergence curves for each value of weight factor are presented in Figures 2-6. As we can notice from Table II, the performance of SMA in reducing cost and emissions comparing to HSABC is noticeable. For instance, the profit in cost and NO_x emissions for ω=0 is 16% and 39% respectively.

TABLE II. IEEE 30-BUS RESULTS COMPARISON FOR CASE STUDY 1

Weight factor	$\omega = 0$		$\omega = 0.25$		$\omega = 0.5$		$\omega = 0.75$		$\omega = 1$	
Method	**HSABC**	**SMA**	**HSABC**	**SMA**	**HSABC**	**SMA**	**HSABC**	**SMA**	**HSABC**	**SMA**
P_{G1}(MW)	112.29	124.7182	117.60	127.4754	126.07	128.9988	140.68	151.8794	177.46	175.4329
P_{G2}(MW)	46.96	51.80738	48.26	54.08803	49.74	47.30148	50.66	56.72804	49.35	47.10369
P_{G3}(MW)	34.87	27.31135	31.48	28.10535	28.40	27.02738	25.25	18.81466	19.63	21.20746
P_{G4}(MW)	31.48	31.79245	31.66	28.93342	31.80	32.73101	30.90	18.44586	22.83	25.15064
P_{G5}(MW)	30.00	28.87296	29.54	25.6102	26.63	24.14822	21.74	23.57249	12.11	10.78865
P_{G6}(MW)	33.29	24.91275	30.71	25.44564	27.17	29.36644	21.54	21.93089	12.00	12.88029
P_L(MW)	5.49	6.0085	5.85	6.2447	6.41	6.1785	7.37	7.9714	9.98	9.1631
Cost ($)	854.11	**715.9176**	843.10	**743.8086**	830.28	**772.8311**	815.89	**797.7263**	803.89	**801.9348**
NO_x emissions (kg/h)	610.07	**370.8056**	611.76	**373.4120**	619.81	**372.7811**	645.57	**409.4590**	765.87	**456.2331**
Convergence time (s)	-	71.458	-	72.695	-	71.368	-	69.124	-	69.847

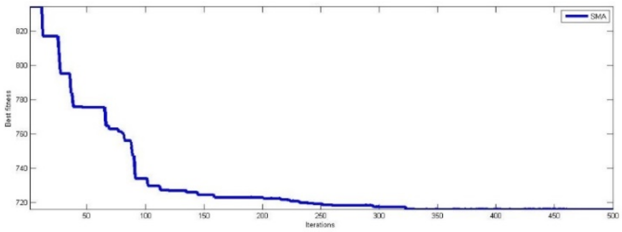

Fig. 2. IEEE 30-bus SMA simulation results for case study 2 ($\omega = 0$).

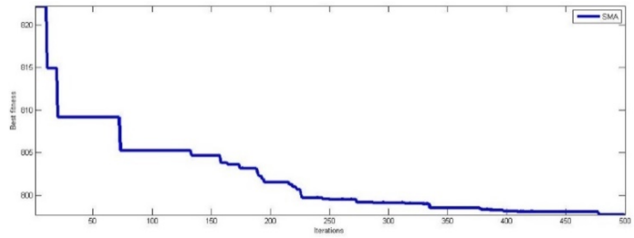

Fig. 5. IEEE 30-bus SMA simulation results for case study 2 ($\omega = 0.75$).

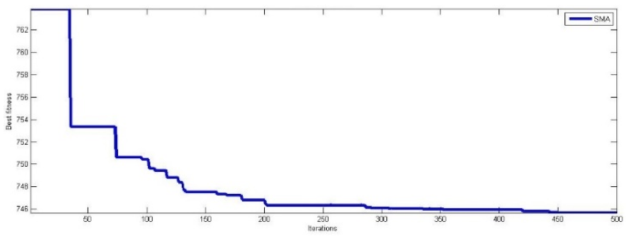

Fig. 3. IEEE 30-bus SMA simulation results for case study 2 ($\omega = 0.25$).

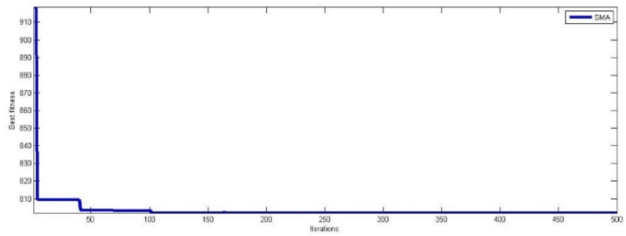

Fig. 6. IEEE 30-bus SMA simulation results for case study 2 ($\omega = 1$).

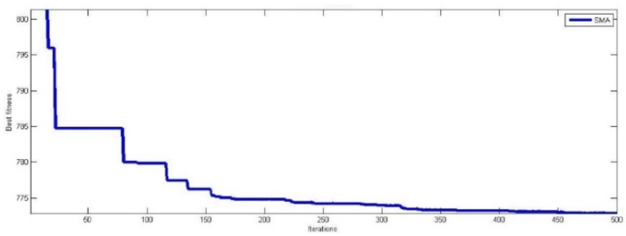

Fig. 4. IEEE 30-bus SMA simulation results for case study 2 ($\omega = 0.5$).

B. Case study 2

1) 9-Bus System

In this case study, the EED problem is solved with power losses and VPE consideration. The power demand that should be met by the three units is 451 MW. SMA simulation results are compared to LMA [19] and are presented in Table III. For comparison reasons we set the weight factor to 0.5. Figure 7 represents the convergence curve of SMA with 500 iterations for this case study. In this scenario, SMA has over performed the conventional LMA technique in finding the global optimal solution that provides the best compromise between cost and emission quantity where the profit in cost and emissions are about 15% and 0.65% respectively.

TABLE III. IEEE 9-BUS RESULTS COMPARISON FOR CASE STUDY 2

Unit	Method	
	LMA	SMA
$P_{G1}(MW)$	162.1612	299.4662
$P_{G2}(MW)$	193.0458	100.0000
$P_{G3}(MW)$	102.0527	55.49374
$P_L(MW)$	6.2597	3.9598
Cost ($)	7393.200	**6288.5132**
NO_x emissions (kg/h)	0.0923	**0.0917**
Convergence time (s)	-	15.098

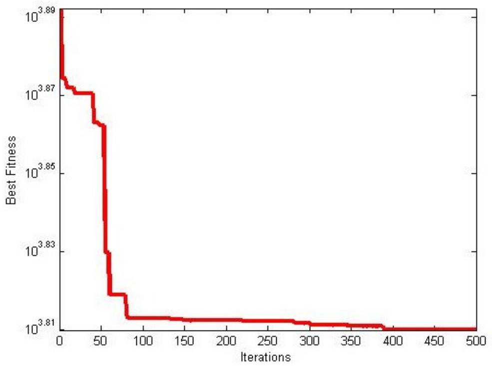

Fig. 7. IEEE 9-bus SMA simulation results for case study 2.

2) 30-Bus System

The bi-objective optimization problem is considered here taking into account the sine component due to the VPE. The required power to be satisfied by the 6 generating units is 250 MW. Table IV presents the comparison of the simulation results of SMA along with LR, PSO, and SA [15]. The final solutions of the committed generating units' output power to meet this specific load demand at the minimum cost along with the pollutant emissions are listed in Table V.

TABLE IV. IEEE 30-BUS RESULTS COMPARISON FOR CASE STUDY 2

Unit	Method			
	LR	SA	PSO	SMA
P_L(MW)	5.4046	5.8215	5.8	5.1493
Cost ($)	741.9553	741.2545	737.3	**687.6154**
NO_x emissions (kg/h)	288.3688	321.3507	296	**314.9093**
Convergence time (s)	0.212367	1.787088	0.01	71.366

These results are obtained by using ω=0.5. The convergence curve of the SMA results is illustrated in Figure 8. According to the results presented in Table IV, we can see clearly that SMA provided the lowest fuel cost comparing to LR, SA and PSO. However, when it comes to NOx emissions LR and PSO provide better emissions index which explains that SMA is succeeded in reaching the best compromise between reducing cost and emissions unlike other approaches.

TABLE V. RESULTS OF THE COMMITTED POWER OUTPUTS

Unit	SMA
P_{G1}[MW]	112.217
P_{G2}[MW]	50.48498
P_{G3}[MW]	15
P_{G4}[MW]	25.70552
P_{G5}[MW]	22.5664
P_{G6}[MW]	29.1755
P_L[MW]	5.1493
Cost [$]	314.9093
NO_x emissions [kg/h]	687.6154

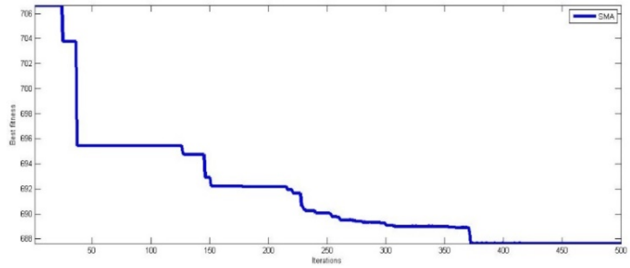

Fig. 8. IEEE 30-bus SMA simulation results for case study 2.

C. Case Study 3

In this case study, we propose solving the EED problem with VPE consideration integrating renewable energy power in the conventional production system. The penetration of renewable energy power should not exceed the 30% of the total power demand.

1) 9-Bus System

To discuss the impact of integrating renewable energy in the network, the program was run for several power demand level with a random penetration level of solar and wind power as well. The weight factor is set to 0.5 in order to give the same importance to the cost and the emissions. Table VI represents three instances of the simulation results.

TABLE VI. IEEE 9-BUS RESULTS COMPARISON FOR CASE STUDY 3

Power demand	700 (MW)		925 (MW)		1050 (MW)	
P_{Ren}(MW)	-	122.5553	-	118.3594	-	156.5803
P_{G1}(MW)	299.4662	294.8317	498.9322	399.1993	576.4808	546.6408
P_{G2}(MW)	249.5997	100	398.0833	322.9384	399.1588	295.3748
P_{G3}(MW)	59.65865	87.02962	50.015	99.86653	99.86655	68.78856
Cost ($)	6982.79	**6390.7747**	9285.8048	**8069.0452**	10252.7283	**8804.1483**
NO_x emissions (kg/h)	0.0924	**0.0893**	0.1129	**0.0969**	0.1148	**0.0997**
Convergence time (s)	15.011	14.454	14.951	15.650	15.036	15.865

The penetration impact of renewable energy power on reducing the cost and the emission quantity is noticeable in the results shown in Table VI. In other hand, we notice that when the penetration of renewable energy is higher, the reduction in cost and emissions is also higher. Although, the renewable energy power is a great option to reduce cost and pollutant gases, it is challenging to model it for its stochastic availability.

2) 30-Bus System

In order to investigate the influence of integrating renewable energy sources in the conventional production power system, a 6-unit test system with 3 different power demand levels randomly chosen was solved. SMA was run to converge to the optimum values of the committed generating units for a weight factor equal to 0.5. The SMA solutions for various values of power demand are displayed in Table VII.

The presence of external power in the conventional power system alleviates the committed generating unit while satisfying the load demand, with minimum cost and emissions. As we can notice in Table VII, penetration of renewable energy that doesn't exceed 30% of the power demand has an important impact on reducing significantly cost and pollutant emissions.

TABLE VII. IEEE 30-BUS RESULTS COMPARISON FOR CASE STUDY 3

Power demand	**150 (MW)**		**283.4 (MW)**		**400 (MW)**	
P_{Ren}(MW)	-	28.4593	-	39.6582	-	84.3431
P_{G1}(MW)	85.1806	53.4728	128.9988	117.1773	199.5841	147.3343
P_{G2}(MW)	20	20	47.30148	46.3378	73.19402	57.35425
P_{G3}(MW)	15	15	27.02738	15.07434	36.4338	19.62882
P_{G4}(MW)	10	10	32.73101	25.70792	35	31.38732
P_{G5}(MW)	10	10	24.14822	22.56547	30	22.5693
P_{G6}(MW)	12	12	29.36644	12	40	29.42706
Cost ($)	388.7041	**323.0898**	372.7811	**633.0691**	1338.5613	**865.7911**
NO_x emissions (kg/h)	184.9422	**158.0846**	772.8311	**298.1571**	710.8778	**426.3729**
Convergence time (s)	68.956	65.368	67.784	66.258	69.320	69.152

V. CONCLUSION

In this paper we presented the recently developed metaheuristic method SMA that mimics the behavior of slime mould in finding the optimal trajectory that leads to the source of food. SMA is applied here to solve the multi-objective constrained static EED problem for three different case studies. The proficiency of this method was studied on standard IEEE systems of 3 and 6 generating units. This paper contributed to studying a comparative analysis between the proposed method in this paper and other existing methods in an attempt to sort out the approach that yields the best-compromised solution between cost and emissions. Also, the SMA approach is introduced for the first time in this paper as an optimization tool for the EED problem with renewable energy power integration.

According to the results presented in this paper, SMA proved to be a powerful and efficient tool in handling economic dispatch problems. SMA provided global optimum or near solutions with a very insignificant gap. When it comes to solving the whole EED problem with the addition of the challenge of integrating renewable energy power, SMA was run multiple times for different power demand levels and stochastic penetration percentages of renewable energy. SMA has shown its efficiency and robustness in handling such a multi-objective constrained optimization problem.

As a result, the meta-heuristic approach proposed by this work succeeded to deliver better solutions for almost all the studied economic dispatch issues. Hence, it is capable of being used for more complicated economic dispatch problems such as the dynamic economic dispatch.

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