Congestion Management using the Circulatory System Based Optimization Algorithm

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ABSTRACT

Congestion management is one of the most important issues in power system operation, especially in competitive electricity markets. The main aim of Congestion Management (CM) is to eliminate congestion in transmission lines. The most common technique to deal with the CM problem is re-dispatching the generator. However, finding an optimal solution for the CM problem constitutes a challenge for many researchers. Recently, a new biologically inspired metaheuristic algorithm, called Circulatory System Based Optimization (CSBO), was developed and proven to be effective in handling optimization issues. The CSBO algorithm was applied to solve the CM problem for the IEEE-30 bus system in two different cases. The former was compared with the Crayfish Optimization Algorithm (COA), Artificial Rabbits Optimization (ARO), Improved Grey Wolf Optimizer (I-GWO), and other existing methods. The simulation results revealed that the cost obtained from the proposed CSBO algorithm was lower than 14.5%, 11.31%, 9.97%, and 4% compared to PSO, FPA, FFA, and ALO. In addition, the stability of the proposed algorithm was higher than that of the other methods after 30 trials.

Keywords-congestion management; optimization algorithm; re-dispatching generator; circulatory system based optimization; IEEE-30 bus system

I. INTRODUCTION

In the modern electric power industry, the electricity market is switching from regulated to deregulated policies. A regulated electricity market is one in which electricity companies own and operate all the electricity. All generators, infrastructure, and transmission lines are completely controlled by the utility. Therefore, customers have to follow the price proposed by the utility [1]. However, reliability and stable prices are guaranteed in a regulated power market. On the other hand, the deregulated power market allows many competitors to participate in the electricity market by investing in transmission lines and generators. The owner of the generator sells power electricity to the customer through retail suppliers, establishing a competitive electricity market. In such a market, prioritizing the dispatch of some generators with low electricity prices may cause some technical violations in the transmission system. This problem poses challenges for many Independent System Operators (ISO). Congestion Management (CM) must be addressed to solve this issue. In transmission lines, the power flow is limited by voltage and thermal limits [1]. Whenever the power flow in branches exceeds these limits, line congestion may appear, putting the power system in an unstable condition. The primary goal of resolving the CM problem is to restore the power system to its normal operation. The most commonly used technique for solving the CM problem is the re-dispatching generation. Many methods have been proposed for finding the most optimal re-dispatching plan for the generator. These methods can be divided into two different approaches: mathematical and metaheuristic approaches. In the mathematical approach, Benders Decomposition (BD) [2] and Relative Electrical Distance (RED) [3] were proposed to solve the CM problem with real power generation. On the other hand, fuzzy adaptive bacterial foraging [4], hybrid Differential Evolution with Particle Swarm Optimization (DEPSO) [5], fuzzy [6], Multi-objective Particle Swarm Optimization (MPSO) [7], Particle Swarm Optimization (PSO) [8], Teaching-Learning-Based Optimization (TLBO) [9], Artificial Bee Colony (ABC) [10], Moth Flame Optimization (MFO) [11], Genetic Algorithm (GA) [12], Cuckoo Search Algorithm

(COA) [13], Improved Manta Ray Foraging Optimization (IMRFO) [14], and Twin Extremity Chaotic Map Adaptive Particle Swarm Optimization (TECM–PSO) [15] have been proposed as metaheuristic approaches. In general, both mathematical and metaheuristic approaches are successfully applied to figure out CM problems. In the mathematical approach, although the simulation time is short, the value found commonly falls into the local optima value. Metaheuristic approaches can overcome local optima values. However, the calculation time is significant. Therefore, finding a suitable technique to provide a solution to the CM problem has become an important task for many researchers. In [16], the Flower Pollination Algorithm (FPA) was proposed to solve the CM problem, but this algorithm requires many input parameters. The FireFly Algorithm (FFA) was proposed in [17] to solve the CM problem in two different systems, the IEEE 30 bus and the IEEE 57 bus. Although the effectiveness of the FFA method was proven, it requires many control parameters to operate similarly to the FPA method. In [18], the CM problem was solved by rescheduling the real power generator using the Ant Lion Optimizer (ALO) algorithm. In [19], the Symbiotic Organisms Search (SOS) algorithm was proposed to solve the CM problem. This algorithm was effective in dealing with CM, but the simulation time was not reported. Therefore, the evaluation of the SOS algorithm to solve the CM problem may not be very convincing.

Recently, a new biologically inspired metaheuristic algorithm, called Circulatory System Based Optimization (CSBO), was proposed [20]. This algorithm was designed based on the operation of the body's blood vessels. The common weak point of all meta-heuristic algorithms is the unbalance of exploitation and exploration. However, the CSBO algorithm was tested on a wide variety of complex functions and was validated with standard metaheuristic algorithms. The CSBO algorithm achieved satisfactory results while avoiding local optima values. In addition, the CSBO algorithm does not require any additional control parameters, except the number of populations and iterations. This study applies the CSBO algorithm to solve the CM problem for the IEEE 30-bus system. Furthermore, the effectiveness of the CSBO algorithm is evaluated by comparing it with three other recently published metaheuristic methods, including Crayfish Optimization Algorithm (COA) [21], Artificial Rabbits Optimization (ARO) [22], Improved Grey Wolf Optimizer (I–GWO) [23], and others. The contribution of this study can be listed as:

- Apply the metaheuristic CSBO algorithm to solve the CM problem.
- Evaluate the effectiveness of the proposed CSBO algorithm, comparing it with COA, ARO, I–GWO, and other methods.
- In each case, obtain the optimal results of the algorithms used after 30 trials to prove their stability, robustness, and accuracy.

II. MATHEMATICAL MODELING

The primary task of the CM problem is to minimize the congestion cost while satisfying the system constraints. In this study, the CM problem is solved by re-dispatching the active power of the generator. However, this cost depends on the bid price of the generating companies (GENCOs). The objective function of this study can be calculated as [17]:

$$C_t = \sum_{\forall i \in N_g} (I_k \Delta P_{Gi}^{+} + D_k \Delta P_{Gi}^{-}) \tag{1}$$

where C_t is the total cost for charging active power output ($/h), I_k and D_k are the incremental and the decremental price bids submitted by GENCOs ($/MWh), ΔP_{Gi}^{+} and ΔP_{Gi}^{-} represent the incremental and the decremental active power of the generator (MW), and N_g is the number of generators.

A. Equality Constraints

The power flow constraints of the CM problem can be presented as follows [17]:

$$P_{Gk} - P_{Dk} = \sum_j |V_j||V_k||Y_{kj}| \cos(\delta_k - \delta_j - \theta_{kj})$$
$$j = 1, \dots N_b \tag{2}$$

$$Q_{Gk} - Q_{Dk} = \sum_j |V_j||V_k||Y_{kj}| \sin(\delta_k - \delta_j - \theta_{kj})$$
$$j = 1, \dots N_b \tag{3}$$

$$P_{Gk} = P_{Gk}^{C} + \Delta P_{Gi}^{+} - \Delta P_{Gi}^{-}, k = 1, \dots N_g \tag{4}$$

$$P_{Dj} = P_{Dj}^{C}, j = 1, \dots N_d \tag{5}$$

where P_{Gk} and Q_{Gk} are the active and reactive power generated by the generator at bus *k*, respectively, P_{Dk} and Q_{Dk} are the active and reactive demand power at bus *k*, correspondingly, V_j, V_k, δ_k, δ_j are the voltages and phase angle values at bus *j* and *k*, accordingly; θ_{kj}, Y_{kj} are the admittance angle and admittance matrix of the line between bus *k* and bus *j*, P_{Gk}^{C} and P_{Dj}^{C} denote the active power produced by the generator at bus *k* and the active power consumed by the load at bus *j*, respectively, and N_b and N_d are the number of buses and loads, accordingly.

B. Inequality Constraints

The inequality constraints represent the operational limits of transmission lines, transformers, and generators, as in [17]:

$$P_{Gk}^{min} \le P_{Gk} \le P_{Gk}^{max}, \forall k \in N_g \tag{6}$$

$$Q_{Gk}^{min} \le Q_{Gk} \le Q_{Gk}^{max}, \forall k \in N_g \tag{7}$$

$$(P_{Gk} - P_{Gk}^{min}) =$$
$$\Delta P_{Gk}^{min} \le \Delta P_{Gk} \le \Delta P_{Gk}^{max} = (P_{Gk}^{max} - P_{Gk}) \tag{8}$$

$$V_n^{min} \le V_n \le V_n^{max}, \forall n \in N_l \tag{9}$$

$$P_{ij} \le P_{ij}^{max}, ij \in N_b \tag{10}$$

where P_{Gk}^{min}, P_{Gk}^{max}, Q_{Gk}^{min}, and Q_{Gk}^{max} are the minimum and maximum of active and reactive power generated at generator *k*, respectively, V_n^{min} and V_n^{max} are the minimum and maximum values of the voltage at bus *n*, accordingly, ΔP_{Gk}^{min} and ΔP_{Gk}^{max} are the maximum and minimum of active power re-disparting at generator *k*, and N_l is the number of lines.

III. THE PROPOSED METHOD

A. Circulatory System Based Optimization (CSBO)

CSBO is a biologically inspired metaheuristic algorithm based on the operation of the blood vessels in the body, with two distinct circuits: the pulmonary and systemic circuits [20]. In the human body, the heart plays an important part in the circulatory system and can be considered the pump of the body, with the main role of carrying blood to any part of the body and coming back to it. On the other hand, blood plays a crucial role in transporting oxygen from the lungs to different parts of the body and in eliminating waste products, such as carbon dioxide. This process is vital for the health and growth of the body. According to these processes, the body's blood vessels can be divided into two circuits: the pulmonary and systemic circuits. In all cases, blood can be considered a Newtonian fluid with flow, pressure, and volume as the main variables in the circulatory system. Like other metaheuristics, the CSBO begins with a generated initial population known as blood masses. This process can be described as follows:

$$bm_i = Var^{min} + rand(1, dim) \times (Var^{max} - Var^{min}),\quad i = 1, \dots Npop \tag{11}$$

where Var^{min} and Var^{max} are the minimum and maximum variable ranges of the problem, bm_i is the *i*-th blood mass, dim is the number of dimensions, $rand$ is the random number in the range [0,1], and $Npop$ is the number of individuals in the population. The movement of blood in veins is very impactful on the pulmonary and systemic circuits. However, the blood typically moves in the most optimal direction. Thus, blood movement is highly dependent on the objective function values. The movement of blood, based on the objective function values, can be described by:

$$bm_i^{new} = bm_i + K_{i1} \times r_i \times (bm_i - bm_1) + K_{23} \times r_i \times (bm_2 - bm_3) \tag{12}$$

$$K_{ij} = \frac{F(bm_j) - F(bm_i)}{|F(bm_j) - F(bm_i)| + \varepsilon} = \begin{cases} 1, F(bm_i) < F(bm_j) \\ -1, F(bm_i) > F(bm_j) \\ 0, F(bm_i) = F(bm_j) \end{cases} \tag{13}$$

In this context, K_{i1} is the value of the blood movement direction. This parameter determines the decision to move toward a better value or away from a less favorable one. r_i is the random value within the range [0,1], and $F(bm_i)$ is the objective function value of the *i*-th blood mass.

The main function of the pulmonary circuits is to supply oxygenated blood to the body and to recycle deoxygenated blood. In the CSBO algorithm, deoxygenated blood is considered the weakest individual in the population. Therefore, these individuals need to move toward the lungs to gain oxygen. This process can be described as follows:

$$bm_i^{new} = bm_i + \left(\frac{randn}{it}\right) \times randc(1, dim),\quad i = 1 \dots NR \tag{14}$$

where $randn$ is a random normal number, it is the current interaction of the algorithm, NR is the number of deoxygenated blood vessels, and $randc$ is the random vector from Cauchy probability [20].

On the other hand, strong individuals (oxygenated blood) are transported to the part of the body, and this process can be referred to as systematic circulation. The systematic circulation function can be described as follows:

$$bm_{ij}^{new} = bm_{1,j} + p_i \times (bm_{3,j} - bm_{2,j}) \tag{15}$$

$$p_i = \frac{F(bm_i) - F_{Worst}}{F_{Best} - F_{Worst}},\quad i = 1, \dots NL \tag{16}$$

where F_{Best} and F_{Worst} are the best and worst values of the objective function obtained up to the current iteration, and NL is the number of oxygenated blood vessels ($NL = Npop - NR$).

B. Application of CSBO for solving the CM Problem

To apply the CSBO algorithm to solve the CM problem, the objective function must be considered as the Fitness Function (FF). FF includes the objective function and constraints in Section 2. Constraints are expressed as penalty values in the fitness function. Thus, the fitness function can be described as follows [9]:

$$FF = C_t + PF_1 \times \sum_{i=1}^{N_l} (P_{ij} - P_{ij}^{max})^2 + PF_2 \times \sum_{j=1}^{N_b} (\Delta V_j)^2 + PF_3 \sum_{k=1}^{N_g} (\Delta PG_k)^2 \tag{17}$$

where:

$$\Delta V_j = \begin{cases} (V_j^{min} - V_j), if\ V_j \le V_j^{min} \\ (V_j - V_j^{max}), if\ V_j \ge V_j^{min} \end{cases} \tag{18}$$

$$\Delta PG_k = \begin{cases} (PG_k^{min} - PG_k), if\ PG_k \le PG_k^{min} \\ (PG_k - PG_k^{max}), if\ PG_k \ge PG_k^{min} \end{cases} \tag{19}$$

where PF_1, PF_2, and PF_3 are the penalty values, which are set at 10^4 throughout the simulation process, and V_j^{min}, V_j^{max}, PG_k^{min}, PG_k^{max} are the minimum and maximum values of voltage in bus *j* and the active power at generator *k*, respectively. The CM problem is solved using the CSBO algorithm via the following steps:

Step 1: Read the data from the system and input the number of populations, interactions, upper bound, lower bound, and the number of deoxygenated blood vessels (NR).

Step 2: Initialize the initial population as follows:

$$Sol_i = Sol_i^{min} + rand(1, d) \times (Sol_i^{max} - Sol_i^{min}),\quad i = 1 \dots N_{sol} \tag{20}$$

where Sol_i is the *i*-th solution, d is the number of variables, N_{sol} is the maximum number of solutions, and Sol_i^{max} and Sol_i^{min} are the upper and lower bounds of the control variables, identified as follows:

$$Sol_i^{max} = \left[P_{Gi}^{max} \dots P_{GN_g}^{max}\right],\quad i = 1 \dots N_g \tag{21}$$

$$Sol_i^{min} = \left[P_{Gi}^{min} \dots P_{GN_g}^{min}\right], i = 1 \dots N_g \quad (22)$$

where P_{Gi}^{max} and P_{Gi}^{min} are the maximum and minimum of generation at the i-th generator, and N_g is the total number of generators.

Step 3: Calculate the fitness value of all solutions in the initial population using (17).

Step 4: Determine the new solution by the movement of blood in veins as follows:

$$Sol_i^{new} = Sol_i + K_{i1} \times r_i \times (Sol_i - Sol_1) + K_{23} \times r_i \times (Sol_2 - Sol_3) \quad (23)$$

where Sol_i^{new} is the new solution given through the movement of blood in veins process, Sol_i, Sol_1, Sol_2, and Sol_3 are the i-th, 1st, 2nd, and 3rd solutions, K_{i1} and K_{23} can be calculated using (13), and p_i is a random value in the range [0, 1].

Step 5: Calculate the fitness value of the new solution using (17) and update the population as follows:

$$Sol_i = \begin{cases} Sol_i^{new}, \ if \ FF(Sol_i^{new}) < FF(Sol_i) \\ Sol_i, \ else \end{cases} \quad (24)$$

Step 6: Sort the number of solutions in the population based on their fitness value.

Step 7: Determine the new solution by blood mass flow in pulmonary circulation as follows:

$$Sol_i^{new} = Sol_i + \left(\frac{randn}{t}\right) \times randc(1,d), \quad i = 1 \dots NR \quad (25)$$

where Sol_i^{new} is the new solution given through the blood mass flow in pulmonary circulation, $randn$ is the random normal value, $randc$ is the random vector from Cauchy probability, t is the current interaction, and NR is the number of deoxygenated blood vessels.

Step 8: Calculate the fitness value of the new solution using (17) and update the population using (24).

Step 9: Determine the new solution by blood mass flow in systematic circulation as follows:

$$Sol_i^{new} = Sol_i + p_i \times (Sol_2 - Sol_3) \quad (26)$$

where Sol_i^{new} is the new solution given through the blood mass flow in systematic circulation. Sol_i, Sol_2, and Sol_3 are the i-th, 2nd, and 3rd solutions. p_i can be calculated as follows:

$$p_i = \frac{FF(Sol_i) - FF_{Worst}}{FF_{Best} - FF_{Worst}}, \ i = 1, \dots NL$$

where FF_{Worst} and FF_{Best} are the worst and best fitness values. $NL = N_{sol} - NR$.

Step 10: Calculate the fitness value of the new solution using (17) and update the population using (24).

Step 11: Check the stop condition. If the maximum interaction is reached, go to the next step, else go back to step 4.

Step 12: Print out the optimal solution and end the program.

IV. RESULTS

This section discusses the performance of the proposed CSBO algorithm for solving the CM problem following the generation schedule approach. Furthermore, the effectiveness of the proposed method with 20 individuals and 200 iterations was compared to COA, ARO, I–GWO, and other methods, such as PSO [8], FPA [16], FFA [17], ALO [18] and SSO [19]. The simulation program was developed in the MATLAB environment and the MATPOWER toolbox [24]. The IEEE 30 bus system [9] was deployed to test the proposed method for the CM problem in two different cases:

- Case 1: Line 1-2 outage.
- Case 2: Line 1-7 outage, and the active load of all buses is increased by 50%.

The IEEE 30 bus system has 30 buses, 6 generators, 24 load buses, and 41 transmission lines. The total power generation was 283.4 MW and 126.25 MVAR. A single diagram and more detailed information on the system can be found in [9]. The increase and decrease price bids submitted by GENCOs are detected in Table I [1].

TABLE I. INCREASE AND DECREASE PRICE BIDS SUBMITTED BY GENCOS

Generator Number	Increment ($/MWh)	Decrement ($/MWh)
1	22	18
2	21	19
3	42	38
4	43	37
5	43	35
6	41	39

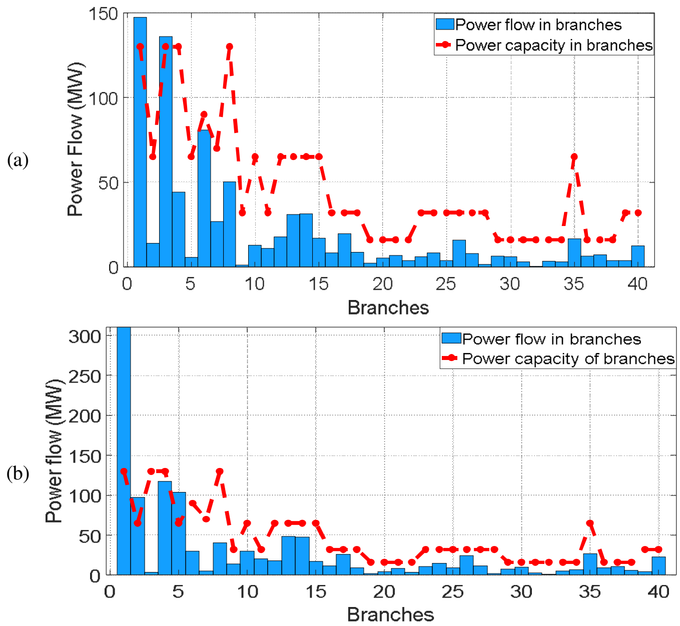

Fig. 1. The power flow in branches in the IEEE 30 bus system: (a) an outage of line 1-2, (b) an outage of line 1-7.

A. Case 1: Line 1-2 Outage

Figure 1(a) demonstrates that lines 1-7 and 7-8 are congested when line 1-2 outages. The power flows in lines 1-7 and 7-8 are 147.22 MW and 136.10 MW, respectively, which are overloaded by 17.22 MW and 6.10 MW. To eliminate congestion, the proposed CSBO method is applied to find the optimal solution to the rescheduled power problem. Table II presents the details of the results obtained by the proposed CSBO method and other algorithms. Generator 01 decreased by 8.75 MW and generator 02 increased by 14.43 MW. From (1) and the price bids in Table I, with the rescheduled power, the total cost obtained from CSBO was 460.83 \$/h (21 \$/MWh x14.43 MW+ 18 \$/MWh x 8.75 MW = 460.83 \$/h). Table II presents the details of the rescheduled power results of the suggested CSBO and the other methods. The total cost acquired from the CSBO algorithm (460.83 \$/h) was lower than COA (463.2 \$/h), ARO (462.47 \$/h), and I-GWO (467.62 \$/h). To prove its robustness, the proposed algorithm was compared with other existing methods. Table II indicates that the optimal value obtained from the CSBO method was smaller by 14.5% compared to PSO [8], 11.31% compared to FPA [16], 9.97% compared to FFA [17], and 4% compared to ALO [18]. Furthermore, the convergence speed and accuracy of the proposed CSBO method were higher than the other methods, as showcased in Figure 2.

TABLE II. COMPARISON OF THE PROPOSED ALGORITHM WITH OTHER METHODS IN CASE 1

Algorithm	Generators re-dispatching (MW)						Total cost (\$/h)
	ΔPG1	ΔPG2	ΔPG 3	ΔPG 4	ΔPG5	ΔPG 6	
PSO[8]	-8.61	10.40	3.03	0.02	0.85	-0.01	538.95
FPA[16]	-9.13	14.14	-0.21	-0.02	0.19	1.01	519.62
FFA[17]	-8.78	15	0.11	0.06	0.17	-0.62	511.87
ALO[18]	-9.09	15.07	0	0	0	0	480.04
SOS[19]	-8.6	14.58	0	0	0	0	460.83
COA	-8.76	14.33	0.07	0	0.02	0.02	463.2
ARO	-8.76	14.36	0	0.02	0.04	0.02	462.47
I-GWO	-8.82	14.4	0	0.01	0.02	0.12	467.62
CSBO (proposed)	-8.75	14.43	0	0	0	0	460.83

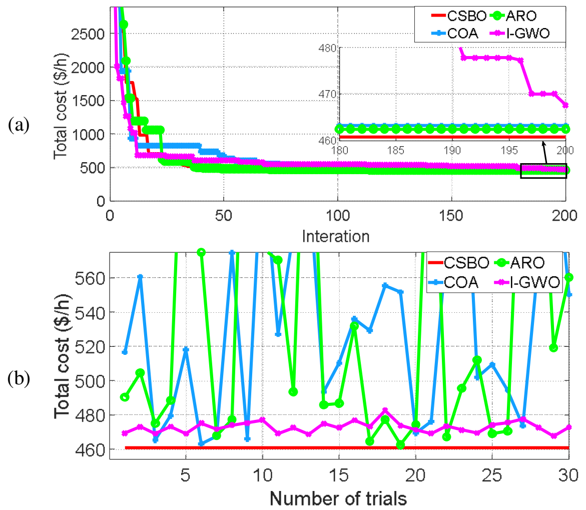

Fig. 2. Comparison of CSBO with other algorithms in the first case: (a) convergence curve, (b) results after 30 trials.

B. Case 2: Line 1-7 Outage, and All Active Loads Increased by 50%

This case considers Line 1-7 outage and all active loads increased by 50%. As portrayed in Figure 1(b), lines 1-2, 2-8, and 2-9 are congested. The power flows in lines 1-2, 2-8, and 2-9 are overloaded by 180.85 MW, 32.38 MW and 38.48 MW, respectively. To eliminate congestion, the proposed CSBO method is adopted to reschedule power as follows. Generator 01 decreases by 8.76 MW, while generators 2-6 increase by 8.76 MW, 76.21 MW, 53.03 MW, 18.98 MW, and 10.64 MW, respectively. From (1) and the price bids in Table I, with the rescheduled power, the total cost obtained from the proposed CSBO algorithm was 5291.34 \$/h. Table III presents the results obtained by the proposed and other algorithms. The total cost obtained from the proposed method (5291.34 \$/h) was lower than PSO (5335.5 \$/h) [8], FPA (5320.8 \$/h) [16], FFA (5304.40 \$/h) [17], ALO (5296.75 \$/h) [18], and SOS (5303 \$/h) [19], correspondingly. The optimal solution of the CSBO algorithm was also less than COA (5308,20 \$/h), ARO (5296,24 \$/h), and I-GWO (5296.96 \$/h). Furthermore, the convergence speed and the accuracy of the proposed CSBO method were higher than those of the other methods, as depicted in Figure 3.

TABLE III. COMPARISON OF THE PROPOSED ALGORITHM WITH OTHER ALGORITHMS IN CASE 2

Algorithm	Generators re-dispatching (MW)						Total cost (\$/h)
	ΔPG1	ΔPG2	ΔPG3	ΔPG4	ΔPG5	ΔPG 6	
PSO[8]	_	_	_	_	_	_	5335.5
FPA[16]	-8.59	74.02	0	13.52	43.86	27.89	5320.8
FFA[17]	-8.58	75.99	0.06	42.99	23.83	16.51	5304.40
ALO[18]	-8.59	76.4	0.06	42.84	24.57	15.53	5296.75
SOS[19]	-8.76	76.46	0	41.08	30.23	11.62	5303
COA	-8.76	73.22	0.44	33.14	18.19	33.84	5308.20
ARO	-8.76	76.98	0.2	51.62	29.76	0.32	5296.24
I-GWO	-8.79	76.09	0.36	50.09	23.56	8.73	5296.96
CSBO (proposed)	-8.76	76.21	0	53.03	18.98	10.64	5291.34

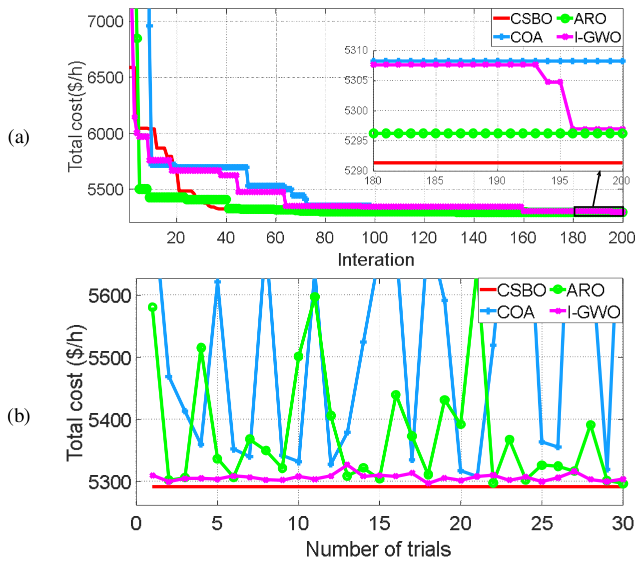

Fig. 3. Comparison of CSBO with other algorithms in the second case: (a) convergence curve, (b) results after 30 trials.

V. CONCLUSION

The main objective of the CM problem is to eliminate congestion while minimizing the re-dispatching cost of the generator. This study utilized the CSBO algorithm to solve the CM problem. The CSBO algorithm is inspired by the operation of the blood vessels of the body, which have two distinct circuits: the pulmonary and systemic circuits. The effectiveness of the proposed CSBO algorithm was proven in two different cases of the IEEE 30 bus system. The solution provided by the CSBO algorithm to solve the CM problem reduced congestion cost by 14.5%, 11.31%, 9.97%, and 4% compared to PSO [8], FPA [16], FFA [17], and ALO [18], respectively, in the first case. In addition, the solution provided by the CSBO algorithm was also lower than the COA, ARO, and I-GWO methods. Furthermore, the stability of the proposed method was higher than that of the compared methods after 30 trials. Therefore, CSBO is identified as one of the most effective and reliable algorithms for solving the CM problem.

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