Coot Bird Behavior-Based Optimization Algorithm For Optimal Placement Of Thyristor Controlled Series Compensator Devices In Transmission Power Networks

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Abstract. *This study presents the new application of Coot bird behavior-based optimization algorithm (COOTBA) for optimal placement of Thyristor Controlled Series Compensator (TCSC) devices in an IEEE 30-node transmission power network with three single objectives, including fuel cost, power loss, and voltage deviation. COOTBA is implemented for the system with one case without TCSC devices and three others with TCSC. COOTBA can reach smaller cost and loss than previous algorithms by from 0.04% to 3.78%, and from 6.7% to 40.3% in the first case without TCSC. In the second case with TCSC, COOTBA can reach smaller cost than others by from 0.008% to 0.66%. In addition, the comparisons of results from COOTBA in the three cases with TCSC indicate that TCSC should be optimized for both location and reactance, and the limitation of TCSC devices should be high enough. Thus, COOTBA is an effective algorithm for optimizing TCSC devices on transmission power systems.*

Keywords

Coot birds, Thyristor controlled series compensator, transmission power network, fuel cost, power loss, voltage deviation.

1. Introduction. Problem Definition

A power system's most basic electric parts are power plants, transmission grids, distribution grids, and loads [1]. Typically, the two primary components of power plants are generators and transformers, whereas transmission grids and distribution grids are mainly comprised of lines, transformers, buses, and loads. Transmission and distribution grids have almost the same electric components but different sizes. Greater component size is for transmission grids, but a smaller size is for distribution grids. Generators and transformers at power plants are in charge of producing and transmitting electricity to transmission lines [2]. Distribution lines receive electricity from transmission lines and provide electricity to loads. Transmission lines play a very important role in power systems since they receive a very high power from power plants and supply the power to distribution power networks. If the transmission lines cannot work stably, power generated by power plants cannot be provided to distribution lines and loads [3]. So, optimal power flow (OPF) for transmission power networks has become a significant problem in power systems.

The conventional OPF problem has attracted a vast number of studies for reaching different objective func-

Tab. 1: Nomenclature

N_{TGs}	Number of thermal generators in existing power system
α_{1n}, α_{2n}, α_{3n}	Fuel coefficients of thermal generator n
PG_n, QG_n	Active and reactive power generated by the thermal generator n
CD_{ab}	Conductance of the transmission line $a-b$
U_a and U_b	Voltage amplitudes at node a and node b
N_{ND}	Number of nodes of the given transmission network
PG_n^{lst}, PG_n^{hst}	The lowest and highest active power generation of the nth thermal generator
QG_n^{lst}, QG_n^{hst}	The lowest and highest reactive power generation of the nth thermal generator
SC_a^{lst}, SC_a^{hst}	The lowest and the highest reactive power generation of the shunt capacitors at node a
U_{load}^{lst}, U_{load}^{hst}	The lowest and the highest voltage magnitudes of load at the load node d
U_n^{lst}, U_n^{hst}	The lowest and the highest voltage magnitudes of the thermal generator n
N_{NLS}	Number of load nodes
TS^{lst}, TS^{hst}	The lowest and the highest tap setting value of all transformers
TS_p	Tap setting value of the transformer p
N_{tfms}	Transformer number
AP_k	Apparent power transmitted through the branch k
AP_k^{hst}	The highest apparent power of the branch k
N_{Brs}	Branch number
X_{TCSC}^{lst},X_{TCSC}^{hst}	The lowest and highest reactance values of TCSC devices
$X_{TCSC,q}$	The reactance of the TCSC q
N_{TCSC}	The number of TCSC
$Br_{TCSC,q}$	The branch with the qth TCSC
$rdn_{0\div1}$	A random number within one and zero

tions such as electric generation fuel cost reduction [4] and polluted emission reduction [5] for thermal power plants (ThPPs), and voltage profile enhancement [6]. When the trend of using renewable energies becomes popular, wind and solar photovoltaic power plants are considered with ThPPs as major power sources in transmission power networks [7]. However, a big problem of transmission power networks is the contingency of transmission lines once power plants upgrade their power or loads need more power [8]. The additional installation of thermal generating units, the installation of new wind power plants and new solar photovoltaic power plants, the additional installation of wind turbines or solar photovoltaic arrays in existing renewable power plants, or changes in modern technologies are the reason that transmission lines cope with the status of overcurrent [9].

The key motive of OPF is to find the optimal operation plan for generating units and other electric devices for cutting the electric production cost and energy loss and enhancing power quality such as frequency, voltage, and high reliability while satisfying all constraints from these components [10]. In simulating the OPF problem, thanks to the aid of software, parameters of electric components are modeled as control variables and dependent variables in which control variables and dependent variables are, respectively, regarded as input data and results of the Newton-Graphson method [11]. If the two types of variables are within allowable limits, there is a valid solution for power flow. However, an optimal solution must satisfy all constraints and have a good objective function [12]. Considering the serious issue of contingency, finding solutions to the OPF problem take more challenges, or even there are no valid solutions found by very strong methods for the cases. Combining power flow methods such as Gaussidel/Newton-Graphson and the metaheuristic algorithms is the most effective trend [13]-[15]. Mathpower was run for calculating power flows; meanwhile, an improved genetic algorithm [13], improved cuckoo search [14], and Jellyfish search algorithm (JSA) [15] were successfully applied to finding control variables. However, if power plants must produce high power and transmit to loads, these very high-performance methods also fail to find reasonable solutions.

Derived from the unexpected issues, Flexible Alternating Current Transmission System (FACTSs) components have been suggested to be used in power systems. Several FACTS devices have been applied to minimize active power loss, reduce voltage drop, and avoid contingency, such as Static Var Compensator (SVC) [16], static synchronous compensator (STATCOM) [17], Thyristor Controlled Series Compensator (TCSC) [1], [18]-[24], Unified Power Flow Controller (UPFC) [25, 26], Thyristor Controlled Phase-Angle Regulator (TCPAR) [25], the combination of TCPAR and TCSC [27]-[30], and the combination of SVC and TCSC [31]. Several studies have considered the same FACTs, but different metaheuristic algorithms were used. The study [1] was a very early study about TCSC by proposing a hybrid Simulated annealing algorithm and Tabu search algorithm (SAA/TSA) in 2002. The study has also implemented Genetic algorithm (GA), Tabu search algorithm (TSA), and Simulated annealing algorithm (SAA) for investigating the solutions obtained by SAA/TSA. The study [16] has solved a multiobjective function, and it has used A multiobjective biogeography-based optimization algorithm (MOBBO). The study [17] also optimized the installation of STATCOM and UPFC to reduce current on transmission lines. Particle swarm optimization (PSO) [18], improved antlion algorithm (IALA) [19], and Genetic algorithm (GA) [20, 21] were respectively applied for optimizing TCSC in transmission power networks. Two improved versions of particle swarm optimization were respectively applied in the studies [22, 23], including Constriction factor-based particle swarm optimization algorithm (CF-PSO) [22], and challengers and aging leader algorithm-based particle swarm optimization (CALA-PSO) [23]. CF-PSO was a popular improved version of PSO that has been applied for many optimization problems in engineering. Meanwhile, CALA-PSO was first developed in the study [23]. The study [24] has developed a hybrid harmony search algorithm and differential evolution algorithm (HAS/DE) for the OPF problem with TCSC; however, the study has not implemented single algorithms, such as harmony search algorithm and Differential evolution for the same problem in the study [24]. The study [25] has suggested using an improved grasshopper algorithm (IGRA) to optimize the installation of either UPFC or TCPAR in the transmission power network. Different algorithms, such as hybrid PSO [27], krill herd algorithm (KHA) [28], symbiotic organisms search algorithm (SOSA) [29], and nondominated sorting genetic algorithm-II (NSGA-II) [30], have been applied for optimizing TCPAR and TCSC simultaneously. The studies have indicated that the number of FACTs devices had a clear impact on the improvement of the voltage of loads, energy loss reduction, and reduction of electric generation costs. GA, differential evolution (DE), and particle swarm optimization have been applied for optimizing both SVC and TCSC. SVC could compensate for reactive power at nodes installed with SVC; meanwhile, TCSC could reduce a part of a parameter of transmission lines. So, the three algorithms have improved the technical indicators for the applied systems, but their effectiveness was different. In general, these studies have applied different FACTs in transmission power systems for technical and economic factors. The results were much better than those for base transmission power systems without the FACTs device.

In this study, we apply an effective metaheuristic algorithm, Coot bird behaviour-based optimization algorithm (COOTBA) for the OPF problem with the placement of TCSC devices in a transmission power network with 30 nodes. COOTBA has been proven to be very effective for placing solar generators in distribution systems [31, 32]. The study [33] applied COOTBA for an optimal power flow considering load nodes with aluminum plants for reducing emission and power loss. COOTBA was proved to be successful for the problem and to be more effective than glowworm swarm algorithm (GWSA) for all study cases. The performance of COOTBA was proved to be high for optimization problems in transmission and distribution networks, although it has not been shown to be better than all existing methods. So, COOTBA is applied in the study for the OPF problem with the presence of TCSC. The novelty of the study is as follows:

- Find the maximum limit of TCSC for the highest cost and loss reductions, and the best voltage improvement.
- Compare the performance of COOTBA and previous algorithm in [34] in finding optimal locations of TCSC.

The contribution of the study are as follows:

- Reach smaller electricity generation costs, smaller power losses and better voltage profile than previous studies.
- Find the most optimal solutions to TCSC in reducing electricity generation cost and power loss, and improving voltage.
- Find a suitable algorithm, COOTBA, for the placement of TCSC in transmission power networks.

2. Problem description

2.1. Objective functions

This study considers three objective functions (OFs) while evaluating the contributions of TCSC in transmission power networks, including total fuel cost minimization (TFC) [35], active power loss minimization (APL) [36], and voltage deviation minimization (VD) [12]. Their mathematical expressions are, respectively, presented as follows:

$$TFC = \sum_{n=1}^{N_{TGs}} \alpha_{1n} + \alpha_{2n}.PG_n + \alpha_{3n}.PG_n^2 (\$/h), \quad (1)$$

$$APL = \sum_{a=1}^{N_{ND}} \sum_{b=1, b\neq a}^{N_{ND}} CD_{ab}.(U_a^2 + U_b^2 - 2.U_a.U_b.\cos\phi_{ab})(MW), \quad (2)$$

$$VD = \sum_{a}^{N_{ND}} |U_a - U_{STR}| (Pu). \quad (3)$$

In Equation (2), φ_{ab} is obtained by using $\varphi_{ab} = \varphi_a - \varphi_b$ where φ_a and φ_b are voltage phase angels at node a and node 4. In Equation (3), U_{STR} is the standard voltage value, and its value is set to a rated value of 1.0 pu.

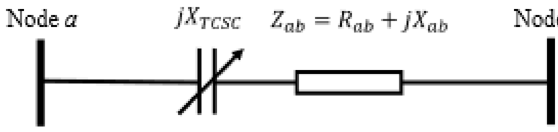

Fig. 1: A simple illustration of the TCSC installed in the specific transmission line.

2.2. The description of TCSC

Thyristor controlled series compensator (TCSC) is one of the FACTs devices that can be installed in transmission power networks for economic and technical targets such as power generation, voltage drop reduction, power loss reduction, etc. In a transmission line with the presence of TCSC, the line model is plotted in Figure 1 [37].

The reactance model of the line after installing TCSC is obtained by:

$$X'_{ab} = X_{ab} - X_{TCSC}. \tag{4}$$

In addition, the transfer conductance and the susceptance of the line $a - b$ after installing a TCSC device are recalculated by [38]:

$$CD_{ab}^{TCSC} = \frac{R_{ab}}{R_{ab}^2 + (X_{ab} - X_{TCSC})^2}, \tag{5}$$

$$ST_{ab}^{TCSC} = \frac{-(X_{ab} - X_{TCSC})}{R_{ab}^2 + (X_{ab} - X_{TCSC})^2}, \tag{6}$$

where CD_{ab}^{TCSC} and ST_{ab}^{TCSC} are, respectively, the conductance and the susceptance of the line $a - b$ after the TCSC device is placed on the line; R_ab and X_ab are, respectively, the resistance and reactance of the transmission line $a - b$ before installing TCSC; X_{TCSC} is the reactance of the TSCS device placed on the transmission line $a - b$. Note that $CD_{ab}^{TCSC} = CD_{ba}^{TCSC}$ and $ST_{ab}^{TCSC} = ST_{ba}^{TCSC}$ are used as considering the factors in transmission power networks.

2.3. Constraints of OPF problem with TCSC

1) Equality constraint

In OPF problem, the active and reactive power balance constraints at each node a (where $a = 1, \ldots, N_{ND}$) must be satisfied as shown in the following expressions [39]:

$$PG_a - PD_a = U_a \sum_{b=1}^{N_{No}} U_b \begin{bmatrix} CD_{ab}^{TCSC}.\cos(\phi_{ab}) \\ +ST_{ab}^{TCSC}.\sin(\phi_{ab}) \end{bmatrix}, \tag{7}$$

$$QG_a + SC_a - QD_a = U_a \sum_{b=1}^{N_{No}} U_b \begin{bmatrix} CD_{ab}^{TCSC}.\cos(\phi_{ab}) \\ -ST_{ab}^{TCSC}.\sin(\phi_{ab}) \end{bmatrix}, \tag{8}$$

where PG_a and QG_b are, respectively, the active and reactive power injected at node a by thermal generators; PD_a and QD_b are, respectively, the active and reactive power demands of loads at node a; and SC_a is the reactive power supplied by the reactive power compensators connected at node a.

2) Inequality constraints

These constraints are considered to satisfy operation limits of electric components in the transmission power networks, such as thermal generators, shunt capacitors, loads, transformers, transmission branches, and additionally added TCSC devices. The constraints are expressed as follows [1],[37],[40]:

$$PG_n^{lst} \leqslant PG_n \leqslant PG_n^{hst}, \tag{9}$$

$$QG_n^{lst} \leqslant QG_n \leqslant QG_n^{hst}, \tag{10}$$

$$SC_a^{lst} \leqslant SC_a \leqslant SC_a^{hst}; a = 1, ..., N_{ND}, \tag{11}$$

$$U_{load}^{lst} \leqslant U_{load} \leqslant U_{load}^{hst}; load = 1, ..., N_{NLs}, \tag{12}$$

$$U_n^{lst} \leqslant U_n \leqslant U_n^{hst}; n = 1, ..., N_{TGs}, \tag{13}$$

$$TS_p^{lst} \leqslant TS_p \leqslant TS_p^{hst}; p = 1, ..., N_{Tfms}, \tag{14}$$

$$AP_k \leqslant AP_k^{hst}; k = 1, ..., N_{Brs}, \tag{15}$$

$$X_{TCSC}^{lst} \leqslant X_{TCSC,q} \leqslant X_{TCSC}^{hst}; q = 1, 2, .., N_{TCSC}, \tag{16}$$

$$1 \leqslant Br_{TCSC,q} \leqslant N_{Brs}; q = 1, 2, ..., N_{TCSC}. \tag{17}$$

3. Coot bird behaviour-based optimization algorithm (COOTBA)

COOTBA is also a metaheuristic algorithm based on population and randomization. COOTBA is a mathematical model expressing the behaviors of an average-size water bird species, Coots, while searching for food. Coots tend to gather in a group with many individuals, and they move to find food together. Based on the amount of food found, all coots are classified into a member group and a leader group. COOTBA has a different construction from other metaheuristic algorithms due to the special characteristic of the coot bird species. COOTBA also needs a randomly initial solution set, and then the solution set can be improved based on two techniques. The initial solution set and its update process are produced and implemented as follows:

The initial solution set has an upper bound and a lower bound, $Bound^{up}$ and $Bound^{low}$, in which the bounds contain the maximum and minimum values of control variables in a considered optimization problem, respectively. Each solution is represented for a coot in the swarm, and it is modeled by $Coot_c$ (where $c = 1, \ldots, S_{Po}$, and S_{Po} is the value of population). Each $Coot_c$ is produced within the range $[Bound^{low}, Bound^{up}]$. Each solution is expressed by $MCoot_a$ in a low-quality set and $LCoot_b$ in a high-quality set. There are N_{low} and N_{high} solutions in the two sets, respectively. COOTBA updates new solutions for the two sets as follows:

3.1. Updating solutions for the low-quality set

In the low-quality solution set, COOTBA considers three conditions to update current solutions accordingly. The current and new solutions are set to $MCoot_a$ and $MCoot_a^{new}$, respectively. One out of the following equations is applied to produce the new solutions.

$$MCoot_a^{new} = MCoot_a + SF_1.(Coot_{rd} - MCoot_a), \tag{18}$$

$$MCoot_a^{new} = SF_2.(MCoot_a + MCoot_{a'},) \tag{19}$$

$$MCoot_a^{new} = LCoot_{rd} + SF_3.(LCoot_{rd} - MCoot_a), \tag{20}$$

Where SF_1, SF_2, and SF_3 are scaling factors given in Appendix A; $MCoot_{a'}$ is the closest solution to $MCoot_a$; $MCoot_{rd}$ is a newly generated solution within the range $[Bound^{low}$,$Bound^{up}]$; and $LCoot_{rd}$ is a random solution in the high-quality set.

3.2. Updating solutions for the high-quality solution set

COOTBA uses two formulas to search new solutions in the solution space, either Equation (21) or Equation (22). In the equations, $LCoot_b$ and $LCoot_b^{new}$ are the bth current and new solutions in the population. To select one out of the two equations, a random number within zero and one is produced and compared to 0.5. If the number is smaller than 0.5, Equation (21) is applied. Otherwise, Equation (22) is selected. The two equations are as follows:

$$LCoot_b^{new} = Coot_{best} + SF_4\left(Coot_{best} - LCoot_b\right) \tag{21}$$

$$LCoot_b^{new} = -Coot_{best} + SF_4\left(Coot_{best} - LCoot_b\right) \tag{22}$$

where $Coot_{best}$ is the best solution in the high-quality set; and SF_4 is a scaling factor given in Appendix A.

3.3. Application of COOTBA for OPF problem with TCSC

In this study, COOTBA is responsible for finding control parameters of the conventional OPF problem and TCSCs' parameters. Section 2 has mentioned these parameters. The conventional OPF problem's parameters must satisfy constraints (9), (11), (13) and (14) meanwhile TCSCs' parameters must satisfy constraints (16) and (17). After having these parameters, Mathpower program is run for reaching dependent parameters of the OPF problem, which can satisfy constraints (10), (12) and (15). If these dependent parameters are not fallen into the limits, they must be fined for finding penalty terms. Finally, objective functions in Eqs. (1)-(3) can be obtained.

The flowchart of applying COOTBA for the problem is presented in Figure 2.

4. Numerical results

In the section, COOTBA is implemented for the IEEE 30-node transmission power system for optimizing the placement of TCSC devices with three different single objective functions, including cost, active power loss, and voltage deviation. In addition, COOTBA is also implemented for the base system without TCSC for the same objectives. The system is plotted in Figure 2, and its data can be taken from [41]. The limitations of reactance for TCSC are from 0.0 to 0.02 pu [1]. For the case of using a suitable location for TCSC without using the search from COOTBA, the sole location obtained by implementing the loss sensitivity index method [34] is inherited to be branch 3-4. The three study cases are expressed in detail as follows:

- Case 1: COOTBA is implemented for the system without TCSC devices. For this case, S_{Po} and MIter are, respectively, set to 20 and 200 by experiment
- Case 2: Line 3-4 is employed for placing TCSC. COOTBA is implemented for finding parameters in the power system and reactance of TCSC. For this case, S_{Po} and $MIter$ are, respectively, set to 40 and 200 by experiment.
- Case 3: COOTBA is implemented for finding parameters in the power system, and location and reactance of TCSC. For this case, S_{Po} and $MIter$ are, respectively, set to 40 and 500 by experiment.
- Case 4: Similar to Case 3, but the maximum limit of TCSC is one pu instead of 0.02 pu as in Case 3. The settings of S_{Po} and $MIter$ are similar to those of Case 3.

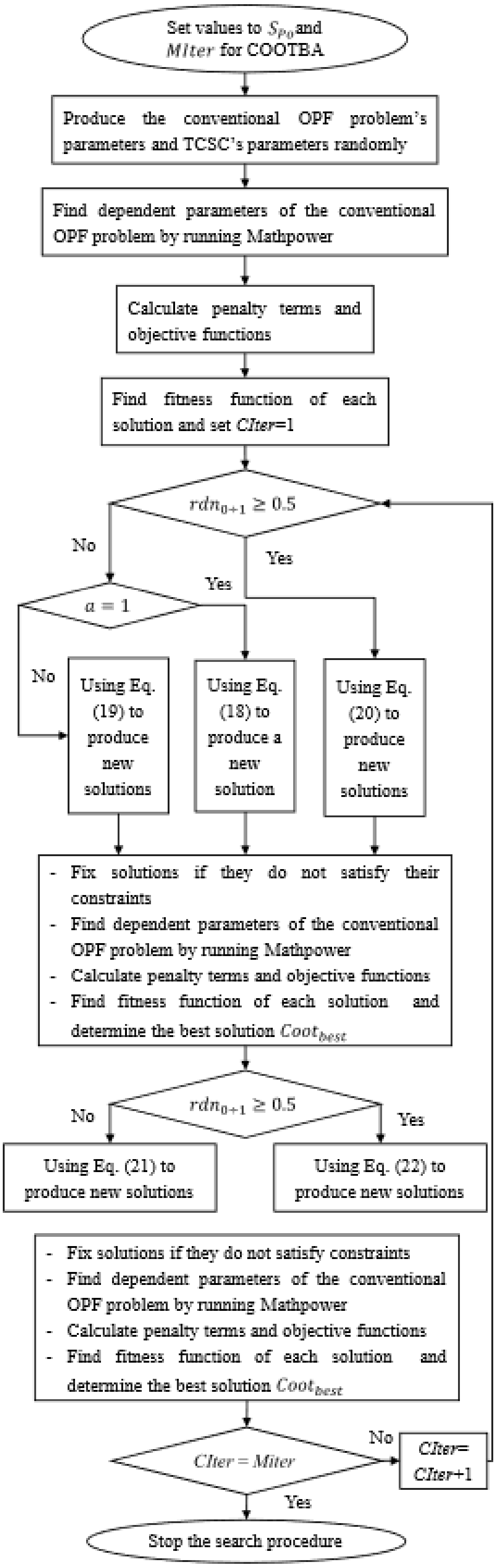

Fig. 2: Application of COOTBA for OPF problem with TCSC devices.

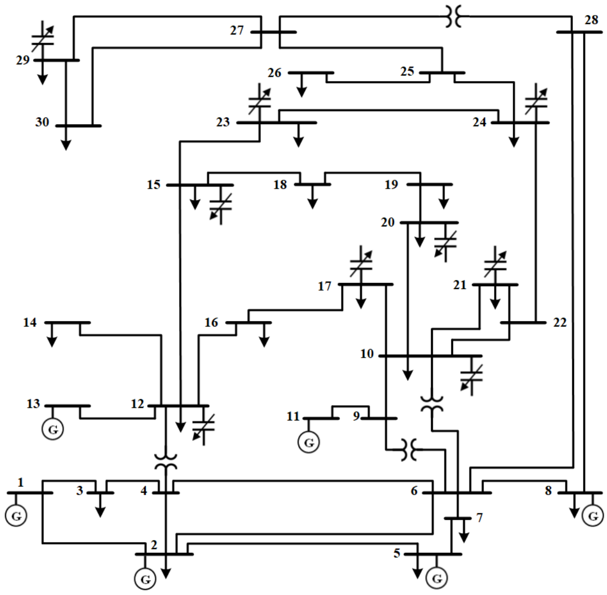

Fig. 3: The IEEE 30-node system.

To reach objectives in the four cases above, COOTBA is implemented for 50 trial runs. Matlab software with version 2018b is used to code the program, and a personal computer with the processor of 2.4 GHz and 8 GB of RAM is provided for installing the Matlab software.

4.1. Result comparison for 3 cases

Table 2 presents the best fuel cost, the best power loss, and the best voltage deviation for the three cases above from 50 successful runs for each case. In general, Case 3, with optimal location and parameter of TCSC, is the best for optimizing the considered objectives, cost, loss, and voltage. The base system without TCSC in Case 1 is the worst case for reducing fuel cost and improving voltage, but Case 2 is the worst for reducing power loss. In detail, the three values are respectively \$799.378, 2.946 MW and 0.142 Pu in Case 1, \$799.314, 2.954 MW and 0.140 pu in Case 2, and \$799.207, 2.929 MW, and 0.138 pu in Case 3. A strange issue is that Case 2 with TCSC at the predetermined line 3-4 suffers a higher power loss than the base system of Case 1 by (2.954-2.946=0.008 MW). This unexpected result indicates that the placement of TCSC on transmission line 3-4 is ineffective in reducing power loss. Case 3 finds the transmission line 2-5 for TCSC, and this solution is more effective than Case 2 by reaching a loss reduction of (2.954-2.929=0.025 MW).

Taking a look at the reactance of TCSC can see that Case 2 needs a 0.0176-pu, 1.52e-06-pu, and 0.0067-pu TCSC but Case 3 needs the maximum reactance of 0.02 pu for all three study cases. Case 2 with power loss objective needs approximately zero reactance for TCSC

Tab. 2: Summary of the best results from three study cases by running COOTBA

Study Case	Result	Objecitve function		
		Fuel cost ($)	Power loss (MW)	Voltage deviation (pu)
Case 1	Objective value	799.378	2.946	0.142
Case 2	Objective value	799.314	2.954	0.140
	X_{TCSC} (Pu)	0.0176	1.52e-06	0.0067
Case 3	Objective value	799.207	2.929	0.138
	X_{TCSC} (Pu)	0.02	0.02	0.02
	Location of TCSC	Line 2-5	Line 2-5	Line 1-18

with the value of 1.52e-06 pu. The optimal transmission line for placing a TCSC device is line 2-5 for cost and loss objectives and line 18-1 for the voltage objective. It is noted that if the TCSC device with a higher maximum limit of 0.02 Pu, the effectiveness of the TCSC device is greater than Case 3. In fact, Case 4 is implemented, and its results are presented in Table 3. It can be seen clearly that the cost, loss, and voltage deviation of Case 4 are better than those of Case 3 in Table 2 by $0.08, 0.033 MW, and 0.026 pu. Case 4 uses the same line 2-5 as Case 3 for cost optimization but different lines for loss and voltage deviation objectives. Line 27-28 and line 10-20 are employed by Case 4 instead of line 2-5 and line 1-18 for loss and voltage deviation. The reactance of TCSC is also different between Case 3 and Case 4. The reactance values of Case 4 are, respectively, 0.0497, 0.2620, and 0.3998 pu, while those of Case 3 are 0.02.

Tab. 3: Summary of the best results from Case 4 by running COOTBA

Result	Objecitve function		
	Cost ($)	Loss (MW)	Vol. Dev. (pu)
Objective value	799.127	2.896	0.116
XTCSC (Pu)	0.0497	0.2620	0.3998
Location of TCSC	Line 2-5	Line 27-28	Line 10-20

The fuel cost of generators is plotted in Figure 4 and Figure 5 to compare Case 2 and Case 1, and Case 3 and Case 1. The two figures show that the same generators have a very small cost difference. In addition, the saving cost of each generator in Case 2 and Case 3 is also calculated as compared to Case 1 and plotted by using blue areas in the two figures. Generators 1 and 5 of Case 2 and Case 3 use smaller cost than those of Case 1 by $0.65 and $2.03, and $0.68 and $0.95 but other generators 2, 3 and 4 of Case 2 and Case 3 use higher cost than those of Case 1. Generator 6 of Case

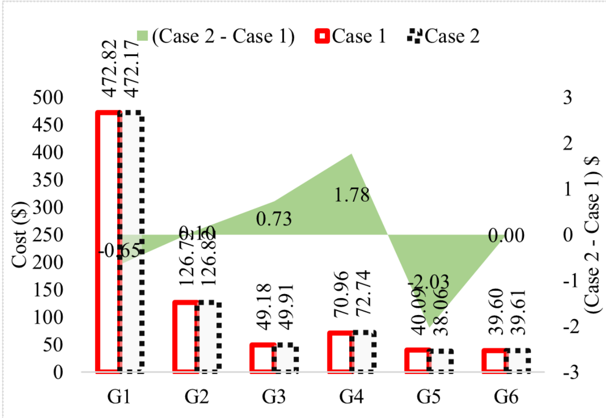

Fig. 4: Comparison of generator fuel cost between Case 2 and Case 1.

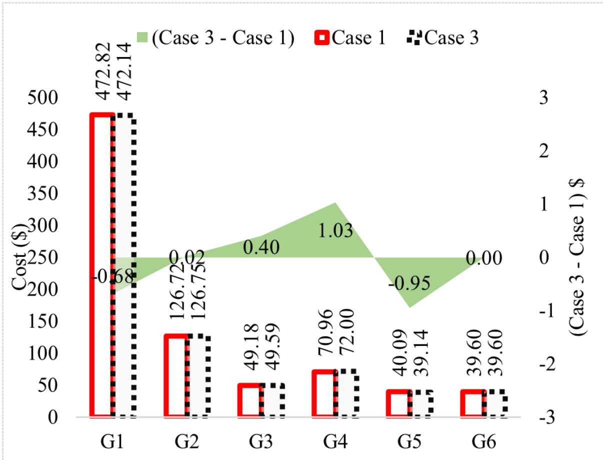

Fig. 5: Comparison of generator fuel cost between Case 3 and Case 1.

2 and Case 3 have the same cost as Case 1. The results indicate that the placement of TCSC on transmission line 3-4 in Case 2 and transmission line 2-5 in Case 3 changed the power generated by generators and led to cost reduction.

The convergence processes to reach the best cost for Cases 1 and 2, and Cases 3 and 4 are given in Figure 6 and Figure 7. The figures show that COOTBA always reach better cost in Case 2 than Case 1, and in Case 4 than Case 3 at the same iteration. At the final iteration, the costs of Case 2 and Case 4 are respectively better than those of Case 1 and Case 3.

The voltage of 30 nodes for the voltage deviation objective is plotted in Figure 8 for comparing Case 2 and Case 1, and in Figure 9 for comparing Case 3 and Case 1. The two figures indicate that the power system in the three study cases can satisfy voltage constraints. Nodes have a range of voltage from higher than 0.97 pu and smaller than 1.04 pu, in which the limits of voltage are from 0.95 to 1.05 pu. The voltage difference at nodes is not clear between Case 2 and Case 1, and

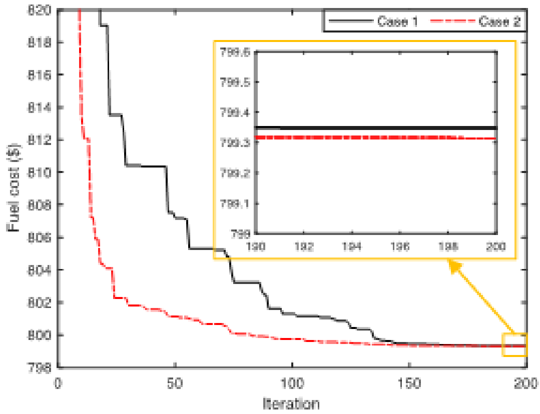

Fig. 6: Convergence processes to reach the best cost for Cases 1 and 2.

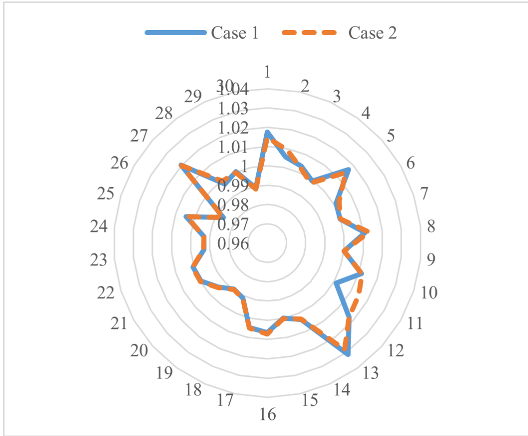

Fig. 8: Voltage of nodes in Case 1 and Case 2.

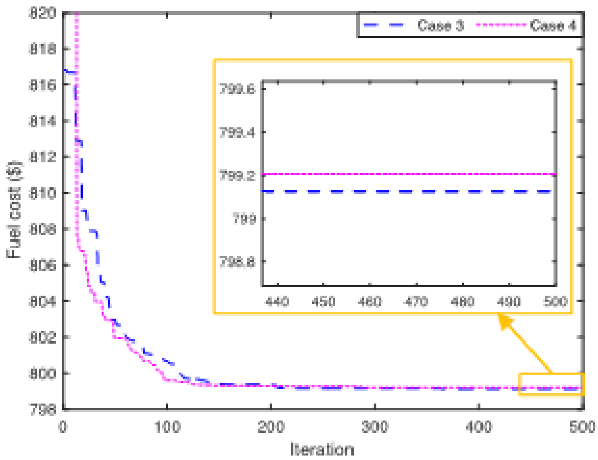

Fig. 7: Convergence processes to reach the best cost for Cases 1 and 2.

Case 3 and Case 1. Clearly, COOTBA is very useful in optimizing the control parameters of the base system in Case 1. So, the use of TCSC in Case 3 cannot reach much better results than in Case 1. To clarify the effectiveness of COOTBA, the following section will compare the performance of COOTBA with previous methods for study cases.

4.2. Comparison of performance between COOTBA and others

COOTBA is compared to other methods for Case 1 without TCSC for cost and loss objectives in Table 4. COOTBA is compared to adaptive PSO (APSO) [42], constriction factor-based PSO (CF-PSO) [43], improved CF-PSO (ICF-PSO) [43], improved group search optimization algorithm (IGSOA) [44], conventional Honey Bee Mating algorithm (CHBMA) and improved of CHBMA (IHBMA) [45], multi-objective mathematical programming algorithm (MOMPA) [46], Gaussian bare bone imperialist competitive optimization algorithm (GBBICOA), modified social spider algorithm (MSSA) [48], improved evolution programming algorithm (IEPA) [49], teaching and learning based algorithm (TLBA) [50] and hybrid TLBA, and imperialist competitive algorithm (HTLBA-ICA) [50]. The cost comparison shows that COOTBA is superior to many algorithms for cost objective and loss objectives, excluding ICF-PSO [43] and MSSA [48]. For the cost comparison, COOTBA has found a smaller cost than others, from \$0.292 (compared to CF-PSO[43]) to \$31.472 (compared to GBBICOA [47]), corresponding to 0.04% to 3.78%. For loss comparison, COOTBA has found a smaller loss than others, from 0.21 MW to 1.991 MW, corresponding to from 6.7% to 40.3%. However, COOTBA is worse than MSSA and ICF-PSO due to a higher cost of \$0.038. So, COOTBA is also a highly effective algorithm, and its results from TCSC device placement are highly reliable.

Tab. 4: Comparison of cost and power loss from Case 1

Method	SAA/TSA [1]	APSO [42]
Cost (\$)	804.7837	801.97
Method	GBBICOA [47]	MSSA [48]
Cost (\$)	830.85	799.34
Method	IGSOA [44]	CHBMA [45]
Cost (\$)	801.75	802.21
Method	HTLBA-ICA [50]	CF-PSO [22]
Cost (\$)	801.0488	799.9512
Method	CF-PSO [43]	ICF-PSO [43]
Cost (\$)	799.67	799.34
Method	IEPA [49]	TLBA [50]
Cost (\$)	802.465	801.6524
Method	IHBMA [45]	MOMPA [46]
Cost (\$)	801.99	801.76
Method	HAS/DE [24]	COOTBA
Cost (\$)	799.5762	799.378
Method	MOMPA [46]	GBBICOA [47]
Power loss (MW)	3.156	4.937
Method	MSSA [48]	COOTBA
Power loss (MW)	2.945	2.946

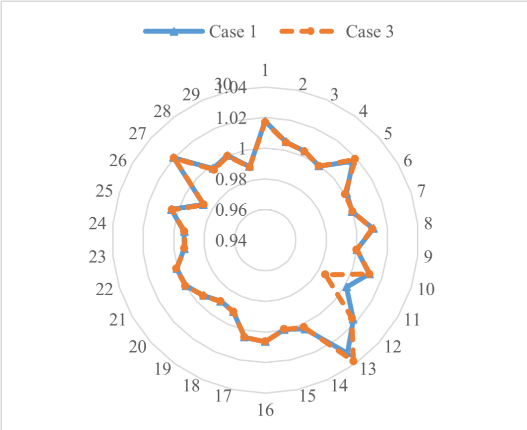

Fig. 9: Voltage of nodes in Case 1 and Case 3.

As considering the OPF problem with TCSC, the fuel costs are compared in Table 5. About the fuel cost of Case 2, COOTBA has reached a smaller cost than all compared algorithms, including SAA/TSA [1], CF-PSO [22], HAS/DE [24] by \$5.335, \$0.460, \$0.060, corresponding 0.66%, 0.058%, and 0.008%. Clearly, COOTBA is a high-performance algorithm for the OPF problem with the placement of TCSC devices. However, when applying the novelty with the determination of optimal locations (Case 3) and increase of TCSC limit, which is higher than 0.02 Pu (Case 4), COOTBA could reach much smaller costs than these methods. COOTBA still used the upper limit with 0.02 Pu for TCSC in Case 3, but it used a higher value for TCSC with 0.0497 Pu in Case 4. And the change of assumptions (location for placing TCSC and TCSC limit) has led to a clear effectiveness in reducing electricity generation cost.

Tab. 5: Comparison of cost and power loss from Case 1

Method Fuel	cost (\$)	X_{TCSC} (pu)
SAA/TSA [1] (Case 2)	804.6497	0.02
CF-PSO [22] (Case 2)	799.7741	0.0107
HAS/DE [24] (Case 2)	799.3743	0.0200
COOTBA (Case 2)	799.314	0.0176
COOTBA (Case 3)	799.207	0.02
COOTBA (Case 4)	799.127	0.0497

5. Conclusion

This study applied Coot bird behavior-based optimization algorithm for solving optimal power flows of the IEEE 30-node transmission power network. Four study cases have been implemented, in which Case 1 neglects, but others consider TCSC devices. Case 2 only optimized the reactance of TCSC, while Case 3 and Case 4 optimized both location and reactance of TCSC. Case 3 used the maximum reactance of 0.02 pu; meanwhile, Case 4 expanded the range to 1.0 Pu. The results can be summarized as follows:

- COOTBA was superior to about fifty other algorithms in previous studies for Case 1. As compared to the worst compared algorithm, COOTBA could reach a smaller cost and loss by 3.78% and 40.3%, respectively.
- COOTBA could reach less cost than three algorithms, including a hybrid metaheuristic algorithm and improved versions of PSO for Case 2. The highest reduction in cost could be up to 0.66%.
- Case 3 could reach smaller cost, loss, and voltage deviation than Case 1 and Case 2, but it reached worse values than Case 4.

The results indicated that COOTBA is very effective for the conventional OPF problem and expanded OPF problem with TCSC devices. COOTBA was effective in searching the location and reactance of TCSC devices. Another algorithm based on loss sensitivity factors was applied to find transmission line 3-4 for TCSC placement, but COOTBA could find more suitable transmission lines. With different limits of TCSC's reactance, COOTBA found different lines, and the different lines could lead to better results than other studies. So, the study has high contributions to applying COOTBA and suggests optimizing both reactance and location for TCSC. However, the study has unexpected shortcomings in terms of the performance of COOTBA and the consideration of more serious constraints. In the future, the study will be improved by considering more FACTs devices such as SVC, UPFC, and TCPAR for improving the effectiveness of transmission power networks with large-scale up to 118 nodes. On the other hand, renewable energies will be employed, and the FACTS devices will be employed to avoid the overload status of lines as well as improve fuel cost, power loss, and voltage profile of transmission power systems.

Author Contributions

Both N.A.T. and T.M.P. performed the analytic calculations and performed the numerical simulations. L.C.K. and T.T.N wrote the whole paper. N.A.T. and T.T.N contributed to the final version of the manuscript.

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Appendix A

This section presents the calculation of scaling factors of COOTBA. There are four scaling factors used to update new solutions for COOTBA, and they are obtained by:

$$SF_1 = rdn_{0\div 1} \times \frac{MIter - CIter}{MIter}, \tag{23}$$

$$SF_2 = 0.5, \tag{24}$$

$$SF_3 = 2rdn_{0\div 1}.\cos\left(2.\pi.rdn_{-1\div 1}\right), \tag{25}$$

$$SF_4 = \frac{2.MIter - CIter}{MIter}.rdn_{0\div 1}.\cos\left(2.\pi.rdn_{-1\div 1}\right), \tag{26}$$

where, $rdn_{0\div 1}$ and $rdn_{-1\div 1}$ are random numbers within 0 and 1, and within -1 and 1; $CIter$ and $MIter$ are the present iteration and maximum iteration.