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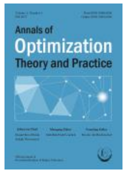

Transmission network expansion planning using crow search algorithm

Jitesh Jangid[1]✉ • Aishwarya Mehta[2] • Akash Saxena[2] • Shalini Shekhawat[2] • Rajesh Kumar[2]

[1] 1-A-62 SHIV SHAKTI COLONY SHASTRI NAGAR

[2] Swami Keshvanand Institute of Technology, Management & Gramothan, India

✉ jj90946@gmail.com

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Abstract In the power market, the rapidly growing demand for power is a challenging task. Power production is also a difficult job with scarce fossil fuel supplies. There are many interconnected operations involved in running and managing the power grid. Expansion of the transmission line is a workaround by the addition of transmission circuits to satisfy aggressive load demand. The proposal for expansion should be cost-effective and sustainable. With the aid of optimization algorithms, the challenge of expansion has been solved in recent years. This paper first explains various aspects and solution techniques of transmission expansion planning by taking inspiration from this fact, and then the implementation of the Crow Search Algorithm (CSA) is stated to solve the problem of Transmission Expansion Planning (TEP). Two standard bus systems namely the Garver 6 bus system and the Brazilian 46-bus system are used for experiment to measure the effectiveness of CSA. CSA is a competitive algorithm which has been shown its outperformance very well in some literature.

Keywords Crow Search Algorithm; Transmission line expansion; Metaheuristic; Garver 6-Bus System; Brazilian 46-Bus system

1. Introduction

In electrical power system network, transmission network plays an important role. The transmission network does not only provide a connecting link between the power generation and distribution network but also provide a reliable network to supplier and

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consumers. To maintain this reliability of the system a good design of transmission network is required.

In the current scenario demand for power is regularly increasing day by day. To fulfill this demand, it is required to generate more power with the conventional and nonconventional methods and transmit this power to end-users. To supply this energy, the transmission network expansion is required. Establish a new transmission network is a very costly approach, to avoid this we try to expand the existing transmission network. This expanded network helps to fulfill the demand of end-users and maintains the reliability of the power system network. TNEP is basically divided into two categories: first one Dynamic TNEP and the second one Static TNEP. Dynamic TNEP helps to restrict the investment cost of the network during the planning of the transmission network. It also defines which facilities are needed or not needed in the expansion network. Dynamic TNEP problem is solved by metaheuristic and mathematical approach. Static TNEP is used to check that transmission expansion is financially possible or not and which facilities are required for this. Static TNEP is solved by heuristic, mathematical and metaheuristic approaches.

Transmission expansion planning requires that this expansion does not affect the security constraints of the power system network. TNEP problem is solved by different methods like Modified Grey Wolf Optimization (MGWO) khandelwal *et al.* (2018), Artificial Bee Colony (ABC) Rathore *et al.* (2013), specialized branch and bound (sp.BB) algorithm Haffner *et al.* (2001) , Haffner *et al.* (2000) and greedy randomized adaptive path relinking (GRAPR) approach Faria *et al.* (2005). In recently many metaheuristic approaches are used to solve the optimization problem because these approaches have the capability to search global optima without stucking into local optimas. Metaheuristic approaches are classified into four categories which are described as,

1. **Based on Physics and Chemical phenomena: -** These approaches are inspired by the chemical reaction, quality of atoms, and formulas of physics. The examples of these approaches are Atom Search Optimization (ASO) Zhao *et al.* (2019) , Quantum-Inspired Evolutionary Algorithm (QEA) Han & Kim (2002), Big Bang-Big Crunch (BB-BC) Algorithm Erol & Eksin (2006) and Chemical reaction optimization (CRO) Bhattacharjee *et al.* (2013) etc.
2. **Based on Natural Phenomena: -** These approaches get inspiration from the environment, this environment inspires researchers to develop more environment based approaches that help to solve research problems. Spider Monkey Optimization (SMO) Bansal et al. (2014), Cuckoo Search (CS) Yang & Deb (2010) and Particle Swarm Optimization (PSO) Kennedy & Eberhart (1995) are examples of the nature-inspired approach.
3. **Based on Evolution process: -** This approach is inspired by the Evolution theory which is given by Darwin. Evolution theory states that every individual has different qualities and try to generate a better individual by the mutation process in the next generation. Example of these approach are Backtracking Search Optimization

algorithm (BSA) Civicioglu (2013), Differential Search Algorithm (DSA) Civicioglu (2012) and Genetic Algorithm (GA) Whitley (1994) etc.

4. **Hybrid Approach**: - Hybrid approaches are a combination of two or more than two approaches that deal with the research problem. Grey Wolf Optimizer (GWO), Sine Cosine Algorithm (SCA) Singh & Singh (2017), Teaching-learning-based cuckoo search algorithm (TLCS) Huang *et al.* (2015) and Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) Kao & Zahara (2008) etc. are examples of this approach.

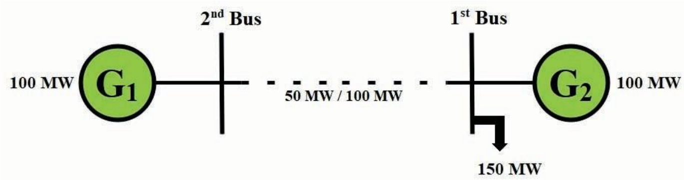

Figure 1. Basic Transmission Circuit

In nature, any algorithm is not sufficient to solve all types of research problems which is known as the free lunch theorem. This statement is an inspiration for researchers and helps to solve real-world optimization problems. In this consequence, we use crow search algorithm (CSA) to solve the transmission network expansion planning. CSA is introduced by Askarzadeh *et al.* in (2016) and inspired by the intelligent behavior of crow. Recently, several improved prototypes of CSA were developed and applied to a variety of engineering problems. The Modified CSA (MCSA) has been constructed to solve an economic load dispatch dilemma by Mohammadi *et al.* (2018), The work has resulted in chaotic versions of CSA by Sayed *et al.* (2019) for the feature selection problem and Shekhawat *et al.*(2020) proposed two phase modifications in CSA which improved the performance of basic CSA algorithm. After inspecting the literature it is found that CSA has the ability to search global optima in minimum time and this approach is not used to solve the TNEP problem. In this consequence, we try to solve the TNEP problem with CSA. Objectives of this paper are listed below

- To evaluate TEP problem by Crow Search Algorithm (CSA).
- To design a new network model of the test bus systems and test the ability, effectiveness of CSA algorithm.

Remaining part of paper is divided in section 2,3,4 and 5 those describes representation of TEP, Crow Search, Analysis of the results and conclusion of the proposed work respectively.

2. Mathematical Representation of TEP Problem

For illustration of TEP problem, a DC model is used in this work. It is a known fact that system security plays an essential role in the TEP system. After a single line malfunction, N-1 contingency analysis views device status. Security limitations of mathematical model of TEP can be represented as eq. 1 (Das & Suganthan (2010)). It can be converted into optimization process and expressed as follows:

$$\min \qquad v = \sum_{l \in \omega} C_l \cdot n_l \tag{1}$$

s.t

$$Jt^s + u = p \tag{2}$$

$$q_v^s - \gamma(r_v^0 + r_v)(\delta\phi_v^s) = 0,\ q\, or\, v \in 1, 2, \ldots.., rv \,\&\, v \neq s \tag{3}$$

$$q_v^s - \gamma(r_v^0 + r_v - 1)(\delta\phi_v^s) = 0,\ f\, or\, v = s, \tag{4}$$

$$|\, t_1^s \,| \leq (r_v^0 + r_v)\bar{q}_1,\ f\, or\, v \in 1, 2, \ldots..rv \ \&\ v \neq s \tag{5}$$

$$|\, q_1^s \,| \leq (r_v^0 + r_v - 1)\bar{q}_1,\ q\, or\, l = k, \tag{6}$$

$$0 \leq r_1 \leq \bar{r}_1 \tag{7}$$

$$r_1 \geq 0 \tag{8}$$

and integer, for $v \in 1, 2, \ldots.., rv \ \&\ v = s$

$$(r_1 + r_1 - 1) \geq 0 \quad \text{and integer,} \quad f\ \ or\ \ v = s \tag{9}$$

Where,

v= Overall Cost.

C= Cost of new line to be added.

n= New line to be added in network.

l = line between node i and j.

s= 0, Refers to the base case without any line interruption

J= Matrix displacement of branch-node events force Structure,

t^s= Vector with element l,

U= Total Load,

P=Total generation,

q^s= Elements of vectorq_v^s,

γ_v= The vulnerability of the circuit to be added in v^{th}.

r_v^0= Base case circuits.

$\delta\phi_v^s = v^{th} \,\&\, s^{th}$ line phase difference.

$q_v^s = v^{th} \,\&\, s^{th}$ total real power flown by circuit.

ω =Collection of the right way.

rv =Circuits total branches.

The basic TEP model is the same as shown in Sharma *et al.* (2017) and Verma *et al.* (2009). Different approaches to solve security constraint planning issues. Due to this reason to make the mathematical model more tractable, the mathematical model was updated to include these techniques given below at each load bus.

3. Crow Search Optimization

In nature, different types of birds are existing, crow is also one of them. Crow is the cleverest bird in nature and the size of its brain is bigger in comparison to body size. The crow has the capability to feel the dangerous situation, copy the voice of others, and also has good memory. Mirror-test and tool-making Prior *et al.* (2008) help to verify the capability and cleverness of the crow. A crow steals the food of another crow and tries to hide this food in the best place. In this hiding process, the crow tries to misguide the bird by going from one place to another and meanwhile it also remembers the best place in its mind. This process to find the best place is used in optimization. The behavior of crow is mainly dependent on four attributes which are listed below:

1. Crow always lives in a group
2.Crow always remembers their hiding place of food.
3.During the food searching crow follows each other and steal othersfood.
4.After stealing food crow misguide the other crows and save its food.

Every crow recalls the best place of hiding food which is expressed byW_x^t. This represents the best hiding place of the x^{th}crow. In this sequence, the crow chases the other crow to get information about the hiding place of food. Here ($x=1,2,3...B$), B is used to represent the number of crows that live together in a group. The position of the crow is represented by D_x^c for x^{th} crow in c^{th} iteration. Considering an iteration t, x^{th}crow tries to follow the crow z .In this case, two possibilities are assumed

- When crow z does not know that it is chased byx^{th}crow. In this case x^{th}crow update in their position to get the best position which is expressed as

$$H_x^{t+1} = H_x^t + R_x \times L_x^t \times (W_X^t - H_x^t) \tag{10}$$

- Where L is used to represent flight length while R_x is a random number that lies between 0 to 1.

- When crow z knows that it was followed by another crow, then he tries to misguide another crow by going one place to another place.

Both possibilities can be mathematically combined by the following the equation

$$H_x^{t+1} = \begin{cases} H_x^t + R_x \times L_x^t \times (W_X^t - H_x^t) & if \;\; L_x \geq AP^{x,t} \\ a \;\; random \;\; position & otherwise \end{cases} \tag{11}$$

Where R_x represents random numbers which are uniformly distributed between 0 to 1.$AP_{x,t}$ is known as crow z awareness probability factor for i^{th}iteration. This awareness probability factor is a control parameter that lies between exploration and exploitation. When$AP_{x,t}$ is less means it is the exploitation phase, and otherwise it is the exploration phase.In the initialization phase of CSA, some parameters are changeable like flight length (L), group size (B), maximum iteration number ($iter_{max}$), and awareness probability factor. In the initialization phase crow randomly generate its own initial position. In the initial phase, crow U does not know to hide food and initially hiding place of food is represented by W. After that crow updates their position according to equation 11. Memory updating of a crow can be expressed as

$$W_x^{t+1} = \begin{cases} H_x^{t+1}, \;\; f_n(H_x^{t+1}) \;\; is \; better \; than \;\; f_n(w_x^t) \\ w_x^t \qquad\qquad otherwise \end{cases} \tag{12}$$

Where fun () is known as objective function of the research problem. The solution steps of CSA are given in Algorithm 1.

4. Simulation Results and Analysis

The implementation of CSA in this segment is stated on two standard test bus systems. Some recently published methods have been considered to carry out this analysis: Modified Grey Wolf Optimizer (MGWO) Khandelwal et al. (2018), Grey Wolf Optimizer (GWO), Sine Cosine Algorithm (SCA), Whale Optimization Algorithm (WOA) and Artificial Bee Colony (ABC) Rathore et al. (2013). To make a fair comparison between all algorithms flock size, endpoint criterion and number of runs are kept constant. These are mentioned as under:

- Number of Search Agents = 30
- Number of runs = 100
- Number of Maximum Function Evaluation = 200000
- The whole evaluation process is done on MAT-LAB 2015a, on Intel core i3 4^{th} Generation system with 8GB ram and 240GB SSD.

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Algorithm 1. Crow Search Algorithm (CSA)

Begin
Initialize the position of N crows in search space
Position evaluation of Crows
Initialize the memory of each crow
While $iteration\ < Max_{iteration}$
for $\boldsymbol{i = 1}: \boldsymbol{N}$ (all N crows of the flock)
Randomly choose one of the crow to follow (for eg. j)
Define AP (awareness probability)
If $\boldsymbol{r > AP_j^{iteration}}$
$\boldsymbol{x_i^{iteration+1} = x_i^{iteration} + r_i \times fl_i^{iteration}} \times (\boldsymbol{m_i^{iteration} - x_i^{iteration}})$
else
$\boldsymbol{x_i^{iteration}}(\boldsymbol{search\ space\ random\ position})$
End if
End for
Check new feasibility positions
Evaluate new position of crows
update memory of crows
end while

4.1. Case 1: Garver 6-Bus system

In this section, we applied Crow search algorithm to solve the TEP problem for Garver's 6-Bus system. This system consists of 6 buses as figure 2 with a load of 760MW and 15 different candidate paths. All mandatory data is mentioned and taken from Romero et al. (2002) for the evaluation of this system. The methodology proposed for solving TEP has been tested 100 times and the data obtained is then sorted. Specific values are stored as final results from sorted data, which appears most consistently in the array. The result obtained is then compared with the GWO, MGWO Khandelwal et al. (2018) and ABC Rathore et al. (2013) results, previously reported in table 1. The results are shown in this table in terms of some parameters where the success rate of evaluation is shown by (SR), (AFE) is used for average function evaluation and (OC) for operational cost in $\times 10^3$\$. Following observation of the results reported in Table 1.

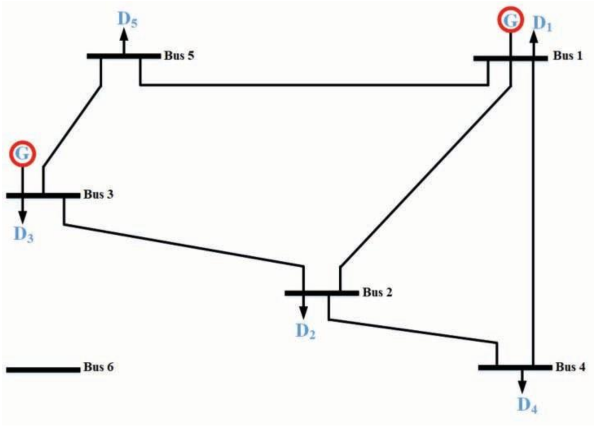

Figure 2. Garver 6 bus system with no distributed generation

It is noted that in terms of SR and AFE parameters, CSA performs better. It has been found that compared to other opponents, CSA achieves 93% SR for this system. As conclusion of experiment on this test bus system, CSA algorithm performs better than the GWO, MGWO and other competitor algorithms as we can say that CSA is winner from all other with highest SR, minimum OC and AFE. As shown in the table, 3 lines can be added between nodes 6 and 2, 1 line added between node 3 and 5, and 2 lines between node 4 and 6, which shows that the new lines added are done between less numbers of nodes.

4.2. Brazilian 46-Bus system

In this, we implemented CSA on Brazilian 46-Bus system as second test bus system which consists 79 lines and 46 number of bused with 6880MW load and all kind of relative data have been taken from Romero et al. (2002). The technique used for solving TEP has been evaluated 100 times and the collected data is further sorted. Common values are stored as final results from sorted data, which occurs more frequently in the array. In table 2, the results of the optimization process are shown. The observations are illustrated in terms of AFE, SRand operating expense in 10^6 US $. In comparison to other participant algorithms, CSA has been secured 98% SR. According to the results reported for Brazilian 46-Bus System in table 2, 2 lines are proposed between node (26-29) and 1 line between all the nodes as per classification node (5-11), node (14-15), node (15-16), node (24-25), node (27-29), node (28-30), node (28-31), node (31-32), node (40-41) and node (46-11).

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Table 1. Result Analysis of Garver 6-Bus System

	Terminals	N 6-2 = 3, N 3-5 = 1, N 4-6 = 2,
CSA	O. Cost 10^3 *US* $	170
	S.R.	93
	S.D.	36.2
	A.F.E.	68287.2
MGWO Khandelwal *et al.* (2018)	Terminals	N 4-6 = 2, N 6-2 = 3, N 3-5 = 1, N 2-3 = 1
	O. Cost 10^3 *US* $	190
	S.R.	90
	S.D.	5.6796
	A.F.E.	49237
WOA	Terminals	N 4-6 = 3, N 6-2 = 2, N 5-6 = 2
	O. Cost 10^3 *US* $	262
	S.R.	20
	S.D.	28.42
	A.F.E.	126092.1
ABC Rathore et al. (2013)	Terminals	N 4-6 = 2, N 6-2 = 4, N 3-5 = 1
	O. Cost 10^3 *US* $	200
	S.R.	N/A
	S.D.	N/A
	A.F.E.	N/A
Special B.B. Haffner et al. (2001)	Terminals	N 4-6 =2, N6-2=1, N3-5=2, N2-3=2, N1-5=1
	O. Cost10^3 *US* $	192
	S.R.	N/A
	S.D.	N/A
	A.F.E.	N/A

Table 2.Result Analysis of Brazilian 46-Bus System

	Terminals	N 2-3 =1, N 5-11 =1, N 14-15 =1, N 15-16 =1, N 24-25 =1, N 26-29 =2, N 27-29 =1, N 28-30 =1, N 28-31 =1, N 31-32 =1, N 40-41 =1, N 46-11 =1
CSA	O. Cost 10^3 *US* $	118
	S.R.	98
	S.D.	12.3
	A.F.E.	3254.7
MGWO Khandelwal *et al.* (2018)	Terminals	N 2-4=3, N 14-15=2, N 28-31=1, N 27-29=2, N 26-29=2, N 15-16=1, N 2-3=1, N 9-10=1
	O. Cost 10^3 *US* $	118.8
	S.R.	88
	S.D.	1.807
	A.F.E.	59918
WOA	Terminals	N 14-15 =3, N 5-11 =1, N 28-31 =1, N 27-29 =1, N 26-29=1, N 15-16= 1, N 46-11= 1, N 29-30= 1, N 40-41= 1, N 5-6= 1, N 9-10= 2
	O. Cost 10^3 *US* $	123
	S.R.	98
	S.D.	28.42
	A.F.E.	3240.2
Branch Bound Rider *et al.* (2008)	Terminals	N 5-6 = 2, N 26-29 = 3, N 42-43 = 2, N 20-21 =1, N 29-30 = 2, N 19-25 = 1, N28-30 = 1, N 46-06 = 1, N 24-25 = 2, N 31-32 = 1
	O. Cost 10^3 *US* $	154.20
	S.R.	N/A
	S.D.	N/A
	A.F.E.	N/A

5. Conclusion

CSA is based on a comprehensive search strategy that has previously applied to a number of issues. The authors of this paper have investigated CSA for TEP. On standard test bus systems, namely the Garver 6-bus system and Brazilian 46-bus system, the performance of the algorithm was investigated. It has been noted that in terms of running expense and performance rate, CSA seeks better solutions than other participating algorithms. For CSA, Average Function assessments are also optimal. With MGWO, GWO and ABC, a fine comparison was derived. This comparison gives an idea that, in less computational time, CSA is quick to provide the best solutions. It is concluded that the CSA algorithm has less processing time and ideal convergence properties, based on simulation performance. In the future, studies of more complex issues of wider networks will be explored.

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