Comparative Analysis of Different Optimization Algorithms on Transmission Expansion Planning Problem

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Abstract **Transmission expansion planning problem is a crit¬ical issue in power system due to competitive business environ¬ment and escalating power demand. Power system is expanding with every passing day from both generation and distribution side. However, for matching the demand, expansion plan of transmission network has been addressed in previous researches. This paper presents comparative analysis of recently published application of swarm algorithms for carrying out the expansion plan of a power network. These algorithms are namely Crow Search Algorithm (CSA), Moth Flame Optimization Algorithm (MFO), Artificial Bee colony Algorithm (ABC), Teaching Learn¬ing Based Optimization Algorithm (TLBO), Grey Wolf Algorithm (GWO) and Whale Optimization Algorithm (WOA). These algorithms are tested on two different power networks and a decisive evaluation of the optimization performance of algorithms are carried out. It has been observed that performance of CSA is found superior to other algorithms.**

Keywords- Network Expansion, Garver 6-Bus System, Brazilian 46-Bus System, Meta-Heuristics, Optimisation..

1. INTRODUCTION

Modern power systems have emerged as complex interconnected networks. Operation and control of the power system is a major issue with these interconnections. Also, the demand growth and diversity of the demand patterns at different locations pose a complex challenge to the planners of modern power system. To meet demand, generation expansion as well as expansion plan of transmission networks are going hand in hand. With the escalating load demand and limited transmission capacity, Transmis¬sion Expansion Planning (TEP) is now a major concern for the sustained energy system. The issue of strengthening the existing transmission network in order to meet the growing demand of electricity is the fulcrum of transmission planning. Expansion plan of transmission network would be decided by planners and that includes when and where new transmission lines are incorporated in the power system. This expansion plan also ensures that there should no overload pathways for the construction of new line connections during the design period.

Generally, the TEP problem is categorized into two types, first one is the Static TEP (STEP) [1] and the second one is the Dynamic TEP (DTEP) [2]. Static transmission expansion planning determines when and where new lines are to be added to the existing system, while dynamic transmission ex-pansion planning is a time-based approach. Often, generators are situated far away from load centers of power systems.

Under these circumstances, the cost of transmission is immense. Therefore, the issue of static transmission network expansion planning plays a key role in the planning of power systems and must be carefully evaluated. As the population is increasing with every passing year, the size of the system is also increasing, that also makes the calculation for incorporation of new lines more stringent in the system. This causes TEP to become a major non-linear, mixed integer linear [2] and non-convex optimization problem. Garver, first took the initia¬tive to solve the problem of TEP through linear programming in 1970 [3]. Subsequently, many researchers used a number of strategies to solve the TEP problem. Both conventional and modern meta-heuristic optimization approaches have been used to solve this problem. This involves Hierarchical Decom¬position (HD), Dynamic Programming (DP), Simulated An¬nealing (SA) used for long term TEP, Constructive Heuristic Algorithm (CHA) [4] for TEP problems. CHA is also applied in a branch and bound to fix static TEP issue of the DC model. There are many other methods also used in order to solve TEP problem including artificial techniques such as Artificial Neural Network (ANN) [5], Fuzzy processes, Discrete Particle Swarm Optimization (DPSO) [6] algorithm, Branch and Bound method [7], and novel Differential Evolution Algorithm (DEA) [8] etc.

This paper uses a DC power flow model to discover the right number of lines and types of additional lines to be added in existing system to minimize overall cost of transmission. The overall cost is the actual value of the cost of investment, congestion, and load control cost under N-1 contingency states. In fact, it is common to build a new right-of-way with a higher voltage than current voltage levels in order to pass a significant volume of electricity. The power transfer capability of the line also increases with the rise of the voltage level with a huge margin. Consequently, the formation of new lines in the transmission planning process is highly important to consider. The applied optimization based approaches consider the possibility of adding new circuits at varying standard voltage levels in order to provide a realistic solution.

The problem used in this paper conceived as a problem of mixed integer optimization and solved using a variety of meta heuristic approaches, for example Teaching Learning Based Optimization (TLBO) [9], Artificial Bee Colony (ABC) [10], Grey Wolf Optimization (GWO) [11], Moth Flame Optimization (MFO) [12] and Crow Search Algorithm (CSA) [13]. All these approaches are inspired from different behaviours of nature and living organism shown in given Table I.

The objectives of this paper are framed as below

- To apply and evaluate performance of various optimization algorithms on TEP problem.
- To conduct several analyses for judging the efficacy of the optimization algorithms.

Table 1 Comparison of Algorithms

Algorithms	Behaviour	Applied Problems
ABC	The ABC algorithm is a meta-heuristic, a swarm-oriented algorithm based on honey bee colonies' foraging behaviour.	• Protein Structure Prediction [14].
TLBO	TLBO is inspired from teaching learning process.	• Harmonic Estimator Design using TLBO [15]. • Basic model of TLBO Applied on TEP Problem [16].
GWO	The GWO algorithm mimics the hierarchical and social interactions of the grey wolves.	• Modified grey wolf optimizer based on chaos [17]. • Harmonic estimator design problem with genetic operators enabled grey wolf optimizer [18].
MFO	MFO is a population-based approach, called transverse navigation orientation, which imitates the moths' travel technique in the night.	• Strategic bidding problem in uniform spot energy market [19].
CSA	The CSA algorithm is inspired by the intelligent behaviour of crows while food is concealed and snatched.	• Intelligent crow search algorithm for control Engineering, estimation and other problems [20].
WOA	It is a herd meta-heuristic algorithm based on a bubble-net hunting strategy for humpback whales.	• Opposition Theory Enabled Intelligent Whale Optimization Algorithm [21].

1.1 Layout of paper

In the first section problem is introduced after that in the second section mathematical formulation of the problem is explained. In the third section different meta-heuristic approaches are explained briefly. In the fourth section, TEP problem for two systems namely Garver six bus and southern Brazilian 46 bus system are considered. In the last section, we concluded the paper.

2. PROBLEM FORMULATION

The basic TEP [22, 23] without security restrictions defines the collection of new lines to be built in such a way that the cost of the expansion plan is minimal and no overloads are created during the planning horizon. The model based on DC power for TEP is used. Where first term represents Overall Cost (O. Cost), middle term shows real power flow constraint limitations and last term shows maximum number of circuits can be added. H_1 and H_2 are constraints. Where middle and last terms are added in case of violation of fitness function. Without security restrictions TEP can be defined as such,

$$\min \quad c = \sum_{k\in\omega} a_k\, j_k + H_1 \sum_{yz} \det\left(l_k - l_k^{\max}\right) + H_2 \sum_{yz} \left(m_k - m_k^{\max}\right) \tag{1}$$

$$O.\,Cost = \sum_{k\in\omega} a_k\, j_k \tag{2}$$

Subject to

$$Rl + y = b \tag{3}$$

$$l_k - \sigma_k - \left(m_k^0 + m_k\right)\left(\delta\phi_k\right) = 0 \tag{4}$$

for $k \in 1, 2, \ldots\ldots,$

$$\left|l_k\right| \le \left(m_k^0 + m_k\right)\overline{l_k} \tag{5}$$

for $k \in 1, 2, \ldots\ldots mk,$

$$0 \le m_k \le \overline{m_k} \tag{6}$$

l_k and ϕ_k are unrestricted,

$m_k \ge 0$, and integer, for $k \in 1, 2, \ldots\ldots, mk,$

$k \in \omega$, where,

c = Overall cost,

k = Link between node i and node j,

a_k = Line cost added in k right of way,

j_k = Extra line between node i and j,

b = Total Generation,

R = Transposed branch-node incidence matrix of the power system,

l = Vector with element k ,

y = Total load,

σ_k = Circuit susceptance and can be applied to the k^{th} right of way,

m_k = The number of lines inserted in k^{th} right of way,

m_k^0 = Number of lines in base network,

$\delta\phi_k$ = Difference of phase angle in k^{th} right of way,

l_k = Cumulative real power transfer from the circuit in from the circuit in k^{th} right of way,

$\overline{m_k}$ = The maximum number of circuit paths which can be added to the k^{th} right of way,

ω = Collection of right of ways,

mk = Circuit total branches.

$\overline{l_k}$ = Maximum allowed cumulative real power transfer k^{th} right of way,

The aim is to reduce the O. costs represents equation 2 of the new transmission lines to be built in order to satisfy the existing power flow limits of the network lines. The power balance at each node is defined by equation 5. Equation 4 is the DC network's actual power flow equations. Equation 6 is a limit on the construction of lines per path. Decision variables are the transmission lines added to every right-of-way.

3. SOLUTION ALGORITHMS

In this segment, various algorithms (GWO, CSA, WOA, MFO, ABC, and TLBO) are compared for estimation of cost for transmission network expansion planning. The following algorithms are well defined to assist in this comparison.

3.1 Artificial Bee Colony (ABC)

The ABC algorithm was introduced by Karaboga in 2005. This algorithm developed on the social activities of bees [24]. A large number of bees lives in a community, known as a hive. These bees are divided into three categories according to their working process, first one is onlooker bees, second is employed bees and the third is scout bees. Initially hive population is divided into two equal parts i.e. onlooker bees and employed bees. Where employed bees are responsible to search for good quality of food to form a significant amount of nectar. Employed bees share their location of new food with onlooker bees. After confirming the location of food source onlooker bees collect the food. These bees have a special characteristic to forget the previous location of food source having less amount of nectar. Some of the employed bees who failed to update the food location become scout bees. These scout bees randomly search for new food locations.

$$v_{ij} = X_{ij} + \phi_{ij}\left(X_{ij} - X_{kj}\right) \quad (7)$$

Where X_{ij} represents location of food source and $\phi_{ij}\left(X_{ij} - X_{kj}\right)$ shows step size.

3.2 Teaching Learning Based Optimization (TLBO)

In 2010, The teaching learning based optimization algorithm was invented by R.V.Rao. et al. [9]. This algorithm represents a relationship between instructor and learner is defined by this algorithm. The instructor tries to give his own best in this process, and the learner also expects to get 100% from the instructor. Learner's recognizing and understanding capacity play a major role in receiving the information offered by instructor. The learner's performance is assessed by test. The test helps to find out which learner has more information and which instructor is able to provide own best to the learner.

$$Y'_{c,e,w} = Y_{c,e,w} + Diff\_mean_{c,e,w} \quad (8)$$

Here $Y_{c,e,w}$ is the current function value, and $Diff\_mean_{c,e,w}$ is the difference between the old and the new mean.

3.3 Grey Wolf Optimization (GWO)

Seyedali Mirjalili proposed Grey Wolf Optimization in 2013. This algorithm is influenced by the social behaviour of grey wolves which includes leadership and hunting characteristics. In GWO, wolves live together in a herd, these wolves are categorized into three classes according to their functioning. Alpha wolves are the first type of wolves that are dominant in the herd. Alpha wolves have the capability to take decisions, and their decision is followed by other wolves. Beta wolves and Omega wolves are sub ordinate wolves and follow the instruction given by alpha wolves. In the hunting process first step to search for food (prey) then encircling the prey and lastly updating their position according to previous position.

$$\vec{W} = \frac{\vec{W_1} + \vec{W_2} + \vec{W_3}}{3} \quad (9)$$

Equation 9 calculates the location of prey from the updated positions of α , β and Δ wolves represented by $\vec{W}$.

3.4 Moth Flame Optimizer (MFO)

In 2016, Moth Flame Optimization is proposed by Mirjalili. MFO [12] algorithm is a nature inspired algorithm. This algorithm uses a special orientation mechanism known as a transverse orientation. This moth continuously updates its position according to flame and provides a better solution.

$$H_i = V(H_i, G_j) \tag{10}$$

Where, V represents the spiral function, H_i represents the i^{th} moth, and G_j represents the j^{th} flame.

3.5 Crow Search Algorithm

In 2016, Alireza Askarzadeh et. al developed a nature motivated algorithm labelled Crow Search Algorithm (CSA) [13]. Among the category of birds crow is a common specie known for its intelligent behaviour. This intelligent behaviour is an inspiration of researchers, crow has a large size of brain in comparison to its body size. Crow has special capabilities like mimics of action, remembering capability, making fool of others etc. The cleverness of the crow can be validated by the mirror-test and capability of tool making. When crows steal food it tries to hide this food from other crows and tries to make fool of other crows by going from one place to another. In this process crow always remembers its hiding place. When the crow gets another hiding place then it forgets the previous one.

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

(11)

Where R_x represents uniformly distributed random numbers between 0 to 1. $AP_{x,t}$ is known as crow's awareness probability factor for i^{th} iteration.

3.5Whale Optimization Algorithm (WOA)

In the year 2016, Mirjalili developed the WOA [25]. This algorithm mimics the hunting system of humpback whales. A specific process whose hunting system is known by bubble net foraging. This foraging process is achieved by producing bubbles in a circular or '9-shape' direction, and during this the prey is surrounded by a hump whale. This is typical of these hump whales in which these whales dive 10-15 meters below and then form bubbles in a spiral shape and come to the surface and surround the prey with glowing feathers, here the process prevents the prey from escaping.

$$\vec{P}(m+1) = \begin{cases} \vec{P} * (m) - \vec{J}.\vec{K} & if\ z < 0.5 \\ \overline{D'} * (m).v^{ch}.\cos(2 \times \pi \times l) + \vec{P} * (m) & f\ z \geq 0.5 \end{cases} \tag{12}$$

Where k is an arbitrary number which is uniformly distributed in the range of [- 1, 1] and z represents a constant for explaining the shape of the logarithmic spiral.

4. SIMULATION RESULTS

As defined in previous section, TEP problem has been analysed with the help of different optimization algorithms on following two systems:

1. 6-Bus Garver System
2. 46-bus South Brazilian System

During simulation, we have implemented the criterion of CEC-2011 as mentioned in [27]. It is assumed that maximum no. of permissible lines is limited to five between any two buses. The investment cost of the systems are taken from reference [27]. Readers may refer to the reference for details. For evaluating optimization performance of various algorithms mentioned in previous sections following evaluating criteria are considered.

4.1 Evolution Criterion of Performance

Following criteria have been used for judging the optimization performance of the algorithms.

4.1.1 Average Function Evaluation

Average Function Evaluation (AFE) depends on following parameter's which are also given in literature [26]. These are as follows

1) Number of Runs (In this simulation we are using 100 number of runs).
2) Maximum Number of Function Evaluation = No. of Search Agents x Iteration.
3) Termination Criterion

$$(TE_{criterion} = 10^{-8})$$
$$(TolerableError)$$

Using the function error value, we have compared the performance of the various algorithms for the objective function. Where error value of a function represented as $\left[fun(a) - fun(a^*) \right]$, here a^* shows the function global minimum.

To minimize this error, we allowed each algorithm to perform function evaluation as much as possible until it reaches the maximum number of function evaluations or Termination Criterion is satisfied. Average of these function evaluation during 100 runs is calculated for each algorithm and the algorithm which has lowest average value is considered as superior algorithm.

4.1.2 Success Rate

The ratio of number of successful runs upon number of total runs is called Success Rate (SR). An optimization run is denoted as successful when it achieves global minimum.

$$Success\,Rate = \frac{NSR}{NTR}$$

- NSR = Number of Successful Runs.
- NTR = Number of Total Runs.

4.1.3 Standard Deviation

Standard Deviation (SD) is a term that measures the square root of the variance and checks the dispersion of the data set against the obtained mean value.

$$SD = \sqrt{\frac{\sum_{g=1}^{h}(x_g - \bar{a})}{h-1}}$$

$x_g = g^{th}$ point value in data set consists of fitness function values.

$\bar{a} =$ Mean value of fitness function values.

$h =$ Number of data points in data set.

4.1.4 Simulation System Configuration

This validation process is completed on a system this system environment which includes Intel Core i3 3rd generation with 8GB of ram and 240GB SSD on compiler MATLAB 2015a.

4.2 6-Bus Garver System

In Garver 6 bus system, there are six buses and there are 15 candidate lines that can be utilized for expansion of the network. Load capacity of this bus system is 760 MW. The data of this system are available in literature [27]. The optimization process is run 100 times using various optimization algorithms. Most replicated response is adopted and considered as final solution of the problem. The results for STEP using optimization algorithms are evaluated in the term of Overall Cost (OC) in $\times 10^3 US\$$, Success Rate (SR) and Average Function Evaluation (AFE) as shown in the table 2. Following conclusions can be derived from the obtained results:

a. It has been observed from table II that as per SR TLBO gave best results on the other hand the cost optimized by this algorithm is $190 \times 10^3 US\$$. However, CSA gave optimal cost with 94% SR. Hence on the basis of (OC), CSA algorithm performs better than other competitor algorithms.

b. However, we have also observed that TLBO also provides a high SR but value of objective function achieved from this algorithm is not optimal.

c. As shown in the table 2, 1 line can be added between buses 4 and 6, 3 lines added between buses 6 and 2, and 2 lines between buses 3 and 5, which shows that less number of new lines are added between buses when optimization process is handled by CSA.

d. Comparative analysis of the results is showcased with the boldface, we observe that solutions obtained from CSA are optimal as only six lines are added between various buses.

1.

Table 2 Result Analysis of 6-Bus Garver System

Garver 6 Bus System TEP Comparison							
Algorithm	**Bus Topology**			**O. Cost**	**SR**	**SD**	**AFE**
	From	**To**	**No. of Lines**				
ABC [28]	4	6	2	200	N/A	N/A	N/A
	6	2	4				
	3	5	1				
TLBO	6	2	3	190	99	351.57	10722.9
	3	5	2				
	4	6	2				
GWO	4	6	2	190	60	8.5798	91490
	6	2	3				
	3	5	1				
	2	3	1				
MFO	2	3	1	**262**	43	5845	36476
	6	2	2				
	3	5	1				
	4	6	2				
	5	6	2				
CSA	4	6	1	**170.1**	94	37.1	68200.1
	6	2	3				
	3	5	2				
WOA	4	6	3	**262**	20	28.42	126092.1
	6	2	2				
	5	6	2				

4.3 46-Bus Southern Brazilian System

The Brazilian system is chosen as a second system for assessment which consists of 79 lines and 46 bus numbers with load capacity of 6880 MW. All mandatory data was taken from literature [27] in order to test this. Using different optimization algorithms elaborated in section 3, the objective function is solved 100 times and the most prominent solution is taken. The results for this system using above discussed optimization algorithms are evaluated in terms of OC in $\times 10^6 US\$$, Average Function Evaluation (AFE) and Success Rate (SR) are as shown in the table 3. Following conclusions can be drawn from this work:

2. Table 3 depicts the optimized results of various

algorithms. CSA outperforms with 99 % SR as compared to other algorithms. We observe that CSA obtains highest SR along with lowest OC and AFE.

Table 3 Result Analysis of 46-Bus South Brazilian System

Brazilian 46 Bus System TEP Comparison							
Algorithm	Bus Topology			O. Cost	SR	SD	AFE
	From	To	No. of Lines				
ABC	2	4	1	119	91	19.6	3254.7
	14	15	2				
	16	32	1				
	27	29	2				
	28	41	3				
	21	25	2				
	2	3	1				
	9	10	1				
TLBO	2	4	3	131.5	88	6.3	4161.44
	14	15	2				
	28	31	1				
	27	29	2				
	26	29	2				
	15	16	1				
	2	3	1				
	9	10	1				
GWO	2	4	3	120.053	75	1.7626	89899
	14	15	3				
	28	31	2				
	5	11	1				
	26	29	1				
	4	11	1				
	5	6	1				
	9	10	1				
MFO	5	6	1	145.2	27	18.9	28265
	26	29	3				
	42	43	2				
	20	21	1				
	29	30	1				
	19	25	2				
	28	30	3				
	46	6	1				
	24	25	1				
	31	32	1				
CSA	2	3	1	117	99	3.99	1476.3
	5	11	1				
	14	15	1				
	15	16	1				
	24	25	1				
	26	29	2				
	27	29	1				
	28	30	1				
	28	31	1				
	31	32	1				
	40	41	1				
	46	11	1				
WOA	42	43	3	133.7	81	14.5	26619.5
	20	21	1				
	29	30	1				
	19	25	1				
	28	30	2				
	2	4	3				
	28	31	1				
	46	11	1				

CSA based solution proposes 1 line between different pairs of buses and 2 lines between buses 26 and 29. As compared with other optimization algorithms, the number of lines placed between buses are much higher as compared to CSA.

5. CONCLUSION

This paper is an attempt to apply different nature based optimization algorithms for solving TEP problem. Efficacy of the optimization algorithms has been tested over two different standard power systems namely 46-bus South Brazilian system and 6-bus Garver system. Following are the major conclusions of this work.

1. Paper has presented a comparative analysis of different optimization algorithms and problem of Static TEP is addressed to judge the comparative performance of optimization algorithms.
2. Comparative analysis of ABC, TLBO, MFO, GWO, WOA and CSA has been presented. It is worth mentioning here that all these algorithms come from nature inspired algorithm group.
3. It has been observed that performance of CSA is better as compared with other algorithms. Further, on the basis of success rate, average function evaluation and standard deviation obtained from the independent runs, the performance of CSA was found better. Application and development of new variants of CSA will be addressed in near future.

6. REFERENCES

[1] Javier Contreras and Felix F Wu. A kernel-oriented algorithm for transmission expansion planning. IEEE Transactions on Power Systems, 15(4):1434-1440, 2000.

[2] Sebastian De La Torre, Antonio J Conejo, and Javier Contreras. Transmission expansion planning in elec¬tricity markets. IEEE transactions on power systems, 23(1):238-248, 2008.

[3] Len L Garver. Transmission network estimation using linear programming. IEEE Transactions on Power Ap-paratus and Systems, (7):1688-1697, 1970.

[4] R Romero, C Rocha, JRS Mantovani, and IG Sanchez. Constructive heuristic algorithm for the dc model in net-work transmission expansion planning. IEE Proceedings-Generation, Transmission and Distribution, 152(2):277-282, 2005.

[5] Tawfiq Al-Saba and Ibrahim El-Amin. The application of artificial intelligent tools to the transmission expansion problem. Electric Power Systems Research, 62(2):117- 126, 2002.

[6] Yi-Xiong Jin, Hao-Zhong Cheng, Jian-yong Yan, and Li Zhang. New discrete method for particle swarm optimization and its application in transmission network expansion planning. Electric Power Systems Research, 77(3-4):227-233, 2007.

[7] S Haffner, A Monticelli, A Garcia, J Mantovani, and R Romero. Branch and bound algorithm for transmis¬sion system expansion planning using a transportation model. IEE Proceedings-Generation, Transmission and Distribution, 147(3):149-156, 2000.

[8] Taylor Sum-Im, GA Taylor, MR Irving, and YH Song. Differential evolution algorithm for static and multistage transmission expansion planning. IET generation, trans¬mission & distribution, 3(4):365-384, 2009.

[9] R Venkata Rao, Vimal J Savsani, and DP Vakharia.

Teaching-learning-based optimization: a novel method for constrained mechanical design optimization prob¬lems. Computer-Aided Design, 43(3):303-315, 2011.

[10] Dervis Karaboga. Artificial bee colony algorithm. scholarpedia, 5(3):6915, 2010.

[11] Seyedali Mirjalili, Seyed Mohammad Mirjalili, and An¬drew Lewis. Grey wolf optimizer. Advances in engineering software, 69:46-61, 2014.

[12] Seyedali Mirjalili. Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm. Knowledge-based systems, 89:228-249, 2015.

[13] Alireza Askarzadeh. A novel metaheuristic method for solving constrained engineering optimization problems:crow search algorithm. Computers & Structures, 169:1¬12, 2016.

[14] Akash Saxena, Shalini Shekhawat, Ajay Sharma, Harish Sharma, and Rajesh Kumar. Chaotic step length artificial bee colony algorithms for protein structure prediction. Journal of Interdisciplinary Mathematics, 23(2):617-629, 2020.

[15] Rajesh Kumar. Directed bee colony optimization algorithm. Swarm and Evolutionary Computation, 17:60-73,2014.

[16] Geetanjali Singh, Nirmala Sharma, and Harish Sharma. Intelligent neighbourhood teaching learning based opti-mization algorithm. In 2017 International conference on computing, communication and automation (ICCCA), pages 986-991. IEEE, 2017.

[17] Akash Saxena, Rajesh Kumar, and Swagatam Das. ft-chaotic map enabled grey wolf optimizer. Applied Soft Computing, 75:84-105, 2019.

[18] Saxena, Akash, Ashutosh Sharma, and Shalini Shekhawat. "Parameter extraction of solar cell using intelligent grey wolf optimizer." Evolutionary Intelligence (2020): 1-17.

[19] Pooja Jain and Akash Saxena. An opposition theory enabled moth flame optimizer for strategic bidding in uniform spot energy market. Engineering Science and Technology, an International Journal, 22(4):1047-1067,2019.

[20] Shalini Shekhawat and Akash Saxena. Development and applications of an intelligent crow search algorithm based on opposition based learning. ISA transactions, 2019.

[21] Prateek Jain, Pooja Jain, and Akash Saxena. Opposition theory enabled intelligent whale optimization algorithm. In Intelligent Computing Techniques for Smart Energy Systems, pages 485-493. Springer, 2020.

[22] Swagatam Das and Ponnuthurai N Suganthan. Problem definitions and evaluation criteria for cec 2011 compe-tition on testing evolutionary algorithms on real world optimization problems. Jadavpur University, Nanyang Technological University, Kolkata, pages 341-359, 2010.

[23] I de J Silva, MJ Rider, R Romero, AV Garcia, and CA Murari. Transmission network expansion planning with security constraints. IEE Proceedings-Generation, Transmission and Distribution, 152(6):828-836, 2005.

[24] Bahriye Akay and Dervis Karaboga. A modified artificial bee colony algorithm for real-parameter optimization. Information sciences, 192:120-142, 2012.

[25] Seyedali Mirjalili and Andrew Lewis. The whale opti¬mization algorithm. Advances in engineering software, 95:51-67, 2016.

[26] Ponnuthurai N Suganthan, Nikolaus Hansen, Jing J Liang, Kalyanmoy Deb, Ying-Ping Chen, Anne Auger, and Santosh Tiwari. Problem definitions and evaluation criteria for the cec 2005 special session on real-parameter optimization. KanGAL report, 2005005(2005):2005, 2005.

[27] Das, Swagatam, and Ponnuthurai N. Suganthan. "Problem definitions and evaluation criteria for CEC 2011 competition on testing evolutionary algorithms on real world optimization problems." Jadavpur University, Nanyang Technological University, Kolkata (2010): 341-359.

[28] R Romero, A Monticelli, Ae Garcia, and S Haffner. Test systems and mathematical models for transmission net-work expansion planning. IEE Proceedings-Generation, Transmission and Distribution, 149(1):27-36, 2002

APPENDIX

Table 4 Data set for Garver 6-Bus System

Generation and Load Data for Garver 6-Bus			
Bus No.	**Generation (MW)**		**Load (MW)**
	Maximum	**Level**	
1	150	50	80
2	0	0	240
3	360	165	40
4	0	0	160
5	0	0	240
6	600	545	0

Table 5 Data set for Southern Brazilian 46-Bus System

Generation and Load Data for Brazilian 46-Bus System							
Bus No.	**Generation (MW)**		**Load (MW)**	**Bus No.**	**Generation (MW)**		**Load (MW)**
	Maximum	**Level**			**Maximum**	**Level**	
1	0	0	0	24	0	0	478.2
2	0	0	443.1	25	0	0	0
3	0	0	0	26	0	0	231.9
4	0	0	300.7	27	220	54	0
5	0	0	238	28	800	730	0
6	0	0	0	29	0	0	0
7	0	0	0	30	0	0	0
8	0	0	72.2	31	700	310	0
9	0	0	0	32	500	450	0
10	0	0	0	33	0	0	229.1
11	0	0	0	34	748	210	0
12	0	0	511.9	35	0	0	216
13	0	0	185.8	36	0	0	90.1
14	1275	944	0	37	300	212	0
15	0	0	0	38	0	0	216
16	2000	1366	0	39	600	221	0
17	1050	1000	0	40	0	0	262.1
18	0	0	0	41	0	0	0
19	1670	773	0	42	0	0	1607.9
20	0	0	1091.2	43	0	0	0
21	0	0	0	44	0	0	79.1
22	0	0	81.9	45	0	0	86.7
23	0	0	458.1	46	700	599	0