Optimal Power Flow Solution with Nature Inspired Antlion Meta-Heuristic Algorithm

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Abstract. Currently, optimal power flow (OPF) problem is widely encountered issue. This has been formulated and programmed with the help of nature-inspired meta-heuristic approach known as Antlion Optimization algorithm (ALO) in this work. The algorithm is built upon the basic hunting procedure of ant lions. The ant lion's hunting behavior is summarized into prominent set of steps like random walks, trap building to clasp ants, catching ants, and five pit reorganizations. This behavior is then exploited to resolve OPF problem. The ALO technique has shown higher convergence characteristics with the help of the Roulette Wheel selection. A typical system of IEEE 30 bus has been considered for validating the proposed method. Moreover, with suitable OPF formulation, numerous objectives could be solved. Some of which have been taken into account here. The results of ALO are studied and their effectiveness is compared with the OPF algorithms like Particle Swarm Optimization (PSO) method and Black Hole-Based Optimization (BHBO) method. The results demonstrate the usefulness of ALO with the improved convergence for OPF problem based on the population of 40 when compared to nature-inspired techniques like PSO and BHBO.

Introduction

Present day scenario portrays the ever-increasing demand on load side of a power system but then again, the generation of the electricity is not fulfilling the essential load demand. This is because of continuous diminution of the fossil fuels. The power system is supposed to be in the steady state i.e. generated electricity should be equal to overall load of the power system network plus transmission line losses. The elementary idea in this notion is to find out the economic operating conditions for the generating units so the total production cost can minimize for electricity generation. Although in every 5 minutes the OPF problem must be solved numerous times in a day at all the control centres. From the historical notes on power system, there are three classes of problems that were talked about viz. load flow, OPF and economic dispatch. The optimal solution for the given problem is formulated for the above three classes. India has a mounted capacity of around 349.288 GW as on 31 December 2018. In current scenario, India possesses 3rd ranked in electrical power generation as well as electrical power consumption in the world.

Around 32.0% of total generated power has been spent in the distribution and transmission losses as reported in the recent years. If the losses are not reduced to a substantial level, India would be having requirement of approximately 132GW of surplus power in the coming times. Owing to this, issues like energy management and optimization of power flow are playing crucial role in transmission and distribution system. Meanwhile, conventional approaches seem to provide the solutions of the power flow but are bounded with some limitations. A critical study of power flow while considering all limitations needs a fresh method i.e. meta-heuristic method to get accurate as well as fast solutions. The objective functions employed for the OPF is nonlinear problem and it has been recognized as a non-differential type of problem. Consequently, complications in the traditional methods can be resolved to some extent for OPF problem for local optimum only rather than global optimum. However, to eradicate these drawbacks, earlier artificial intelligence techniques were introduced as the alternative approach (stochastic algorithms) to solve the associated problem of optimal load flow (OLF). These are then replaced with meta-heuristics which is widely used now a days.

Zwe-Lee and Giang, [1] considered generator constraints to solve particle swarm optimization. Genetic algorithm (GA) is developed by Al-Turki, Yusuf A et al., [2] to solve OPF problem. Fuzzy algorithms were developed by Liang Ruey-Hsun et al., [3] to solve a multi-objective OPF with certain uncertainties. Boukhtir T et al., [4] presented an ant colony meta-heuristic technique for obtaining solution for the OPF problem. An improved ABC (artificial bee colony) algorithm has established by Dinu Calin Secui., [5] for solving economic load dispatch (ELD) while incorporating contaminations, valve point loading effects and diverse generator constraints. A primal dual predictor corrector interior point algorithm reported by Antonio Robert Balbo et al., [6] for the ELD problem.
Besides all these methods, some other recent techniques have been already introduced by H.R.E.H. Bouchekara, M.A. Abido et al., which are OPF with Teaching-learning-based optimization technique [7], Black hole based meta-heuristic algorithm [10] by H.R.E.H. Bouchekara and League championship algorithm [8], Gravitational search optimization algorithm [9] was developed by Serhat Duman, Ug˘ur Güvenç et al. The major analysis was done by performing OPF with ALO [11] by Seyedali Mirjalili has been projected in the period between 2015-16 for better computation and operation time. Additionally, a hybrid bacterial foraging (BF) method has been presented to solve the ELD including constraints [12]. A compressive sensing based stochastic ELD for the multi-dimensional uncertainty system case has been proposed in [13]. Moreover, embedded dynamic loss factor and dynamic tracking of transmission network loss presented in [14].

2. Problem Formulation

2.1. Production cost minimization

Thermal power plant total fuel cost saving, is the foremost objective of OLF problem. This is given by

\[
P = \sum_{i} f_i P_i
\]

where, \( f_i \) is a cost function of \( i^{th} \) generating unit, and

\[
f_i = x + v + w_i x^2
\]

where, \( x \), \( v \), and \( w_i \) are \( i^{th} \) generator linear and quadratic coefficients correspondingly. ALO and comparison with various methods have been manifested, and the results stated that total fuel cost is expansively reduced when compared with traditional techniques.

2.2. Transmission line losses minimization

In the presented event, for minimization of transmission line active power losses the function can be described as

\[
H = \sum_{n=1}^{NG} P_{nm} = \sum_{n=1}^{NG} P_{pm} = \sum_{n=1}^{NG} P_{dm}
\]

2.3. Minimization of deviations in voltage

Bus voltages are a desirable and important security index. Thus, the main objective is to uphold the voltage profile (default 1.0 pu) and minimising the voltage deviation when variation at load (PQ) occurs.

Hence, the objective function for voltage deviation can be expressed as

\[
R_{v-d} = \sum_{m=1}^{NG} |v_m - 1.0|
\]

where, \( v_m \) is the magnitude of the voltage at bus m.

3. ALO- Antlion Optimization Technique

3.1. Antlion Optimization Technique

The set of rules depicted below is based on the idea of hunting process of ant. It involves following five optimization procedure as illustrated below:

Antlions are net feathered bugs and emanates from the families named Myrmeleontidae and Neuroptera. The lifespan of antlion depicts two stages i.e. larva and adult. An antlion lives for 3 years approximately. These names have their origin from the selective behavior of antlion and his desired prey. Mostly, antlion starts its hunt in its primitive or larva stage; also, it digs a conical pit by flinging sand outward by using power of its jaw. Afterwards, the antlion in larva stage hides itself underneath the pit, in the wait for the ants to get seized inside the pit hole. At the instant the antlion finds out that ants are struck inside the cone, it starts moving to catch it but the ants are not trapped immediately, they will make an attempt to escape from the conical pit. During that moment, antlions start throwing silt at quicker rate on the target prey. Owing to this situation, if ants are incapable of going out, antlions drag them underneath the silt to consume them as prey.
The impetus of ALO technique is based upon the foraging actions of the antlion. Here, the mathematical modeling is categorized into two parts. Firstly, antlion nature and behavior of the prey is modeled. Secondly, the proposed technique is associated with the several mathematical equations.

### 3.2. ALO Operators

The antlion technique bears a resemblance with the mutual interaction between ants and antlions. Antlions have the ability to catch the ants and get healthier or fitter. The random motion of ants while looking for food can be mathematically expressed as

$$X(P) = [0, CS[2f(p_1)-1], CS[2f(p_2)-1], ..., CS[2f(p_n)-1]]$$  \hspace{1cm} (5)

where,

- $CS$ = cumulative sum of ants
- $p$ = random walk step size
- $n$ = max no. of iterations
- $f(p)$ = stochastic function

$$f(p) = \begin{cases} 0; & \text{if } rnd \leq 0.5 \\ 1; & \text{if } rnd > 0.5 \end{cases}$$  \hspace{1cm} (6)

![Figure 1 – Random motion of three ants](image)

Figure 1: Random motion of three ants.

where, $rnd$ denotes random number achieved through uniform distribution $[0,1]$. Figure 1 demonstrates the idea of random walk of three ants for 500 iterations. Afterwards the effective initialization of arbitrary walks of ants, it is necessary to recognize their spots by making use of subsequent matrix.

$$A_{ant} = \begin{bmatrix}
M_{11} & M_{12} & \cdots & M_{1d} \\
M_{21} & M_{22} & \cdots & M_{2d} \\
\vdots & \vdots & \ddots & \vdots \\
M_{n1} & M_{n2} & \cdots & M_{nd}
\end{bmatrix}$$  \hspace{1cm} (7)

where,

- $A_{ant}$ is a matrix to store the positions of all the ants
- $M_{ij}$ = the value of $i^{th}$ ant $j^{th}$ dimensions
- $d$ = total number of variables
- $n$ = total number of ants

Here, one similarity that should be kept in mind is that the ants in ALO are like the individuals in genetic algorithm (GA) and the particles in particle swarm optimization (PSO). In the optimization process, an objective function needs
to be set for the estimation of each ant and its fitness value must be stored in matrix form as expressed below.

\[ A_{OM} = \begin{bmatrix}
  f\{M_{11} \ M_{12} \ \ldots \ M_{1d}\} \\
  f\{M_{21} \ M_{22} \ \ldots \ M_{2d}\} \\
  \ldots \ \ldots \ \ldots \\
  f\{M_{n1} \ M_{n2} \ \ldots \ M_{nd}\}
\end{bmatrix} \]

where, \( f \) = objective function
\( n \) = number of ants
\( A_{OM} \) = matrix for loading the fitness value of ants

Lookup of antlions is random in the search space likely to ants. To fix their positions and fitness or objective values, the corresponding matrices are expressed as follows

\[ A_{antlion} = \begin{bmatrix}
  M_{L11} \ M_{L12} \ \ldots \ M_{L1d} \\
  M_{L21} \ M_{L22} \ \ldots \ M_{L2d} \\
  \ldots \ \ldots \ \ldots \\
  M_{Ln1} \ M_{Ln2} \ \ldots \ M_{Lnd}
\end{bmatrix} \]

\[ A_{OAL} = \begin{bmatrix}
  f\{M_{L11} \ M_{L12} \ \ldots \ M_{L1d}\} \\
  f\{M_{L21} \ M_{L22} \ \ldots \ M_{L2d}\} \\
  \ldots \ \ldots \ \ldots \\
  f\{M_{Ln1} \ M_{Ln2} \ \ldots \ M_{Lnd}\}
\end{bmatrix} \]

where, \( A_{OAL} \) = matrix that is storing the objective function of all the antlions
\( f \) = objective function or fitness function
\( n \) = number of antlions.

There are quite a few conditions which are to be applied while considering this optimization problem.

- Haphazard way of walking of ants is subjected to each and every dimension.
- The crusade of the random walk in the search area may be dissimilar.
- Antlions affects the haphazard walking of ants because of the traps.
- Depending on fitness value, ant-lions can set up larger pits that implies more is the fitness value, more the size of pit.
- Every ant that shall be caught by an antlion is taken as an “elite” (i.e. fittest antlion).
- Supposing if ant turns into sturdier, than the antlion, corresponding ant will be cached as a target for antlion.
- Range of the ants doing random walk successively declines.
- Antlion changes the position after eating the prey and shapes a new pit in order to catch additional prey in the very next hunt.

An initial value for the randomized walks has been already set, using equation (5) and the ants would keep on updating their positions throughout the procedure of optimization. Though, the search space has a restricted boundary, equation (5) do not alter the positions of ants as it will be used for the initialization of the ants’ random walks. So, randomized walks could be bounded by the max-min normalization of the below equation.

\[ y_i^t = \frac{(X_i^t - \alpha_j) \times (\delta_i - \gamma_i)}{\beta_i - \alpha_i} + \gamma_i \]

where \( \alpha_i \) = min. randomized walk of the \( i^{th} \) variable
\( \beta_i \) = max. randomized walk of the \( i^{th} \) variable
\( t \) = iteration number
\( \gamma \) = smallest value of the \( i^{th} \) variable
and \( \delta \) = maximum value of the \( i^{th} \) variable

The duping behavior is mathematically modeled and has been projected as shown below.
\[ y_t^j = \text{Ant}_t^j + y^t \]  
\[ \delta_t^j = \text{Ant}_t^j + \delta^t \]  
(12)  

(13)

where \( \delta^t \) & \( y^t \) is the higher and lower value of each variable at the \( t \)th iteration

\( \text{Ant}_t^j \) equals the \( j \)th antlion location at the \( t \)th iteration

The given equations give the randomized walk in a specified hyperspace by \( y \) and \( \delta \) vectors respectively for a certain antlion. The pictorial mathematical modeling of the equations (11) and (12) has been denoted in a two-dimensional space. The pictographic depiction for the model is exemplified as given below.

3.3. Building of the trap

The chasing capability of the antlions is being mathematically modeled with the process of roulette wheel selection. The Figure 2 given above displays all the ants are hunted by one antlion at a time that is carefully chosen by the roulette wheel operator according to the fitness values. The corresponding procedure provides more probabilities to the antlions in search for the fittest of all.

3.4. Sliding of the ants near the antlion

In the phases discussed till now, the antlions hold the ability to build the pits using the set reference position of their calculated fitness. Still, the ant-lions hurl out of the silts in the mid of the pit as soon as they realize that the ant is trying to come out from the pit. Because of the force of the sand, ants which are trying to escape from the pit go down further sliding. This type of physical behavior of ants is detected and mathematically modeled as.

\[ y_t^j = \frac{y^t}{I} \]  
\[ \delta_t^j = \frac{\delta^t}{T} \]  
(14)  

(15)  

where \( I = \text{ratio} \). \( y_t^j \) & \( \delta_t^j \) are the min and max of variables at iteration number “t”.

\[ I = \frac{t}{T} * 10^w \]  
(16)  

where \( t \) is a present iteration, 
\( T = \text{max no. of iterations} \)
\( w = \text{constant. The value of } w \text{ is varies based on current iteration.} \)
\( \text{i.e. } w = 2, 3, 4, 5, 6; \text{ if } t > 0.1T, 0.5T, 0.75T, 0.9T, 0.95T \text{ respectively} \)

Figure 3 shown diminishing nature of curve using the equations (13) & (14). These equations squeeze the radius of ants’ positions and sliding behavior of the ants in the pits.
3.5 Catching of the prey and rebuilding the pit

When an ant falls inside the pit the last phase of this process will start, and it gets caught by ant-lion. In order to depict this process, in this work it is presumed that catching of the ants will be done when an ant becomes supplementary fitter than the corresponding antlion. In that case, ant-lion necessitates to updating its previous position to a newer location to enhance the probability of holding the prey. Hence, to analyze the catching of prey and rebuilding the pit, subsequent mathematical equations are proposed below.

\[ A_t^j = Antlion_t^i; : f(Antlion_t^i) > f(Ant_t^j) \]  
where \( A_t^j \) = position of jth antlion  
\( Ant_t^i \) = position of ith ant and t specifies contemporary iteration.

3.6. Elitism

In EA (evolutionary algorithms) Elitism is the most important characteristic and it allows to upholding best challenging solutions throughout the optimization process. In recent practice, the superlative antlion touches the present iteration is to be called as “Elite”. Furthermore, with the course of iterations, the best antlion would have the power to affect the travels of the ants. In the end, the randomized motion of the ants round the finest antlion is decided with help of Roulette wheel selection.

\[ Antlion_t^i = \frac{R_A^t + R_E^t}{2} \]  
where \( R_A^t \) = random walk of ant about antlion at tth iteration  
\( R_E^t \) = random walk of ant about elite antlion.

3.7. Standard IEEE-30— bus system

Figure 3– Reduction in radius of ants’ positions

Figure 4–Transmission bus test system (standard IEEE 30 Bus)
To verify the performance success of the ALO technique as proposed, it is applied on standard IEEE bus system (here IEEE 30 bus) as shown in Figure 4. The chosen test system bears the respective specifications.

Buses numbered as 1, 2, 5, 8, 11 and 13 represents six power generation units, transformers tap changings are present at line numbered as 11, 12, 15 and 36, shunt VAR compensators are located at bus numbered as 10, 12, 15, 17, 20, 21, 23, 24 and 29. PG1 to PG6 indicates active power of the generators. VG1 to VG6 shows voltages of the generators. T11, T12, T15 and T36 gives the tap changing positions of the transformers with line numbers 11, 12, 15 and 36. Shunt connected VAR compensators are present at bus numbers indicated as 10, 12, 15, 17, 20, 21, 23, 24 and 29.

Using the above said data, OPF for minimization of the voltage deviations, active power loss and similarly production cost is performed on the considered IEEE 30-bus system.

The controlling parameters that are utilized in ALO and PSO are illustrated in the Table 1.

| Sr. No. | Parameters Name           | Values  |
|---------|---------------------------|---------|
| I       | Maximum number of iterations | 500.00  |
| II      | Variables                 | 06.00   |
| III     | Population of ants        | 40.00   |
| IV      | Random number             | [0 to 01.00] |

4. Results and Discussion

4.1. Total production cost minimization

The PSO method used essentially for OPF individually gives the variations in graphical characteristics. From the Figure 5, primarily, the fuel cost is 901.9516 $/hr and thereafter, incessantly decreasing when number of iterations increases. Hence, at the end of 500 iterations, the minimized cost is found to be 800.410 $/hr.

| Control Variable | Min values | Max values | Initial values | RHBO technique | PSO technique | ALO technique |
|------------------|------------|------------|----------------|----------------|---------------|---------------|
| PG1              | 50.0000    | 200.0000   | 99.2230        | 175.3418       | 176.9600      | 177.0800      |
| PG2              | 20.0000    | 80.0000    | 80.0000        | 48.3528        | 48.9800       | 48.7250       |
| PG5              | 15.0000    | 50.0000    | 50.0000        | 21.5323        | 21.3000       | 21.3120       |
| PG8              | 10.0000    | 35.0000    | 20.0000        | 20.0198        | 21.1900       | 21.0310       |
| PG11             | 10.0000    | 30.0000    | 20.0000        | 13.4241        | 11.9700       | 11.9530       |
| PG13             | 12.0000    | 40.0000    | 20.0000        | 13.4081        | 12.0000       | 12.0000       |
Table 3: Comparative study of the $f_{\text{cost}}$ with other techniques

| Sr.No. | Type of Algorithm                  | Total fuel cost ($/hr) |
|--------|-----------------------------------|------------------------|
| I      | Antlion optimization algorithm    | 799.6320               |
| II     | Black-hole based optimization     | 799.9210               |
| III    | Electro-magnetism-based mechanism | 800.0780               |
| IV     | Particle swarm optimization       | 800.4100               |
| V      | Enhanced genetic algorithm        | 802.0600               |
| VI     | Modified differential algorithm   | 802.3760               |
| VII    | Improved evolutionary programming | 802.4650               |
| VIII   | Evolutionary programming          | 802.6200               |
| IX     | Gradient method                   | 804.8530               |

4.2. Minimization of losses in transmission lines

The optimization of the active power loss by ALO and PSO has been plotted and it accepts the trustworthiness of the presented algorithm with the conventional prevailing methods. Control parameters optimal values shown in Table 5. The losses got reduced to a value 3.0261 MW. Analogous variations for Antlion OPF are likewise detected and the losses are computed to be 2.9013 MW.

![Figure 6– Comparison of different techniques for active power loss](image.png)
Table 4: Comparing $P_{\text{loss}}$ with different algorithms

| Sr.No. | Type of Algorithm          | $P_{\text{loss}}$ (MW) |
|--------|----------------------------|------------------------|
| I      | Antlion Optimizer (ALO)    | 02.9013                |
| II     | Particle Swarm Optimizer (PSO) | 03.0261             |
| III    | Black Hole Based Optimizer (BHBO) | 03.5035             |

Table 5: Control parameter optimal values for $P_{\text{loss}}$ using various techniques

| Control Variable | Min. value | Max. value | Int. value | BHBO technique | PSO technique | ALO technique |
|------------------|------------|------------|------------|----------------|---------------|---------------|
| $P_{G1}$         | 50.0000    | 200.0000   | 99.2230    | 67.3549        | 51.4270       | 51.2900       |
| $P_{G2}$         | 20.0000    | 80.0000    | 80.0000    | 72.8998        | 80.0000       | 80.0000       |
| $P_{G5}$         | 15.0000    | 50.0000    | 50.0000    | 48.1774        | 50.0000       | 50.0000       |
| $V_{G1}$         | 00.9500    | 01.1000    | 01.0500    | 01.0689        | 01.1000       | 01.1000       |
| $V_{G2}$         | 00.9500    | 01.1000    | 01.0400    | 01.0622        | 01.1000       | 01.1000       |
| $V_{G5}$         | 00.9500    | 01.1000    | 01.0500    | 01.0456        | 01.1000       | 01.1000       |
| $T_{11}$         | 00.0000    | 01.1000    | 01.0780    | 00.9907        | 01.0580       | 01.0580       |
| $T_{12}$         | 00.0000    | 01.1000    | 01.0500    | 01.0465        | 01.1000       | 01.1000       |
| $T_{15}$         | 00.0000    | 01.1000    | 01.0500    | 01.0465        | 01.1000       | 01.1000       |
| $T_{36}$         | 00.0000    | 01.1000    | 01.0680    | 00.9822        | 00.9980       | 00.9950       |
| $QC_{10}$        | 00.0000    | 05.0000    | 00.0000    | 02.8915        | 04.0650       | 04.7800       |
| $QC_{12}$        | 00.0000    | 05.0000    | 00.0000    | 02.5199        | 03.0260       | 03.0260       |
| $QC_{15}$        | 00.0000    | 05.0000    | 00.0000    | 03.5486        | 04.9950       | 04.9950       |
| $QC_{17}$        | 00.0000    | 05.0000    | 00.0000    | 02.0410        | 04.9360       | 04.9360       |
| $QC_{20}$        | 00.0000    | 05.0000    | 00.0000    | 03.1853        | 04.9980       | 04.9980       |
| $QC_{21}$        | 00.0000    | 05.0000    | 00.0000    | 02.7309        | 04.9980       | 04.9980       |
| $QC_{23}$        | 00.0000    | 05.0000    | 00.0000    | 03.1663        | 04.3010       | 04.3010       |
| $QC_{24}$        | 00.0000    | 05.0000    | 00.0000    | 03.3136        | 05.0000       | 05.0000       |
| $QC_{29}$        | 00.0000    | 05.0000    | 00.0000    | 02.5200        | 05.0000       | 05.0000       |
| $P_{\text{loss}}$ (MW) | -         | -         | 05.8219    | 03.5035        | 03.0260       | 02.9013       |

4.3. Voltage deviation minimization

The minimized or optimal voltage deviation values for the different methods presented in Table 7 shows that the antlion optimization algorithm reduced the voltage fluctuations from 1.150 pu to 0.1220 pu. The voltages deviation values with different conventional algorithms are tabulated in Table 6. When these methods compared with ALO, ALO is giving better voltage deviation value.

Table 6: Comparing voltage deviation obtained by ALO with different algorithms

| Sr.No. | Type of Algorithms          | Voltage deviation (pu) |
|--------|----------------------------|------------------------|
| I      | Antlion Optimizer (ALO)    | 00.1220                |
| II     | Black Hole Based Optimizer (BHBO) | 00.1262             |
| III    | Electro Magnetism (EM) based mechanism | 00.1270             |
| IV     | Differential Evolution (DE) | 00.1357               |
| V      | Particle Swarm Optimizer (PSO) | 00.1910              |
**Figure 7** – Comparison of voltage deviation for various techniques

**Table 7:** Comparative study of control variables using various techniques for voltage deviation

| Control Variables | Min value | Max value | Initial value | BHBO technique | PSO technique | ALO technique |
|-------------------|-----------|-----------|---------------|----------------|---------------|---------------|
| PG1               | 50.0000   | 200.0000  | 99.2230       | 172.0250       | 175.9220      | 176.4220      |
| PG2               | 20.0000   | 80.0000   | 80.0000       | 48.09360       | 46.3890       | 49.0120       |
| PG5               | 15.0000   | 50.0000   | 50.0000       | 21.87360       | 21.5970       | 21.8290       |
| PG8               | 10.0000   | 35.0000   | 20.0000       | 20.82570       | 19.3960       | 19.9740       |
| PG11              | 10.0000   | 30.0000   | 20.0000       | 14.88640       | 17.6560       | 14.0730       |
| PG13              | 12.0000   | 40.0000   | 20.0000       | 15.27250       | 12.0000       | 12.0010       |
| VG1               | 00.9500   | 01.1000   | 01.0500       | 01.0338        | 01.0470       | 01.0380       |
| VG2               | 00.9500   | 01.1000   | 01.0400       | 01.0170        | 01.0340       | 01.0220       |
| VG5               | 00.9500   | 01.1000   | 01.0100       | 01.0116        | 00.9990       | 01.0140       |
| VG8               | 00.9500   | 01.1000   | 01.0100       | 01.0027        | 01.0050       | 01.0060       |
| VG11              | 00.9500   | 01.1000   | 01.0500       | 01.0435        | 00.9990       | 01.0040       |
| VG13              | 00.9500   | 01.1000   | 01.0500       | 01.0141        | 01.0180       | 01.0060       |
| T11               | 00.0000   | 01.1000   | 01.0780       | 01.0236        | 00.9540       | 00.9930       |
| T12               | 00.0000   | 01.1000   | 01.0690       | 00.9250        | 00.9690       | 00.9390       |
| T15               | 00.0000   | 01.1000   | 01.0320       | 00.9786        | 00.9890       | 00.9710       |
| T36               | 00.0000   | 01.1000   | 01.0680       | 00.9633        | 00.9600       | 00.9660       |
| QC10              | 00.0000   | 05.0000   | 00.0000       | 02.9696        | 03.9480       | 03.0510       |
| QC12              | 00.0000   | 05.0000   | 00.0000       | 02.3947        | 01.7650       | 03.5520       |
| QC15              | 00.0000   | 05.0000   | 00.0000       | 03.1905        | 04.8440       | 03.9250       |
| QC17              | 00.0000   | 05.0000   | 00.0000       | 03.0773        | 03.0750       | 04.2210       |
| QC20              | 00.0000   | 05.0000   | 00.0000       | 04.0279        | 04.6870       | 03.2300       |
| QC21              | 00.0000   | 05.0000   | 00.0000       | 03.8901        | 04.9480       | 04.9990       |
| QC23              | 00.0000   | 05.0000   | 00.0000       | 03.7811        | 01.6230       | 04.4850       |
| QC24              | 00.0000   | 05.0000   | 00.0000       | 03.7777        | 03.5590       | 04.5970       |
| QC29              | 00.0000   | 02.3794   | 00.0000       | 02.3794        | 02.0340       | 02.4790       |

| Voltage deviations (pu) | PG1 | PG2 | PG5 | PG8 | PG11 | PG13 | VG1 | VG2 | VG5 | VG8 | VG11 | VG13 | T11 | T12 | T15 | T36 | QC10 | QC12 | QC15 | QC17 | QC20 | QC21 | QC23 | QC24 | QC29 |
|-------------------------|-----|-----|-----|-----|------|------|-----|-----|-----|-----|------|------|-----|-----|-----|-----|------|------|------|------|------|------|------|------|------|------|
| Min                     | 50.0000 | 20.0000 | 15.0000 | 10.0000 | 10.0000 | 12.0000 | 00.9500 | 00.9500 | 00.9500 | 00.9500 | 00.9500 | 00.9500 | 00.0000 | 00.9500 | 00.9500 | 00.9500 | 00.9500 | 00.9500 | 00.9500 | 00.9500 | 00.9500 | 00.9500 | 00.9500 | 00.9500 |
| Max                     | 200.0000 | 80.0000 | 50.0000 | 35.0000 | 30.0000 | 40.0000 | 01.1000 | 01.1000 | 01.1000 | 01.1000 | 01.1000 | 01.1000 | 01.1000 | 01.1000 | 01.1000 | 01.1000 | 01.1000 | 01.1000 | 01.1000 | 01.1000 | 01.1000 | 01.1000 | 01.1000 | 01.1000 |
| Initial value           | 99.2230 | 80.0000 | 50.0000 | 20.0000 | 20.0000 | 20.0000 | 01.0500 | 01.0400 | 01.0100 | 01.0100 | 01.0100 | 01.0100 | 01.0500 | 01.0500 | 01.0500 | 01.0500 | 01.0500 | 01.0500 | 01.0500 | 01.0500 | 01.0500 | 01.0500 | 01.0500 | 01.0500 |

Voltage deviations (pu): 01.1500 00.1262 00.1910 00.1220.
5. Conclusion

The efforts have been made in the present work in directive to solve the OPF problem. For accomplishing this task, advanced computational methods are used. A new Meta–heuristic technique called Antlion optimizer is implemented to solve OPF and it is applied to an IEEE 30 bus transmission system while considering different parameters. The proposed ALO technique has provided upgraded results when compared to the previously current methods alike TLBO, DE, BHBO and PSO. Moreover, the effectiveness of proposed technique is tested with the various controlling parameter (with optimum values) and hence it manifests the superiority over the existing techniques. The detailed characteristics of OPF is plotted graphically which gives a pictorial scrutiny for each of the cases. The future scope of this work comprises OPF studies with wind energy, solar energy, tidal energy etc. Further work can be extended by running OPF with increased complexities by including constraints like power generator ramp limits.

References

[1]. Zwe-Lee Giang, Particle swarm optimization for solving the economic dispatch considering the generator constraints, (2003), IEEE Transactions on Power Systems, Volume 18.

[2]. Al-Turki Yusuf A, Abdel Fattah Attia, Optimal power flow using adapted genetic algorithm with adjusting population size, (2012), Electric Power Components and Systems, Volume 40, pp.1285–1299.

[3]. Liang, Ruey-Hsun, Sheng-Ren Tsai, Yie-Tone Chen and Wan-Tsun Tseng, Optimal power flow by a fuzzy based hybrid particle swarm optimization approach, (2011), Electric Power Systems Research, Volume 81, pp. 1466 - 1474.

[4]. Tarek Bouktir Linda Slimani, Optimal power flow of the algerian electrical network using an ant colony optimization method, Leonardo Journal of Sciences, (2005).

[5]. Dinu Calin Secui, A new modified artificial bee colony algorithm for the economic dispatch problem, Energy Conversion and Management, 89 (2015), pp. 43–62.

[6]. Antonio Roberto Balbo, Mar’cio Augusto da Silva Souza, Edme’a Ca’ ssia Baptista, Leonardo Nepomuceno, Predictor-Corrector primal-dual interior point method for solving economic dispatch problems: a post optimization analysis, Mathematical Problems in Engineering, (2012).

[7]. H.R.E.H. Bouchekara, M.A. Abido, M. Boucherma, Optimal power flow using teaching-learning-based optimization technique, Electr. Power Syst. Res. 114(2014), pp. 49–59.

[8]. H.R.E.H. Bouchekara, M.A. Abido, A.E. Chaib, R. Mehasni, Optimal power flow using the league championship algorithm, a case study of the Algerian Power System, Energy Convers. Manag. 87 (2014), pp. 58–70.

[9]. Serhat Duman, Ug’ur Güvenç, Yusuf Sönmez, Nuran Yörtükeren, Optimal power flow using gravitational search algorithm, Energy Conversion and Management 59 (2012), pp. 86–95.

[10]. H.R.E.H. Bouchekara, Optimal power flow using black-hole-based optimization approach, Applied Soft Computing, (2014).

[11]. Seyedali Mirjalili, The Ant Lion Optimizer, Advances in Engineering Software, 83 (2015).

[12]. B.K. Panigrahi, V. Ravikumar Pandi, Bacterial foraging optimisation: Nelder–Mead hybrid algorithm for economic load dispatch, IET Generation, Transmission & Distribution, 4 (2008), pp. 556-565.

[13]. Jing Li, Na Ou, Guang Lin, Wei Wei, Compressive Sensing Based Stochastic Economic Dispatch With High Penetration Renewables, IEEE Transactions in Power systems, 34(2019), pp. 1438-1449.

[14]. Tang Jianxing, Sun Bin, Chen Rui, Yao Yao, Wang Guosong, Economic Dispatching Method Based on Dynamic Network Loss Factor, International Conference on Power System Technology, (2018)