Optimization algorithms for steady state analysis of self excited induction generator

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ABSTRACT

The current publication is directed to evaluate the steady state performance of three-phase self-excited induction generator (SEIG) utilizing particle swarm optimization (PSO), grey wolf optimization (GWO), wale optimization algorithm (WOA), genetic algorithm (GA), and three MATLAB optimization functions (fminimax, fmincon, fminunc). The behavior of the output voltage and frequency under a vast range of variation in the load, rotational speed and excitation capacitance is examined for each optimizer. A comparison made shows that the most accurate results are obtained with GA followed by GWO. Consequently, GA optimizer can be categorized as the best choice to analyze the generator under various conditions.

Keywords:
Genetic algorithm
Grey wolf optimization
MATLAB optimizers
Particle swarm optimization
Whale optimization algorithm

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1. INTRODUCTION

Nowadays induction generators are extensively used in renewable energy systems, especially hydro and wind-based energy systems. This is due to a number of advantages of this generator type including low cost, simple construction, ease of maintenance and natural protection against short circuits [1]. To supply electrical loads in remote rural areas, where the network is far away, standalone induction generator is the most attractive choice [2]. An induction machine can be operated as a self-excited induction generator (SEIG) due to the presence of residual flux in the stator and rotor cores. If the generator is driven at a suitable speed and appropriate excitation capacitors are connected across the stator terminals, the voltage is built up until saturation region is attained [3]. In the literature, a great number of publications have been directed to evaluate the steady state performance of SEIG using various optimization techniques.

Nigim et al. [4] have implemented MathCad software package to estimate the unknown parameters of SEIG, which is operated in the saturation region to achieve better performance. Singaravelu and Velusami [5] have used fuzzy logic approach to find the unknown variables of SEIG under steady state operation. Mahato et al. [6] have avoided the solution of high order polynomial by using the eigen value sensitivity technique to determine the excitation capacitance limits in achieving high SEIG performance under steady state operation. Haque [7] have utilized fsolve algorithm, which is built in MATLAB, to analyze different configurations of SEIG. They found that short shunt SEIG type has possessed the best steady state performance, compared with shunt and long shunt schemes. Kheldoun et al. [8] have implemented the DIRECT algorithm to find the frequency and magnetizing reactance by minimizing the total admittance of the SEIG equivalent circuit. In this algorithm, an initial guess for the unknowns is not needed, only their boundaries are required.
Hasanien and Hashem [9] have used cuckoo search algorithm (CSA) to minimize the total impedance equation of wind driven SEIG and assess the steady state performance of the generator. Boora et al. [10] have used the concept of symmetrical components with the fsolve algorithm to find the unknown parameters of a capacitive excited induction generator (CEIG) under unbalanced operating conditions. Saha and Sandhu [11] have made a comparison for the implementation of genetic algorithm (GA), particle swarm optimization (PSO) and simulated annealing (SA) algorithm for predicting the steady state performance of SEIG feeding balanced resistive load.

In the present research work PSO, grey wolf optimization (GWO), WOA, GA and three MATLAB optimization functions (fminimax, fmincon, fminunc) are utilized for minimizing the total impedance equation of SEIG circuit model in order to find the two unknown parameters $F$ and $X_m$. The behaviors of the voltage and frequency when applying changes in the load impedance, speed or excitation capacitance are examined for each algorithm. The same operating conditions are considered when applying the optimization approaches, and based on the obtained results a comparison is made. The generator’s steady state model is derived from its dynamic direct quadrature (DQ) representation.

2. MATHEMATICAL MODELING

The DQ steady state (SS) model of a SEIG can be derived by setting the time derivative of the DQ dynamic model to zero [12]. The SS model can be given in (1) to (4):

\[ v_{qs} = r_s l_{qs} + \omega_e (L_s l_{ds} + L_m l_{dr}) \] (1)

\[ v_{ds} = r_s l_{ds} + \omega_e (L_s l_{qs} + L_m l_{qr}) \] (2)

\[ v_{qr} = r_r l_{qr} + (\omega_e - \omega_r) (L_r l_{dr} + L_m l_{ds}) \] (3)

\[ v_{dr} = r_r l_{dr} - (\omega_e - \omega_r) (L_r l_{qr} + L_m l_{qs}) \] (4)

where $L_s = L_{ls} + L_{mr}$ and $L_r = L_{lr} + L_{mr}$, $l_{ls}$ and $l_{lr}$ are the leakage inductances of stator and rotor winding; $L_m$ is the mutual inductance; $r_s$ and $r_r$ are stator resistance and rotor resistance; $v_{qs}$ and $v_{ds}$ are $qd$-stator voltages; $v_{qr}$ and $v_{dr}$ are $qd$-rotor voltages; $l_{qs}$, $l_{ds}$ are $dq$-stator currents; $l_{qr}$ and $l_{dr}$ are $dq$-rotor currents; $\omega_e$ and $\omega_r$ are the synchronous and rotor speeds. Equations (1) to (4) can be rewritten in terms of the complex rms space voltage vectors as (5) and (6).

\[ \bar{v}_{qs} - j \bar{v}_{ds} = (r_s + j \omega_e L_s) (I_{qs} - j I_{ds}) + j \omega_e L_m (i_{qr} - j i_{dr}) \] (5)

\[ \bar{v}_{qr} - j \bar{v}_{dr} = j(\omega_e - \omega_r) L_m (\bar{I}_{qs} - j \bar{I}_{ds}) + [r_r + j(\omega_e - \omega_r) L_s] (\bar{I}_{qr} - j \bar{I}_{dr}) \] (6)

Using the relationships between the rms space vectors and rms time phasors, rewriting the slip frequency ($\omega_e-\omega_r$) by the slip multiplied by synchronous speed ($s\omega_e$), and dropping the common $e^{j\omega_{ct}}$ term yields (7) and (8) [12].

\[ V_s = (r_s + j \omega_e L_{ls}) I_s + j \omega_e L_m (I_s + I_r) \] (7)

\[ V_r = (r_r + j s \omega_e L_{lr}) I_r + j s \omega_e L_m (I_s + I_r) \] (8)

Divide the last equation by the per unit slip $s$ yields (9).

\[ \frac{V_r}{s} = \left( r_r + j s \omega_e L_{lr} \right) I_r + j s \omega_e L_m (I_s + I_r) \] (9)

The slip $s$ can be expressed as (10).

\[ s = \frac{\omega_e - \omega_r}{\omega_e} = \frac{f_r - \frac{\omega_r}{2\pi f_b}}{f_b} = \frac{f_s - f_{m}}{f_b} \] (10)
where $F$ is the ratio of the actual frequency to base frequency and $u$ is the ratio of the running speed to the synchronous speed, which corresponds to the base frequency. Since SEIG could be driven at different speeds and accordingly variable stator frequency, it is convenient to refer all of the machine parameters to rated frequency. Application of Kirchhoff's voltage law (KVL) to the circuit model of SEIG providing that the equivalent Thevenin impedance must equal to zero, since the current $I_s \neq 0$ [14]:

$$Z_{total} = Z_s + (Z_c // Z_L) + (Z_r // Z_m) = 0$$

(11)

3. OPTIMIZATION ALGORITHMS

To achieve numerical solution for the total impedance equation of SEIG, it is required to formulate the equation as an objective function [14], which is given in (12). An optimization algorithm could be used to solve this equation and find the two unknown parameters under different operating conditions. The performance of the SEIG can be evaluated using the obtained values of the unknown parameters, with the help of the generator equivalent circuit. In the current research work several optimization techniques are utilized to find the two unknown parameters $X_m$ and $F$. The main concepts for each of these techniques are presented in the following sub-sections.

$$Min[Z_{total}(F, X_m)]$$

Subject to the constraints

$$0.5 \leq F \leq 1.0$$

$$0.2 \leq X_m \leq 2.25$$

(12)

3.1. Particle swarm optimization

PSO is involved in several iterations of updating both the position and velocity of each particle in the swarm to achieve the best solution, with respect to a certain quality measure [15]. Figure 2 presents the algorithm’s flowchart. The position and velocity of a particle in the swarm can be mathematically represented in the (13) and (14) [16], [17]:

$$V_j^{(K+1)} = \mu V_j^K + \delta_1 rand[0,1](P_{best} - X_j^K) + \delta_2 rand[0,1](G_{best} - X_j^K)$$

(13)

$$X_j^{(K+1)} = X_j^K + V_j^{(K+1)}$$

(14)

where $V_j^{(K+1)}$ is the particle speed, $X_j^{(K+1)}$ is the particle position, $u$ is the inertia of the particle, $\delta_1$ and $\delta_2$ are positive constants, $P_{best}$ is the best solution for the particle and $G_{best}$ is the best position of the swarm. Using the objective function $f(F, X_m)$, $P_{best}$ and $G_{best}$ can be defined in (15)-(16):
\[ p_{\text{best}}^{(K+1)} = \begin{cases} \frac{p_{\text{best}}^{(K)}}{X_j^{(K+1)}} & \text{if } f_{p_{\text{best}}}^{(K)} \\
ave & \text{if } f_X^{(K+1)} < f_{\text{best}}^{(K)} \end{cases} \]  

(15)

\[ G_{\text{best}}^{(K)} = \arg_i \min_{1 \leq n} f(p_{\text{best}}^{(K)}) \]  

(16)

where \( f(P_{\text{best}}^{(K)}) \) is the \( K \)th value of our objective function \( f(F, X_m) \) and \( n \) is the total number of particles [18], [19].

3.2. Grey wolf optimization algorithm

The implementation of GWO is performed based on the hunting mechanism of grey wolves: alpha, beta, delta, and omega [20]–[22]. The mathematical representation of GWO is given in (17) to (20) [23]:

\[ D = |C \times X_p(q) - X(q)| \]  

(17)

\[ X(q + 1) = X_p(q) - A \times D \]  

(18)

\[ C = 2 \times r_2 \]  

(19)

\[ A = a \times (2 \times r_1 - 1) \]  

(20)

where \( D \) is the distance of the wolf, \( q \) is the iteration, \( X_p \) is the prey position, \( X \) is the wolf location, \( C, A \) and \( a \) are coefficients, \( r_1 \) and \( r_2 \) are random vectors. The objective function \( f(F, X_m) \) can be mathematically formulated based on GWO algorithm, as given in (21) to (23). The unknowns \( X_m \) and \( F \) are called and compared with the wolf locations (\( X_\alpha, X_\beta, X_\delta \)), and these locations are then updated to reach the final best solution.

\[ \text{If } \{ f(F, X_m) < X_\alpha \} \text{ then } X_\alpha = f(F, X_m) \]  

(21)

\[ \text{If } \begin{cases} f(F, X_m) > X_\alpha \\ f(F, X_m) < X_\beta \end{cases} \text{ then } X_\beta = f(F, X_m) \]  

(22)
\[
\begin{align*}
\text{If } & \begin{cases} f(F,X_m) > X_\alpha \\ f(F,X_m) > X_\beta \\ f(F,X_m) < X_\delta \end{cases} \text{ then } X_\delta = f(F,X_m) \\
\end{align*}
\]

(23)

The distances as well as locations of wolfs can be recalculated and updated based on the (24) to (29).

\[
\begin{align*}
D_\alpha &= |C_1 \times X_\alpha - X(q)| \\
D_\beta &= |C_2 \times X_\beta - X(q)| \\
D_\delta &= |C_3 \times X_\delta - X(q)| \\
X_1 &= |X_\alpha - \alpha_1 D_\alpha| \\
X_2 &= |X_\beta - \alpha_2 D_\beta| \\
X_3 &= |X_\delta - \alpha_3 D_\delta| \\
\end{align*}
\]

(24) - (29)

The new position of the prey, which depends on the locations and distances of the three main wolfs, can be recalculated and updated based on the (30) [23].

\[
X_\rho(q + 1) = \frac{X_1 + X_2 + X_3}{3}
\]

(30)

### 3.3. MATLAB based algorithms

The three algorithms \textit{fminimax}, \textit{fmincon}, and \textit{fminunc} are built in MATLAB optimization toolbox. The operation of \textit{fminimax} optimizer is based on Newton optimization approach [24]. It minimizes the worst-case value for a set of multivariable functions, starting at an initial estimate. Since the objective function \(f(F,X_m)\) is differentiable and the aim is to approach \(f(F,X_m) = F(X) = 0\), it is possible to solve the equation by letting \(X_0\), as an initial point, and expressing the current value of an unknown variable in the (31).

\[
X_{n+1} = X_n - \frac{f'(x_n)}{f(x_n)} \quad n = 0,1, \ldots \text{ etc}
\]

(31)

\textit{fmincon} can find a constrained minimum of a scalar function of several variables starting at an initial estimate. It is usually applied to solve medium and large scale optimization problems [25]. The use of \textit{fmincon} function to minimize the total impedance equation can be represented as (32).

\[
\text{\textit{fmincon}} \quad \text{such that} \quad \begin{cases} C(x) \leq 0 \\ Ceq(x) = 0 \\ A.x \leq b \\ Aeq.x = beq \\ lb \leq x \leq ub \end{cases}
\]

(32)

\textit{fminunc} could be used to find an unconstrained minimum of a scalar function having several variables starting at an initial estimate [26]. It is similar to \textit{fmincon} in the way of its utilization for the objective function \(f(F,X_m)\), but the iterations are not bounded with any constraint.

### 3.4. Whale optimization algorithm

\(\text{WOA}\) is based on humpback whales hunting method, which involves in shrinking encircling mechanism and spiral updating position. It starts with a set of random solutions followed by iterations trying to find the best solution. The search agents are updated their locations based on either a randomly selected search agent or the best obtained solution in the prior iteration [27]. The method of WOA can be formulated in (33) and (34) [14], [28]:

\[
\bar{D} = |\overline{C} \ddot{X}^2(t) - \ddot{X}(t)|
\]

(33)

\[
\ddot{X}(t + 1) = \begin{cases} \dot{X}^2(t) - \overline{A} \bar{D} \\ \bar{D} . e^{it} \cos(2\pi t) + \ddot{X}(t) \end{cases} \quad \text{if } p < 0.5
\]

(34)

\[\text{Optimization algorithms for steady state analysis of self excited induction generator (Ibrahim Athannah)}\]
where $t$ is the present iteration, $\vec{X}$ is the position vector, $\vec{X}^*$ is the position vector of the obtained best solution of the present iteration and is updated at each iteration, $p$ is a random number in the interval of $[0,1]$, $l$ is a random number in the interval of $[-1,1]$, $b$ is a constant. The coefficient vectors $\vec{A}$ and $\vec{C}$ can be expressed in (35) and (36).

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \quad (35)$$

$$\vec{C} = 2 \cdot \vec{r} \quad (36)$$

where $\vec{r}$ is a random vector, $\vec{a}$ is located between 2 and 0. The unknown variables of the objective function $f(F, X_m)$ are called and compared with the values of the whale leader vector position $\vec{X}$. The values of the vector are updated, if the comparison for the obtained result does not satisfy the preset criteria. The comparison can be mathematically represented as (37).

$$\text{If } f(F, X_m) < \vec{X} \quad \text{then } \vec{X} = f(F, X_m) \quad (37)$$

### 3.5. Genetic Algorithm

The process of GA optimization is started with initial population depending on the formulated chromosomes, which represent the unknown variables of the problem. The population which is also called generation provides a set of possible solutions. To reach the best solution, the population is subjected to repetitive iterations for selection crossover, mutation and inversion. The GA optimization process flowchart is presented in Figure 3.

![Figure 3. The process of GA optimization](image)

In the present work, the parameters of each individual (chromosome) represent the unknown parameters $X_m$ and $F$; chromosome = $[X_m F]$. If $Pop$ is the total number of the population then the crossover process is reiterated by $(Pop/2)$ times, and moreover another $Pop$ children will be produced [29]. If parents are $[X_m F_1]$ and $[X_m F_2]$ then:

$$\text{Child } 1 = \begin{cases} X_m = rX_m + (1 - r)X_m^2 \\ F = rF_1 + (1 - r)F_2 \end{cases} \quad (38)$$

$$\text{Child } 2 = \begin{cases} X_m = (1 - r)X_m + rX_m^2 \\ F = (1 - r)F_1 + rF_2 \end{cases} \quad (39)$$

where $r$ is the crossover rate, which is selected randomly between 0 and 1, and is selected to be 0.9. High value of crossover rate is selected to preserve genetic information for each individual and moreover maintaining acceptable behavior for the crossover process. To prevent local optima premature convergence, mutation process is applied. Equations (40) and (41) describe the mutation operator for real valued encoding.

$$X_m = X_m + (r_1 - 0.5)(2 X_{m_{max}}) \quad (40)$$

$$F = F + (r_2 - 0.5)(2 F_{max}) \quad (41)$$
where $X_m$ and $F$ are the parameters in each child, $X_{m,\text{max}}$ and $F_{\text{max}}$ are the maximum variations in the variables $X_m$ and $F$ when applying the mutation process, $r_1$ and $r_2$ are two random numbers representing the mutation rate; $r_1, r_2 \in (0, 1)$.

4. RESULTS AND DISCUSSION

The machine used in the current investigation is 1.5 kW 380 V 3.7 A 50 Hz 1.415 r.p.m 4-pole 0.77 PF lagging Y-connected three-phase squirrel cage induction generator. The per unit values of stator resistance, rotor resistance, stator reactance, rotor reactance, and saturated magnetizing reactance are 0.07, 0.16, 0.22, 0.34 and 2.25, respectively. The nonlinear relation between $E_g/F$ and $X_m$ is given by:

$$
\frac{E_g}{F} = -0.46 X_m^3 + 1.32 X_m^2 - 1.31 X_m + 1.54.
$$

To assess the implementation of the considered optimization techniques for steady state analysis of SEIG, the behavior of the output voltage ($V_o$) and output frequency ($F$) under the variations in the load impedance ($Z_L$), rotational speed ($u$) or excitation capacitance ($C$) are examined. The considered ranges in varying these three parameters are given in Table 1. To achieve fair comparison for the utilized optimization approaches, extensive MATLAB/Simulink simulations under the same operating conditions for all approaches are conducted. The obtained results for each algorithm are presented in this section.

<table>
<thead>
<tr>
<th>Case No.</th>
<th>Range $Z_L$ (p.u.)</th>
<th>$u$ (p.u.)</th>
<th>$C$ (µF)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.2-10</td>
<td>variable</td>
<td>1.0</td>
</tr>
<tr>
<td>2</td>
<td>0.8-1.6</td>
<td>2.2</td>
<td>variable</td>
</tr>
<tr>
<td>3</td>
<td>50-220</td>
<td>2.2</td>
<td>1.0</td>
</tr>
</tbody>
</table>

The results of utilizing the PSO algorithm to examine the behavior of the obtained voltage ($V_o$) and frequency ($F$) when varying the load impedance ($Z_L$), speed ($u$) and excitation capacitance ($C$) are presented in Figure 4: the behavior of $V_o$ and $F$ versus $Z_L$ is shown in Figure 4(a), the variation of $V_o$ and $F$ versus $u$ is presented in Figures 4(b) and 4(c) demonstrates the changes of $V_o$ and $F$ against $C$. It can be clearly noticed that the PSO algorithm fails to find the optimum unknown values at some values of the load impedance and speed. Figure 5 shows the obtained results for the voltage and frequency when implementing GWO algorithm under the same operating conditions. Figure 5(a) shows the behavior of $V_o$ and $F$ versus $Z_L$, the variation of $V_o$ and $F$ versus $u$ is presented in Figure 5(b) and the behavior of $V_o$ and $F$ against $C$ is demonstrated in Figure 5(c). It can be observed that GWO is succeeded in finding the unknown variables $F$ and $X_m$ for the whole considered ranges of variations in $Z_L$, $u$ or $C$. As a result, acceptable curves representing the behavior of $V_o$ and $F$ are acquired. Comparing the GWO results with the corresponding PSO results, tremendous improvement is achieved when using GWO algorithm.

![Figure 4](image1.png)

![Figure 5](image2.png)

The obtained results when using MATLAB built in algorithms *fminimax*, *fmincon* and *fminunc*, under the same considerations for PSO and GWO algorithms, are presented in Figures 6 to 8, respectively. The variations of $V_o$ and $F$ with $Z_L$, their variations with $u$ and the behavior of these two outputs versus $C$, when utilizing *fminimax* algorithm, are shown in Figures 6(a), 6(b) and 6(c), respectively. The results of *fmincon* algorithm that demonstrating the behavior of $V_o$ and $F$ against the changes in $Z_L$, $u$ and $C$ are presented in

*Optimization algorithms for steady state analysis of self excited induction generator (Ibrahim Athamnah)*
Figures 7(a), 7(b), and 7(c), respectively. The changes of the two outputs; $V_o$ and $F$, versus $Z_L$, $u$ and $C$, when implementing $\text{fminunc}$, are shown in Figures 8(a), 8(b), and 8(c), respectively. It can be seen that $\text{fminimax}$ and $\text{fmincon}$ algorithms fail to find the optimum unknown values below 1 per unit speed. Therefore, these two algorithms are not appropriate to be used under low-speed operation. From the results in Figure 8, it can be noticed that $\text{fminunc}$ is unable to find the optimum unknown values under the variations in the load impedance or rotational speed.

Figure 5. The results of GWO algorithm for the obtained voltage and frequency against the load, speed or the excitation capacitance (a) $V_o$ and $F$ versus $Z_L$, (b) $V_o$ and $F$ versus $u$, and (c) $V_o$ and $F$ versus $C$

Figure 6. The results of $\text{fminimax}$ algorithm for the obtained voltage and frequency against the load, speed or the excitation capacitance (a) $V_o$ and $F$ versus $Z_L$, (b) $V_o$ and $F$ versus $u$, and (c) $V_o$ and $F$ versus $C$

Figure 7. The results of $\text{fmincon}$ algorithm for the obtained voltage and frequency against the load, speed or the excitation capacitance (a) $V_o$ and $F$ versus $Z_L$, (b) $V_o$ and $F$ versus $u$, and (c) $V_o$ and $F$ versus $C$

Figure 8. The results of $\text{fminunc}$ algorithm for the obtained voltage and frequency against the load, speed or the excitation capacitance (a) $V_o$ and $F$ versus $Z_L$, (b) $V_o$ and $F$ versus $u$, and (c) $V_o$ and $F$ versus $C$
The results of the output voltage and frequency against load impedance, speed and excitation capacitance using WOA algorithm are presented in Figure 9. The behavior of $V_o$ and $F$ versus $Z_l$ is shown in Figure 9(a), the variation of $V_o$ and $F$ versus $u$ is presented in Figures 9(b) and 9(c) demonstrates the changes of $V_o$ and $F$ against $C$. It can be noticed that WOA algorithm fails to find accurate unknown values for load impedance greater than 3 per unit, and moreover inaccurate results are obtained for excitation capacitance above 125 uF. In addition, the algorithm could not find the optimum unknown values below 1 pu speed. The weakness in the accuracy of the obtained results for the unknown variables is reflected in the smoothness of the curves repenting $V_o$ and $F$ results.

Figures 10 presents the results of genetic algorithm for the output voltage and frequency against the variations in $Z_l$, $u$ or $C$, under the same operating conditions of the previous techniques. The changes of $V_o$ and $F$ versus $Z_l$ are demonstrated in Figure 10(a), the variation of $V_o$ and $F$ versus $u$ is shown in Figures 10(b) and 10(c) presents the behavior of $V_o$ and $F$ against $C$. It can be observed that GA succeeded in finding the optimum unknown values for the whole considered range of variations in $Z_l$, $u$ and $C$ parameters. The high accuracy in the results obtained for the unknowns can be clearly realized in the smoothness of $V_o$ and $F$ curves.

![Figure 9](image9.png)

Figure 9. The results of WOA algorithm for the obtained voltage and frequency against the load, speed or the excitation capacitance (a) $V_o$ and $F$ versus $Z_l$, (b) $V_o$ and $F$ versus $u$, and (c) $V_o$ and $F$ versus $C$.

![Figure 10](image10.png)

Figure 10. The results of GA for the voltage and frequency against the load, speed or the excitation capacitance (a) $V_o$ and $F$ versus $Z_l$, (b) $V_o$ and $F$ versus $u$, and (c) $V_o$ and $F$ versus $C$.

The GA results for the generator’s output power ($P_{out}$) and efficiency ($\eta$) versus the changes in $Z_l$, $u$ and $C$ parameters are shown in Figure 11. The variations of $P_{out}$ and $\eta$ versus $Z_l$ is presents in Figure 11(a), the behavior of $P_{out}$ and $\eta$ against $u$ is demonstrated in Figure 11(b) and the changes of $P_{out}$ and $\eta$ with $C$ is shown in Figure 11(c). It can be seen that the shape of the obtained curves for $P_{out}$ and $\eta$ is smooth since GA approach has the ability to find the unknown parameters with high accuracy for the whole range of changes in the load, rotational speed or excitation capacitance. It is important to realize that the best output power and efficiency of the SEIG are not necessarily achieved by keep increasing the speed or the excitation capacitance. However, certain operating conditions based on optimum $Z_l$, $u$, and $C$ values can lead to the highest possible $P_{out}$ and $\eta$ values.

Based on the comparison made between GA results with the corresponding results of each other optimization technique, it can be observed that GA is the most powerful optimization approach in finding the optimum values of unknown variables under wide range of variations in SEIG parameters. Therefore, it can be strongly recommending utilizing GA algorithm for steady state (SS) analysis of SEIG under different operating conditions. The next candidate algorithm for SS analysis of SEIG is GWO algorithm. The other five approaches (PSO, fmincon, fminimax, fminunc, and WOA) have failed to find accurate results for the unknown parameters under certain speed, load or excitation capacitance. Therefore, it is not recommended to utilize these five algorithms for SS analysis of SEIG, especially for wide ranges of variations in $Z_l$, $u$, or $C$ parameters.
Figure 11. The results of GA for the efficiency ($\eta$) and output power ($P_{out}$) against the load, speed or the excitation capacitance (a) $P_{out}$ and $\eta$ versus $Z_L$, (b) $P_{out}$ and $\eta$ versus $u$, (c) $P_{out}$ and $\eta$ versus $C$

5. CONCLUSION

The seven optimization approaches PSO, GWO, fmincon, fminimax, fminunc, WOA and GA have been applied to predict the steady state performance of three-phase SEIG under the changes in rotational speed, excitation capacitance and load. Based on the results obtained, it can be concluded that the optimization approach which has the ability to find the most accurate solution for the unknown parameters is GA followed by GWO algorithm. This can be realized in the results representing the behavior of the voltage, frequency under the wide range of changes in the generator parameters.

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