Research Article

Improved Gradient-Based Optimizer for Modelling Thermal and Hydropower Plants

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Adequate and accurate models of thermal power plants (TPP) and hydropower plants (HPP) are of great importance for the optimal economic functioning of electric power systems. The extracted models have a direct impact on economic dispatch calculations. In this research, a modified optimization algorithm called an improved gradient-based optimizer (IGBO) is deployed for the optimal extraction of TPP and HPP input-output parameters. Firstly, the IGBO is tested for use with well-known benchmark functions and shows outstanding performance over the original GBO and other competitive algorithms. For the input-output parameters extraction of TPP and HPP, the sum of the absolute error (SAE) is utilized as a fitness function to be minimized. Secondly, nine models of TPP and HPP are employed for parameter identification using IGBO. Simulation outcomes prove the capability of IGBO to accurately extract input-output parameters of TPP and HPP. Moreover, the convergence characteristics of IGBO are remarkable among investigated optimization algorithms.

1. Introduction

The reliable, secure, and economical operation of electrical power systems is the major concern of power systems planners [1, 2]. One of the planning tools is the economic dispatch (ED) of generation units. Its economic scheduling is proportional to operating cost [3, 4]. Hence, the ED aims to determine the generation share of power plants that will keep a certain fitness function minimized [5, 6]. The fitness function can be, for example, the operation cost and emission cost [7–9]. Moreover, the overall accuracy of the ED is entirely dependent on numerous elements such as the chosen model, input data and parameters employed, and even the technique that is used for the solution of this optimization problem [10, 11]. The input-output curves of thermal power plants (TPP) or nonthermal like hydropower plants (HPP) are influenced by a variety of factors, including ambient operating temperature and generating unit ageing [12]. Because the accuracy of the estimated parameters impacts the final accuracy of the ED problem, it is critical to precisely estimate the numerical values of these coefficients.

1.1. Literature Review. A long time ago, several mathematical techniques were deployed for the parameter identification of input-output curves of TPP and HPP. Among these techniques are the least square error, Marquardt algorithm, Powell regression algorithm, least absolute value,
and Kalman filters that have been investigated in [13–17]. Unfortunately, these mathematical procedures necessitate a significant amount of computational work, resulting in a long computation time. Furthermore, in the presence of significant errors, these classical estimators underachieve. Also, the recursive nature of dynamic filters like Kalman filters necessitates a huge amount of data to achieve a steady-state solution.

It is worth mentioning that the input-output curves of power plants are nonconvex and highly nonlinear, and their discontinuity may result from the valve point effect [18]. This makes the use of conventional techniques of estimation like the Newton–Raphson method [19] leaving much to be desired. The metaheuristic optimization techniques surpass the mathematical ones as per their fast convergence, robustness, and avoidance trapping in regional optimal points. Recently, many metaheuristic algorithms are deployed for the parameter extraction of input-output curves of power plants like particle swarm optimization (PSO) [20], least error square (LES) [20], artificial bee colony (ABC) [21], differential evolution (DE) [22], cuckoo search (CS) [23], radial movement optimization (RMO) [24], genetic algorithm [25], teaching learning-based optimization (TLBO) [26], crow search algorithm (CSA) [27], and whale optimization algorithm (WOA) [28].

1.2. Motivation. Despite the succinct literature representation, the No Free Lunch theorem steers us that the extraction of TPP and HPP input-output parameters is probably improved using modern optimization approaches. Hence, in this study, we proposed a gradient-based optimizer (GBO) to extract TPP and HPP input-output parameters. The GBO algorithm is considered a metaheuristic optimization technique inspired by gradient descent and the Newton method [29]. GBO has the benefit of rapid convergence due to gradient search rules. In order to decrease the probability of escaping from local optima, the improved GBO (IGBO) technique is a modified version of GBO proposed in this paper. The improved optimization algorithms show enhanced performance where they are employed, for example, solving optimum reactive power dispatch problem [30], day-ahead scheduling in microgrids [31], and unit commitment [32]. The IGBO technique is an enhancement applied to the GBO using utilization from one of the recent metaheuristic algorithms that are named Marine Predators Algorithm (MPA) [33] to enhance the balance between global search and exploration and increase the strength of the proposed IGBO technique for several high-dimensional optimization problems.

1.3. Contributions and Paper Organization. To the best of the authors’ knowledge, there is no research work on the application of GBO for the parameter extraction of input-output curves of TPP and HPP as a resource of renewable energy. Also, the outstanding performance of its improved version for the application (IGBO) to one of the nonconvex, nonlinear engineering optimization problems motivates the authors for this performance investigation.

The following are the paper’s contributions:

(i) Proposing an innovative approach known as IGBO via improving the original GBO.

(ii) The execution of the suggested algorithm is certified via fair comparisons among the suggested IGBO and other earlier optimizers, and the conventional GBO is based on employing 23 benchmark functions.

(iii) Utilization of suggested IGBO for modelling TPP and HPP.

(iv) Fair comparison among the suggested optimizer and other earlier optimizers for modelling TPP and HPP.

The rest of this manuscript can be organized as follows. The mathematical formulation of the input-output curves of both thermal and hydropower plants and the utilized fitness function are illustrated in Sections 2 and 3, respectively. Section 4 presents the idea of GBO and its modified version, while Section 5 demonstrates the simulation outcomes. The main findings from this research are summarized in Section 6.

2. Modelling Thermal and Hydropower Plants

The input-output curves of mathematical models of both TPP and HPP are introduced in this section. As per literature, there are five mathematical models which can express the smooth and nonsmooth incremental fuel cost; \( F_i \) corresponds to the active power generated by a thermal unit \( i \) as can be depicted in Figure 1.

2.1. Smooth Models of Thermal Units’ Fuel Cost. The thermal units’ fuel cost can be smoothly modelled via linear, quadratic, or cubic formulas as follows:

Model 1:

\[
F_i(P_i) = a_{0i} + a_{1i}P_i,
\]
2.2. Nonsmooth Models of Thermal Units’ Fuel Cost. The nonsmoothness of the model of thermal units’ fuel cost due to valve loading can be presented via quadratic or cubic formula as follows:

Model 4:
\[ F_i(P_i) = a_{0i} + a_{1i}P_i + a_{2i}P_i^2 + a_{3i} \sin(a_{4i}P_i), \]  
where \( P_{i,\text{Min}} \) is the thermal generating unit’s lowest generated active power.

2.3. Thermal Units’ Emission Cost. The relationship between the generated power \( P_i \) of the thermal unit and the related emissions \( E_i \) that is emitted into the atmosphere can be modelled using one of two models as given in equations (6) and (7):

Model 6:
\[ E_i(P_i) = e_{0i} + e_{1i}P_i + e_{2i}P_i^2. \]  

Model 7:
\[ E_i(P_i) = e_{0i} + e_{1i}P_i + e_{2i}P_i^2 + e_{3i} \exp(e_{4i}P_i), \]  
where \( e_{0i}, e_{1i}, e_{2i}, e_{3i}, e_{4i} \) represent the \( i \)th unit emission cost parameters.
Figure 3: Qualitative metrics of six benchmark functions: 2D views of the functions, search history, average fitness history, and convergence curve using the IGBO technique.
Figure 4: Continued.
head $H_i$ and the water discharge rate $Q_i$ of the unit $i$. This can be attained with one of the following models:

**Model 8:**

$$Q_i(H_i, P_i) = K_i(a_{0i} + a_{1i}H_i + a_{2i}H_i^2)(b_{0i} + b_{1i}P_i + b_{2i}P_i^2),$$

(8)

where $a_{0i}, a_{1i}, a_{2i}, b_{0i}, b_{1i}, b_{2i}$ represent the Glimm–Kirchmayer model parameters of the $i^{th}$ unit.

**Model 9:**

$$Q_i(H_i, P_i) = \frac{(a_{0i} + a_{1i}P_i + a_{2i}P_i^2)(b_{0i} + b_{1i}H_i + b_{2i}H_i^2)}{H},$$

(9)

Figure 4: The convergence curves of all optimization algorithms for 23 benchmark functions.
with \(a_{0i}, a_{1i}, a_{2i}, b_{0i}, b_{1i}, b_{2i}\) represents Hamilton-Lamont's model parameters of \(i^{th}\) unit.

### 3. Formulating the Objective Function

The accurate estimation of the input-output coefficients of TPP or HPP calls for the use of optimization algorithms. The input-output relations can be arranged in the following form:

$$S_i = f_i(P_j, X_i) + \epsilon_i,$$  

(10)

where \(f_i\) represents the input-output curve model of a generation plant (thermal/hydro) and \(S_i\) can be, for example, the fuel cost measurement vector of length \(N\) that is combined with an error vector \(\epsilon_i\). Also, \(X_i\) denotes the plant \(i\) parameters, which are specified as

$$X = [a_{0i}, a_{1i}, a_{2i}, a_{3i}, a_{4i}, a_{5i}],$$  

(11)

for models 1–5,

$$X = [e_{0i}, e_{1i}, e_{2i}, e_{3i}, e_{4i}],$$  

(12)

for models 6–7,

$$X = [a_{0i}, a_{1i}, a_{2i}, b_{0i}, b_{1i}, b_{2i}],$$  

(13)

for models 8–9.

The IGBO will deploy the fitness function (sum of the absolute error, SAE) in (14) that is required to be minimized to attain the accurate coefficients of the input-output curves of TPP and HPP.

$$\text{SAE} = \sum_{j=1}^{N} S_{\text{actual},j} - S_{\text{estimated},j},$$  

(14)

### 4. The Proposed Optimization Algorithm

This section describes the concept of the conventional GBO algorithm. Then, the process of the proposed improved GBO technique is presented.
4.1. The Original GBO Algorithm. The conventional gradient-based optimizer (GBO) algorithm [29] combines gradient and population-based approaches, and it employs Newton’s method that requires the search direction to observe the search domain with the use of a collection of vectors and two main operators, namely, gradient search rule (GSR) and local escaping operators (LEO).

4.1.1. Initialization Process. The first stage of the GBO algorithm includes the number of populations \( N \) in the D-dimensional search space. The initial position is randomly formed as follows:

\[
X_n = X_{\text{min}} + \text{rand}(0, 1) \times (X_{\text{max}} - X_{\text{min}}),
\]

where \( X_n \) is the \( n \)th vector, \( X_{\text{min}}, X_{\text{max}} \) refer to the bounds of the solution space in each problem, and \( \text{rand}(0, 1) \) is a random number which is defined between \([0, 1]\).

4.1.2. Gradient Search Rule (GSR) Process. The GSR is according to the gradient-based approach, and the targets of the GSR method are increasing the convergence rate and exploration development. Thus, the new location \( X_{n+1} \) can be calculated as follows:

\[
X_{n+1} = X_n - \frac{2\Delta x \times f(X_n)}{f(X_n + \Delta x) - f(X_n - \Delta x)}.
\]  

Equation (16) will be edited to contain the population-based search principle that is described by

\[
\text{GSR} = \text{rand} n \times \frac{2 \Delta x X_{n}}{X_{\text{worst}} - X_{\text{best}} + \varepsilon}
\]

where \( \text{rand} n \) denotes a random number with a normal distribution, \( X_{\text{best}} - X_{\text{worst}} \) are the best and worst solutions attained through the procedure of optimization, \( \varepsilon \) is a number in the range \([0, 0.1]\), and \( \Delta x \) denotes the variation in location at each iteration. From these equations, the gradient search rule (GSR) is defined as

\[
\text{GSR} = \text{rand} n \times \rho_1 \times \frac{2 \Delta x X_{n}}{X_{\text{worst}} - X_{\text{best}} + \varepsilon}
\]

where \( \rho_1 \) is the randomly produced parameter, and it can be calculated as follows:

<table>
<thead>
<tr>
<th>Function</th>
<th>IGBO</th>
<th>GBO</th>
<th>HPO</th>
<th>WOA</th>
<th>SDO</th>
<th>GWO</th>
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Table 2: Results of multimodal benchmark functions.

The best obtained values are in bold.
Table 3: Results of composite benchmark functions.

<table>
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<th>Function</th>
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<th>HPO</th>
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<td>0.998004</td>
<td>0.998004</td>
<td>0.998004</td>
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<tr>
<td>Mean</td>
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<td>2.371342</td>
<td>2.230204</td>
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<td>1.495017</td>
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<tr>
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<td>2.982105</td>
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<td>0.000307</td>
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<td>Worst</td>
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<td>10.76318</td>
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<td>STD</td>
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<td>2.980135</td>
<td>2.241367</td>
<td>3.953203</td>
<td>3.726781</td>
</tr>
</tbody>
</table>

The best obtained values are in bold.
Figure 5: Continued.
\[ \rho_1 = (2 \times \text{rand} \times \alpha) - \alpha, \]
\[ \alpha = \left| \beta \sin \left( \frac{3\pi}{2} + \sin \left( \beta \frac{3\pi}{2} \right) \right) \right|, \]
\[ \beta = \beta_{\text{min}} + (\beta_{\text{min}} - \beta_{\text{max}}) \left(1 - \left(\frac{m}{M}\right)^3\right)^2, \]

where \( \alpha \) is a sine function for the transference from exploration to exploitation, \( \beta_{\text{min}}, \beta_{\text{max}} \) are equal to 0.2 and 1.2, respectively, \( m \) denotes the present number of iterations, and \( M \) refers to the maximum value of iterations. The modification \( \Delta x \) between the optimal solution \( x_{\text{best}} \) and a randomly selected location \( x_{r1}^m \) can be given by

\[ \Delta x = \text{rand}(1: N) \times |\text{step}|, \]
\[ \text{step} = \frac{(x_{\text{best}} - x_{r1}^m) + \delta}{2}, \]
\[ \delta = 2 \times \text{rand} \times \left(\left|\frac{x_{r1}^m + x_{r2}^m + x_{r3}^m + x_{r4}^m}{4} - x_n^m\right|\right), \]

where \( \text{rand}(1: N) \) is a random vector with \( N \) dimensions, \( r1, r2, r3, \) and \( r4 (r1 \neq r2 \neq r3 \neq r4 \neq n) \) represent the different integers randomly selected from \([1, N]\), and \( \text{step} \) is the size of step. The new location \( X_{n+1} \) is updated according to the GSR from the following equation:

\[ X_{n+1} = X_n - \text{GSR}. \]
Table 4: P-values based on Wilcoxon signed-rank for GBO algorithm versus the other algorithms.

<table>
<thead>
<tr>
<th>Function</th>
<th>GBO</th>
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<th>WOA</th>
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<td>6.3761141E−08</td>
</tr>
<tr>
<td>F19</td>
<td>NaN</td>
<td>NaN</td>
<td>8.0065450E−09</td>
<td>NaN</td>
<td>8.0065450E−09</td>
</tr>
<tr>
<td>F20</td>
<td>3.2288712E−01</td>
<td>3.3597749E−04</td>
<td>1.5664002E−06</td>
<td>6.8447150E−05</td>
<td>1.3484931E−04</td>
</tr>
<tr>
<td>F21</td>
<td>5.5601480E−01</td>
<td>7.4969392E−03</td>
<td>1.2942514E−03</td>
<td>1.4262340E−02</td>
<td>1.9228882E−02</td>
</tr>
<tr>
<td>F22</td>
<td>5.7573143E−02</td>
<td>4.2852539E−03</td>
<td>6.6063841E−02</td>
<td>1.0519912E−01</td>
<td>4.3772517E−01</td>
</tr>
<tr>
<td>F23</td>
<td>5.9049481E−01</td>
<td>2.6482175E−03</td>
<td>8.6380041E−04</td>
<td>1.5332149E−03</td>
<td>4.5619330E−02</td>
</tr>
</tbody>
</table>

Table 5: Parameters of GBO and IGBO.

<table>
<thead>
<tr>
<th>Model</th>
<th>Unit</th>
<th>Population</th>
<th>Maximum iterations</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1-3</td>
<td>20</td>
<td>100</td>
</tr>
<tr>
<td>2</td>
<td>1-3</td>
<td>20</td>
<td>500</td>
</tr>
<tr>
<td>3</td>
<td>1-3</td>
<td>60</td>
<td>800</td>
</tr>
<tr>
<td>4</td>
<td>1 and 2</td>
<td>40</td>
<td>700</td>
</tr>
<tr>
<td>5</td>
<td>1-13</td>
<td>50</td>
<td>1200</td>
</tr>
<tr>
<td>6</td>
<td>1-5</td>
<td>20</td>
<td>400</td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>60</td>
<td>5000</td>
</tr>
<tr>
<td>8</td>
<td>2-5</td>
<td>20</td>
<td>150</td>
</tr>
<tr>
<td>9</td>
<td>1</td>
<td>20</td>
<td>400</td>
</tr>
</tbody>
</table>

Table 6: Optimized parameters and SAE of model 1.

<table>
<thead>
<tr>
<th>Unit</th>
<th>Optimized parameters using IGBO</th>
<th>SAE (GJ/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unit 1 (coal)</td>
<td>45.2</td>
<td>10.56</td>
</tr>
<tr>
<td>Unit 2 (oil)</td>
<td>47.6</td>
<td>11.03</td>
</tr>
<tr>
<td>Unit 3 (gas)</td>
<td>48.4</td>
<td>11.22</td>
</tr>
</tbody>
</table>
Table 7: Optimized parameters and SAE of model 2.

<table>
<thead>
<tr>
<th>Unit</th>
<th>Optimized parameters using IGBO</th>
<th>SAE (GJ/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>--------</td>
<td>---------</td>
<td>---------</td>
</tr>
</tbody>
</table>

The direction of movement (DM) is added for improved exploitation of the neighboring area of \(X_n\) that can be calculated as follows:

\[
DM = \text{rand} \times \rho_2 \times (x_{\text{best}} - x_n),
\]

\[
\rho_2 = (2 \times \text{rand} \times \alpha) - \alpha.
\]  

Consequently, the new location \(X_n^m\) can be calculated after considering the GSR and DM from the following equation:

\[
X_n^m = X_n^m - \text{GSR} + DM,
\]

\[
X_n^m = X_n^m - \text{rand} \times \rho_1 \times \frac{2\Delta x \times x_n^m}{(x_{\text{worst}} - x_{\text{best}} + \epsilon)} + \text{rand} \times \rho_2 \times (x_{\text{best}} - x_n^m).
\]  

The GBO used another location to improve the local search using putting the best-so-far solution \(x_{\text{best}}^m\) instead of the location \(x_n^m\). The new location \(X_2^m\) can be calculated as follows:

\[
X_2^m = x_{\text{best}} - \text{rand} \times \rho_1 \times \frac{2\Delta x \times x_n^m}{(y_{p_n}^m - y_{q_n}^m + \epsilon)} + \text{rand} \times \rho_2 \times (x_{r_1}^m - x_{r_2}^m),
\]  

where

\[
y_{p_n} = \text{rand} \times \left(\frac{[z_{n+1} + x_n]}{2}\right) + \text{rand} \times \Delta x,
\]

\[
y_{q_n} = \text{rand} \times \left(\frac{[z_{n+1} + x_n]}{2}\right) - \text{rand} \times \Delta x.
\]

Based on the locations \(X_1^m\) and \(X_2^m\) and the current location \(X_n^m\), the new location at the next iteration \(X_n^{m+1}\) is formulated as

\[
x_n^{m+1} = r_a \times (r_b \times X_1^m + (1 - r_b) \times X_2^m) + (1 - r_a) \times X_n^m.
\]

\[
X_3^n = X_n^m - \rho_1 \times (X_2^m - X_1^m).
\]  

4.1.3. Local Escaping Operator (LEO). The LEO is used to improve the effectiveness of the GBO technique and to escape the local optima for finding the solution to complex problems. The LEO produces a suitable solution \(X_{\text{LEO}}^m\) by using numerous solutions that include \(x_{\text{best}}^m\) solutions \(X_1^m\) and \(X_2^m\), two random solutions \(x_1^m\) and \(x_2^m\), and a new randomly generated solution \(X_3^m\). The solution \(X_{\text{LEO}}^m\) is given as

\[
X_{\text{LEO}}^m = X_{\text{LEO}}^{m+1} + f_1 \times (u_1 \times x_{\text{best}} - u_2 \times x_1^m)
\]

\[
+ f_2 \times \rho_1 \times \left(\frac{(u_2 \times (X_2^m - X_1^m) + u_2 \times (x_2^m - x_1^m))}{2}\right).
\]

\[
X_{\text{LEO}}^m = X_{\text{LEO}}^{m+1}
\]  

End,

End,

where \(f_1\) is a uniformly distributed random number in the range \([-1,1]\), \(f_2\) denotes a random number from a normal
Table 8: Optimized parameters and SAE of model 3.

<table>
<thead>
<tr>
<th>Unit</th>
<th>Optimized parameters using IGBO</th>
<th>SAE (GJ/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unit 1 (coal)</td>
<td>127.0667</td>
<td>3.1187</td>
</tr>
<tr>
<td>Unit 2 (oil)</td>
<td>132.4999</td>
<td>3.3325</td>
</tr>
<tr>
<td>Unit 3 (gas)</td>
<td>132.3331</td>
<td>3.625</td>
</tr>
<tr>
<td>Unit</td>
<td>( a_0 )</td>
<td>( a_1 )</td>
</tr>
<tr>
<td>------</td>
<td>--------</td>
<td>--------</td>
</tr>
<tr>
<td>1</td>
<td>550</td>
<td>8.1</td>
</tr>
<tr>
<td>2</td>
<td>308.9999</td>
<td>8.1</td>
</tr>
<tr>
<td>Unit</td>
<td>( a_0 )</td>
<td>( a_1 )</td>
</tr>
<tr>
<td>------</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td>1</td>
<td>550.0</td>
<td>8.0909</td>
</tr>
<tr>
<td>2, 3</td>
<td>309.0</td>
<td>8.1001</td>
</tr>
<tr>
<td>4–9</td>
<td>239.99</td>
<td>7.7405</td>
</tr>
<tr>
<td>10, 11</td>
<td>126.0</td>
<td>8.6002</td>
</tr>
<tr>
<td>12, 13</td>
<td>125.99</td>
<td>8.6005</td>
</tr>
</tbody>
</table>
distribution with a mean of 0 and a standard deviation of 1, 

\( pr \) refers to the probability, and \( u_1, u_2, \) and \( u_3 \) are random values produced as follows:

\[
\begin{align*}
    u_1 &= \begin{cases} 
    2 \times \text{rand}, & \text{if } \mu_1 < 0.5, \\
    1, & \text{otherwise}, 
    \end{cases} \\
    u_2 &= \begin{cases} 
    \text{rand}, & \text{if } \mu_1 < 0.5, \\
    1, & \text{otherwise}, 
    \end{cases} \\
    u_3 &= \begin{cases} 
    \text{rand}, & \text{if } \mu_1 < 0.5, \\
    1, & \text{otherwise}, 
    \end{cases}
\end{align*}
\]

(28)

where \( \text{rand} \) is a random number in the range of \([0, 1]\) and \( \mu_1 \) represents a number in the range of \([0, 1]\). The above equations are simply clarified as follows:

\[
\begin{align*}
    u_1 &= L_1 \times 2 \times \text{rand} + (1 - L_1), \\
    u_2 &= L_1 \times \text{rand} + (1 - L_1), \\
    u_3 &= L_1 \times \text{rand} + (1 - L_1),
\end{align*}
\]

(29)

where \( L_1 \) is a binary parameter with a value of 0 or 1. If parameter \( \mu_1 < 0.5 \), the value of \( L_1 = 1 \); otherwise, \( L_1 = 0 \). The solution \( x^m_k \) is created as follows:

\[
\begin{align*}
    x^m_k &= \begin{cases} 
    x_{\text{rand}}, & \text{if } \mu_2 < 0.5, \\
    x^m_p, & \text{otherwise}, 
    \end{cases} \\
    x_{\text{rand}} &= X_{\text{min}} + \text{rand} \times (X_{\text{max}} - X_{\text{min}}),
\end{align*}
\]

(30)

(31)

where \( x_{\text{rand}} \) refers to a randomly produced solution, \( x^m_p \) denotes a randomly selected solution, and \( \mu_2 \) denotes a random number in the range of \([0, 1]\). Equation (30) is adjusted as follows:

\[
\begin{align*}
    x^m_k &= L_2 \times x^m_p + (1 - L_2) \times x_{\text{rand}},
\end{align*}
\]

(32)

where \( L_2 \) refers to a binary parameter with a value of 0 or 1. If \( \mu_2 < 0.5 \), the value of \( L_2 = 1 \); otherwise, \( L_2 = 0 \).

4.2. Improved Gradient-Based Optimizer (IGBO). The original GBO algorithm suffers from the local minima when handling nonlinear objective functions. Also, the convergence rate and accuracy are low because of the randomness [34]. To overcome all these shortcomings and develop the solution competence as well as the speed of convergence and to improve the strength of the proposed IGBO technique for several high-dimensional optimization problems, the way is to utilize one of the recent metaheuristic algorithms that are named the Marine Predators Algorithm (MPA). This MPA is presented in [30]. The fittest solution is nominated as the best solution to construct a matrix which is called Elite. The Elite is calculated from the following equation:

\[
\begin{align*}
    &\begin{bmatrix} 
    x_1^1 & x_1^2 & \cdots & x_1^n \\
    x_2^1 & x_2^2 & \cdots & x_2^n \\
    \vdots & \vdots & \ddots & \vdots \\
    x_n^1 & x_n^2 & \cdots & x_n^n 
    \end{bmatrix} \\
    &\begin{bmatrix} 
    x_1^1 & x_1^2 & \cdots & x_1^n \\
    x_2^1 & x_2^2 & \cdots & x_2^n \\
    \vdots & \vdots & \ddots & \vdots \\
    x_n^1 & x_n^2 & \cdots & x_n^n 
    \end{bmatrix},
\end{align*}
\]

(33)

where \( x_{1,1}^i \) is the best solution that is replicated \( n \) times to construct the Elite matrix. The modification process is divided into two phases:

Phase 1: the mathematical model of this phase is given as

\[
\text{while } \text{It} < \frac{1}{3} \text{Max_it},
\]

\[
S_i = R_B \otimes (\text{Elite}_i - R_B \otimes x_i),
\]

(34)

\[
x_i = x_i + P.R \otimes S_i,
\]

Phase 1: the population is moving to exploit the detected best locations. Therefore, populations have divided into two groups: the first group follows the Levy flight, and the second group follows the Brownian distribution during their movement, as described in the following:

\[
\text{while } \text{It} > \frac{1}{3} \text{Max_it},
\]

\[
S_i = R_L \otimes (\text{Elite}_i - R_L \otimes x_i),
\]

(35)

\[
x_i = \text{Elite}_i + P.CF \otimes S_i,
\]

\[
CF = \left( 1 - \frac{\text{It}}{\text{Max_it}} \right)^{(2lt/\text{Max_it})},
\]

where \( R_L \) is a vector that follows the Levy flight distribution, and it can be calculated as follows:

\[
\text{Levy}(\lambda) = 0.05u \left| v \right|^{\lambda-1},
\]

(36)

where \( \lambda \) denotes the Levy flight exponent and \( u \) and \( v \) are calculated as

\[
\text{Table 11: Optimized parameters and SAE of model 6.}
\]

<table>
<thead>
<tr>
<th>Unit</th>
<th>( c_0 )</th>
<th>( c_1 )</th>
<th>( c_2 )</th>
<th>WOA [28]</th>
<th>GBO Min</th>
<th>IGBO Min</th>
<th>GBO Max</th>
<th>IGBO Max</th>
<th>SAE (kg/h)</th>
<th>STD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.74551E8</td>
<td>-4.495E7</td>
<td>7.5E5</td>
<td>1E-5</td>
<td>3.1182E-2</td>
<td>1.8238E-2</td>
<td>1.2833E-6</td>
<td>1.4225E-6</td>
<td>3.78775E-8</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>51.7436</td>
<td>-0.6189</td>
<td>0.0162</td>
<td>5E-4</td>
<td>1.8971E-12</td>
<td>1.42109E-13</td>
<td>1.53541E-13</td>
<td>3.3245E-15</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>64.16</td>
<td>-1.5092</td>
<td>0.012107</td>
<td>1.3E-4</td>
<td>1.15818E-12</td>
<td>1.20792E-13</td>
<td>1.31096E-13</td>
<td>2.71407E-15</td>
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<td></td>
</tr>
<tr>
<td>4</td>
<td>56.609</td>
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<td>0.010241</td>
<td>28.491E-6</td>
<td>2.13163E-13</td>
<td>7.10543E-14</td>
<td>7.77356E-14</td>
<td>1.90323E-15</td>
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<td></td>
</tr>
<tr>
<td>5</td>
<td>102.08</td>
<td>-2.3725</td>
<td>0.020084</td>
<td>1.213E-4</td>
<td>3.40052E-10</td>
<td>5.68434E-14</td>
<td>6.29285E-14</td>
<td>1.78004E-15</td>
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<td></td>
</tr>
</tbody>
</table>
Table 12: Optimized parameters and SAE of model 7.

<table>
<thead>
<tr>
<th>Unit</th>
<th>$e_0$</th>
<th>$e_1$</th>
<th>$e_2$</th>
<th>$e_3$</th>
<th>$e_4$</th>
<th>TLBO [26]</th>
<th>WOA [28]</th>
<th>GBO</th>
<th>IGBO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Min</td>
<td>Max</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>83.0081</td>
<td>-1.0142</td>
<td>0.0088</td>
<td>0.6551</td>
<td>0.2846</td>
<td>1.29921</td>
<td>6E-5</td>
<td>2.82826E-3</td>
<td>5.68434E-14</td>
</tr>
<tr>
<td>2</td>
<td>51.2513</td>
<td>-0.6113</td>
<td>0.016</td>
<td>0.2965</td>
<td>0.019</td>
<td>0.879284</td>
<td>1E-5</td>
<td>1.65027E-5</td>
<td>2.60175E-6</td>
</tr>
<tr>
<td>3</td>
<td>61.6652</td>
<td>-1.426</td>
<td>0.0112</td>
<td>0.454</td>
<td>0.0206</td>
<td>1.494093</td>
<td>1.1E-4</td>
<td>4.85102E-3</td>
<td>2.46765E-5</td>
</tr>
<tr>
<td>4</td>
<td>49.2043</td>
<td>-0.7369</td>
<td>0.0088</td>
<td>0.5184</td>
<td>0.0177</td>
<td>0.82333</td>
<td>9.95E-6</td>
<td>8.40092E-6</td>
<td>5.987E-6</td>
</tr>
<tr>
<td>5</td>
<td>39.9759</td>
<td>-0.8078</td>
<td>0.0131</td>
<td>0.4895</td>
<td>0.0204</td>
<td>0.676372</td>
<td>9E-5</td>
<td>1.46309E-5</td>
<td>7.03012E-6</td>
</tr>
</tbody>
</table>

Table 13: Optimized parameters and SAE of model 8.

<table>
<thead>
<tr>
<th>Unit</th>
<th>$a_0$</th>
<th>$a_1$</th>
<th>$a_2$</th>
<th>$b_0$</th>
<th>$b_1$</th>
<th>$b_2$</th>
<th>NR [19]</th>
<th>PSO [20]</th>
<th>WOA [28]</th>
<th>GBO</th>
<th>IGBO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Min</td>
<td>Max</td>
<td>STD</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-9.5839</td>
<td>22.8439</td>
<td>-12.0218</td>
<td>0.1143</td>
<td>0.6179</td>
<td>0.0756</td>
<td>0.00679</td>
<td>0.00667</td>
<td>0.00637</td>
<td>0.00612</td>
<td>0.00669</td>
</tr>
</tbody>
</table>

Table 14: Optimized parameters and SAE of model 9.

<table>
<thead>
<tr>
<th>Unit</th>
<th>$a_0$</th>
<th>$a_1$</th>
<th>$a_2$</th>
<th>$b_0$</th>
<th>$b_1$</th>
<th>$b_2$</th>
<th>NR [19]</th>
<th>PSO [20]</th>
<th>WOA [28]</th>
<th>GBO</th>
<th>IGBO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>Min</td>
<td>Max</td>
<td>STD</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.1455</td>
<td>0.965</td>
<td>0.0485</td>
<td>-6.2466</td>
<td>14.1596</td>
<td>-7.0498</td>
<td>0.95767</td>
<td>0.0781</td>
<td>0.0086</td>
<td>0.006877</td>
<td>0.006243</td>
</tr>
</tbody>
</table>

5. The Simulation Results and the Discussion

5.1. The Performance of IGBO. The proposed IGBO technique competence and ability are tested on the numerous benchmark functions, using the statistical measurement including the minimum values, mean values, median values, maximum values, and standard deviation (STD) for optimal solutions attained using the IGBO technique and the other recent algorithms. The data of the 23 benchmark functions are taken from [35]. The results achieved with the IGBO technique are compared with five recent techniques, hunter–prey optimization (HPO) [36], whale optimization algorithm (WOA) [37], supply demand-based optimization (SDO) [38], grey wolf optimizer (GWO) [39], and the original (GBO). All these algorithms were implemented for the maximum number of iterations of 200 and population size of 50 for 20 independent trails using MATLAB R2016a. All computations were executed on a Core i5-4210U CPU@ 2.40 GHz speed and 8 GB RAM. Figure 3 displays the qualitative metrics on F1, F1, F3, F5, F8, F9, F12, F15, and F18: 2D views of the functions, convergence curve, average fitness history, and search history.

Tables 1–3 tabulate the statistical analysis results of the IGBO algorithms and five optimization algorithms when used for three types of benchmark functions (unimodal functions, multimodal functions, and composite functions, resp.). The optimum values were attained using the IGBO, GBO, HPO, WOA, SDO, and GWO techniques displayed in bold. It is obviously clear that the IGBO technique reaches the optimum values for most of these benchmark functions. The convergence rates of all techniques for those functions
are illustrated in Figure 4, and the Boxplots for those techniques are shown in Figure 5. From Figures 4 and 5, it is seen that the IGBO technique reached a stable point for all functions and the boxplots of the proposed IGBO technique are very narrow and stable for most functions compared to the other techniques.

Table 4 contains the obtained results using the Wilcoxon signed-rank test. The proposed IGBO algorithm is compared with five well-known algorithms in the literature, including GBO, HPO, WOA, SDO, and GWO, respectively, for the 23 benchmark functions.

5.2. Case Studies. This section contains the generated results of employing GBO and IGBO to identify parameters of nine models of TPP and HPP. Fuel costs of TPP are modelled using models 1 to 5. Emissions of TPP are modelled using models 6 and 7. Relationships of HPP are modelled using models 8 and 9. We use the top and bottom bounds for the parameters of models of TPP and HPP in [28]. The parameters of GBO and IGBO are listed in Table 5.

Fifty independent runs for all tested models are operated. All models are implemented using MATLAB-R2020b on a laptop with Intel Core i7-1065G7 CPU at 1.3 GHz (8 CPUs), ~1.5 GHz, and 16 GB RAM.

All nine models are compared with other approaches which were employed in the literature in accordance with their results.

5.2.1. Clarification of the Tested Models

(1) Models of Fuel Costs of Thermal Units (Models 1–5). The models of fuel cost of three power systems that own thermal generating units are studied. Models 1–3 are employed for a 3-unit thermal system (TS3). Models 4 and 5 are employed for 2-unit (TS2) and 13-unit thermal systems (TS13), respectively.

TS3 comprises three thermal power generating units (units 1–3) which are coal-, oil-, and gas-fired, respectively.
The actual values of generated power ($P$) and the fuel cost ($F_{\text{actual}}$) are in [40]. The relationships between $P$ and $F_{\text{actual}}$ in models 1–3 are linear, quadratic, and cubic, respectively.

TS2 comprises two thermal units (units 1 and 2). The actual values of $P$ and $F_{\text{actual}}$ are in [20]. Model 4 is used for two units and includes five parameters, which should be extracted.

TS13 comprises thirteen thermal units (units 1–13). The actual values of $P$ and $F_{\text{actual}}$ are in [24]. Six parameters of model 5, which is used for thirteen units, should be extracted.

(2) Models of Emissions of Thermal Units (Models 6 and 7). A power system of five thermal generating units (TS5) is studied. The actual values of $P$ and emissions ($E_{\text{actual}}$) are in [26]. The relationships between $P$ and $E_{\text{actual}}$ in models 6 and 7 are quadratic and quadratic plus an exponential term, respectively. The parameters to be extracted are three and five in models 6 and 7, respectively.

(3) Models of Hydropower Units (Models 8 and 9). A power system of one hydrogenerating unit (HS1) is studied. The actual values of $P$, effective head ($H$), and the rate of water discharge ($Q$) are in the Newton–Raphson methodology [19]. The relationships between $P$, $H$, and $Q$ in models 8 and 9 are based on Glenn-Kirchmayer and Hamilton-Lamont’s models, respectively. There are six parameters in both models 8 and 9.

5.2.2. Results with Discussion. Tables 6–14 include optimized parameters of models 1–9 using IGBO, respectively. Additionally, attained $SAE$ of models 1–9 using GBO, IGBO, and other approaches are written in Tables 6–14, respectively. Comparisons of IGBO with other employed approaches in the literature, NR [19], LES [20], PSO [20], ABC [21], DE [22], CS [23], RMO [24], TLBO [26], CSA [27], WOA [28], reveal that IGBO has the minimum $SAE$. The $SAE$ of GBO are the same as those of IGBO in models 1–3, which have linear, quadratic, and cubic equations; that is, they are either linear or low nonlinear, while IGBO produces $SAEs$ with fewer values in models 4–9 which have high nonlinearity. Therefore, we can conclude that the effectiveness of IGBO is more apparent when optimizing high nonlinear problems. Subsequently, the statistical indexes have been computed, that is, minimum (min) and maximum (max) values of $SAE$ and standard deviation (STD). Smaller STD values assert the efficacy of IGBO in modelling TPP and HPP.

Regarding the $SAE$ convergence curves which were obtained using IGBO in Figures 6–14, we can observe that
quickness, smoothness, and absence of oscillations are consistent features of the SAE convergence curves until attaining the optimal SAE. The population and maximum iterations differ from one model to another due to the difference in nonlinearity between models. As the nonlinearity increases, the population and maximum iteration increase. In model 7, unit 1 requires population and maximum iterations more than other units since its data are very different from other units.

6. Conclusions

An innovative improvement for conventional GBO has been suggested in this study. The IGBO technique is considered an enhancement for the conventional GBO to improve the balance between exploration and exploitation and enhance the algorithm performance. Then, the suggested IGBO was tested for 23 benchmark functions, and it revealed good functioning compared to the conventional GBO and other earlier algorithms. Economic dispatch is one of the powerful electric power planning tools that is highly coupled with the accurate input-output curves of generation units. Extracting the parameters of input-output curves of TPP and HPP using IGBO has been illustrated in this research. With the aid of the sum of the absolute errors (SAE) that has been utilized as a cost function to be minimized, the IGBO has shown excellent performance in identifying the TPP and HPP curves parameters through conducted case studies. Moreover, with the comparison with GBO and previously utilized optimization algorithms, the IGBO convergence curve is rapidly converged to the lowest value.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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