An Optimal Microgrid Operations Planning Using Improved Archimedes Optimization Algorithm

TRONG-THE NGUYEN1,3,4, THI-KIEN DAO1, THI-THANH-TAN NGUYEN2, AND TRINH-DONG NGUYEN3,4

1Fujian Provincial Key Laboratory of Big Data Mining and Applications, Fujian University of Technology, Fujian 350118, China
2Information Technology Faculty, Electric Power University, Hanoi 100000, Vietnam
3University of Information Technology, Ho Chi Minh City 700000, Vietnam
4Vietnam National University, Ho Chi Minh City 700000, Vietnam

Corresponding author: Trong-The Nguyen (thent@uit.edu.vn)

This work was supported in part by the VNUHCM-University of Information Technology’s Scientific Research Support Fund.

ABSTRACT More new energy sources have been incorporated into a microgrid model with parameter space growing exponentially, causing optimization scheduling as a nonlinear issue to become more complex and difficult to calculate. This study suggests an improved Archimedes optimization algorithm (IAOA) increases optimal performance for the microgrid operations planning issue. A multiobjective function about optimization planning issues is constructed with relevant economic costs and environmental profits for a microgrid community system (MCS). The IAOA is implemented based on the Archimedes optimization algorithm (AOA) by adding reverse learning and multi-directing strategies to avoid the local optimum trap when dealing with complicated situations. The experimental results of the suggested approach on the CEC2017 test suite and microgrid operations planning problem are compared to the various algorithms in the identical condition scenarios to evaluate the recommended approach performance. Compared findings reveal that the suggested IAOA outperforms the various algorithms in comparison, practical solution, and high feasibility.

INDEX TERMS Microgrid operations planning, archimedes optimization algorithm, microgrid community system, improved archimedes optimization algorithm.

I. INTRODUCTION

Operations planning of a microgrid community system (MCS) is one of the vital consideration tasks policies for raising the share of clean energy power generation [1], [2], offering a safe symmetrical power grid among scattered natural power sources, minimizing the power loss and consumption cost, and ensuring the overall power system’s stability [3], [4]. Formed MCS is where medium, and low voltage distribution lines of load power have a wide range of applications in hilly locations, distant settlements, island groups, and remote urban distribution networks [5], [6]. The microgrid is a new power supply solution at the distribution network’s end that can efficiently take in intermittent and distributed generation outputs while improving consumer power supply dependability [7], [8].

Categories of the MCS can be classified according to the planning modes, e.g., critical supportive techniques and collaborative economics operations [9], [10]. The required supportive methods focus on essential supporting technologies, e.g., controlling, clustering transactions, directing, and configuring. It means that support plans are not affected much by the factor of the investor’s profits. On the other hand, the collaborative operation schemes focus on interested organizations to increase mutual energy assistance amongst microgrids to enable flexible transactions, e.g., the multiagent management, the cooperative strategy, and effective stakeholder economics operations [9]. Table 1 displays a microgrid modeling operations planning classification with the representative works.

The composition and structure of power sources will become more intricate and diversified as integrated clean technologies cause difficulties with reactive power balance and power quality throughout the entire power generation system [24].

As energy demand rises, grid dependability and power quality make the operations planning of power distribution challenge more difficult [4]. The traditional methods...
for the large-scale nonlinear problem, such as programming linear, least-squares equations typical operations planning, would face difficulties and suffer from high computational costs. The metaheuristic algorithm is considered one of the most promising methods for dealing with large-scale nonlinear issues [25], [26]. The metaheuristic algorithm has advanced quickly with applications in engineering, security, and finance [27], [28] which has become one of the most popular strategies to solve complex optimization problems. The metaheuristic algorithm is often inspired by natural behaviors of selecting biological, social swarm, natural, and autocatalytic physical [29], [30]. For example, several popular algorithms, e.g., Genetics-algorithms (GA) [31], [32], Memory-based genetic algorithm (MBGA) [33], Particles swarm algorithm optimizations (PSO) [34], Parallel PSO (PPSO) [35], Artificial bees colony-algorithm (ABC) [36], Ants colony optimization (ACO) [37], Cats swarms optimization algorithm (CSO) [38], Differential evolution (DE) [39], Bats algorithm (BA) [40], Whale optimization algorithm (WOA) [41], Moth–flame optimization (MFO) [42], Flowers pollination algorithm (FPA) [43], Sine- Cosines algorithm (SCA) [44], etc. The metaheuristic algorithms show some advantages, e.g., few parameters understood and robustness in providing the optimal global solution that can overcome the challenges of traditional methods for failing to figure out complex nonlinear problems [45], [46]. The metaheuristic algorithms also have the disadvantages, e.g., dropping optima local and ot guaranteeing high quality of obtaining the optimal solution [47], [48].

Archimedes optimization algorithm (AOA) [49] is a recent meta-heuristic optimization algorithm based on physical laws of buoyancy principle, inspiring the position updating algorithm by simulating the collision between objects. The optimization is carried out by simulating the process that the object gradually presents neutral buoyancy after the collision. A variant version of the AOA used a strategy of changing the F-factor with four directions instead of the two in the original version to improve its performance [50]. However, this variant is still fixed in searching trends. The AOA is needed improvement with the handling flexibility and diversity in exploring search. AOA has fewer parameters, so programming makes it easy to optimize different engineering problems. However, the algorithm also has some shortcomings in solving some issues, such as the speed of the solution being slow and the quality of the obtained solution being poor.

This paper proposes an improved Archimedean algorithm (IAOA) based on reverse learning and multi-directing strategies for dealing with the microgrid operation planning problem. The difference between this study with the original AOA and other ones is multi-directional flexibility. The original AOA [49] used a direct search factor (F) set in two fixed directions, and another enhanced AOA [50] that used an explicit search F was set fixedly in four directions. We set factor F as multi-directional flexibility by adding random orientation. Moreover, increasing the exploitation phase of the optimization algorithm, there are many generating techniques for new solutions, such as random generation, forward direction, or reverse space generation by reverse learning. We used the reverse learning strategy for this purpose. The problem relates to the area’s internal power system and load, including power production, transmission, and distribution, to fulfill dynamic load and power quality demands. The operating model and critical technical requirements are established for control operation MCS as the objective function of allocation optimization. The objective function is constructed as a multi-object function of relevant economic costs and environmental profits.

The behind of that suggested approach is several highlighted contributions as this is the first time the AOA and IAOA are applied for optimal microgrid operations planning. Suggest strategies to the IAOA, e.g., the reverse learning and multi-directing techniques for avoiding the trap of dropping local optimum and speeding up convergence. The suggested method performance is evaluated by comparing the results with the other algorithms in the literature on testing benchmark functions.

Establish the multiobject approach for the suggested method (MOIAOA) based on the Pareto optimality. The appropriate point on the optimal Pareto front graph curve is selected and analyzed for optimal planning results.

Apply the recommended IAOA for effective microgrid operations planning, and assess the efficacy of the proposed method through analysis and discussion.

The rest of the paper is arranged as follows: Section 2 presents related work with modeling the MCS model and reviewing the AOA. Section 3 describes the proposed IAOA and its performance evaluation under the test suit. Section 4 presents the IAOA for tackling the operations planning issue with multi-object functions. The ending is discussed as the conclusion in Section 5.

II. RELATED WORK

The section will present the operation planning problem of the microgrid community system (MCS) and review the original algorithm of the AOA [49]. Presentation detail is stated in the following subsections.
A. MICROGRID OPERATION PLANNING MODEL

Due to more and more demand for improving power supply quality in isolated or remote areas, the MCS model is one of the most effective alternative ways for consuming better quality power supply [51].

An MCS model would meet the needs of meeting dynamic power load, power capacity, and quality and prevent efficient power outages. A typical structure of the MCS may describe as a model of some supply resources, e.g., micro gas turbine (MT), photovoltaic power generation (PV), fuel cell (FC), storage battery (SB), etc., and various equipment sets [52]. These resources are connected to the grid distribution net via the voltage control points known as PCC (point common coupling). Figure 1 shows a schematic of a typical microgrid structure with dispersed power sources.

Storage battery (SB) is a type of electric energy storage device that may reduce peaks, fill valleys, and increase the reliability of the power supply. Charging and discharging power is assumed as a constant variable at the end of the period (t) connected to the next at the end of the period (t−1). Its characteristics allow for a brief dispatching interval. The link between energy storage capacity and charge-discharge power in the electric energy storage model is expressed for the generated operation cost as follows.

\[
C_{SB} (t) = (1 - \tau) P_{SB} (t - 1) + \frac{P_{ESB,dis} (t)}{\eta_{ESB,dis}} \times \Delta t,
\]

where \( C_{SB} (t) \) is a relevant operation cost of the SB in period t; \( P_{SB} (t) \), \( P_{ESB,dis} (t) \), and \( \eta_{ESB,dis} \) are the power of storage capacity, charge, and discharge of the BS in period t, respectively; \( \eta_{ESB,dis} \) are coefficients of the SB efficiency adjustment respectively t time; \( \tau \) is a variable rate of the energy self-discharge.

Wind turbine (WT) is considered a subset of the phrases “wind energy” and “wind power,” which describe the process of generating mechanical or electrical power by harnessing the force of the wind. The natural wind speed primarily determines the output of wind turbines in WT power generation. The operations relevant economic costs of the WT are related to the power outcome given as follows.

\[
C_{WT} (t) = \frac{1}{\eta_{WT} (t)} \times P_{WT} (t),
\]

where \( C_{SB} (t) \) and \( P_{WT} (t) \) are relevant operation costs and output power capacity of the WT in period t; \( \eta_{WT} (t) \) is a converted coefficient parameter that is related to unit prices of some kinds of operations, e.g., investment, depreciation, maintenance. \( \eta_{WT} \) is set to as an expression of 0.057 + 0.34 \( \left( \frac{P_{WT} (t)}{35} \right) \)−0.3095 \( \left( \frac{P_{WT} (t)}{35} \right)^2 \) + 0.033 \( \left( \frac{P_{WT} (t)}{35} \right)^3 \) in the experiment section. Let \( P_{r(t)} \) be the rated power of the fan. As a piecewise function modeled after the output power model, the characteristics output values comprise numerous factors of the wind turbine’s power output connected to wind speed.

\[
P_{WT} (t) = \begin{cases} 0, & 0 \leq v (t) < v_{ci} \\ A + B \times v (t) + C \times v (t)^2, & v_{ci} \leq v (t) \leq v_r \\ P_{r(t)}, & v_r \leq v (t) \leq v_{co} \\ 0, & v_{co} < v (t) \end{cases}
\]

where \( v (t) \) is the wind-cut, wind-rated, and wind-cutting velocities; the WT parameters of A, B, C are coeffective of the power characteristic curve.

Microturbine (MT) is also called a small thermal generator, e.g., a Micro gas turbine with a power range of 25 to 300 kW. MT’s output power can be adjusted because it runs on natural gas gasoline. A micro-gas turbine’s power output is usually proportional to fuel consumption; the more fuel, the higher the power outcomes. Let \( P_{MT} (t) \) be the MT’s output power (unit kW) in period t. Let \( L_{gas} \) be natural gas’s low calorific value (normal is set to 12.7kWh/kg). Let \( G_{price} \) be natural gas price (unit is $ /m³, normal is set to 25.05$/m³) [1]. The mathematical model is expressed of the energy consumption cost generated during the operation as a miniature gas turbine is stated in the fuel cost of a WT [15] as follows.

\[
C_{MT} (t) = \frac{G_{price} \times P_{MT} (t)}{L_{gas}} \times \eta_{MT} (t),
\]

where \( C_{MT} (t) \) and \( \eta_{MT} (t) \) are the cost function of miniature MT and the coeffective parameter of adaptive function efficiency in period t. In the experiment part, the relationship function between \( C_{MT} (t) \) and \( \eta_{MT} (t) \) is expressed in MT output power and power generation efficiency as following \( \eta_{MT} (t) = 0.1068 + 0.4174 \left( \frac{P_{MT} (t)}{65} \right) -0.3095 \left( \frac{P_{MT} (t)}{65} \right)^2 + 0.0753 \left( \frac{P_{MT} (t)}{65} \right)^3 \), [1]. Diesel engine (DE) is a thermal generator that runs on diesel. DE generators play an important role in peak regulation in microgrids, and their power generation characteristics are similar to those of traditional generators [11], as shown below.

\[
C_{DE} (t) = a(P_{DE})^2 + bP_{DE} + c,
\]
where $C_{DE}(t)$ is the fuel consumption of a diesel engine generator; $P_{DE}$ is the output power of generator; variables of $a, b, c$ are the fuel cost coefficients of a generator respectively.

Fuel cell (FC) is a technology that efficiently converts a form of chemical energy into electric power through acting chemical reactions. This technique is an efficiency of power generation as substantially better than that of other methods. It has a lot of potential in microgrid applications [16]. The mathematical expression of the energy consumption cost generated $d$ using the operation of the FC is as follows.

$$C_{FC}(t) = \frac{G_{price}}{L_{gas}} \times P_{FC}(t) \Delta t \eta_{FC}(t),$$  \hspace{1cm} (6)

where $P_{FC}(t)$ is the output power of the fuel cell and $\eta_{FC}(t)$ is the efficiency in the period of $t$ [17]; $L_{gas}$ is natural gas’s low calorific value. A relationship between $P_{FC}(t)$ and $\eta_{FC}(t)$ of the FC power generation efficiency and outcome power is expressed as the following function of $\eta_{FC}(t) = 0.6735 - 0.0023 \times P_{FC}(t)$, [1], [2].

Photovoltaic power supply (PV) is a method of efficiently converting illumination into electric power due to illumination intensity and power temperature. Let $P_{pv}$ and $P_{pv}$ be the PV’s output power value and the rated power value of supplying the PV system. The operations relevant economic costs of the PV are related to the solar cell sampling point’s ambient temperature value depending on the formula the power outcome given.

$$C_{pv}(T) = P_{pv}(t) \times \eta_{pv} = P_{pv} \frac{I_{F}(T) \times 800}{[1 + \lambda_{t}(T(t) - T_{st})]},$$  \hspace{1cm} (7)

where $I_{F}(t)$ and $\lambda_{t}$ are practical illumination brilliance and temperature coefficient at measuring or sampling point $t$ of power-temperature in the optimized operation; $T(t)$ and $T_{sc}$ are the PV ambient temperature value with sampling point at time $t$, and the under the common test of temperature value respectively; $\eta_{pv}$ is the output efficiency of PV power supply. The relationship of the $T(t)$ and $T_{sc}$ is given as $T(t) = 25.6 + \frac{I_{F}(T)}{800} (T_{sc} - 20)$ in experiment [1]. The safety grid and power balance must be considered when conducting microgrid planning, including the output power constraint of distributed power supply, the climbing rate limits of unit generators, and power interaction constraints. A parameter $P_{EX}$ is used as an exchanging factor at PCC that linked the large grid and microgrid in the period $t$. Let $P_{load}$ and $P_{l}(t)$ be the MCS power load and vector output powers ($BS, WT, \ldots, EX$) in period $t$ as follows:

$$P_{l,min} \leq P_{l}(t) \leq P_{l,max}$$  \hspace{1cm} (8)

A power balance equal constraint of MCS system’s power load in period $t$ is expressed as.

$$P_{load}(t) = P_{BS} + P_{WT} + P_{DE} + P_{MT} + P_{FC} + P_{pv} + u P_{EX},$$  \hspace{1cm} (9)

where $P_{l,min}$, and $P_{l,max}$ are the minimum and maximum active power output of the $i$-th power supply. The active power output constraints of MCS unit climbing rates with $P_{l}(t)$, and $P_{l}(t-1)$ in periods $t$ and $t-1$ respectively, are summarized as follows.

$$\begin{align*}
|P_{DE}(t) - P_{DE}(t - 1)| & \leq P_{\text{max}}^{DE}, \\
|P_{MT}(t) - P_{MT}(t - 1)| & \leq P_{\text{max}}^{MT}, \\
\ldots & \ldots, \\
|P_{FC}(t) - P_{FC}(t - 1)| & \leq P_{\text{max}}^{FC}, 
\end{align*}$$  \hspace{1cm} (10)

where, $P_{l}(t), P_{l}(t-1)$ are the active power outputs of the plants (i.e., $DE, MT, .. FC$) in period $t$ and period $t-1$, respectively. $P_{\text{max}}^{DE}, P_{\text{max}}^{MT}, P_{\text{max}}^{FC}$ are the upper power limit of the constraints of MCS climbing, respectively. The constraints of power interaction connected points of the microgrid, and the large grid are expressed as follows.

$$P_{EX,min}(t) \leq P_{EX}(t) \leq P_{EX,max}(t),$$  \hspace{1cm} (11)

where $P_{EX}(t)$ is the power of points of common coupling of exchanged grids between the microgrid and the large grid; $P_{EX,min}(t)$, and $P_{EX,max}(t)$ are the minimum and maximum powers of a exchanged grid in the period of $t$.

**B. ARCHIMEDES OPTIMIZATION ALGORITHM (AOA)**

The AOA is a meta-heuristic optimization algorithm based on the physical laws of Archimedes’ buoyancy principle [49]. The algorithm updates the position by simulating the process of the object presenting neutral buoyancy after the collision gradually. The volume, density, and acceleration are properties that can determine their position in the fluid. The significant processing steps of the AOA consist of the phases of initialization, updating object properties, updating the object’s position, and evaluation, which are as follows.

$$x_{i} = lb_{i} + rand() \times (ub_{i} - lb_{i}),$$  \hspace{1cm} (12)

where $x_{i}$ is the $i$-th object of the population size, i.e., $N$ objects; $i=1,2,\ldots,N$; the searching space of $lb_{i}$ and $ub_{i}$ are the upper and lower boundaries of the problem space, respectively. $rand$ is a $d$-dimensional vector generated randomly between $[0,1]$. $acc_{i}$, $vol_{i}$, and $den_{i}$ are the variables of acceleration, volume, and density of the $i$-th object, respectively; $vol_{i} = rand()$, $den_{i} = rand()$, and $acc_{i} = lb_{i} + rand() \times (ub_{i} - lb_{i})$. After initialization, the objects with the best fitness value are selected by evaluating each object, and the position and attribute of the optimal object indicates $x_{\text{best}}, den_{\text{best}}, vol_{\text{best}}$ and $acc_{\text{best}}$, respectively.

**Updating object properties** phase: during the iteration, the volume and density of the object are updated according to the following formula.

$$vol_{i}^{t+1} = vol_{i}^{t} + rand \times (vol_{\text{best}} - vol_{i}^{t}),$$  \hspace{1cm} (13)

$$den_{i}^{t+1} = den_{i}^{t} + rand \times (den_{\text{best}} - den_{i}^{t}),$$  \hspace{1cm} (14)

where $vol_{i}^{t+1}$ and $den_{i}^{t+1}$ denotes the volume and density of the $i$-th object in the $t+1$ iteration. The collisions between objects would happen in the AOA, and as time goes on, the things will gradually reach equilibrium. The simulation of
the process can realize the transformation of the algorithm from searching exploration to exploitation as with a transform variable. Let \( TF \) denotes the transition transform variable that is given as follows.

\[
TF = \exp \left( \frac{t - t_{\text{max}}}{t_{\text{max}}} \right),
\]

where \( t \) and \( t_{\text{max}} \) denotes the current number of iterations and the maximum number of iterations, respectively. \( TF \) will gradually increase to 1 overtime. \( TF \leq 0.5 \) means that one-third of the iteration is in the exploration phase. The update of acceleration in object attributes is related to the collision between objects.

\[
\text{acc}_{i}^{t+1} = \begin{cases} 
\frac{\text{den}_{\text{mr}} + \text{vol}_{\text{mr}} \times \text{acc}_{\text{mr}}}{\text{den}_{\text{best}} + \text{vol}_{\text{best}} \times \text{acc}_{\text{best}}} \times \text{TF}^4, & \text{if } TF \leq 0.5 \\
\text{den}_{\text{best}} \times \text{vol}_{\text{best}} \times \text{acc}_{\text{best}}, & \text{the otherwise,}
\end{cases}
\]

where \( \text{den}_{\text{mr}}, \text{vol}_{\text{mr}} \) and \( \text{acc}_{\text{mr}} \) is the density, volume, and acceleration of random material (mr). If \( TF \leq 0.5 \), there is a collision between objects, the acceleration update formula of object \( i \) in iteration \( t \); otherwise, there is no collision between objects. The normalization strategy for the acceleration is updated as follows.

\[
\text{acc}_{i,\text{norm}}^{t+1} = u \times \frac{\text{acc}_{i}^{t+1} - \min (\text{acc})}{\max (\text{acc}) - \min (\text{acc})} + l,
\]

where \( \text{acc}_{i,\text{norm}}^{t+1} \) represents the normalized acceleration of the \( i \)-th object in the \( t + 1 \) iteration. \( u \) and \( l \) are the normalized ranges, which are set to 0.8 and 0.2, respectively.

**Updating the position of the objects** is conducted as follows descriptions. If \( TF \leq 1/2 \) (expansion phase), the position update formula of object \( i \)-th at the \( t + 1 \) iteration is helpful to search from global to local and converge in the region where the optimal solution exists; otherwise, it is as a searching exploitation phase for the position updating. When the object is far from the best position, the acceleration value is enormous, and the object is in the expansion phase. The acceleration value is small, and the object is close to the optimal solution. The exploitation phase is described as follows.

\[
x_{i}^{t+1} = x_{i}^{t} + C_{1} \times \text{rand} \times \text{acc}_{i,\text{norm}}^{t+1} \times d \times (x_{\text{rand}} - x_{i}^{t}),
\]

where \( C_{1} \) is constant that set to 2; \( d \) is the density factor that decreases over time as such \( d = \exp \left( \frac{t - t_{\text{max}}}{t_{\text{max}}} \right) - \left( \frac{t}{t_{\text{max}}} \right) \). The acceleration changes from big to small, indicating the algorithm from the exploration phase to the exploitation phase, which helps the object approach the optimal global solution.

\[
x_{i}^{t+1} = x_{\text{best}}^{t} + F \times C_{2} \times \text{rand} \times \text{acc}_{i,\text{norm}}^{t+1} \times d \times (T \times x_{\text{best}} - x_{i}^{t})
\]

where \( C_{2} \) is constants \( t \); \( T \) is a variable proportional to the transfer operator, the percentage used to grab the best position, \( T = C_{3} \times TF \); \( F \) is the direction of motion and its expression is as follows.

\[
F = \begin{cases} 
+1 & \text{if } P \leq 0.5 \\
-1 & \text{if } P > 0.5,
\end{cases}
\]

where \( P = 2 \times \text{rand} - C_{4} \).

**The evaluation phase** is computed the fitness values for the objective function after updating the object’s position each iteration time. The optimization problem is modeled as the objective function is used for evaluation by evaluating each object that is recorded with the best fitness value found in the position, e.g., \( x_{\text{best}}, \text{den}_{\text{best}}, \text{vol}_{\text{best}} \) and \( \text{acc}_{\text{best}} \) are updated for the next generations.

**III. IMPROVED ARCHIMEDES OPTIMIZATION ALGORITHM**

This section presents an improved version of the Archimedes optimization algorithm (IAOA) to enhance diverse objects population based on the strategies of the opposite learning and multiverse-directing. First, the suggested procedures are stated, then evaluation and discussion results are presented detail as follows.

**A. IMPROVED ARCHIMEDES OPTIMIZATION ALGORITHM**

Despite having several advantages, such as ease of understanding and implementation, and local search capability, the AOA [49] algorithm faces issues such as optimal local, a slow convergence capability, or vulnerability to a local optimum when dealing with a complex problem. The opposite learning and multiverse-directing for changed reaching and mutation are excellent ways of overcoming the AOA algorithm’s shortcomings and restrictions. The detail of reverse learning and multiverse-directing are described as follows.

1) **ELITE DIRECTING WITH REVERSE LEARNING STRATEGY**

The original and reverse solutions are sorted fitness values based on objective function issues to forward reversing objects in a searching exploiting phase in the optimization problem space. Through direct screening or other optimization procedures, the best fitness values by evaluating the object position in the solution space can be selected as new objects set, causing the agents in the optimization space to converge to the optimal solution’s work swiftly.

A new solution set is generated by applying reverse learning with a specific rate to join the original for further optimization. Let \( S(x_{1}, x_{2}, ..., x_{i}, ..., x_{D}) \), and \( S'(x_{1}', x_{2}', ..., x_{D}') \) be solutions of forwarding and corresponding inverse sets, with \( x_{i} \in [a_{i}, b_{i}] \). \( i=1,2, ..., D \). A range \([a, b]\) of the opposite solution set can be expressed as \( x'_{i} = a_{i} + b_{i} - x_{i} \). The same idea of the opposite learning applied for a new solution is as follows.

\[
S'_{\text{new}} = S \times \alpha_{r},
\]

where \( \alpha_{r} \) is a variable as adjustment coefficient for generating affect new solution object set. A portion of worst solution,
Algorithm 1 An Improved Archimedes optimization algorithm (IAOA) pseudo-code

1. \textbf{Input:} the Materials_no as population size \( N_p \), dimension \( D \), the Max_iter \( T \), \( C_1 \), \( C_2 \), \( C_3 \), \( C_4 \), and \( \alpha \), \( \omega \), \( R_{\text{mu}} \), \( R_{\text{cr}} \).
2. \textbf{Output:} the optimal object of the whole population

3. \textbf{Initialization:} initialize the position, volume, density, and acceleration of each object in the population Eq. (12); evaluate the position of each object by calculating the fitness function, and select the best object in the population; the iteration counter, \( t = 1 \).

4. \textbf{While} \( t < T \) \textbf{do}
5. \hspace{1em} For \( i = 1 : N_p \) \textbf{do}
6. \hspace{2em} Update the position of the object by Eq. (18)
7. \hspace{2em} Update the acceleration of the object by Eq. (17)
8. \hspace{2em} Evaluate the position of each object and select the optimal object of the whole population
9. \hspace{1em} End for
10. \textbf{End while}

11. Record the optimal object of the global outcome.
12. \textbf{Output:} the optimal object of the whole population.

B. EXPERIMENTAL RESULTS FOR GLOBAL OPTIMIZATION

This subsection presents verification results of testing performance and the potential feasibility of the suggested algorithm for the function benchmark CEC 2017 [53] test suite. The test suite has 29 different test functions used to evaluate the IAOA algorithm. The benchmark test suite contains various types of complexity and dimension settings, e.g., \( f_1 \sim f_3 \): unimodal, \( f_4 \sim f_{10} \): multimodal, \( f_{11} \sim f_{20} \): hybrid, and \( f_{21} \sim f_{29} \): compound test functions.

The obtained results from the algorithms are the global optimum in the form of tables and figures with the values of best, mean, standard, and runtimes. The error function corresponding to each benchmark function of the obtained is expressed as follows: \( \Delta f = f_i - f_i^* \), where, \( f_i^* \) is the minimum value of the \( i \)-th benchmark test function; \( f_i \) is the actually obtained value of the \( i \)-th benchmark test function.

Algorithm 1 shows an improved Archimedes optimization algorithm (IAOA) pseudo-code.

\[
\begin{align*}
x_i^{t+1} & = \begin{cases}
x_i^t + \alpha_r \times C_1 \times r_i \times \text{rand} \times \text{acc}_{i,norm}^{t+1} \times d \times (x_{\text{rand}} - x_i^t), & \text{if } TF \leq 0.5 \\
x_i^{\text{best}} + F_{\text{new}} \times C_2 \times r_i \times \text{rand} \times \text{acc}_{i,norm}^{t+1} \times d \times (T \times x_{\text{best}} - x_i^t), & \text{otherwise}
\end{cases}
\end{align*}
\]
FIGURE 2. The IAOA affected strategy differences: comparing the activity graph curves of the strategy with the original algorithm for the selected testing functions with various dimensions. a) reverse-learning and b) multi-directing.
TABLE 3. Comparison of the affected strategy different in applying in the IAOA with the original AOA algorithm.

| Fun Test | Strategy 1 | | Strategy 2 | | Original | | Strategies 1&2 |
|----------|------------|---|------------|---|----------|---|---------|
|          | AVG.       | RUTNME | AVG.       | RUTNME | AVG.       | RUTNME | AVG.       | RUTNME |
| f1       | 1.11E+01  | 34.30 | 1.46E+01  | 34.20 | 3.25E+00  | 32.93 | 2.71E+00  | 38.52 |
| f2       | 1.11E+01  | 34.12 | 1.54E+01  | 34.02 | 2.21E+02  | 32.76 | 1.85E+01  | 38.32 |
| f3       | 5.52E-02  | 47.23 | 1.58E-01  | 47.09 | 2.66E-01  | 45.34 | 1.44E-01  | 53.04 |
| f4       | 4.59E-02  | 46.00 | 1.45E-01  | 45.86 | 3.02E-01  | 44.16 | 1.11E-02  | 51.66 |
| f5       | 1.38E-02  | 42.00 | 7.86E-03  | 41.87 | 7.99E-02  | 40.32 | 5.38E-03  | 47.17 |
| f6       | 6.21E-02  | 89.00 | 2.11E-01  | 88.73 | 5.58E-01  | 85.44 | 1.92E-01  | 99.95 |
| f7       | 2.44E-01  | 212.00 | 1.07E-01  | 211.36 | 2.21E-01  | 203.52 | 1.26E-01  | 238.08 |
| f8       | 1.97E+00  | 122.00 | 6.61E-01  | 121.63 | 6.32E+00  | 117.12 | 7.17E-01  | 137.01 |
| f9       | 4.25E+00  | 135.00 | 4.81E+00  | 134.60 | 7.20E+00  | 129.60 | 4.36E+00  | 151.61 |
| f10      | 1.01E-01  | 234.00 | 2.03E-01  | 233.30 | 1.20E+00  | 224.64 | 2.10E-02  | 262.78 |
| f11      | 8.09E+03  | 234.00 | 1.77E+03  | 233.30 | 4.45E+04  | 224.64 | 1.06E+03  | 262.78 |
| f12      | 8.09E+01  | 239.00 | 3.65E+01  | 238.28 | 1.66E+02  | 229.44 | 2.29E+01  | 268.40 |
| f13      | 3.30E+01  | 125.00 | 2.87E+00  | 124.63 | 3.58E+01  | 120.00 | 1.53E+00  | 140.38 |
| f14      | 1.09E+01  | 101.00 | 1.62E+00  | 100.70 | 2.96E+01  | 96.96 | 1.26E+00  | 113.42 |
| f15      | 4.74E+01  | 231.00 | 7.88E-01  | 230.31 | 2.05E+00  | 221.76 | 7.27E-01  | 259.41 |
| f16      | 2.59E-01  | 132.00 | 1.85E-01  | 131.60 | 4.73E-01  | 126.72 | 1.30E-01  | 148.24 |
| f17      | 5.53E+02  | 233.00 | 5.63E+02  | 232.30 | 4.04E+02  | 223.68 | 7.90E+01  | 261.66 |
| f18      | 1.46E+01  | 105.00 | 3.70E-01  | 104.69 | 2.49E+02  | 100.80 | 1.09E+00  | 117.92 |
| f19      | 3.79E-01  | 215.00 | 3.24E-01  | 214.36 | 4.06E-01  | 206.40 | 3.86E-01  | 241.45 |
| f20      | 4.34E-02  | 311.00 | 4.11E-01  | 310.07 | 5.87E-01  | 298.56 | 3.98E-02  | 349.25 |
| f21      | 8.29E-02  | 341.00 | 2.25E-01  | 339.98 | 6.51E-01  | 327.36 | 2.10E-01  | 382.94 |
| f22      | 7.63E-01  | 326.00 | 6.22E-01  | 325.02 | 9.94E-01  | 312.96 | 6.79E-01  | 366.10 |
| f23      | 5.72E-02  | 316.00 | 7.63E-01  | 315.05 | 1.02E+00  | 303.36 | 7.59E-02  | 354.87 |
| f24      | 4.75E-01  | 294.00 | 6.63E-01  | 293.12 | 7.38E-01  | 282.24 | 4.12E-01  | 330.16 |
| f25      | 1.51E+00  | 215.00 | 7.26E-01  | 214.36 | 3.28E+00  | 206.40 | 7.74E-01  | 241.45 |
| f26      | 2.78E-02  | 264.00 | 8.03E-01  | 263.21 | 8.53E-01  | 253.44 | 7.78E-01  | 296.47 |
| f27      | 5.19E-01  | 264.00 | 7.74E-01  | 263.21 | 8.28E-01  | 253.44 | 7.41E-02  | 296.47 |
| f28      | 3.34E-01  | 235.00 | 1.09E-00  | 234.30 | 2.37E+00  | 225.60 | 9.39E-01  | 263.91 |
| f29      | 3.14E+02  | 231.00 | 8.37E+00  | 230.31 | 4.15E+03  | 221.76 | 4.89E+01  | 259.41 |
| Avg.     | 3.15E-01  | 186.47 | 6.88E-01  | 185.91 | 1.72E-01  | 179.01 | 4.30E-02  | 209.41 |

In addition, to eliminate the experimental contingency, all the algorithms are tested 30 times, which makes the experimental results more objective. The basic parameters of each algorithm are shown in Table 2.

First, we compare the obtained results from different applied strategies with the original AOA algorithm [49]. Then we compare the obtained results from the IAOA with the other algorithms, e.g., GA [31], PSO [34], BA [40], PPSO [35], MFO [42], and WOA [41] algorithms. Table 3 shows the comparison of the affected strategy different in applying the IAOA with the original AOA algorithm. The valuable attributes in the Table are the denoted symbol average (AVG) and runtime.

In order to ensure the fairness of the experiment, we set the primary conditions for all the algorithms: the number of objects or population size is set to 80; max-iterations is set to 1000; dimension is set to 30; and the solution range of all the test functions is between $[-100, 100]$. The optimization effect. The optimum results of the IAOA are compared with the other popular algorithms in the literature, e.g., original AOA [49], Genetics algorithm (GA) [31], Particle swarm algorithm (PSO) [34], Bats algorithm (BA) [40], Parallel PSO (PPSO) [35], Moth Flame optimization (MFO) [42], and Whale optimization algorithm (WOA) [41].
**TABLE 4.** The performance of the IAOA, GA, and PSO for the CEC2017 test suite.

| Funs | GA | PSO | IAOA |
|------|----|-----|------|
| Mean | Best | Std | Mean | Best | Std | Mean | Best | Std |
| f1   | 5.66E-5 | 1.46E-5 | 5.19E-5 | 7.16E-5 | 1.25E-5 | 2.38E-5 | 1.29E-5 | 2.71E-5 | 1.11E-5 |
| f2   | 3.72E+1 | 1.54E+1 | 1.01E+1 | 3.78E+2 | 2.21E+2 | 9.86E+1 | 3.57E+1 | 1.85E+1 | 1.11E+1 |
| f3   | 2.57E-1 | 1.58E-1 | 5.11E-2 | 4.92E-1 | 2.66E-1 | 1.28E-1 | 2.33E-1 | 1.44E-1 | 5.52E-2 |
| f4   | 2.31E-1 | 1.45E-1 | 4.84E-2 | 4.58E-1 | 3.02E-1 | 4.34E-2 | 1.91E-1 | 1.11E-1 | 4.59E-2 |
| f5   | 3.90E-2 | 7.86E-3 | 1.68E-2 | 1.12E-2 | 7.99E-2 | 1.63E-2 | 2.57E-2 | 5.38E-3 | 1.38E-2 |
| f6   | 3.28E-1 | 2.11E-1 | 7.81E-2 | 8.30E-1 | 5.58E-1 | 1.26E-1 | 2.68E-1 | 1.92E-1 | 6.21E-2 |
| f7   | 1.95E-1 | 1.07E-1 | 3.69E-2 | 3.59E-1 | 2.21E-1 | 8.33E-2 | 1.66E-1 | 1.26E-1 | 2.44E-2 |
| f8   | 3.43E+0 | 1.21E+1 | 1.64E+0 | 1.32E+0 | 6.32E+0 | 4.29E+0 | 3.23E+0 | 7.17E-1 | 1.97E+0 |
| f9   | 6.43E+0 | 4.81E+0 | 1.19E+0 | 8.79E+0 | 7.20E+0 | 1.09E+0 | 6.53E+0 | 4.36E+0 | 1.25E+0 |
| f10  | 3.99E-1 | 2.03E-1 | 1.03E-1 | 5.33E+0 | 1.20E+0 | 4.24E+0 | 3.81E-1 | 2.10E-1 | 1.01E-1 |
| f11  | 1.02E+4 | 1.77E+3 | 9.36E+3 | 2.81E+5 | 4.45E+4 | 1.90E+5 | 7.58E+3 | 1.06E+3 | 8.09E+3 |
| f12  | 9.53E+2 | 3.65E+1 | 1.07E+2 | 9.30E+2 | 1.66E+2 | 1.10E+3 | 9.47E+1 | 2.29E+1 | 8.09E+1 |
| f13  | 3.62E+1 | 9.87E+0 | 3.51E+1 | 9.11E+3 | 9.80E+0 | 2.89E+2 | 9.23E+1 | 9.83E+0 | 3.30E+1 |
| f14  | 1.21E+1 | 1.62E+0 | 7.68E+0 | 1.66E+2 | 2.96E+1 | 1.15E+2 | 1.05E+1 | 1.26E+0 | 1.09E+1 |
| f15  | 1.57E+0 | 7.88E-1 | 4.83E-1 | 3.69E+0 | 2.05E+0 | 4.63E-1 | 1.66E+0 | 7.27E-1 | 4.74E-1 |
| f16  | 5.97E-1 | 1.85E-1 | 2.70E-1 | 1.30E+0 | 4.73E-1 | 3.87E-1 | 5.77E-1 | 1.30E-1 | 2.59E-1 |
| f17  | 6.05E+2 | 5.63E+1 | 7.15E+2 | 1.01E+4 | 4.04E+2 | 1.60E+4 | 4.81E+2 | 7.90E+1 | 5.53E+2 |
| f18  | 9.73E+0 | 3.70E-1 | 1.74E+1 | 2.11E+4 | 2.49E+2 | 1.87E+4 | 1.10E+1 | 1.09E+0 | 1.46E+1 |
| f19  | 7.95E-1 | 3.24E-1 | 3.13E-1 | 1.29E-1 | 4.06E-1 | 3.70E-1 | 9.79E-1 | 3.86E-1 | 2.79E-1 |
| f20  | 4.87E-1 | 4.11E-1 | 3.48E-2 | 7.39E-1 | 5.87E-1 | 8.77E-2 | 4.80E-1 | 3.98E-1 | 4.34E-2 |
| f21  | 3.46E-1 | 2.25E-1 | 6.95E-2 | 8.38E-0 | 6.51E-0 | 2.32E+0 | 2.95E-1 | 2.10E-1 | 8.29E-2 |
| f22  | 7.69E-1 | 6.22E-1 | 5.70E-2 | 1.21E+0 | 9.94E-1 | 1.04E-1 | 7.46E-1 | 6.79E-1 | 4.63E-2 |
| f23  | 8.64E-1 | 7.63E-1 | 6.44E-2 | 1.26E+0 | 1.02E-1 | 1.34E-1 | 8.49E-1 | 7.59E-1 | 5.72E-2 |
| f24  | 7.34E-1 | 6.63E-1 | 3.85E-2 | 8.77E-1 | 7.38E-1 | 7.48E-2 | 7.00E-1 | 6.12E-1 | 4.75E-2 |
| f25  | 2.79E+0 | 7.26E-1 | 1.62E+0 | 8.04E+0 | 3.28E+0 | 1.63E+0 | 3.45E+0 | 7.74E-1 | 1.51E+0 |
| f26  | 8.44E-1 | 8.03E-1 | 2.31E-2 | 1.13E+0 | 8.53E-1 | 1.82E-1 | 8.29E-1 | 7.78E-1 | 2.78E-2 |
| f27  | 8.55E-1 | 7.74E-1 | 5.76E-2 | 1.02E+0 | 8.28E-1 | 1.38E-1 | 8.17E-1 | 7.41E-1 | 5.19E-2 |
| f28  | 1.74E+0 | 1.09E+0 | 3.76E-1 | 3.66E+0 | 2.37E-1 | 6.31E-1 | 1.49E+0 | 9.39E-1 | 3.34E-0 |
| f29  | 1.12E+3 | 8.37E+1 | 1.16E+3 | 4.33E+4 | 4.15E+3 | 3.70E+4 | 3.55E+2 | 4.89E+1 | 3.14E+2 |

AVG is the value of the optimal output values of (strategy-1, strategy-2, and the AOA, and IAOA), respectively, are taken as the average of thirty runs for the test functions, and RUNTIMEs are their execution times, respectively. It is seen that the proposed IAOA produces results that are better than the AOA in terms of convergence, and the time running is not much longer than the AOA one. Figure 2 compares the activity graph curves of applied suggesting strategies with the original algorithm for the testing functions with various dimensions. The behavior curves of exploiting and exploring search are two characteristic features of the metaheuristic algorithm. It is seen from Figure 2 that strategy-2 has a long jumping distance as assisting exploring feature, whereas strategy-1 can enhance local search in the algorithm. In the second evaluating presentation for the proposed approach, we compare the obtained results from the IAAO with the other algorithms, e.g., GA [31], PSO [34], BA [40], PPSO [35], MFO [42], and WOA [41] algorithms. The compared results are presented in Tables 3~6 and Figure 3. The using measures variables for evaluating the algorithm’s performance are the mean, best, and standard deviation values: e.g., the mean value for evaluating the search capability and
TABLE 5. The performance of the IAOA, BA, and PPSO for the CEC2017 test suite.

| Funs | BA | PPSO | IAOA |
|------|----|------|------|
|      | Mean | Best | Std  | Mean | Best | Std  | Mean | Best | Std  |
| f1   | 2.24E-2 | 1.19E-2 | 5.79E-2 | 4.37E-2 | 2.25E-2 | 1.36E-2 | 1.34E-3 | 2.83E-2 | 1.16E-2 |
| f2   | 1.15E+0 | 7.23E-1 | 2.60E-1 | 8.74E-1 | 5.18E-1 | 6.01E-1 | 7.58E-1 | 3.92E-1 | 4.36E-1 |
| f3   | 2.11E-1 | 1.43E-1 | 3.47E-1 | 2.34E-1 | 1.21E-1 | 3.40E-1 | 2.43E-1 | 1.50E-1 | 5.77E-2 |
| f4   | 3.45E-1 | 2.40E-1 | 5.46E-2 | 2.55E-1 | 1.63E-1 | 3.90E-2 | 2.00E-1 | 1.16E-1 | 4.80E-2 |
| f5   | 6.68E-2 | 2.54E-2 | 1.98E-2 | 7.62E-2 | 4.46E-2 | 1.20E-2 | 2.68E-2 | 5.63E-3 | 1.44E-2 |
| f6   | 4.30E-1 | 3.80E-1 | 2.70E-2 | 3.26E-1 | 2.50E-1 | 4.61E-2 | 2.81E-1 | 2.01E-1 | 6.49E-2 |
| f7   | 2.59E-1 | 1.96E-1 | 3.70E-2 | 1.98E-1 | 1.36E-1 | 2.82E-2 | 1.73E-1 | 1.32E-1 | 1.25E-1 |
| f8   | 4.69E+0 | 1.11E-1 | 2.95E+0 | 4.42E+0 | 1.83E+0 | 1.59E+0 | 3.37E+0 | 7.49E-1 | 2.06E+0 |
| f9   | 9.68E+0 | 7.43E+0 | 1.17E+0 | 7.17E+0 | 4.82E+0 | 5.09E+0 | 6.82E+0 | 4.56E+0 | 1.30E+0 |
| f10  | 4.07E-1 | 2.77E-1 | 6.08E-2 | 3.14E-1 | 2.25E-1 | 4.61E-2 | 3.98E-1 | 2.19E-1 | 1.06E-1 |
| f11  | 3.01E+1 | 2.32E+1 | 3.26E+1 | 3.13E+1 | 3.15E+1 | 3.15E+1 | 3.40E+1 | 3.11E+1 | 3.10E+1 |
| f12  | 7.20E+2 | 3.72E+2 | 8.30E+2 | 1.11E+2 | 4.52E+1 | 4.62E+1 | 9.90E+1 | 2.39E+1 | 8.46E+1 |
| f13  | 7.34E+1 | 8.89E+0 | 6.28E-1 | 2.59E+1 | 5.45E-1 | 2.66E+1 | 3.06E+1 | 1.59E+0 | 3.44E+1 |
| f14  | 3.03E+2 | 8.32E+1 | 2.17E+2 | 4.57E+1 | 1.92E+1 | 2.71E+1 | 1.10E+1 | 1.32E+0 | 1.14E+1 |
| f15  | 2.01E+0 | 1.09E+0 | 3.70E-1 | 2.01E+0 | 1.26E+0 | 4.51E-1 | 1.73E+0 | 7.59E-1 | 4.95E-1 |
| f16  | 7.50E-1 | 2.41E-1 | 2.38E-1 | 6.40E-1 | 1.93E-1 | 2.80E-1 | 6.03E-1 | 1.36E-1 | 2.70E-1 |
| f17  | 9.05E+1 | 5.47E+1 | 1.23E+2 | 9.08E+1 | 1.09E+1 | 8.55E+0 | 1.02E+2 | 1.68E+1 | 1.17E+2 |
| f18  | 1.50E+2 | 4.30E+1 | 1.32E+2 | 2.42E+1 | 1.64E+0 | 2.35E+1 | 1.38E+0 | 1.37E-1 | 1.84E+0 |
| f19  | 7.85E-1 | 4.36E-1 | 2.39E-1 | 7.69E-1 | 5.01E-1 | 1.78E-1 | 8.33E-1 | 4.03E-1 | 2.91E-1 |
| f20  | 6.30E-1 | 5.39E-1 | 4.59E-2 | 5.71E-1 | 4.96E-1 | 4.14E-2 | 5.02E-1 | 4.16E-1 | 4.53E-2 |
| f21  | 1.45E+0 | 2.33E-1 | 3.18E+0 | 7.42E-1 | 2.04E+0 | 2.02E+0 | 3.08E-1 | 2.20E-1 | 8.66E+2 |
| f22  | 1.03E+0 | 7.09E-1 | 9.12E-1 | 9.97E-1 | 8.73E-1 | 9.76E-1 | 7.80E-1 | 7.10E-1 | 4.83E-2 |
| f23  | 1.09E+0 | 9.27E-1 | 7.47E-2 | 1.05E+0 | 8.69E-1 | 8.62E-2 | 8.87E-1 | 7.93E-1 | 5.98E-2 |
| f24  | 7.17E-1 | 6.52E-1 | 3.44E-2 | 7.17E-1 | 6.61E-1 | 3.69E-2 | 7.32E-1 | 6.39E-1 | 4.96E-2 |
| f25  | 3.91E+0 | 6.47E-1 | 2.82E+0 | 3.26E+0 | 5.36E-1 | 2.80E+0 | 3.60E+0 | 8.08E-1 | 1.57E+0 |
| f26  | 9.56E-1 | 8.58E-1 | 8.74E-2 | 9.93E-1 | 8.44E-1 | 7.07E-1 | 8.66E-1 | 8.12E-1 | 2.90E-2 |
| f27  | 7.98E-1 | 7.24E-1 | 3.70E-2 | 7.86E-1 | 6.96E-1 | 4.20E-2 | 8.54E-1 | 7.74E-1 | 5.43E-2 |
| f28  | 2.03E+0 | 1.31E+0 | 4.27E-1 | 2.38E+0 | 1.47E+0 | 4.32E-1 | 1.56E+0 | 9.81E-1 | 3.49E-1 |
| f29  | 5.47E+3 | 1.89E+3 | 2.54E+3 | 2.89E+3 | 4.93E+3 | 1.89E+3 | 3.71E+2 | 1.01E+2 | 3.28E+2 |

The tables show the data analysis that compared the outcome results of the proposed IAOA with the other popular algorithms in the metaheuristics algorithms literature, e.g., GA [31], PSO [34], BA [40], PPSO [35], MFO [42], and WOA [41] algorithms. The three testing batches for suitable format layout paper are carried out for Tables 4 to 6, respectively. The valuable attributes denoted symbol mean, best, and standard deviation (std.) values are measured by the obtained optimal output of the algorithm in terms of average, global best, and variation deviation.

The highlighted values in the Tables are the winner in comparing the proposed IAOA outcome results with the others in each table row. The end of each Table has a summary with variables, e.g., Win, Loss, and Draw. It can be seen that the numbers of ‘Wins’ in the tables belong to the proposed IAOA algorithm. The compared results show that the IAOA produces better results than the others in the competition.
It means that the IAOA has a stunning performance of optimization. Figure 3 shows the comparison of the convergence output curves of the IAOA with GA [31], AOA [49], BA [40], PSO [34], MFO [42], and WOA [41] algorithms for the selected functions. It can be seen from the figure that the IAOA performance is better than other algorithms in terms of convergence speed.

IV. APPLICATION OF THE IAOA FOR MCS OPERATIONS PLANNING

This section presents the multiobjective function for the MSC operational planning issues, optimizing process steps, and analyzing and discussing the results. The detailed presentation is described as follows.

A. MULTIOBJECTIVE MODEL

A mathematical multiobject model [54] of the optimization issues is established based on two aspects: the relevant economic costs and environmental profits of the entire microgrid operations in a scheduling cycle of the MCS implementation [52], [55]. Exploring and exploiting viable optimization feasible areas in the optimization issue search space is figured out by applying the proposed IAOA as its validation test. The objective function is crucially vital in driving fitness forward to the optimum global result derived from the mathematical modeling in optimization processing. The variable electricity costs need to optimize with period changing synchronously for MCS’s active power’s electricity [52]. The objective function of MCS optimization operations is constructed mathematical model with the minimum economic costs of the microgrid and the minimum costs of environmental pollution control as follows.

\[
min F = \sum_{t=1}^{T} (F_1(t) + F_2(t)),
\]

where \( F \) is the multiobjective function for relevant total costs of MCS grid-connected operations; \( F_1 \) and \( F_2 \) are the economic and environmental costs of MCS power generation, and \( T \) is the scheduling period \( t \), the multiobjective function subject to the constraints as mentioned in subsection 2.1.

Time interval and period use can be a year, month, day,
FIGURE 3. Comparison of the convergence output curves of the IOAA with GA, AOA, BA, PSO, MFO, and WOA algorithms for the selected functions.
or hour determined by the MCS power supply outputs. The daily load curve’s unit and the generating plants’ output curve’s period, such as 24 hours, are used, and the same with 12 months for a year and four seasons [52].

The MCS economic costs of power generation include the combustion cost and operation and maintenance cost of micropower sources such as gas turbines and diesel generators and the interaction cost with the large grid power.

\[
F_1(t) = \sum_{i=1}^{T} \left[ C_{DE}(t) + C_{FC}(t) + C_{MT}(t) + C_{PV}(t) + C_{WF}(t) + \mu C_{EX}(t) \right].
\]

(26)

where \( C_i(t) \) are relevant costs of operations (\( i \) is set of \( DE, FC, MT, PV, WT \)); \( \alpha_i \) are the unit prices of some kinds of operations, e.g., maintaining, investing, depreciating, and interactive power with the grid in the period \( t \), respectively; \( \mu \) is a parameter if it is set 1, it means a state of grid-connected operation; otherwise, it is an off-grid operation.

Another function of the object is the environmental costs that are a conversion processing development effected around. The related costs operation parameters are considered with each treatment and the emission coefficients of various pollutants at using period point prices. The cost of treating pollutants discharged \( F_2 \) with expression is calculated as follows.

\[
F_2 = \sum_{i=1}^{T} \sum_{k=1}^{K} b_k \left( \sum_{i=1}^{N} a_{i,k} \cdot P_i \right),
\]

(27)

where \( b_k \) and \( a_{i,k} \) are the treatment cost and coefficient of class \( K \) pollutants discharged, $/kg; P_i \) is the \( i \)-th distributed power source, g/KWh; \( K \) is the serial number of pollutants [55].

**B. PROCESSING STEPS MULTIOBJECT IAOA (MOIAOA)**

There are several techniques dealing with the multiobjective optimal operation model, e.g., the Pareto front [56], and weighting ways [57], [58]. The Pareto optimality is used to figure out the feasible solutions of the MCS optimization operation planning. Then, the best points are selected to provide the suitable weighting values for applying the weighting method objective function. The optimal dominance of the Pareto optimality is denoted as \( \vec{x} < \vec{y} \) that is determined in the feasible solutions [59]. An optimal dominance definition as \( \vec{x} \) is said the dominance solution (\( \vec{y} \)) iff: \( F_1(\vec{x}) <= F_2(\vec{y}) \) for entire feasible sites and \( F_1(\vec{x}) < F_2(\vec{y}) \) for at least a site in the feasible area.

The economic operation and environmental pollution costs are used to construct the multiplicative optimal operation model for the MCS minimizing the objective cost function. It means that \( F_1 \) and \( F_2 \) are two variables that are mutually exclusive. The environmental cost will rise as the economic cost decreases. The environmental benefits will be reduced if the economic cost is increased. However, the minimum economic cost and the maximum ecological benefit are mutually exclusive, so we use the minus technique for converting maximum environmental benefit into minimizing function ones. The solution set in the object space is often built a ranging set 0 to 1, so a safe checking boundary is stated as the following expression.

\[
\begin{align*}
S_{F_1} &= \frac{F_1 - F_{\min}}{F_{\max} - F_{\min}}, \\
S_{F_2} &= \frac{F_2 - F_{\min}}{F_{\max} - F_{\min}}.
\end{align*}
\]

(28)

where \( S_{F_1} \) and \( S_{F_2} \) are two solution sets of checking measure parameter \( s \in [0,1] \) as considering checking boundary factors. The meaning parameters are used with most satisfied and dissatisfied values ranging set 0 to 1, or [0, 1]. The weighting method for multiobjective function can be expressed as follows.

\[
\text{Min} F_3 = \omega_1 \times F_1 + \omega_2 \times F_2,
\]

(29)

where \( \omega_1 \) and \( \omega_2 \) are variables of weights considered the proportion of the relevant economic cost and the practical
environmental benefits, respectively. The comprehensive benefit of the optimal solution set generated by the optimization algorithm is chosen best sites. The best points are selected from the Pareto optimal front to provide suitable weighting values for the weight responding respectively facts. Figure 4 depicts the IAOA’s flowchart for planning microgrid operations.

The IAOA flowchart for planning MCS scheduled operations is shown in Figure 4.

The main optimizing process steps in the IAOA applying for the MCS operation planning problem are described as follows:

Step 1: Input the MCS model parameters: daily load demand \( P_d(t) \), power output curves \( P(t) \), unit generating set \( T \), time-of-use energy pricing \( C_i(t) \), and various pollution cost treatment factors: CO, SO, CO for MT, DE, BS as shown in Tables 6 and 7.

Step 2: Assign randomly \( N_p \); generated population; the objective function \( F(t) \) is computed for each objects’ fitness value; a new solution is set by using the suggested strategies; the items with the best fitness value are selected from the complete collection of forwarding next generation.

Step 3: Rank the fitness to determine who is now the best and worst fitness individual; selected objects in the solution set with the lowest fitness values are removed for the worst solution set; the reverse solution is integrated into the solution set to produce new solutions set.

Step 4: Update the object locations with better fitness and update the positions of selected objects at random to obtain the most up-to-date areas with the feasible ones.

Step 5: Compare the improved object locations: the global solution should be updated if the new site outperforms the previous ones.

Step 6: Determine the fitness value of the object placements, then use the reverse elite learning technique to develop a new set of solutions while preserving the optimal historical values and the global.

Step 7. Verify the termination condition, e.g., repeat steps 2 to 6; if not reach max-iteration; output the object locations and the best global outcome value with the otherwise.

C. THE RESULTS ANALYSIS AND DISCUSSION

The setting parameters for the algorithms and environment for the MCS system are conducted for project operations planning based on several scenarios of scheduling periods of the days, months, and years, e.g., the period day is divided into 24 hours periods; 30 days/month, and 12 months/year. The multiobject IAOA (MOIAOA) outcomes are compared with the popular multiobject methods, e.g., NSGA-II [58] and MOEA/D [60]. After getting the selected point in Pareto optimality, the weighted multiobject would be conducted by applying the IAOA. The outcome results of the IAOA are compared with the other approaches in the literature, e.g., the MBGA [33], PSO [28], and AOA schemes.

The parameters for the algorithms refer to Table 3, and the other setting parameters, e.g., for NSGA-II: the crossover probability \( P_c = 0.3 \), mutation probability \( P_m = 0.01 \); for PSO: inertia factor \( \omega_{\text{max}} = 0.95 \), \( \omega_{\text{min}} = 0.15 \), learning factor \( c_1 = c_4 = 2 \), the maximum number of iterations of the algorithms is 1000, and the population size is 60. The MCS system’s setting environment is set, e.g., emission coefficient of various pollutants, treatment costs, and operations prices. Tables 7 and 8 list the emission-related pollution remediation and emission coefficients and the units of the operation power sources relevant to the operation price for the initial optimization planning of the MCS system’s inputs. Figure 5 displays a graph plot of the daily demanding grid voltage curves of the MCS power loads. The system’s initial data of demanding grid voltages are inputs before scheduling for scheme optimal operations planning.

In the grid-connected state, the operation cost of MCS generating electricity could be more expensive than the large grid’s consumed electricity because of much large-scale consumption and convenient equipment. However, the microgrid

| The emissions | \( CO_2 \) | \( SO_2 \) | \( NO_x \) | \( CO \) |
|---------------|----------|----------|----------|---------|
| MT            | 179      | 0.00089  | 0.621    | 0.16    |
| FC            | 635      | 0        | 0.023    | 0.054   |
| DE            | 542      | 0        | 0.031    | 0.065   |
| Related operations costs\((S/kG^-1)\) | 0.0052 | 0.693 | 1.19 | 0.201 |

Figure 4. An IAOA flowchart for planning MCS scheduled operations planning.
TABLE 8. The relevant parameters of each unit of the operation model of the power sources.

| Power sources | kW-power capacity | Constraint of climb rate | Maintenance Costs ($/kW) | Install Costs ($/kW) | Capacity factors (%) | Service life/years |
|---------------|-------------------|--------------------------|---------------------------|----------------------|---------------------|-------------------|
| BS            | 61.87             | -61.5000                 | 0.0001                    | 0.005                | 0.107               | 40                |
| DE            | 83.25             | 5.0150                   | 0.0600                    | 0.205                | 1.958               | 57                |
| FC            | 69.45             | 5.1500                   | 0.9600                    | 0.107                | 2.258               | 37                |
| MT            | 73.92             | 18.4500                  | 0.1080                    | 0.108                | 1.606               | 68                |
| PV            | 35.52             | 0.0000                   | 0.0012                    | 0.012                | 5.180               | 36                |
| WT            | 39.69             | 0.0000                   | 0.0012                    | 0.036                | 2.915               | 27                |
| EX            | 74.29             | -73.8000                 | 0.0012                    | 0.0001               | 2.001               | 22                |

FIGURE 5. A graph plot of the daily demanding grid voltage curves of the MCS power loads of the initial data of optimal operations planning.

effectively produces balance and service by supplying power to the major grid during peak load hours and peak load times to meet the load demands. The microgrid’s battery storage is charged at the trough hours, but it provides the power to meet the peak load hour demand. The battery storage can also be charged when the system creates excess electric energy to ensure the system’s continuous power supply. The generators of the miniature gas turbines, diesel engineering, and fuel cells in the microgrid operate at full power at peak demands. Whenever the grid is off with the primary grid, its battery storage is powered by battery discharge. Table 9 shows the electricity consumption price on the electricity meter by measuring daily hours.

Table 10 shows a summary output results of three multi-object approaches: the MOIAOA, NSGA-II, and MOEA/D algorithm with a selected specific point $[S_{F_1}, S_{F_2}] = [0.150, 0.250], [0.5, 0.5], [0.5, 0.5], [0.250, 0.150]$ for the MCS Pareto optimal frontier with day periods. The obtained optimal values of the MOIAOA are better performance than NSGA-II and MOEA/D in terms of less cost and power load loss.

Figure 5 displays the obtained result curves of the multiobjective optimal dispatching with Pareto optimal front in MOIAOA, NSGA-II and MOEA/D algorithms.

FIGURE 6. The obtained result curves of the multiobjective optimal dispatching with Pareto optimal front in MOIAOA, NSGA-II and MOEA/D algorithms.

FIGURE 7. The planned curve results of the schemes of the IAOA, MBGA, PSO, and AOA methodologies according to the schedule daily.

function in Eq.(29) with the referred weight that $\omega_1 = 0.6$ and $\omega_2 = 0.4$ respectively.
The weight is referred to the function F3 in Eq.(29) from the obtained Pareto optimality space as a selected point in Figure 6.

As observed from Figures 7 and 8, it is seen that the proposed IAOA’s optimization result curves have a faster-archived convergence speed than that of the other schemes, like the MBGA, PSO, and AOA methods in the selected specific point for the objective function in optimizing the MCS operational planning.

Figures 9, 10, and 11 show the MCS component-distributed power sources’ outputs in the form of the bars of grid-connected optimization according to the intervals cycle periods of the daily, monthly, and year power capacity loads.

The environmental seasons’ factors can impact the subsystem operations, e.g., rainy, windy, solar light, dry seasons, or capacity facilities, such as load shift on long-term capacity planning based on historical data and load demand curves. The other operation scenarios are divided into grid-connected and off-grid operations.

Figures 12 and 13 show the production graphs of the grid-connected and off-grid microgrid subsystem power supplies in daily cycle load. In general, the advantage of the proposed IAOA algorithm can be seen in Figures 6 to 13 and...
Tables 9 and 10. That can be said that the introduced IAOA scheme provides outperform the other schemes in comparison to performing solutions for the MCS operation planning issue.

V. CONCLUSION
This study suggested an improvement for Archimedes optimization algorithm (IAOA) to avoid the drawbacks of the original AOA, e.g., optimum local and sluggish convergence, for the microgrid operations planning and numeral global optimizations problems. The reverse-learning and multi-directing strategies were adapted to the updating equations of exploring and exploiting to enhance diverse objects population and increase optimal performance for implementing the IAOA approach. The operation cycle planning of the microgrid community system (MCS) is figured out as a multi-objective function established based on relevant economic costs and environmental profits. The IAOA’s outcomes findings on the CEC2017 test suite compared against the AOA, FMO, WOA, PSPO, GA, and PSO algorithms showing the IAOA is a sound competitor. The optimal results on the MCS FMO, WOA, PPSO, GA, and PSO algorithms showing the improvements on the multi-agent system operation with multi-subject game, “Energy,” vol. 245, Apr. 2022, Art. no. 123035, doi: 10.1109/energy.2022.123035.

L. Wang, B. Zhang, Q. Li, W. Song, and G. Li, “Robust distributed optimization for energy dispatch of multi-stakeholder multiple microgrids under uncertainty,” Appl. Energy, vol. 255, Dec. 2019, Art. no. 113845.

Z. Zhu, K. Wing Chan, S. Bu, B. Zhou, and S. Xia, “Real-time interaction of active distribution network and virtual microgrids: Market paradigm and data-driven stakeholder behavior analysis,” Appl. Energy, vol. 297, Sep. 2021, Art. no. 117107.

L. Meng, E. R. Sanseverino, A. Luna, T. Dragicevic, J. C. Vasquez, and M. E. Nassar and M. M. A. Salama, “Adaptive self-adaptive microgrids using dynamic boundaries,” IEEE Trans. Smart Grid, vol. 7, no. 1, pp. 105–113, Jan. 2016.

Y. Du, Z. Wang, G. Liu, X. Chen, H. Yuan, Y. Wei, and F. Li, “A cooperative game approach for coordinating multi-microgrid operation within distribution systems,” Appl. Energy, vol. 222, pp. 383–395, Apr. 2018.

A. Anvari-Moghaddam, A. Rahimi-Kian, M. S. Mirian, and J. M. Guerrero, “A multi-agent based energy management solution for integrated buildings and microgrid system,” Appl. Energy, vol. 203, pp. 41–56, Oct. 2017.

M. W. Khan, J. Wang, M. Ma, L. Xiong, P. Li, and F. Wu, “Optimal energy management and control aspects of distributed microgrid using multi-agent systems,” Sustain. Cities Soc., vol. 44, pp. 855–870, Jan. 2019.

S. Sen and V. Kumar, “Microgrid control: A comprehensive survey,” Annu. Rev. Control, vol. 45, pp. 118–151, Jan. 2018.

I. Boussaid, J. Lepagnot, and P. Siarry, “A survey on optimization metaheuristics,” Inf. Sci., vol. 237, pp. 82–117, Jul. 2013, doi: 10.1016/j.ins.2013.02.041.

T.-T. Nguyen, J.-S. Pan, and T.-K. Dao, “An improved flower pollination algorithm for optimizing layouts of nodes in wireless sensor network,” IEEE Access, vol. 7, pp. 75985–75998, 2019, doi: 10.1109/ACCESS.2019.2921721.

T.-T. Nguyen, H.-J. Wang, T.-K. Dao, J.-S. Pan, J.-H. Liu, and S. Weng, “An improved slime mold algorithm and its application for optimal operation of cascade hydropower stations,” IEEE Access, vol. 8, pp. 226754–226772, 2020, doi: 10.1109/ACCESS.2020.3045975.

T.-T. Nguyen, H.-J. Wang, T.-K. Dao, J.-S. Pan, T.-G. Ngo, and J. Yu, “A scheme of color image multithreshold segmentation based on improved moth-flame algorithm,” IEEE Access, vol. 8, pp. 174142–174159, 2020, doi: 10.1109/ACCESS.2020.3025833.

J.-S. Pan, P.-C. Song, S.-C. Chu, and Y.-J. Peng, “Improved compact cuckoo search algorithm applied to location of drone logistics hub,” Math. Comput. Simul., vol. 8, no. 3, pp. 333, Mar. 2020, doi: 10.3390/math8030333.

T.-K. Dao, T.-S. Pan, T.-T. Nguyen, and J.-S. Pan, “Parallel bat algorithm for optimizing makepan in job shop scheduling problems,” J. Intell. Manuf., vol. 29, no. 2, pp. 451–462, Feb. 2018, doi: 10.1007/s10845-015-1121-x.

D. Whiteley, “A genetic algorithm tutorial,” Statist. Comput., vol. 4, no. 2, pp. 65–85, Jun. 1994, doi: 10.1023/B:STAT.0000017554.

M. Srinivasan and L. M. Png, “Genetic algorithms: A Survey,” Computer, vol. 27, pp. 17–26, Jun. 1994, doi: 10.1109/2.294849.

A. Askarzadeh, “A memory-based genetic algorithm for optimization of power generation in a microgrid,” IEEE Trans. Sustain. Energy, vol. 9, no. 3, pp. 1081–1089, Jul. 2018.

J. Kennedy and R. Eberhart, “Particle swarm optimization,” in Proc. Int. Conf. Neural Netw. (ICNN), Nov./Dec. 1995, vol. 6, no. 4, pp. 1942–1948, doi: 10.1109/ICNN.1995.488968.
[35] S. C. Chu and J.-S. Pan, “A parallel particle swarm optimization algorithm with communication strategies,” J. Inf. Sci. Eng., vol. 21, no. 4, p. 9, 2005.

[36] D. Karaboga and B. Basturk, “A powerful and efficient algorithm for numerical function optimization: Artificial bee colony (ABC) algorithm,” J. Global Optim., vol. 39, no. 3, pp. 459–471, Apr. 2007, doi: 10.1007/s10898-007-9149-9.

[37] M. Dorigo and G. Di Caro, “Ant colony optimization: A new heuristicistic,” in Proc. Congr. Evol. Comput. (CEC), vol. 2, Jul. 1999, pp. 1470–1477, doi: 10.1109/CEC.1999.782657.

[38] S. A. Chu, P. W. Tsai, and J.-S. Pan, “Cat swarm optimization,” in Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 4099, Berlin, Germany: Springer, 2006, pp. 854–858, doi: 10.1007/11810603_94.

[39] K. V. Price, R. M. Storn, and J. A. Lampinen, “Differential evolution,” in A Practical Approach to Global Optimization. New York, NY, USA: Springer, 2005.

[40] X. S. Yang, “A new metaheuristic bat-inspired algorithm,” in Nature Inspired Cooperative Strategies for Optimization (Studies in Computational Intelligence), vol. 284, J. Gónzalez, D. Pelta, C. Cruz, G. Terrazas, and N. Krasnogor, Eds. Berlin, Germany: Springer, 2010, pp. 65–74.

[41] S. Mirjalili and A. Lewis, “The whale optimization algorithm,” Adv. Eng. Softw., vol. 95, pp. 51–67, May 2019, doi: 10.1016/j.advengsoft.2016.01.008.

[42] S. Mirjalili, “Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm,” Knowl.-Based Syst., vol. 89, pp. 228–249, Nov. 2015.

[43] X. S. Yang, “Flower pollination algorithm for global optimization,” in Unconventional Computation and Natural Computation (Lecture Notes in Computer Science), vol. 7445, Berlin, Germany: Springer, 2012, pp. 240–249, doi: 10.1007/978-3-642-32894-7_27.

[44] S. Mirjalili, “SCA: A sine cosine algorithm for solving optimization problems,” Knowl.-Based Syst., vol. 96, pp. 120–133, Mar. 2016.

[45] K. Hammouche, M. Diaf, and P. Siarry, “A comparative study of various meta-heuristic techniques applied to the multilevel thresholding problem,” Eng. Appl. Artif. Intell., vol. 23, no. 5, pp. 676–688, Aug. 2010, doi: 10.1016/j.engappai.2009.09.011.

[46] T.-T. Nguyen, J.-S. Pan, and T.-K. Dao, “A novel improved bat algorithm based on hybrid parallel and compact for balancing an energy consumption problem,” Information, vol. 10, no. 6, p. 194, Jun. 2019, doi: 10.3390/info10060194.

[47] M. Abdel-Basset, L. Abdel-Fatah, and A. K. Sangaiah, “Metaheuristic algorithms: A comprehensive review,” in Computational Intelligence and Lecture Notes in Bioinformatics (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 284, J. González, D. Pelta, C. Cruz, and G. Terrazas, Eds. Berlin, Germany: Springer, 2012, pp. 206–237, doi: 10.1007/978-3-642-32894-7_27.

[48] M. B. Shadmand and R. S. Balog, “Multi-objective optimization and real-time systems, formal methods, computational intelligence, electrical engineering, and machine learning.”

[49] H. Chen, L. Gao, and Z. Zhang, “Multi-objective optimal scheduling of a microgrid with uncertainties of renewable power generation considering user satisfaction,” Int. J. Electr. Power Energy Syst., vol. 131, Oct. 2021, Art. no. 107142.

[50] A. S. Desuky, S. Hussain, S. Kausar, M. A. Islam, and L. M. E. Bakrawy, “Multi-objective optimization and electrical engineering,” in Lecture Notes in Computer Science, vol. 96, pp. 120–133, Mar. 2016.

[51] A. K. Raji and D. N. Luta, “Modeling and optimization of a community microgrid components,” Energy Proc., vol. 156, pp. 406–411, Jan. 2019.

[52] G. Wu, R. Mallipeddi, and P. N. Suganthan, “Problem definitions and evaluation criteria for the CEC 2017 competition on constrained real-parameter optimization,” Nat. Univ. Defense Technol., Changsha, Hunan, PR China and Kyungpook Nat. Univ., Daegu, South Korea and Nanyang Technol. Univ., Singapore, Tech. Rep., Sep. 2017.

[53] M. I. 11077-3. Deng, C. Ai, H. Sun, Y.-P. Xu, and N. Nedaei, “Multi-objective optimization and multi-aspect analysis of an innovative geothermal-based multi-generation energy system for power, cooling, hydrogen, and freshwater production,” Energy, vol. 245, Apr. 2022, Art. no. 123198, doi: 10.1016/j.energy.2022.123198.

[54] D. A. Van Veldhuizen and G. B. Lamont, “Apartment agent computation and convergence to a Pareto front,” in Proc. Late Breaking Papers Genetic Prog. Conf., 1998, pp. 221–228.

[55] H. Tamaki, H. Kita, and S. Kobayashi, “Multi-objective optimization by genetic algorithms: A review,” in Proc. IEEE Int. Conf. Evol. Comput., May 1996, pp. 517–522.

[56] K. Deb, S. Agrawal, A. Pratap, and T. Meyarivan, “A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II,” in Parallel Problem Solving from Nature PPSN VI, Berlin, Germany: Springer, 2000, pp. 849–858, doi: 10.1007/3-540-45356-3_83.

[57] F. Al-Atabany, “Archimedes optimization algorithm: A new metaheuristic algorithm for solving optimization problems,” Knowl. Based Syst., vol. 96, pp. 120–133, Mar. 2016.

[58] A. S. Desuky, S. Hussain, S. Kausar, M. A. Islam, and L. M. E. Bakrawy, “EAOA: An enhanced archimedes optimization algorithm for feature selection in classification,” IEEE Access, vol. 9, pp. 120795–120814, 2021, doi: 10.1109/ACCESS.2021.3108553.

[59] M. S. Al-Sawafi and M. A. Al-Mutairi, “Multi-objective optimization and real-time systems, formal methods, computational intelligence, electrical engineering, and machine learning.”

THI-KIEN DAO received the Ph.D. degree in electronics and engineering from the National Kaohsiung University of Technology and Sciences, Taiwan, in 2019. She is currently a Lecturer with the School of Computer Science and Mathematics, Fujian University of Technology. Her current research interests include computational intelligence, grid computing, signal processing, and electrical engineering.

THI-THANH-TAN NGUYEN received the B.S. degree in information technology from the University of Technology, the master’s degree in information technology from the Vietnam National University, Hanoi, and the Ph.D. degree in computer science from the Institute of Information Technology, Vietnam Academy of Science and Technology, in 2012. She is currently the Head of the Department of Computer Science and Information Systems, University of Electrical Engineering (Vietnam). She has a lot of experience in building OCR and IDOCR in Vietnam. She is also the leader of a national project on detecting and predicting faults early on 110-kV high-voltage grids. Her general research interests include image/video processing, object tracking, pattern recognition (character, face, human action, and abnormal object recognition), AI, and big data analysis. On these topics, she has published more than 50 papers in International journals and Conference proceedings.

TRINH-DONG NGUYEN received the Ph.D. degree in software engineering from the VNU Hanoi-University of Engineering and Technology, in 2018. He is currently a Lecturer with the Faculty of Software Engineering, University of Information Technology, VNUHCM, Vietnam. His current research interests include software engineering, real-time systems, formal methods, computational intelligence, electrical engineering, and machine learning.