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Decarbonizing Energy Systems: Smart Grid and Renewable Technologies
Fang Rui-ming and Qiangqiang Liao (Guest Editors)

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Optimal energy generation of hybrid energy systems considering economic and environmental multi-objective functions

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Abstract. This research is dedicated to exploring and identifying the most effective design for an energy source tailored specifically to meet the electricity demands of a residential community. In an era where energy efficiency and sustainability are paramount, this study emphasizes the importance of technical and economic considerations in energy sourcing. It posits that any viable solution must not only be efficient in its energy production and consumption but also reliable in its delivery and financially feasible for the residents who will depend on it. To address this multifaceted challenge, the study proposes the innovative use of a rotation-invariant coordinate convolutional neural network in conjunction with binary battle royale optimization techniques. These advanced methodologies are selected for their potential to enhance the modelling and optimization processes involved in energy source design. The primary goal of employing these methods is to minimize two critical factors: the net present cost of the energy system and the overall energy cost incurred by the residents. By focusing on these objectives, the research aims to ensure that the proposed energy solutions are not only cost-effective but also sustainable over the long term. To rigorously test the proposed model and evaluate its performance, the research is conducted using the MATLAB platform. The study employs established methodologies and performance metrics to assess the outcomes of the model, ensuring that the findings are both credible and applicable to real-world scenarios. Through comprehensive testing and detailed analysis, this research aims to provide significant insights and actionable recommendations for the optimal design of energy sources in residential areas. By contributing to the ongoing discourse on sustainable energy solutions, the study seeks to inform policymakers, energy planners, and community stakeholders about effective strategies for meeting residential energy demands while promoting environmental sustainability. Ultimately, the findings of this research could play a crucial role in shaping the future of energy sourcing in residential communities, paving the way for more resilient and sustainable energy systems.

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Keywords: Energy sources, Cost-effective, MATLAB platform, Performance metrics, Energy solutions.

1 Introduction

1.1 Aims

In the upcoming decades, a significant increase in global energy demand is inevitable. The pursuit of clean energy is becoming increasingly important as concerns about the environmental impact of fossil fuel use rise. Renewable energy stands out as one of the best choices for clean energy due to its significantly lower environmental impact compared to conventional energy sources [1, 2]. To enhance the reliability of electricity generation for off-grid power systems in remote areas, renewable energy sources are integrated with diesel generators [3–5]. Diesel generators can serve as a reliable and efficient backup option when renewable energy sources cannot meet demand or when battery levels are low [6, 7]. Hybrid power systems provide greater cost-effectiveness and reliability when contrasted with single-source energy systems [8–11]. In remote or mountainous regions where connecting to the grid is costly and distant, a decentralized hybrid system plays a vital role in bridging the energy gap [12–14]. Access to electricity serves as a crucial measure of a country's development status. Currently, it is believed that the entire population is connected to the country's electrical grid [15–17]. The electrical supply is inconsistent, and peak demand remains unmet. In this context, renewable energy emerges as a more viable solution.

1.2 Related works

Numerous research studies explore the latest advancements in energy management within energy systems. In [18], a ground-breaking approach is introduced for creating a hybrid system that is perfectly suited for electrifying residences in dry regions. The approach integrates particle swarm optimization with demand-side management. Following the validation with the HOMER program, further techno-economic assessments, along with sensitivity analyses, are performed, considering a range of battery technologies. In [19], a power management strategy was developed to ensure reduced unmet load and surplus energy during the transfer of power between the system's components. To provide a steady supply of hydrogen energy to the system, methane gas produced by an anaerobic reactor was converted into hydrogen through the use of a reformer. The study in [20] successfully examined optimal sizing practices for hybrid biogas energy systems, applicable to both on-grid and off-grid configurations. In [21], the epsilon-constraint method has been employed simultaneously to tackle both the cost of energy and CO_2 emissions. The model proposed by the authors in [22] can be utilized to develop a system that incorporates various types of energy-producing units to meet the demands of diverse consumption rats. One of the primary advantages of the model is its ability to integrate physical, technological, operational, and capacity constraints, aspects that are rarely considered together in existing literature. A smart management strategy is proposed in [23] that factors in current economic conditions, system reliability, and environmental regulations to optimize the sizing and power management of battery resources, ensuring they meet energy demands effectively by a fuzzy decision-making approach.

1.3 Research gaps and contributions

Many proposed optimization techniques involve complex algorithms. When applied to large-scale systems or long-term optimization scenarios, these methods can require significant processing power and time to execute. A crucial aspect of advancing energy systems is mathematical modelling; in which this process often relies on assumptions and simplifications that may not fully capture the complexities of real-world renewable energy systems. Assumptions regarding load demand patterns, weather conditions, and the efficiency of system components can introduce errors and uncertainties in the results of the optimization process. However, this research focuses on identifying the best design for an energy source specifically aimed at meeting the electricity demands of a residential community. It emphasizes both the technical and economic aspects of energy sourcing, highlighting that an effective solution must be efficient, dependable, and financially viable for the residents. The study proposes the use of a rotation-invariant coordinate convolutional neural network alongside binary battle royale optimization as a methods to tackle this challenge. The main objective of these methods is to minimize both the net present cost and the energy cost. To test the proposed model and evaluate its performance, the research is conducted using the MATLAB platform, which is well-regarded for numerical computing and algorithm development. Established methodologies and performance metrics are utilized to assess the model's outcomes, ensuring that the findings are both credible and relevant to practical applications. Through comprehensive testing and analysis, this study aims to offer significant insights and recommendations for the optimal design of energy sources in residential areas, thereby contributing to the ongoing discussion on sustainable energy solutions.

2 Energy system overview

The energy system depicted in Figure 1 is an integrated setup designed to harness multiple sources of renewable and non-renewable energy to meet residential energy demands. This system includes several key components: a diesel generator, Photovoltaic (PV) panels, a battery storage system, a Wind Turbine (WT), and the residential load. This integrated energy system leverages a combination of renewable and conventional energy sources to create a more resilient, efficient, and sustainable energy solution for residential use. By utilizing multiple energy sources and incorporating storage capabilities, the system can adapt to varying energy demands and generation conditions, ultimately contributing to energy independence and reduced costs. The modelling of the system is as follows:

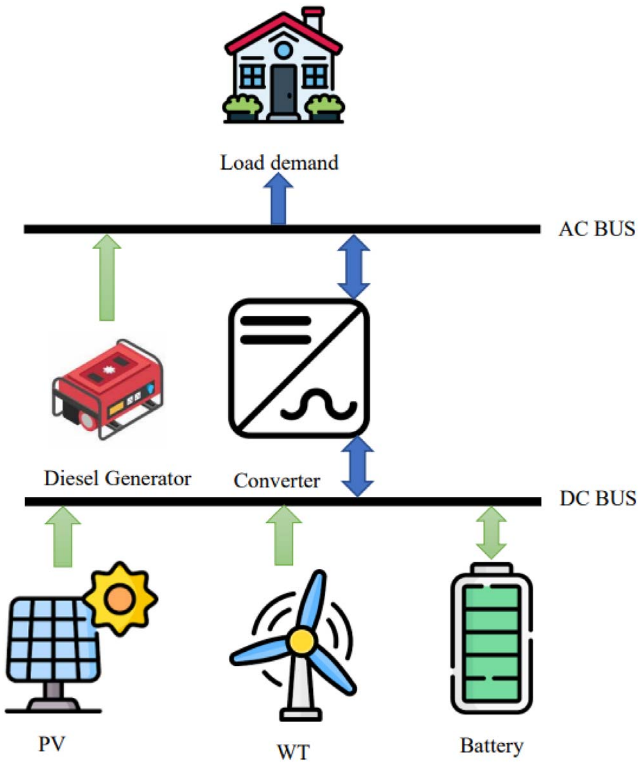

Fig. 1. Energy system overview.

2.1 Modelling WT and PV

The power generation of WT and PV is dependent on climate conditions such as wind speed and solar radiation. Also, some factors like the capacity of resources and technical data have effects on power generation. The modelling of PV and WT in this paper is extracted from references [24–28].

2.2 Modelling battery

The battery is modelled as follows [30–33]:

$$0 \leq P_B^{\mathrm{DIS}}(t) \leq u_B(t) \times P_B^{\max}, \tag{1}$$

$$0 \leq P_B^{CH}(t) \leq [1 - u_B(t)] \times P_B^{\max} \tag{2}$$

where:

P_B^{DIS} = Discharge power.
P_B^{CH} = Charge power.
$\mathrm{u_B}$ = Binary variable.
$P_B^{\max}$ = Maximum capacity.

2.3 Modelling diesel generator

The diesel generator is modelled as follows:

$$G_h = B_h \times Q_{oh} + C_h \times Q_h, \tag{3}$$

where:

C_h = Intercept coefficients.
Q_{oh} = DG power output.
Q_h = Nominal power.
B_h = Fuel curve slope.

2.4. Modelling Objective Function

The objective function is minimizing the cost of energy (COE) as follows:

$$\mathrm{COE} = \left(\frac{\mathrm{NPC}}{F_{\mathrm{served}}}\right) \times \left(\frac{j\left(1 + \left(\frac{j+g}{1+g}\right)\right)^{O_{\mathrm{proj}}}}{\left(1 + \left(\frac{j+g}{1+g}\right)\right)^{O_{\mathrm{proj}}} - 1}\right), \tag{4}$$

where:

F_{served} = Load served rate.
NPC = Net present cost.
O_{proj} = Project lifetime.
j = Interest rate.
g = Annual inflation rate.

In following, NPC can be computed as follows:

$$\mathrm{NPC} = \sum_r D^{\mathrm{cap}} + D^{\mathrm{P}\&N} + D^{\mathrm{rep}}, \tag{5}$$

$$\mathrm{NPC} = \sum_{o=0}^{O_{\mathrm{proj}}} \left(D^{\mathrm{cap}}(o) + D^{\mathrm{P}\&N}(o) + D^{\mathrm{rep}}(o)\right) \times \frac{1}{(1 + J_r)^o}, \tag{6}$$

$$J_r = \frac{(j - g)}{(1 + g)}, \tag{7}$$

where:

O = Number of the years.
D^{cap} = Annual capital cost.
Y = Element type.
$D_{Y\text{-cap}}$ = Unit cost.
O_Y = Quantity of element.

Also:

$$D^{\mathrm{cap}} = \sum O_Y D_{Y-\mathrm{cap}}, \tag{8}$$

where:

$D^{\mathrm{P\&N}}$ = Annual maintenance.
$D_{Y-\mathrm{P\&N}}$ = Maintenance cost.

The above equations can be computed as follows:

$$D^{\mathrm{P\&N}} = \sum O_Y D_{Y-\mathrm{P\&N}}, \tag{9}$$

$$D^{\mathrm{rep}} = \sum O_Y D_{Y-\mathrm{rep}} \tag{10}$$

where:

$D_{Y\text{-rep}}$ = Replacement cost.

D^{rep} = Yearly replacement cost.

2.5 Constraints

The constraints are as follows:

$$0 \le O_{QW} \le O_{QW}^{\max}, \tag{11}$$

$$0 \le O_{XU} \le O_{QU}^{\max}, \tag{12}$$

$$0 \le O_{EH} \le O_{EH}^{\max}, \tag{13}$$

$$0 \le O_{\mathrm{BATT}} \le O_{\mathrm{BATT}}^{\max}, \tag{14}$$

where:

O_{QW} = Number of PV.
O_{XU} = Number of WT.
Q_{EH} = Number of diesel generator.
Q_{BATT} = Number of battery.

3 Solution method

The rotation-invariant coordinate convolutional neural network with binary battle royale optimization techniques is used in this study as solution methods for energy management and optimal design of the proposed energy system.

3.1 Modelling rotation-invariant coordinate convolutional neural network

To enhance the advantages of the subsequent methods, it is essential to consider the input parameters, which encompass load demand, energy resource data, and design constraints. The input current supplies power to the household load. Following the creation of a rotation-invariant coordinate system for load computation, a novel rotation-invariant feature for the equation was developed [34]:

$$R = \left(r \cdot \cos\left(\varphi + \frac{j \cdot 2\pi}{8r}\right), r \cdot \sin\left(\varphi + \frac{j \cdot 2\pi}{8r}\right)\right), \tag{15}$$

where:

r = Radius circle.
y_d = First sample point.

Samples from the remaining locations are collected in a counterclockwise direction around the circle as follows:

$$\Phi_{\mathrm{Ric}-d}(Y_0, G(Y)) = \sum_{R \in T_{Y_0}} X(Q) \cdot \mathrm{G}(Y_0 + R) \tag{16}$$

where:

R = Order.
T_{Y_0} = coordinate system.
$H(Z)$ = rotated version.

It remains unchanged when the image centre is rotated.

$$R'_{\alpha} = \left(r \cdot \cos\left(\varphi' + \frac{j \cdot 2\pi}{8r}\right)\right)$$
$$= \left(r \cdot \cos\left(\varphi' + \theta + \frac{j \cdot 2\pi}{8r}\right), r \cdot \sin\left(\varphi' + \theta + \frac{j \cdot 2\pi}{8r}\right)\right). \tag{17}$$

The final feature map was generated using max-pooling, resulting in a spatial resolution of 1 × 1. Subsequently, the load demand is determined, and the computed voltage and current are provided for optimization.

3.2 Modelling binary battle royale optimization

The optimization for Binary Battle Royale was developed by drawing inspiration from the mechanics of Battle Royale games. This approach employs gaming strategies to lower the COE, aiming to deliver greater benefits. The objective function of the optimization strategy, total NPC, is defined by input parameters that include load demand, energy resource information, and both technical and economic attributes. Decision-makers and designers can evaluate the feasibility from both economic and technical perspectives using optimization algorithms, allowing them to make diverse technological selections depending on resource availability and fluctuations in technology costs. The steps of modelling binary battle royale optimization are as follows:

Step 1: Initialization
Input data of resources and demand in this step is considered.
Step2: Random Generation
After initialization, the input fitness function developed randomness via the binary battle royale optimization method as follows:

$$y_{\mathrm{dam},d}^{j+1} = \begin{bmatrix} y_{1,j} & y_{1,\mathrm{dam},d} & \cdots & y_{1,i} \\ y_{2,j} & y_{2,\mathrm{dam},d} & \cdots & y_{2,i} \\ \cdots & \cdots & \cdots & \cdots \\ y_{n,j} & y_{n,\mathrm{dam},d} & \cdots & y_{n,i} \end{bmatrix}, \tag{18}$$

where:

$y_{\mathrm{dam},d}^{j+1}$ = damage.
n = players.
d = dimension of variables.

Step 3: Fitness Function
The goal function affects fitness. The fitness function is described as:

$$\mathrm{Fitness} = \mathrm{MIN}[\mathrm{NPC}, \mathrm{COE}]. \tag{19}$$

Step 4: Exploration

The purpose of this space constraint is to guide each potential solution toward the optimal one. It is important to note that to preserve elitism, the top solution from each iteration is retained:

$$y_{\mathrm{dam},d}^{j+1} = s(vc_d - mc_d) + mc_d, \tag{20}$$

$$y_{\mathrm{dam,d}}^{j+1} = y_{\mathrm{dam,d}}^{j} + s\left(y_{\mathrm{best},d} - y_{\mathrm{dam,d}}^{j}\right). \tag{21}$$

Here:

mc_d and vc_d = Upper and lower boundaries.
s = Generated number.

Step 5: Exploitation

The purpose of this space constraint is to guide each potential solution toward the optimal one. It's important to highlight that, to preserve elitism, the top solution from each iteration is retained:

$$\begin{aligned} mc_d &= y_{\mathrm{best},d} - TE(y_d), \\ vc_d &= y_{\mathrm{best},d} - TE(y_d), \end{aligned} \tag{22}$$

where:

$y_{\mathrm{best},d}$ = Position of the damage.
$TE(y_d)$ = Standard deviation.

Step 6: Termination

Check the termination criterion; if it is met, the optimal solution has been identified; if it is not, continue the process. In Figure 2, a flowchart of binary battle royale optimization is shown.

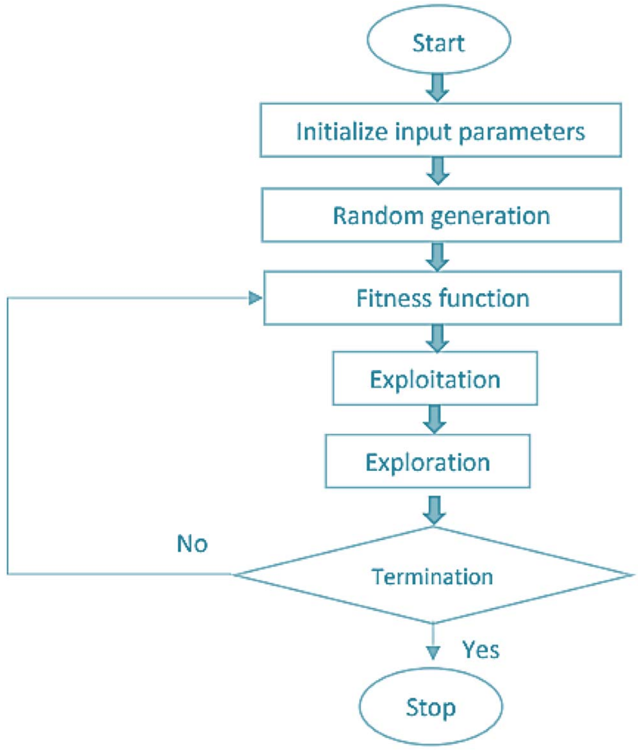

Fig. 2. Flowchart of binary battle royale optimization.

4 Simulation results

This study calculates the current, voltage, and power values of photovoltaic, wind, and battery systems through a hybrid renewable energy systems approach. The effectiveness of the proposed method is demonstrated in the MATLAB Simulink environment and compared with existing techniques. The data on load demand and resources are extracted from references [35–38]. The analysis of PV Power and Wind Power is presented in Figure 3. Subplot 3a shows the PV Power. The secondary load has been activated, indicated by the load power PV, which begins at 0 W and drops to −2 W at 5 and 6 s, respectively. Subplot 3b illustrates the WT Power. The main load remains continuously active, as reflected by the wind power data. The battery requires less energy to maintain the necessary load during periods of low wind. The wind power output begins at 0 W at 5 s and gradually increases to 0.4 W by 6 s. Meanwhile, the DC bus voltage shows a minimal increase due to the decrease in wind power. The examination of AC load voltage and AC current is presented in Figure 4. Subplot 4a depicts the AC load Voltage. The interlinking converter effectively maintained the 3-phase load voltage by utilizing AC to stabilize it during an external load disturbance. Initially, the voltage was at 100 V at 8.2 s, but it dropped sharply to −300 V by 8.7 s. Subplot 4b illustrates the magnitude of the AC current and the condition of the load switch. At 8.2 s, the AC current begins at 1 A and falls to −3 A by 8.7 s.

The analysis of Wind Power and Battery Power is presented in Figure 5. Wind Power is shown in Subplot 5a. To meet the load demand during periods of low wind power, the power supply is drawing less energy. At 5 s, the wind power registers at 0 W, and by 6 s, it rises to 0.4 W. This period sees a minor increase in the DC bus voltage due to the decrease in wind power. Subplot 5b illustrates the Battery Power. Here, the battery's energy is utilized to bridge the energy deficit, starting with a minimal charging power of 1.4 W at 5 s, which then gradually climbs to 1.2 W at the same moment. The analysis of the 3-phase current and voltage is illustrated in Figure 6. Subplot 6a presents the Battery Current. The peak values of the three-phase voltage and current waveforms vary across the phases; the first phase starts at 1 A at 8.2 s, while the second phase drops to nearly −3 A at 8.7 s. Subplot 6b also depicts the Voltage. A notable power injection from the photovoltaic generator causes the three-phase voltage to rise from 100 V at 8.2 s to −300 V at 8.7 s.

In Table 1, value of COE and NPC in proposed method is compared with other optimization methods like Moth Flame Optimization (MFO), Particle Swarm Optimization (PSO) and Multi-Objective Optimization (MOO). The proposed method has optimal values of NPC and COE than other methods.

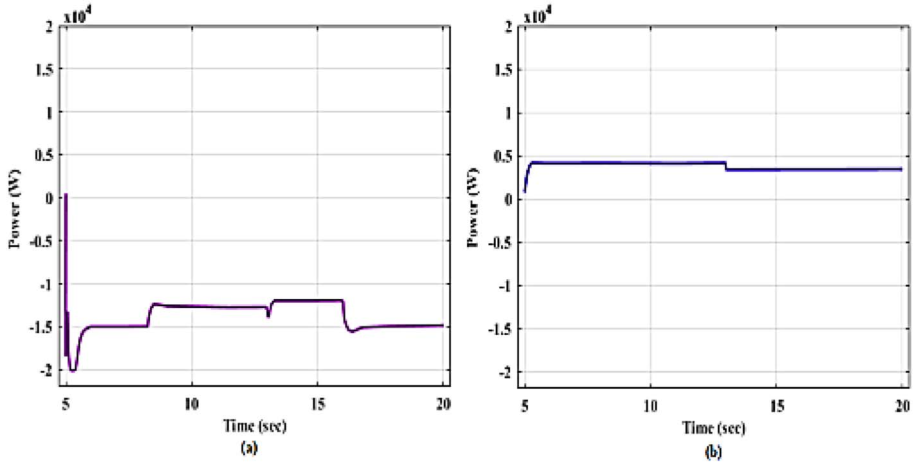

Fig. 3. (a) PV power and (b) WT power.

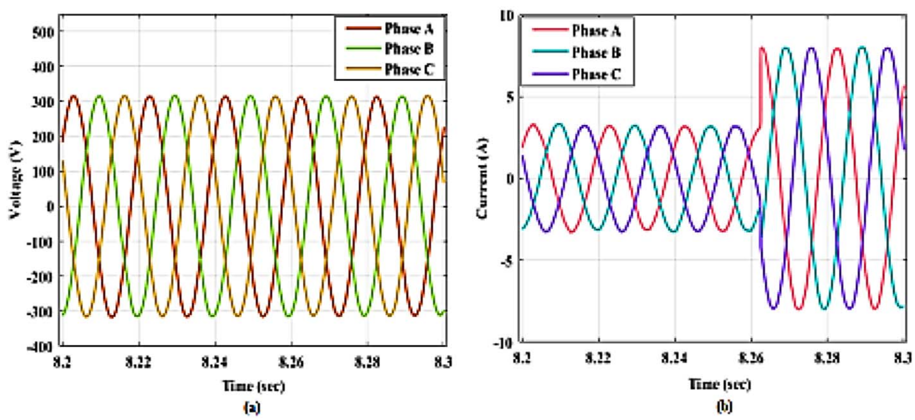

Fig. 4. (a) AC load voltage and (b) AC current.

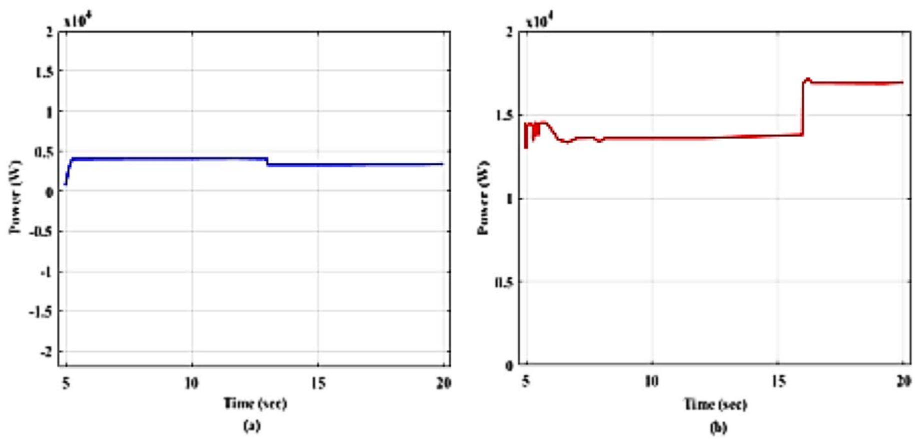

Fig. 5. (a) WT power and (b) battery power.

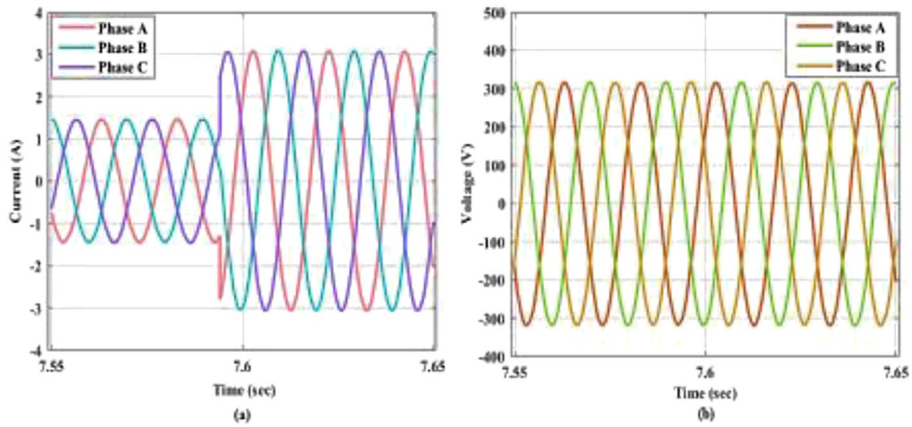

Fig. 6. (a) Three-phase current and (b) three-phase voltage.

Table 1. Value of NPC and COE.

	NPC$	COE$/kWh
Proposed	28,618	0.309
PSO	29,427	0.700
MFO	35,456	0.450
MOO	34,309	0.325

5 Conclusion

This study presented an investigating and determining the most effective design for an energy source specifically aimed at fulfilling the electricity needs of a residential community. In a time when energy efficiency and sustainability are crucial, this study highlights the significance of both technical and economic factors in energy sourcing. It argues that any feasible solution must be efficient in energy production and consumption, dependable in delivery, and financially viable for the residents relying on it. To tackle this complex issue, the study introduces the innovative application of a rotation-invariant coordinate convolutional neural network combined with binary battle royale optimization techniques. These cutting-edge approaches are chosen for their ability to improve the modelling and optimization processes related to energy source design. The main objective of utilizing these methods is to reduce two essential aspects: the net present cost of the energy system and the total energy expenses faced by the residents. The results of this research have the potential to significantly influence the future of energy sourcing in residential areas, leading to the development of more resilient and sustainable energy systems. The suggested approach demonstrates superior values of NPC and COE compared to alternative methods.

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