# Using Imperialist Competitive Algorithm Powered Optimization of Bifacial Solar Systems for Enhanced Energy Production and Storage Efficiency

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*Abstract*—**Interest in renewable energy has grown due to increased environmental awareness and concern about climate change. Among the various renewable energy technologies, grid-connected bifacial PV systems are particularly important due to their higher efficiency compared to conventional systems. However, maximizing energy harvesting and storage efficiency remains a challenge for these systems, requiring the use of an efficient charge controller and an appropriate battery. The process of setting charge controller parameters and selecting the best storage technology is complex and requires a thorough study of various operating conditions. The main research contribution of this paper is the development of an efficient optimization methodology to increase the energy production and storage efficiency of the studied systems using optimization algorithms. The imperialist competitive algorithm (ICA) is used in the system design to improve performance through optimal adjustment of charge controller parameters and selection of appropriate storage technology. This decision was based on factors such as energy production from PV panels, energy consumption from loads, and energy storage in batteries. Performance is also evaluated using both the flower pollination algorithm (FPA) and Gray Wolf optimization (GWO) algorithms. The study evaluated system performance by analyzing energy production, storage efficiency, and cost effectiveness. The results showed that the ICA algorithm is effective in improving energy production and storage, resulting in higher energy output, better battery efficiency, and lower system costs. In addition, lithium-ion batteries were identified as the best storage technology. This research demonstrates the potential of the ICA approach to increase efficiency and reduce costs in the PV systems.**

***Keywords—Renewable Energy; Photovoltaic Systems; Optimization; Grid Integration; Bifacial Solar Panels; Energy Storage; Battery; Imperialist Competitive Algorithm; Lithium-Ion Battery; Lead-Acid Battery.***

## I. INTRODUCTION

The current era is facing significant environmental issues, particularly the impact of global warming and climate change caused by the release of greenhouse gases from the consumption of fossil fuels. This has led to an increased focus on renewable energy as a viable and environmentally friendly alternative for power generation. Among these options, solar energy stands out as a top choice, as it directly harnesses the sun's energy to produce electricity. Grid-connected PV systems are efficient and easy to install, making them a popular choice for power generation in various environments [1], [2].

Solar PV has grown in importance in recent years, driven primarily by cost reductions resulting from policies that promote the transition to a sustainable, green society. In some cases, the levelized cost of electricity (LCOE) for large-scale PV is now lower than that of traditional fossil fuels. A variety of technologies are being used to improve energy capture, including the emerging bifacial PV cells [3]. Bifacial PV systems use cutting-edge technology to capture sunlight from both sides of solar cells, resulting in twice the energy output of conventional systems. While these systems offer numerous benefits, they face obstacles in optimizing energy harvesting and storage efficiency [4]. To realize their full potential, it is critical to have a high-performance charge controller and compatible battery. Fine-tuning charge controller settings and selecting the right battery technology requires a detailed evaluation of several operational factors [5].

Optimization algorithms provide efficient solutions for solving complex problems in various fields, such as renewable energy systems. These algorithms excel at finding optimal solutions through thorough evaluation and analysis of numerous options. In the field of bifacial solar systems, optimization algorithms can be used to improve production and storage efficiency by fine-tuning charge controller settings [6]. The charge controller plays a critical role in managing the power flow between solar panels and batteries.

Optimization algorithms play a critical role in finding the best values for controller parameters, such as charge and discharge voltages, to charge batteries efficiently and avoid overcharging or over-discharging. In addition to selecting the right battery technology, there are several options with different characteristics such as efficiency, capacity and cost. These algorithms help identify the most appropriate battery technology for a bifacial solar system by considering factors such as operating conditions and power requirements [7].

Due to low price and limited space requirement, bifacial solar panels become competitive with traditional ones [8]. A lot of studies have been done about bifacial solar panels, one of them was to compare between bifacial and monofacial PV panels in terms of efficiency. The study was conducted to determine the quality changes of the total amount of solar energy impinging on the surface of solar panels (from solar energy to electrical energy). A study showed that bifacial solar panels have an 11% higher efficiency than monofacial panels. When equipped with a solar tracking system, the efficiency of bifacial panels can reach up to 27%. This means that fewer bifacial panels are needed to generate the same amount of solar power as a traditional monofacial solar array [9]. Fig. 1 shows the growth rate of bifacial vs. monofacial PV cells around the world during (2020-2024).

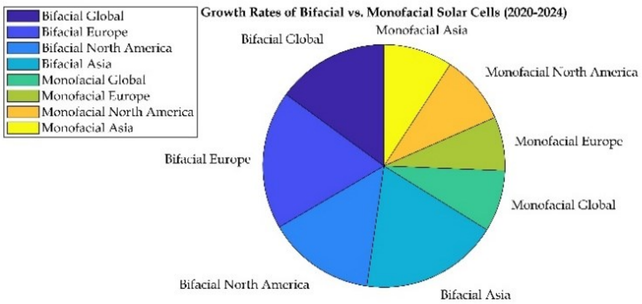


Fig. 1. The growth rate of bifacial vs. monofacial PV cells

In addition, a study conducted in Jordan analyzed real-world data from monofacial (mPV) and bifacial (bPV) solar systems and found that bPV offers increased reliability with fewer panels required. This results in a smaller footprint, lower cost and reduced environmental impact, positioning bPV as a promising technology for future solar projects [10]. The challenges faced by researchers in modeling the electrical behavior of PV panels led to the development of a new method, Novel Hybrid Differential Evolution and Artificial Bee Colony Intelligence (nDEBCO), which combines two established techniques. This method proved to be highly accurate in estimating solar panel parameters under various conditions, with efficient computational times suitable for real-world applications. Real data and simulations confirmed its effectiveness, even for partially shaded panels, although the complexity of the combined techniques posed a challenge. The complexity resulting from the combination of the two techniques used was the only obstacle to the research conducted [11].

A new technology has been used in India called adaptive-local-attractor-based quantum-behaved particle swarm optimization (ALA-QPS) in [12] that works to improve the renewable energy system, solar and wind energy, in smart cities with battery storage systems. In order to maintain a balance of cost, battery life, and no power outages. A promising setup with low cost, reliable power and long battery life was achieved, even considering future challenges.

The design of hybrid renewable energy systems (HRES) incorporating bifacial PV cells has been optimized using a nature-inspired algorithm in [13]. This algorithm attempts to strike a balance between reducing system cost and increasing power output, resulting in more efficient and economical HRES designs. While offering automation and efficiency, further research is needed to compare different optimization algorithms and assess the effects of weather variations and real-world constraints.

In [14], machine learning is used to control energy flow in solar PV systems with battery storage. By examining historical data, the machine learning model can predict future weather patterns and energy demand, ultimately improving system performance and potentially reducing the need for weather forecasts. It is important to note that the success of the model depends on the accuracy of the training data and does not take into account computational requirements or the possibility of bias.

The feasibility of using bifacial solar PV systems was investigated in [15] by comparing different tracking systems and battery storage options. The study evaluates how these choices affect performance, energy output, and overall cost. It provides valuable guidance for selecting the most economical setup based on individual project requirements and financial considerations. However, the analysis did not address optimization of control strategies or the influence of weather variability, and its findings were limited to a specific scenario.

The optimization of a hybrid system using bifacial solar panels and batteries was achieved using the multi-objective evolutionary algorithm in [16]. This algorithm considers several objectives simultaneously, including maximizing power output, minimizing cost, and extending battery life. The study demonstrates the effectiveness of MOEA in balancing these conflicting objectives for this particular system. Although MOEAs are adaptable and ideal for such challenges, they may require computational resources and fine-tuning of the algorithm may be necessary to achieve an optimal balance.

In [17], a new hybrid optimization method is presented that combines the Gray Wolf Algorithm (GWO) and the Whale Optimization Algorithm (WOA) specifically for grid-connected, two-sided PV systems. The aim is to exploit the strengths of both algorithms to achieve superior results. The study shows that this hybrid method outperforms conventional technologies in terms of energy production and cost efficiency, highlighting the potential benefits of combining algorithms to optimize a two-sided solar system. However, careful design and parameter tuning are critical for optimal performance.

The tilt angle and module array of bifacial solar PV systems were optimized using the innovative Moth-Flame Optimization (MFO) algorithm, inspired by the foraging behavior of moths. The results showed that MFO significantly improved the power output and system performance, suggesting its promise as a novel tool for bifacial solar system optimization. Further studies are needed to evaluate MFO against other methods and to determine its sustainable effectiveness in this context [18].

While numerous optimization algorithms have been applied to improve energy efficiency and enhance storage capabilities, most of them lack in-depth analysis and are limited to performing economic comparisons only. Moreover, bifacial PV systems continue to face significant hurdles in energy management and storage due to the complex dynamics of system interactions and the need to harmonize various factors such as cost, battery lifetime, and efficiency in specific operating scenarios. Therefore, it is imperative to explore the appropriate approach and configuration to effectively fine-tune the charge controller and select the optimal battery to improve both energy harvesting and storage efficiency to achieve peak performance of these systems without compromising environmental and economic considerations.

This study presents a method to improve energy harvesting and storage in bifacial solar arrays through the use of ICA. By using an algorithm to automatically regulate the charge controller and determine the appropriate battery, reliance on manual evaluation is minimized, resulting in improved system efficiency.

The potential of this study for the advancement of solar energy is great. By using intelligent algorithms to improve energy capture and storage, the system can increase efficiency, promote sustainability by reducing dependence on non-renewable energy sources, reduce long-term costs, improve system reliability, and drive technological advancements in solar power.

The main focus of this paper is to improve the functionality of bifacial solar systems through several key enhancements. The goals include fine-tuning charge controller configurations to improve efficiency and reduce power waste, identifying the most appropriate battery for extended life and increased storage capacity, and optimizing power output by effectively utilizing sunlight from both panel surfaces. The research also aims to improve system efficiency by reducing energy costs and improving resource utilization. Finally, the Imperial Competitive Algorithm (ICA) is introduced as a novel approach to evaluate and improve the effectiveness of bifacial solar systems.

The main research contribution in this thesis is the development of a more efficient optimization method to improve energy generation and storage in bifacial solar systems using the ICA algorithm. This technique simplifies the process of tuning the charge controller and selecting the optimal battery. Notable aspects of the proposed method include:

- Improved performance: The proposed approach achieves increased energy production, improved storage efficiency, and reduced system cost.
- Automated control: The approach reduces the need for manual analysis and improves overall system efficiency.
- Practical application: The approach can be applied to bifacial solar systems in homes, businesses, and public facilities.

Therefore, the contributions of the system are summarized as follows:

- Interest in bifacial PV energy systems due to their high efficiency compared to traditional photovoltaic systems.
- Highlighting the challenge of maximizing energy harvesting and storage efficiency, which requires optimization of charge controller parameters and battery selection.
- Propose an approach based on the Imperial Competitive Algorithm (ICA) to optimize factors related to energy efficiency and storage and compare it with the Flower Pollination Algorithm (FPA) and the Gray Wolf Optimization (GWO) algorithm.
- Perform a comparative analysis of the effectiveness of each of the algorithms (ICA, FPA, GWO).
- Provide a comprehensive perspective on system optimization by considering factors such as energy production, consumption, storage, and cost.

The rest of this paper is organized as follows: section 2 Bifacial solar panels in terms of efficiency, design, characterization, modules and applications. Section 3 shows the principles of the used algorithms. Section 4 presents the comprehensive comparison for the batteries. Section 5 presents using ICA to improve energy efficiency in grid-connected bifacial PV systems. Finally, section 6 concludes the paper.

## II. Bifacial Solar Panels in Terms of Efficiency, Design, Characterization, Modules and Applications

### A. *The Efficiency of Bifacial PV Panels*

Bifacial PV cells operate over a wide range of voltages and currents. By increasing the resistive load from zero to a high value, where zero represents a short circuit and high value represents an open circuit, it is possible to determine the maximum power as a multiple of the maximum voltage and the maximum current [17]. In order to understand the performance of bifacial PV systems, it is necessary to highlight several factors that are used to evaluate the performance of these systems. Energy conversion efficiency is one of the most important of these factors. It is a measure of the efficiency of the solar cell and expresses the percentage of light energy that can be converted into electrical energy. The energy conversion efficiency $\eta$ of bifacial solar cells is given by (1):

$$\eta = \frac{P_m}{E.A_c} \tag{1}$$

where, $P_m$ is the maximum value of the produced power $(W)$. $E$ is the input light irradiance $(W/m^2)$. $A_c$ is the surface area of the solar cell $(m^2)$.

The fill factor (FF) is another key indicator of solar cell performance, ranging from 0 to 1. Higher quality bifacial PV cells tend to have a higher FF, which affects the overall efficiency. FF is influenced by material properties, cell design, and manufacturing quality. It is calculated as the ratio of maximum power to the product of short-circuit current and open-circuit voltage, as shown in (2).

$$FF = \frac{P_m}{V_{oc}.I_{sc}} = \frac{\eta.E.A_c}{V_{oc}.I_{sc}} \tag{2}$$

where, $V_{oc}$ is the open circuit voltage $(V)$. $I_{sc}$ is the short circuit current $(A)$.

## B. Bifacial PV Panels Losses

The yield of solar cells decreases due to the losses that occur in them. In addition, these losses affect the performance of a solar cell by reducing the short-circuit current. There are several types of loss mechanisms in bifacial solar cells, and each type affects certain parameters. Optical losses affect the short-circuit current. Whereas, recombination losses affect both open circuit voltage and short circuit current. FF is affected by resistive losses. Finally, thermal losses affect both the open circuit voltage and the FF.

Bifacial PV cells experience the same loss mechanisms as standard solar cells, as well as additional factors unique to their bifacial structure. Bifacial solar cells face the usual losses found in all solar cells, including reflection (which can be reduced by anti-reflective coatings), recombination (mitigated by high-quality materials and cell design), and ohmic losses (reduced by using thicker or more conductive materials). In addition, there are specific losses that affect bifacial cells. Back sheet shading can be minimized by adjusting cell spacing and system layout.

Spectral mismatch, where the back side is less responsive to certain wavelengths, can be improved by optimizing cell materials and coatings for a wider spectral range. Finally, dirt on both the front and back surfaces can greatly affect performance. Regular cleaning and selection of an optimal tilt angle to prevent dust buildup are essential to maintaining peak efficiency of bifacial cells.

In addition to typical and special losses, the efficiency of bifacial solar cells depends on the design of the cells and the balance between front and back light capture (bifaciality factor). While it is beneficial to capture more back light, too much can lead to overheating and reduced performance. To maximize the efficiency advantage of bifacial solar cells over traditional options, it is important to optimize cell texture, use passivation layers, and address all loss mechanisms through coatings, design improvements, and regular cleaning in appropriate applications. Fig. 2 shows the losses percentages for traditional and bifacial PV systems.

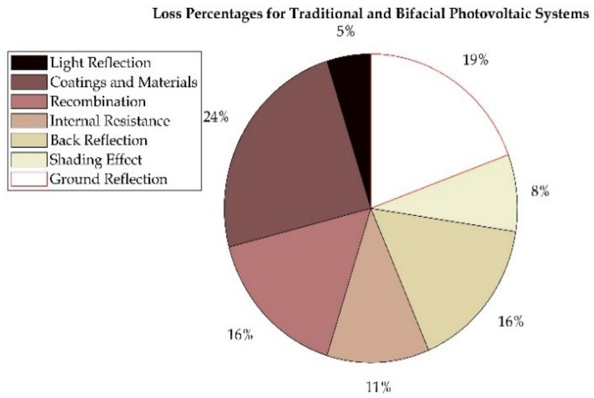


Fig. 2. The losses percentages for traditional and bifacial PV systems

## C. Efficiency Measuring of Bifacial PV Panels

Measuring cell efficiency is one of the most fundamental solar cell characterization techniques, and it is difficult and expensive to construct a system that meets all standard test conditions simultaneously. Measuring solar cells requires a stable light source that closely mimics the conditions of sunlight. Not only the intensity, but also the spectrum must be matched to a standard [19].

Efficiency testing for bifacial PV involves measurements under specific conditions, such as a cell temperature of 25°C, an irradiance of 1000 W/m2, and an AM 1.5 spectrum. Artificial light is used to simulate these conditions on either the front or back of the cell, and current and voltage measurements are taken to determine the maximum power. Measurements can be taken separately for each side or simultaneously for both sides to assess the overall efficiency of the cell. This efficiency is calculated by comparing the maximum power generated by the cell to the optical power applied to it, providing an accurate assessment of how well bifacial cells will perform in real-world conditions.

To improve the accuracy, $V_{oc}$ and $I_{sc}$ be measured separately (by setting the voltage to zero and the current to zero, respectively) from the rest of the curve. The most important characteristics of bifacial solar panels are I-V curves in addition to QE power and transmission among others, for both sides of the solar cell. Reflective surfaces and back sheets have also been characterized in terms of their reflection, absorption and transmission properties [20].

## D. The Characteristics of Bifacial PV Panels

By studying the characteristics of bifacial PV panels, it was discovered that the efficiency of the cell was increased because of the reflected light on the metal chuck after passing through it, as shown in Fig. 3.

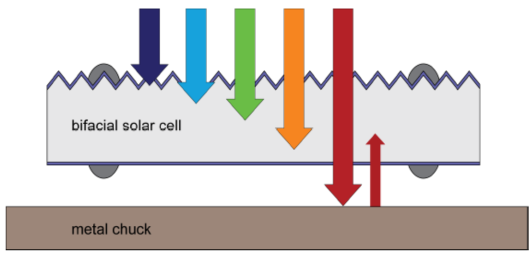


Fig. 3. Scheme of light passing through a bifacial solar cell and reflected back at the surface of a metal chuck

The power of bifacial photovoltaic panels is calculated using mathematical equations that take into account various factors that affect this power, such as the intensity of solar radiation, the angle of incidence, the panel efficiency, and the bifacial factor. The power generated by the front panel is given by (3):

$$E_{front} = G_{front} * A * \eta_{front} \quad (3)$$

where, $E_{front}$ is the front panel power $(W)$. $G_{front}$ is the solar irradiance on the front side $(W/m^2)$. $A$ is the panel surface area $(m^2)$. $\eta_{front}$ is the front panel efficiency (%).

The power generated by the back side is given by (4):

$$E_{back} = G_{back} * A * \eta_{back} \quad (4)$$

where, $E_{back}$ is the back panel power $(W)$. $G_{back}$ is the solar irradiance on the back side $(W/m^2)$. $A$ is the panel surface area $(m^2)$. $\eta_{back}$ is the back panel efficiency (%).

The total panel power is calculated according to (5):

$$E_{total} = E_{front} + E_{back} \quad (5)$$

where, $E_{total}$ is the total panel power $(W)$.

Because of the multiple benefits of bifacial PV panels, they are used in a variety of applications, including large solar farms to increase productivity by capturing light reflected from the ground, and in urban environments such as building rooftops and curtain walls to optimize space and reduce costs. They are also used in snowy and desert regions to take advantage of natural reflections and increase efficiency, and can be paired with sun tracking systems for consistent high performance. These panels are increasingly favoured in projects aimed at increasing the sustainability and efficiency of renewable energy generation.

## III. Introduction about Artificial Intelligence Algorithms

Over millions of years, nature has ingeniously developed various solutions to challenging problems. With the success of biometric features, numerous algorithms have emerged in the last decades [20]. In engineering and industrial design applications, finding the optimal solution under complex conditions is essential. Nonlinear optimization problems pose a significant challenge, as traditional methods often fall short when dealing with multi-constraint systems. The dominant approach today is to use nature-inspired algorithms to solve these complex problems. These techniques have gained popularity due to their simplicity, prompting researchers to innovate and introduce novel methods [21].

The primary goal of improvement is to achieve the most optimal design based on a specific set of criteria or constraints to achieve a solution that excels in cost effectiveness, productivity, strength, performance, reliability, efficiency, and usability [22]. This can be accomplished by maximizing favourable factors and minimizing unfavourable factors within the given constraints. An optimization model is a mathematical representation used to optimize the objective function while satisfying the key constraints [23]. Optimization algorithms involve a repetitive process of evaluating different solutions until the best solution is identified. The integration of computers has made optimization an integral part of computer-aided design processes [24].

### A. The Imperialist Competitive Algorithm ICA

The Imperialist Competitive Algorithm (ICA), inspired by colonization, tackles continuous optimization problems. It starts with a population of "empires" (colonizers and colonies). Stronger empires attract colonies, and weak empires are eliminated until a single empire with the optimal solution remains. This evolutionary algorithm iterates through processes such as movement, revolution, and competition, mimicking the dynamics of colonial expansion [25].

ICA begins by creating a set of variables to optimize, similar to chromosomes in genetic algorithms. These variables, called countries, compete to become colonizers, forming empires that include less powerful countries as colonies [26]. The power of an empire is determined by the number of colonies it has. In this paper, ICA is chosen for its effectiveness in finding optimal solutions in complex optimization problems, and its ability to mine multiple paths simultaneously to avoid being limited to local solutions, making it suitable for improving the efficiency of two-sided solar energy systems and storage management [27].

The country is represented in the ICA algorithm as in (6):

$$country = [p_1 \quad p_2 \quad p_3 \quad . \quad \cdot \quad \cdot \quad p_{nvar} \quad (6)$$

The previous relation indicates the variable that will be modelled by the algorithm studied, that the cost of each country can be calculated by evaluating the location of each country as described in (7):

$$country = f(country) = f(p_1, p_2, p_3, .., p_{nvar} \quad (7)$$

The colony is evaluated based on the strength of the colonists. the distribution of the colonies must depend on the appropriate colonizer, so the cost of the colony must first be evaluated based on certain calculations according to (8):

$$C_n = c_n - \frac{max}{i_i} \quad (8)$$

where, $C_n$ is the nominal cost function. $c_n$ is the colonizer cost.

Empire power is opposite to cost, which means that imperialist competition is minimal technology [28]. Moreover, the power of each colonizer can be calculated as (9), and the number of initial colonies of an empire n can be represented in (10) [29]:

$$p_n = \left| \frac{C_n}{\sum_{i=1}^{Nimp} C_i} \right| \quad (9)$$

$$N.C.n = round\{p_n, N_{col}\} \quad (10)$$

where, $N.C.n$ is the initial number of colonies for the empire nth. $N_{col}$ is the early imperial number.

Each of the colonies together with the colonizer immediately forms the empire $n$, and the empire is formed by the total colony as shown in Fig. 4.

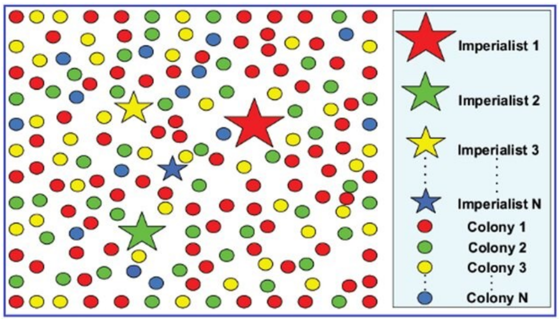


Fig. 4. Initializing Empires in the Imperialist Competitive Algorithm (ICA) [25]

The colonizer tries to improve his colonies by transferring all colonies to him. The movement of his colonies is shown in Fig. 5.

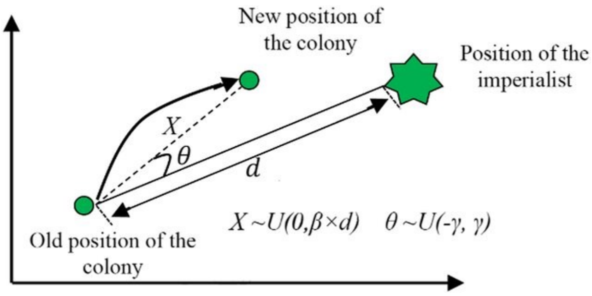


Fig. 5. Movement of the colonies towards colonist [25], [26]

If this movement continues, it will make all the colonies move with the movement of the colonizer, and it is expressed mathematically for the previous form as (11):

$$x \sim \mathrm{U}(\mathrm{o}, \beta_{\mathrm{xd}}) \tag{11}$$

The value of $\beta$ is a fixed number greater than one. For modelling, a non-standard random number of movements was added, which is expressed according to (12):

$$\theta \sim U(-\gamma, \gamma) \tag{12}$$

Since $\gamma$ is the parameter that controls the deviation from the initial direction. The values of each of $\gamma$, $\beta$ aren't chosen at random, $\beta$ values are chosen 2 and $\gamma$ values are chosen $\pi/4$ to ensure a better convergence to the minimum limits [29].

In the Revolution step, a colony may rebel against its current colonizer if it finds a better option (lower cost). If this happens, their positions are swapped, with the colony becoming the new leader and the former colonizer becoming a colony itself. The algorithm then continues with this new configuration as shown in Fig. 6 [26], [27].

During Movement, colonies and colonizers can merge into a new empire if they are very close to each other. The colonizer has a large effect on the power of the empire, but his own costs also play a small role. The total cost of an empire is the sum of the cost of the colonizer and the average cost of his colonies as shown in (13).

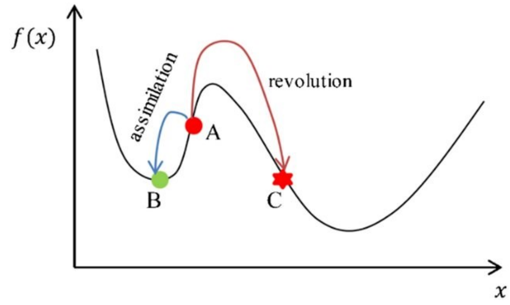


Fig. 6. Revolution and assimilation process in ICA [25]

$$\begin{aligned} T.C_n &= \cos t\,(imperialist_n) \\ &+ \zeta.mean\{\cos t\,(coloniesofempire_n)\} \end{aligned} \tag{13}$$

where, $\zeta$ is the impact of the colony. $T.C_n$ is the total cost of the empire $n_{th}$ with a positive value less than 1.

In the competition phase, weaker empires lose colonies to stronger ones. The probability of losing a colony depends on the overall strength of the empire. This process helps eliminate weak empires and allows strong empires to grow as (14) shows.

$$N.T.C._n = T.C_n - max_i\{T.C_i\} \tag{14}$$

The probability of ownership for each empire is given by (15):

$$p_{pn} = \left| \frac{NTC_n}{\sum_{i=1}^{Nimp} NTC_i} \right| \tag{15}$$

Weaker empires lose colonies to stronger ones during the competition phase. Eventually, the weakest empire loses all its colonies and is eliminated. Fig. 11 shows the flow chart of ICA.

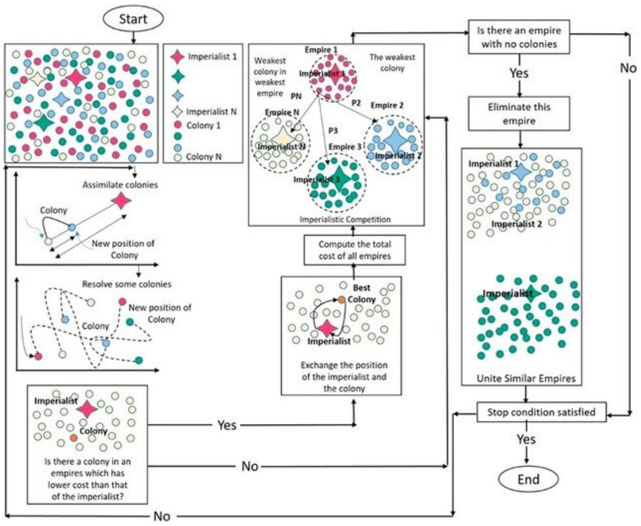


Fig. 7. Flow chart of ICA [26]

## IV. Comprehensive Comparison of Batteries Across Different Specifications

### A. Traditional Comparison

The selection of a suitable battery for storing solar energy in bifacial solar panel systems is subject to a number of criteria, the most important of which are usable storage capacity (kWh), charge and discharge losses, initial cost, lifetime, density, efficiency, ...etc [30].

In home applications, two important things to consider are the type of battery and what we want to get out of it. There are four battery technologies, each with a set of unique characteristics. The most important of these technologies are lead-acid batteries, which are characterized by their deep-cycle energy storage over a long period of time, in addition to their reliability and low economic cost. These batteries require ventilation and periodic maintenance, which increases the likelihood of energy leakage, resulting in reduced battery life [30], [31].

Nickel-cadmium batteries are often used, whose main characteristics are that they are durable, can work in extreme temperatures and don't need maintenance, but they have one big problem, which is that they are very toxic. It is preferable to use it in commercial projects because it doesn't require complex systems to manage it [31].

Flow batteries are an emerging technology in the energy storage sector and contain an electrolytic fluid that flows in tanks inside the battery [32]. Their large size and high price make them difficult to use in residential applications. Their main characteristic is the depth of discharge up to 100%, which means that it is possible to use all the energy stored in the battery without damaging it. These batteries are much more expensive than others and have a relatively low storage capacity, to be effective it must be large in size [33].

Lithium-ion batteries are the newest and best for residential solar installations because they can store more energy in a given space. It has a higher depth of discharge than other batteries and requires no maintenance, but it's expensive and can catch fire [34], [35], [36].

Fig. 8, Fig. 9, and Fig. 10 show the comparison between the most common types of home application batteries in terms of lifetime, density and efficiency. As shown in Fig. 8, lithium-ion batteries have the longest life, about 10 years. On the other hand, nickel-cadmium has the shortest life.

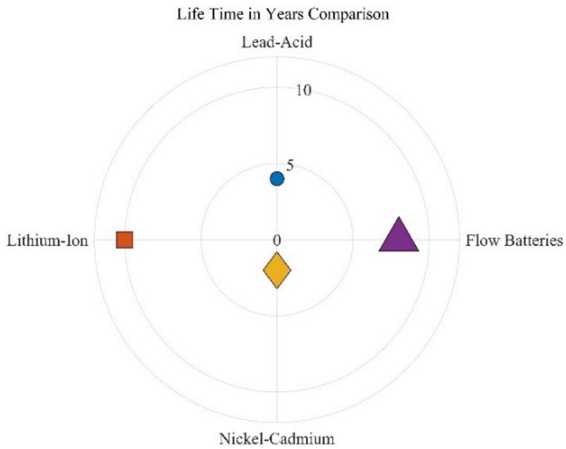


Fig. 8. Comparison of batteries life time

On the other hand, the efficiency of the batteries is between 75% and 95%. The lithium-ion battery has the best efficiency with 95%, then lead-acid with 85%, flow battery with 80% and finally nickel-cadmium with 75%. Fig. 9 shows the efficiency of batteries in domestic applications.

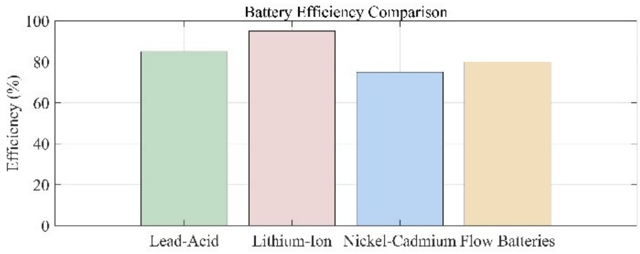


Fig. 9. Comparison of batteries efficiency

Although the nickel-cadmium battery has the lowest characteristics in terms of efficiency and lifetime, the nickel-cadmium battery has the second highest density with 115 Wh/kg. The lithium-ion battery has a density value of 260 Wh/kg. Fig. 10 shows comparison of batteries energy density.

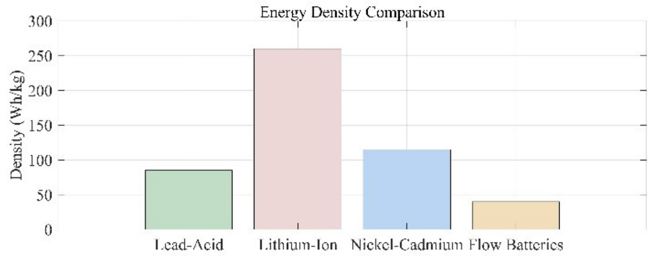


Fig. 10. Comparison of batteries energy density

Table I presents a comprehensive comparison of the batteries used in PV systems (lead-acid, lithium-ion, nickel-cadmium, and flow batteries) in terms of their capacity, cycle life, and self-discharge rate [37]. Whereas, Table II presents a comprehensive comparison of these batteries in terms of cost, size, weight, and applications [38], [39].

TABLE I. PHYSICS CHARACTERISTICS COMPRESSION

| Battery Type | Capacity (Ah) | Cycle Life | Self-Discharge Rate |
|---|---|---|---|
| Lead-Acid | 200 - 1000 | 200 - 500 | 3-5% per month |
| Lithium-Ion | 100 - 500 | 500 - 1000 | 2-3% per month |
| Nickel-Cadmium | 100 - 500 | 500 - 1000 | 20-30% per month |
| Flow Batteries | 100 - 1000 | 1000 - 2000 | 1-2% per month |

Based on comparison tables, lithium-ion batteries are the top choice for residential use because of their high capacity, long cycle life, and minimal self-discharge rate. Although they are the most expensive option, they outperform lead-acid batteries, which are more budget-friendly but have a shorter cycle life and higher self-discharge rate. Nickel-cadmium batteries fall in the middle, with a moderate cycle life and self-discharge rate, making them ideal for power tools. Flow batteries, on the other hand, are best suited for grid-scale applications due to their high capacity and long cycle life, although they come at a higher price [40], [41].

Lithium-ion batteries are preferred for their high energy density and long life, making them a top choice for various applications. However, there is growing concern about the environmental impact of lithium mining and e-waste disposal. In contrast, lead-acid batteries have a low environmental impact and are easy to recycle, but they pose safety risks from acid leaks and lead poisoning. Nickel-cadmium batteries pose environmental risks from cadmium toxicity and are expensive and difficult to recycle.

TABLE II. COST, WEIGHT, AND SIZE COMPRESSION

| Battery Type | Cost | Weight | Size | Other Applications |
|---|---|---|---|---|
| Lead-Acid | Low | Heavy | Large | Residential, Backup Power |
| Lithium-Ion | High | Light | Small | Residential, Electric Vehicles |
| Nickel-Cadmium | Medium | Medium | Medium | Residential, Power Tools |
| Flow Batteries | High | Heavy | Large | Residential, Grid-Scale |

## B. Using ICA Algorithm to Choose the Best Storage Technology

To improve home energy storage using the ICA algorithm, various considerations must be taken into account, with key aspects including cost, storage capacity, charge/discharge cycles, depth of discharge, efficiency, safety, environmental impact, ease of use, performance, and reliability. The optimization process involves comparing nickel-cadmium, LED-acid, and lithium-ion batteries using the ICA algorithm's objective function to identify the battery technology that provides the optimal balance of these factors. It is important to evaluate the factors and adjust the weights based on priorities. For simplicity, the three battery types were compared in terms of cost, storage capacity, charge/discharge cycles, depth of discharge and efficiency. As shown in Table III, the ICA algorithm parameters are set as follows:

TABLE III. ICA PARAMETERS VALUE FOR HOME ENERGY STORAGE

| Parameter | Value |
|---|---|
| Country Numbers | 3 |
| Initial Imperialist | 6 |
| Decades | 50 |
| Revolution ratio | 0.1 |
| Absorption coefficient | 2 |
| Absorption angle coefficient | 0.5 |
| Zeta | 0.1 |
| Dumping ratio | 0.99 |
| Unit threshold | 0.2 |

The steps of the algorithm are implemented as follows:

**First:** Define factors and variables

- Factors: Cost (P): The cost of the battery ($). Storage capacity (C): The energy storage capacity of the battery (Wh). Number of charge/discharge cycles (I): The number of times the battery can be charged and discharged before it is damaged. Depth of Discharge (DOD): The maximum percentage of battery capacity that can be discharged without damage.
- Variables: Pi: The cost of battery type i. Ci: The storage capacity of the battery type i. Ni: The number of charge and discharge cycles of battery type i. DODi: Depth of discharge of battery type i. EEi: Efficiency of the battery type i.

**Second:** Representing Battery Types as Countries.

Each battery type (nickel-cadmium, lead-acid, lithium-ion) is represented as a country in the ICA model.

**Third:** Set initial values.

The Pi, Ci, Ii, DODi and EEi values for each battery type is determine as Table IV shows.

TABLE IV. BATTERIES INITIAL VALUES

| Battery Type | Pi (Cost) ($/kWh) | Ci (Storage Capacity) (KWh) | ni (Cycles) | DODi (Depth of Discharge) (%) |
|---|---|---|---|---|
| Nickel Cadmium | 150 | 0.5 | 2000 | 80% |
| Lead-Acid | 100 | 1.0 | 1500 | 50% |
| Lithium-Ion | 250 | 2.0 | 5000 | 100% |

**Fourth:** Create Colonies

This step involves two steps, the first step is to create a group of colonies, each representing a potential energy storage solution for a home user, and the second step is to assign each colony to a country (battery type) based on its initial characteristics.

**Fifth:** Movement and Revolution

- Movement: Colonies can move to another country (battery type) if they find a better fit based on certain factors.
- Revolution: Colonies may rebel against their current country (battery type) if they are dissatisfied with its performance.

**Sixth:** Exchange and Incorporation

- Exchange: Countries (battery types) can swap colonies (users) to improve their overall performance.
- Incorporation: Weak countries (battery types) with few colonies can merge with stronger countries.

**Seventh:** Calculate the total power:

Calculate the total power of each country (battery type) based on its power and number of colonies (users). This is done by summing the values of each colony (user) using a weighted average, where the weights represent the importance of each factor.

**Eighth:** Imperial Competition:

The algorithm iteratively compares the total performance of all countries (battery types). The weakest country (battery type) is then eliminated and its colonists (users) are redistributed to the remaining countries (battery types).

**Nineth:** Repetition

Steps 5-8 are repeated until only one country (battery type) remains that represents the optimal solution for home energy storage.

The objective function in (16) was used to determine which battery technology achieves the best balance between the specified factors.

$$Maximize\ f(x) = w_P * P + w_C * C + w_I * \left(\frac{1}{I}\right) + w_{DOD} * DOD + w_{EE} * (1 - EE) \quad (16)$$

Where, $w_P$ is the weight of cost factor. $w_C$ is the weight of storage capacity factor. $w_I$ is the weight factor of the number of charge and discharge cycles. $w_{DOD}$ is the weight of depth of discharge factor. $w_{EE}$ is the weight of efficiency factor.

The weight values for each of the factors studied are given in the Table V.

TABLE V. FACTORS WEIGHT VALUES

| Factor | Weight Value |
|---|---|
| $w_P$ | 50 |
| $w_C$ | 20 |
| $w_I$ | 15 |
| $w_{DOD}$ | 10 |
| $w_{EE}$ | 5 |

Based on the weights and criteria in the goal function, the lithium-ion battery stands out with the highest score of 89015, making it the top choice. This analysis concludes that the algorithm favouring the lithium-ion battery is superior in terms of storage technology. Fig. 11 shows the objective function scores for each battery type.

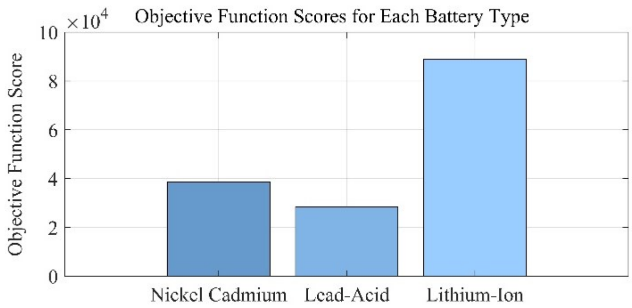


Fig. 11. Objective function score for each battery type

The convergence paths of three unique optimization algorithms-ICA, FPA, and GWO-aimed at achieving optimal values for an objective function representing the peak performance of lithium-ion batteries are shown in Fig. 12. ICA shows rapid convergence, reaching optimal values in the fifth iteration and maintaining stability. FPA shows fluctuations in the 11th iteration, but returns to optimal performance in the 12th iteration. In contrast, GWO shows consistent stability at optimal values after the ninth iteration, eventually reaching the desired goal. These results provide valuable insights into the performance of each algorithm and their respective strategies for finding optimal solutions over multiple iterations, which can help in selecting the most appropriate method based on specific problem requirements.

ICA offers a variety of solutions that effectively combine exploration and exploitation to address numerous challenges. However, its complexity is offset by its speed. On the other hand, FPA is straightforward, extensively studied, and highly flexible, but it can struggle with exploitation and parameter tuning [42]. GWO, on the other hand, is easy to understand, excels at exploitation, and performs effectively on a variety of problems [43]. However, it runs the risk of becoming trapped in local optima and must carefully manage the trade-off between exploration and exploitation.

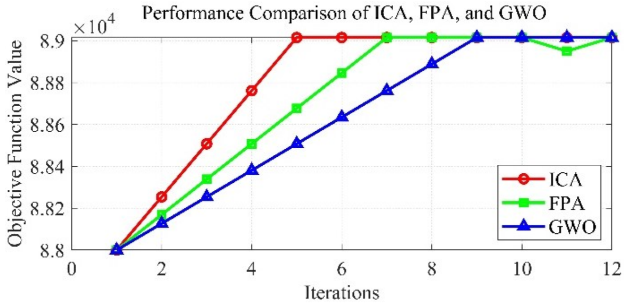


Fig. 12. Performance comparison of the three used algorithms

## V. USING ICA TO IMPROVE ENERGY EFFICIENCY IN GRID-CONNECTED BIFACIAL PV SYSTEMS

The use of ICA to improve the energy efficiency of grid-connected bifacial PV systems represents an advanced optimization approach. Bifacial PV systems offer an increased potential for energy production. To maximize this potential, sophisticated optimization algorithms such as ICA can be used to fine-tune various operating parameters of the system. The ICA navigates a complex multi-dimensional search space to find the optimal set of parameters that result in the highest energy output and efficiency.

The PV modules, inverter, charge controller, battery storage, and load are all part of the studied system shown in Fig. 13, which is also connected to the electrical grid.

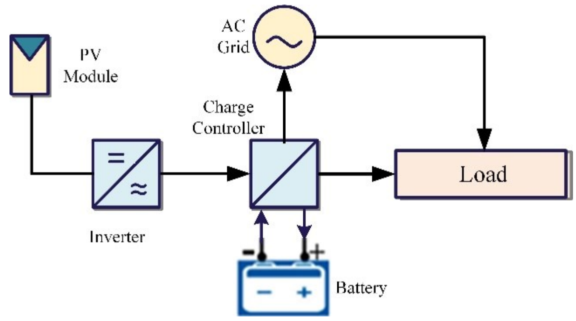


Fig. 13. The main components of the studied system

To increase the efficiency of these systems, a charge controller is used to determine the direction of energy flow. The power produced by the bifacial PV modules is used to meet the load demand, and the excess power produced by the bifacial PV modules is used to charge the battery when it needs to be charged, and the rest is sold to the grid. As for when the production from the modules is less than the demand, the lack of power is compensated by the battery when it's charged, and the rest is purchased from the grid.

For the purpose of this study, the ratio between the battery capacity and the power produced by the PV modules changes from 0 (no charge) to 2 kWh/kWp. Typically, the battery state of charge (CSB) changes according to the limited capacity range, which ensures both good performance and safety, in addition to the long life of the system. Self-sufficiency rate (SSR), another important factor, is defined as the ratio between the power supplied (from bifacial PV modules) and the load demand. The Self-

Consumption Rate (SCR) is the ratio between PV production and the portion of PV production that is consumed by the loads. This ratio can be a value between 0% and 100%, where 100% solar self-consumption means that all the PV energy produced is consumed by the loads.

The maximum state of charge value is set at 95% of the total storage capacity and the depth of discharge is set at 20%, assuming no losses in both the charge and discharge cycles. while the inverter efficiency depends on the efficiency of power conversion from DC to AC, the inverter efficiency is set at 97.15%.

The MATLAB model is created to calculate the power sold and purchased from the grid and to determine the CSB. The block diagram of the system under study is shown in Fig. 14.

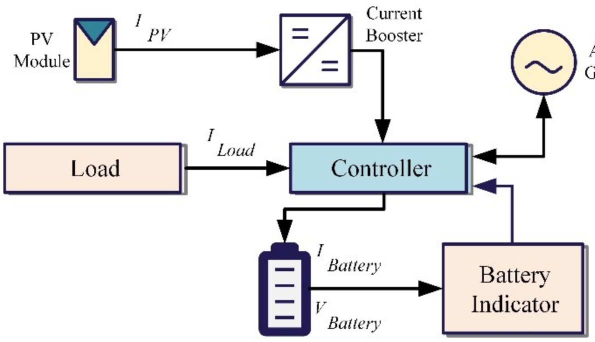


Fig. 14. The block diagram of studied system methodology

### C. PWM Charger

The PWM charge controller circuit consists of the following components:

- Current booster: This booster is used to allow the maximum values of the current generated by the bifacial solar modules to flow to the battery. The circuit consists of booster circuit LM317, transistor and blocking diodes as shown in Fig. 15.

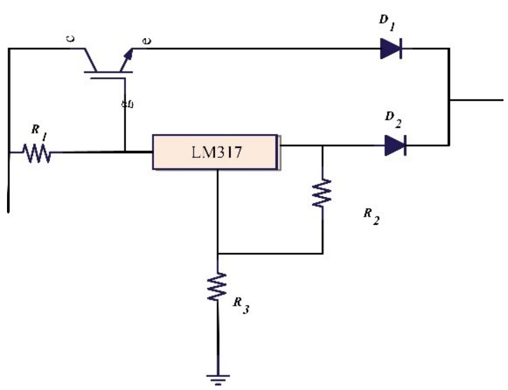


Fig. 15. The current booster circuit

- Battery Level Indicator: This meter monitors the charging of the battery to determine if the battery can meet the load demand. The battery level indicators stop charging the battery when it's full.

- Battery Charge Controller: The charge controller circuit consists of comparators, controllers (Proportional Controller P, Proportional Integral Controller PI). The proportional controller P is used to control the voltage to obtain the required power for the load demand. While the PI controller is used to organize the flow of current.

The type of charge controller is PWM type. The main purpose of the controller is to observe each of load demand and power generated by PV modules, and battery state. The ICA algorithm work for achieving the load demand by optimally adjusting the controller constants to achieve both of VOC and ISC for the module. The typical equivalent circuit for a bifacial solar cell is shown in Fig. 16.

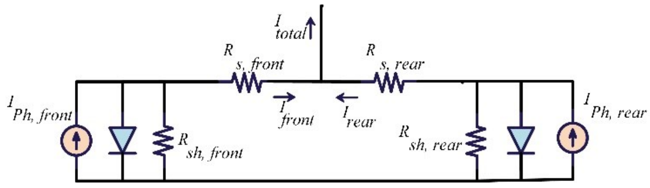


Fig. 16. The typical equivalent electrical circuit for a bifacial solar cell

The mathematical model of bifacial PV cell is as follow:

$$P_{bifacial} = I_{sc,bi}.V_{oc,bi}.FF_{bi} \tag{17}$$

$$I_{sc,bi} = R_{sc}.I_{sc,front} \tag{18}$$

$$V_{oc,bi} = V_{Oc,front} + \frac{(V_{oc,rear} - V_{Oc,front}).\, ln\,(R_{sc})}{ln\,(I_{sc,rear} - I_{sc,front})} \tag{19}$$

### D. The Cost function for Selecting the Best Values of Controllers in Charge Controller

The ICA algorithm is used to determine the best parameters for the controllers used in the charger controller. The objective function of the system involves calculating the integral of the absolute difference between the output current from the bifacial modules and the combined load current and battery charging current.

$$Objective\ Function == \frac{1}{n}.\int_o^t \sum_{i=1}^{n} |Ygi - [YLi + (YMi - Yxi)]|.\,dt \tag{20}$$

Where, $n$ is the observes number. $YLi$ is the generated power from PV modules. $Yxi$ is the storage power in battery. $YMi$ is the total capacities of battery.

The ICA parameters are set to the values listed in Table VI.

TABLE VI. ICA PARAMETERS VALUES FOR CHAGER CONTROLLER ADJUSTMENT

| Parameter | Value |
|---|---|
| Country Numbers | 50 |
| Initial Imperialist | 6 |
| Decades | 50 |
| Revolution ratio | 0.1 |
| Absorption coefficient | 2 |
| Absorption angle coefficient | 0.5 |
| Zeta | 0.1 |
| Dumping ratio | 0.99 |
| Unit threshold | 0.2 |

The high and low limits of the variables are selected as shown in Table VII.

TABLE VII. HIGH AND LOW LIMITS OF CONTROLLER CONSTANTS

| **Proportional Controller P** | **High Limit** | **Low Limit** |
|---|---|---|
| Proportional Gain KP | 0 | 20 |
| **Proportional integral controller** | **High Limit** | **Low Limit** |
| Proportional Gain KP | 0 | 100 |
| Integral Gain Ki | 0 | 10 |

### *E. Studied System Results*

For the generated power in 1 m$^2$ of the used installation, the number of modules varies from 1 to 6 modules, which means that the effective area ranges from 1.34 m$^2$ to 8.04 m$^2$. Thus, the power varies from 0.27 kWp to 1.62 kWp.

To explain the variation of the power generated by bifacial PV modules, a 340W module is mathematically modelled. The average monthly energy consumption is estimated. The results of the monthly average power output per W are shown in Fig. 17, taking into account that the module is fixedly installed to the southwest, tilted at an angle of 45 degrees.

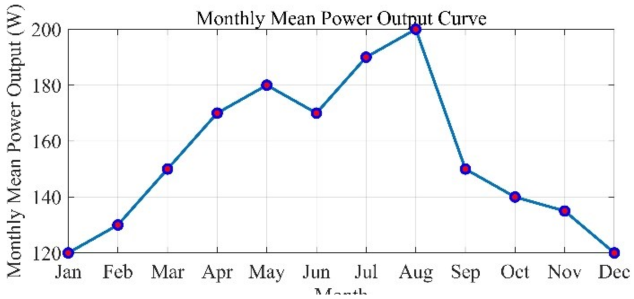


Fig. 17. The monthly mean power output of the studied system

The efficiency of bifacial solar panel used in studied system per kW/kWp is shown in Fig. 18. The outstanding performance of bifacial PV panels is illustrated in Fig. 18, which shows their ability to achieve efficiencies of up to 0.6% in the afternoon. This result demonstrates the significant benefits of harnessing both direct and reflected solar radiation, and highlights the potential for increasing the efficiency of sustainable PV power generation.

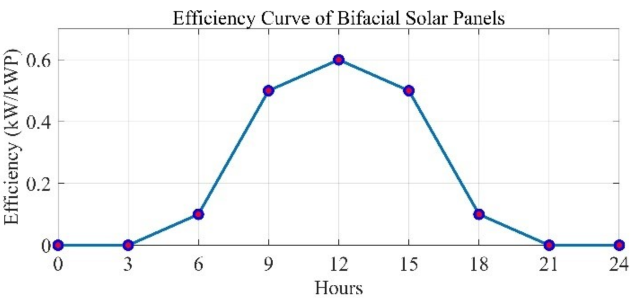


Fig. 18. The efficiency of bifacial PV panels

The lowest obtained value of the objective function (0.29) is reached after 12 frequent as shown in Fig. 19. The value of the objective function starts at 0.3011 and steadily decreases to 0.2912 by the 12th iteration, where it nearly stabilizes. Whereas, the other early used algorithms like GWA and FPA are reached to their lowest value of their cost functions by less than frequent. The optimal obtained values of proposed controller are shown in Table VIII.

TABLE VIII. HIGH AND LOW LIMITS OF CONTROLLER CONSTANTS

| **Proportional Controller P** | **Optimal Value** |
|---|---|
| Proportional Gain KP | 5 |
| **Proportional integral controller** | **Optimal Value** |
| Proportional Gain KP | 8 |
| Integral Gain Ki | 3 |

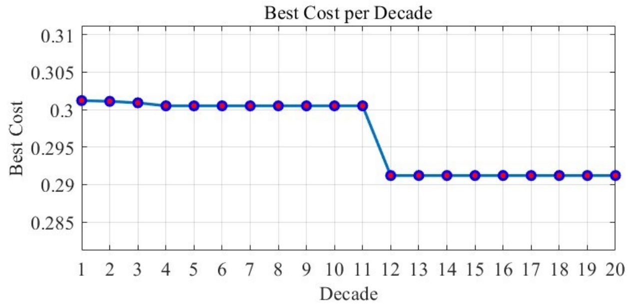


Fig. 19. The ICA objective function during decades

Fig. 20 shows the objective function values in each algorithm. ICA algorithm demonstrates its superiority in achieving the minimum value of the objective function, with a value of 0.24 compared to 0.28 for the FPA algorithm and 0.36 for GWO. Moreover, Fig. 21 shows the comparison of these three algorithms in terms of speed to reach the best values of cost function

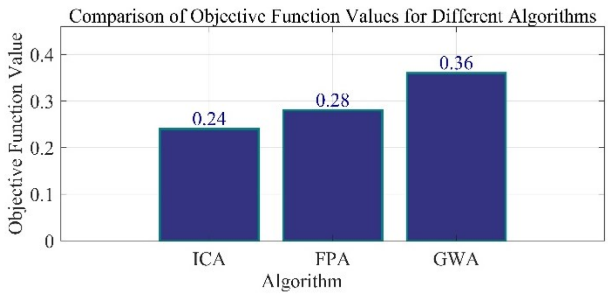


Fig. 20. The best value of the objective function of the studied algorithms

The ICA algorithm outperformed both GWO and FPA in terms of speed, reaching the optimal solution in only 12 iterations. GWO followed with 18 iterations, while FPA was the slowest, taking 24 iterations to reach the optimal value of the objective function.

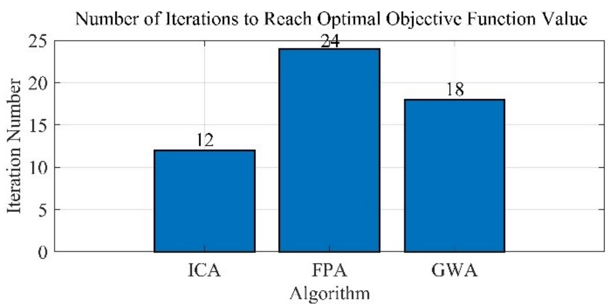


Fig. 21. The comparison algorithms in terms of speed to achieve the best values of the objective function

As Fig. 22 and Fig. 23 show, both SCR and SSR are complementary. The SSR represents the portion of the PV energy that is directly consumed or stored in the battery for use when needed, so the SCR scheme gives an idea of the excess energy that is sold to the grid.


Fig. 22. SSR as a function of installed PV power for 2 kWh/kWp storage system capacity, considering 50º southwest facing bifacial PV modules

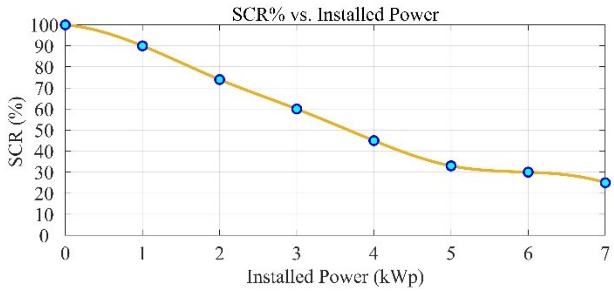


Fig. 23. SCR as a function of installed PV power for 2 kWh/kWp storage system capacity, considering 50º southwest facing bifacial PV modules

## VI. CONCLUSIONS AND RECOMMENDATIONS

This paper proposes the use of ICA to improve the efficiency of grid-connected two-sided PV systems and select the best energy storage technology. Two optimization scenarios using ICA are investigated and compared with FPA and GWO. A conventional analysis is performed for different battery types with the support of the ICA algorithm, considering factors such as cost, capacity, charge/discharge cycles, and depth of discharge. The second optimization scenario focuses on fine-tuning the charge controller constants for efficient energy management, taking into account both solar panel output and load consumption, while also considering battery energy. The results showed that ICA excelled in selecting the optimal storage technology (favoring lithium-ion batteries) and reached the solution faster (5 iterations) compared to other algorithms. It further optimized the system by adjusting the charge controller, maximizing bifacial PV panel yield, improving energy efficiency, and ensuring grid support. Overall, ICA's superior performance demonstrates the potential of innovative optimization techniques for a sustainable renewable energy sector that addresses global energy challenges. It is suggested that the research should be conducted on panels with higher capacities and larger energy storage areas. Furthermore, it is recommended that the study be furthered by integrating a maximum power point tracking algorithm into the charge controller to optimize the power output of bifacial solar panels.

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