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Enhancing microgrid production through particle swarm optimization and genetic algorithm

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ABSTRACT

The growing demand for sustainable and efficient energy solutions has led to research on optimizing renewable energy sources within microgrid systems. This study presents a comparative analysis of two prominent optimization techniques, particle swarm optimization (PSO) and genetic algorithm (GA), to enhance solar photovoltaic (PV) and wind production in microgrids. The aim is to achieve a balanced and efficient energy generation that closely matches the load demand, thereby minimizing energy wastage and ensuring a reliable energy supply. The two algorithms are employed using data representing PV and wind production, as well as load consumption, over a 24-hour period. The results are evaluated based on their ability to reduce the gap between energy production and load demand. Our findings reveal compelling insights into the performance of GA and PSO in the context of microgrid optimization. To validate the results obtained from the simulation, the PSO algorithm is implemented on an actual cart digital signal processor (DSP) platform, using a processor-in-the-loop (PIL). This successful real-world application highlights the practical viability of utilizing PSO to improve solar PV and wind energy generation within microgrids.

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1. INTRODUCTION

Microgrids are autonomous or partially autonomous electrical systems that deliver power to remote locations, vital infrastructure, and isolated settlements that are not easily reachable by the main electrical grid. They are made up of many energy sources, including batteries, wind turbines, backup generators, solar panels, and backup generators. They also include energy management and control technology [1].

In order to address the energy needs of isolated towns and remote locations that are not covered by the main electrical grid, microgrids have developed as a creative alternative. By facilitating the utilization of renewable energy sources and lowering reliance on fossil fuels, they also provide a sustainable alternative to conventional electrical grids [2]. Applications for microgrids include supplying electricity to remote communities, running vital facilities like hospitals, airports, or data centers, delivering energy in emergency or catastrophe scenarios, and lowering rural areas' energy expenses [3].

In this context, microgrids are gaining popularity in areas of the world with high energy prices, sparse infrastructure, or unstable electrical networks. Thus, research into and development of new energy technologies, as well as energy and environmental policy, should pay close attention to microgrids. Microgrids have a number of benefits, such as improved electricity quality and dependability as well as lower energy costs for remote areas. In the event of a power loss, microgrids can increase energy security by supplying backup electricity [4]. Also, by lowering reliance on fossil fuels and greenhouse gas emissions, microgrids powered by renewable energy sources can lower carbon footprints and aid in the battle against climate change. Moreover, microgrids can promote economic growth by generating local jobs in the energy management, maintenance, and production sectors [2]. By reducing reliance on fossil fuels and greenhouse gas emissions, microgrids powered by renewable energy sources can also lessen their carbon footprint and aid in the battle against climate change. By generating local jobs in the fields of energy production, maintenance, and management, microgrids can also aid in economic development. To increase accessibility and the use of microgrids more broadly, there are still obstacles to be solved. These difficulties include the high initial cost of technology and equipment, the complexity of designing and managing microgrids, as well as potential regulatory and governmental barriers to microgrid adoption [5]. There are ongoing attempts to enhance microgrid design and management as well as to create new technologies that can lower costs and boost efficiency in order to address these issues. Advanced energy management systems (EMS) and software platforms, for instance, can help improve microgrid operation and lower energy waste [6]. Improvements are being made to the incorporation of renewable energy sources into microgrids as well. This entails creating technologies that can facilitate the integration of sporadic energy sources like wind and solar power, such as energy storage systems and grid-forming inverters [1].

Kamal *et al.* [7] presents a mixed-integer linear programming (MILP) model for the simultaneous optimization of energy and reserve management in an independent microgrid powered by renewable sources, with a focus on minimizing costs while addressing energy production uncertainty. Similarly, Bhoi *et al.* [8] employs a genetic algorithm (GA) to minimize overall costs and incorporates demand response in a microgrid context. Elaouni *et al.* [9] leverages both GA and particle swarm optimization (PSO) to achieve an optimal configuration for a grid-connected hybrid system, aiming to minimize costs. In the study outlined in [10], GA and PSO techniques are utilized to optimize the sizing of renewable generation units in an isolated microgrid, taking into account cost and peak demand constraints. Muzzammel *et al.* [11] demonstrates a diverse microgrid model's efficient power flow using MATLAB Simulink and PSO, resulting in notable transmission loss reduction during battery charging and discharging. A variety of techniques and tools are utilized to enhance the performance of a microgrid that integrates both wind and solar power generation, as outlined in Table 1 as evidenced by a recent literature review focused on optimization methods for microgrids.

This study presents a unique contribution to the field of microgrid optimization by focusing on the efficient allocation of energy production from photovoltaic (PV) and wind sources to match load demand and minimize energy wastage. Unlike previous works that primarily emphasize cost minimization, optimal sizing, and power flow control, our research specifically addresses the critical issue of preventing unnecessary energy surplus. By comparing the performance of PSO and GA, we highlight their effectiveness in achieving optimal energy utilization. This work extends beyond traditional optimization approaches, providing insights into the most suitable method for enhancing microgrid operation and renewable energy utilization while reducing wastefulness.

Table 1. A recent literature review on optimization techniques for microgrids

Authors	Renewable components			Battery	Grid connected	Objectives	Optimization methods	Year	Ref
	PV	WIND	Diesel						
Muzzammel *et al.*	x	x	_	x	ON	power flow	Newton–raphson and PSO	2023	[11]
Bhoi *et al.*	x	x	x	x	OFF	cost of energy	Evaporation rate water cycle algorithm (ER-WCA)	2023	[8]
Teferra *et al.*	x	x	_	_	OFF	cost of energy	Fuzzy-PSO	2023	[12]
Sayed *et al.*	x	_	_	_	OFF	the sum square of error	Teaching learning based optimization (TLBO)	2023	[13]
Fares *et al.*	x	x		x	OFF	Sizing	Flower pollination algorithm (FPA)	2022	[14]
Emrani *et al.*	x	x			OFF	Gravity energy storage GES	GA	2022	[15]
Makhloufi *et al.*	x	x			OFF	cost of energy	CUCKOO	2022	[16]
Maheri *et al.*	x	x	x	x	OFF	sizing	GA, NSGA	2022	[17]
Mokhtara *et al.*	x	x	x	x	OFF	cost of energy	PSO	2021	[18]
Hassan *et al.*	x			x	ON-OFF	cost of energy	GA	2021	[19]
Das *et al.*	x	x	x		ON-OFF	net present cost	HOMER	2021	[20]
Hong *et al.*		x			ON	Production efficiency	Artificial bee colony algorithm (ABC)	2021	[21]

This paper is structured as follows: an initial section presents the MATLAB Simulink model of PV panels and wind turbines. Within the same section, we provide an overview of PSO and GA, along with their applications in the proposed microgrid. The second section showcases simulation results for each algorithm, followed by the implementation of the PSO algorithm on LaunchPad F28069M board using processor in the loop (PIL) using MATLAB Simulink. The final section contains conclusions and perspectives.

2. METHOD

The proposed microgrid is designed to integrate solar PV and wind turbines as renewable energy sources Figure 1. The microgrid aims to efficiently manage energy production and consumption within a localized area, optimizing the utilization of both solar and wind power to meet the varying demands of a connected load. This optimization process involves the implementation of advanced algorithms such as PSO and GA.

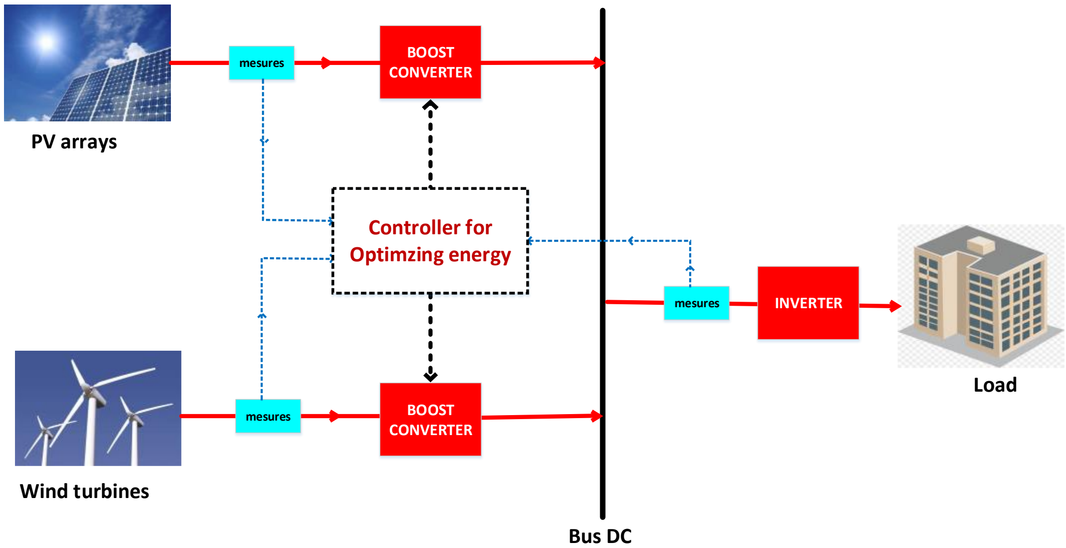


Figure 1. Microgrid proposed

2.1. Modeling of photovoltaic panels

The PV cell, often referred to as a solar cell, is a substantial surface diode or PN junction that interacts with light, particularly photons. This interaction results in the creation of a potential difference through a physical phenomenon known as the PV effect. To describe the characteristics of a PV cell, various mathematical models have been created, as illustrated in Figure 2. These models vary in the number of parameters and mathematical techniques used to compute the behavior of the PV module [22]. In (1) to (3) can be used to represent the equivalent circuit.

$$I_{ph} = [I_{sc} + k_i(T - T_n)] \times \frac{G}{1000} \tag{1}$$

$$I_d = I_{rs} \cdot \left(\frac{T}{T_n}\right)^3 \exp\left[\frac{q.E_{g0}}{n.K} \times \left(\frac{1}{T_n} - \frac{1}{T}\right)\right] \tag{2}$$

$$I = I_{ph} - I_d\left[\exp\left(\frac{q}{K.T.n} \times V\right) - 1\right] \tag{3}$$

Where:
I: Output current (A)
V: Output voltage (V)
T: Cell temperature (K)
T_n: Nominal temperature (K)
G: Solar irradiation (W/m²)

I_{ph}: Photo-current (A)
I_d: PV saturation current (A)
I_{sc}: Short circuit current (A)
K: Boltzmann's constant (J/K)
q: Electron charge (C)
E_{g0}: Band gap energy of the semi-conductor (eV)
n: The ideality factor of the diode
k_i: Short-circuit temperature coefficient (A/K)

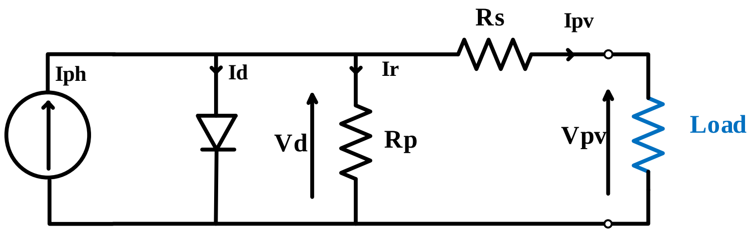


Figure 2. PV panel model

Figure 3 illustrates the block diagram of the PV panel model with maximum power point tracking implemented in MATLAB Simulink. The PV panel is characterized through a mathematical model based on the five-parameter equivalent circuit model. This model comprises a current source, a diode, and a resistor, collectively representing the physical characteristics of the panel. In our study, each PV panel boasts a power rating of 300 Watts peak, and we've strategically employed a fleet of 50 panels. The maximum power point tracking (MPPT) algorithm used in this model is the perturb and observe P and O algorithm. The MPPT block calculates the optimal operating point of the panel and adjusts the duty cycle of the BOOST converter accordingly.

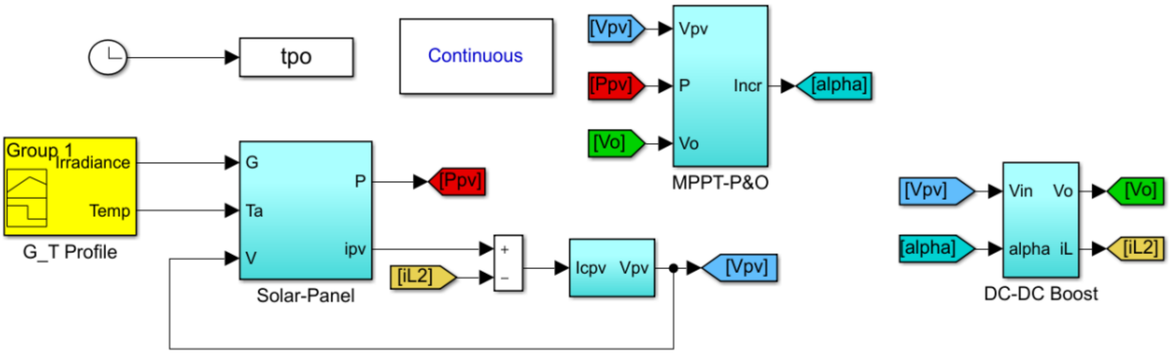


Figure 3. Block diagram of the PV model in simulink

2.2. Modeling of wind turbine

Creating a wind turbine model using MATLAB Simulink requires the development of mathematical descriptions for various components, such as the turbine, generator, and control electronics. These individual representations are subsequently integrated to construct a comprehensive system model, enabling the simulation of the turbine's performance. In our research, the examined wind turbine generates a significant 22 kilowatts of electrical power. In Figures 4 and 5, we visually illustrate the collaborative operation of these components, demonstrating the process by which the wind turbine generates electricity.

The motion of the wind generates a rotational force on the drive shaft [23]. The wind possesses a specific speed "V" at a particular moment and moves through a designated region "S," with "ρ" representing the air density. The wind turbine's aerodynamic power capture can be measured using the subsequent (4).

$$P_{capture} = \frac{1}{2} C_p(\lambda, \beta) \rho \pi R^2 V^3 \tag{4}$$

Here, *R* denotes the rotor radius of the wind turbine. C_p (λ, β) signifies the power coefficient, reflecting the wind turbine's aerodynamic effectiveness and its ability to convert wind kinetic energy into mechanical power. C_p is a non-linear function dependent on both the tip-speed ratio λ and the blade pitch angle β. The tip-speed ratio is defined as (5):

$$\lambda = \frac{\theta_t}{V} R \tag{5}$$

Here, θ_t represents the angular speed of the turbine shaft. The aerodynamic power can also be represented in the following manner:

$$P_{capteur} = \theta_t . T_a \tag{6}$$

Therefore, in accordance with the equations mentioned earlier (4)-(6), the aerodynamic torque Ta applied to the wind turbine shaft can be alternatively formulated as (7).

$$Ta = \frac{1}{2} \frac{C_p(\lambda,\beta)}{\lambda} \rho \pi R^2 V^3 \tag{7}$$

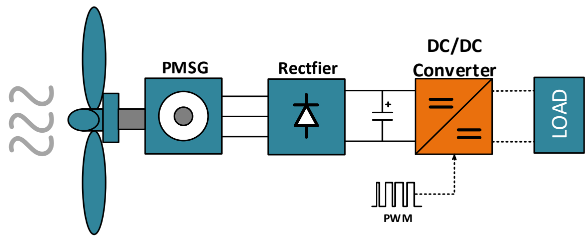


Figure 4. Wind turbine model

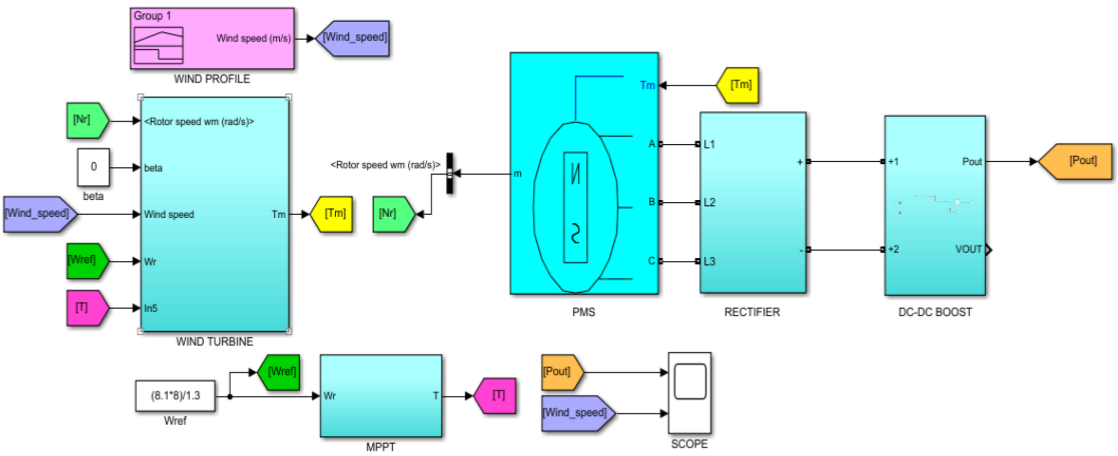


Figure 5. Block diagram of wind turbine model in Simulink

2.3. Optimization algorithm
2.3.1. Genetic algorithm

The fundamental concept underlying the GA is inspired by the principles of biological evolution. GA represents individuals as potential solutions to complex optimization problems, mimicking the natural process of evolution to seek the most optimal solution for the given problem as in Figure 6. This objective is pursued by introducing diversity and quality into its population through the mutation and combination of individuals across multiple generations. These modifications aim to preserve traits that improve the adaptability of individuals to their local environment, outperforming their counterparts. To assess this adaptability, used for individual selection or elimination, their fitness value is calculated. This value measures how well they conform to predetermined fitness functions and constraints Figure 6(a). This cycle of variation and selection is repeated across evolving populations over successive generations until a stopping criterion as generation number is met [9].

This work involves a GA optimization approach to address the challenge of efficiently managing renewable energy production in standalone microgrids. The goal is to determine the optimal distribution of energy production from PV panels and wind turbin sources over a 24-hour period, aligning with the load consumption demand while minimizing energy wastage. In this context, an individual signifies potential power production profiles, encompassing combinations of PV and wind production for each hour. These distinct profiles constitute the solutions that the GA endeavors to optimize. The population is comprised of a collection of such individuals, denoting different energy distribution scenarios [22]. In this study, the key parameters for the GA were configured as follows: a population size of 150 individuals, a maximum of 50 generations, a crossover fraction of 0.8, and a mutation rate of 0.03. The optimization process began by generating an initial population, wherein each individual represented a unique combination of PV and wind power production levels for every hour. To quantify the fitness of each individual, a fitness function was established. This function calculated the absolute differences between the total power generated by PV and wind sources and the corresponding load demand for each hour of the day. Lower fitness values indicated a better alignment between energy production and consumption.

2.3.2. Particle swarm optimization

PSO is a nature-inspired optimization algorithm applied to address intricate problems across diverse domains. It emulates the coordinated behavior of particles within a search space with the goal of discovering the most optimal solutions. In PSO, particles explore the space, adjusting their positions based on personal best-known positions and the global best-known position among all particles [10]. This dynamic process helps particles converge toward an optimal solution. The algorithm begins with random particle initialization and evaluates their fitness. Each particle's position and velocity are updated iteratively, influenced by its personal and global best-known positions. PSO's objective is to either minimize or maximize a problem-specific fitness function. The algorithm continues for a specified number of iterations or until convergence criteria are met. PSO's simplicity, adaptability, and ability to handle high-dimensional spaces make it a versatile optimization technique. Its applications span various tasks, encompassing parameter tuning, feature selection, neural network training, and more. Despite its straightforward nature, PSO's collective exploration and exploitation behavior often lead to effective and efficient solutions for complex optimization problems. The PSO algorithm is defined by two main equations. The initial equation pertains to the update of velocity, where each particle in the swarm modifies its velocity by considering the computed values of the best solutions at both the individual and global levels, in addition to its current position. The coefficients a_1 and a_2 serve as acceleration factors, representing the influences of individual and social aspects. These coefficients, known as trust parameters, play distinct roles. a_1 reflects a particle's self-confidence, determining how much it trusts its own experiences, while a_2 represents a particle's confidence in its neighbors, influencing its trust in collective information. Together with the random values r_1 and r_2, these coefficients define the inherent stochastic effects arising from cognitive and social behaviors [23].

$$\vartheta_i(t+1) = \vartheta_i(t) + a_1 r_1(\mathrm{pbest}_i^t - p_i^t) + a_2 r_2(\mathrm{gbest}_i^t - p_i^t) \tag{8}$$

The second equation is the position equation, where each particle updates its position using the newly calculated velocity:

$$p_i^{t+1} = p_i^t + \vartheta_i^{t+1} \tag{9}$$

The parameters of position and velocity are co-dependent, the velocity depends on the position and vice-versa [24]. Figure 6 illustrates the basic operational principles of two algorithms: Figure 6(a) shows GA and Figure 6(b) shows PSO. Figure 6(a) depicts GA's selection, crossover, and mutation processes for evolving solutions, while Figure 6(b) shows how PSO updates particles' positions and velocities based on the best positions. In this study, we employ PSO to enhance the efficiency of power production from PV and wind sources, aligning energy generation with load demands in microgrid. By defining PSO parameters, including a swarm size of 150 and a maximum of 50 iterations, we adjust the energy output for optimal utilization. Figure 7 shows a flowchart of GA in Figure 7(a) and PSO in Figure 7(b), the algorithm of PSO begins with the initialization of particles, assigning random positions and velocities within a search space. Each particle's fitness is evaluated using a predefined fitness function. Subsequently, the algorithm updates the particles' velocities and positions based on their personal best and the global best solutions found. This iterative process continues until a termination condition, such as a maximum number of iterations or a desired fitness level, is met. The velocity update incorporates factors like inertia, personal cognitive influence, and social influence to guide particles toward optimal solutions.

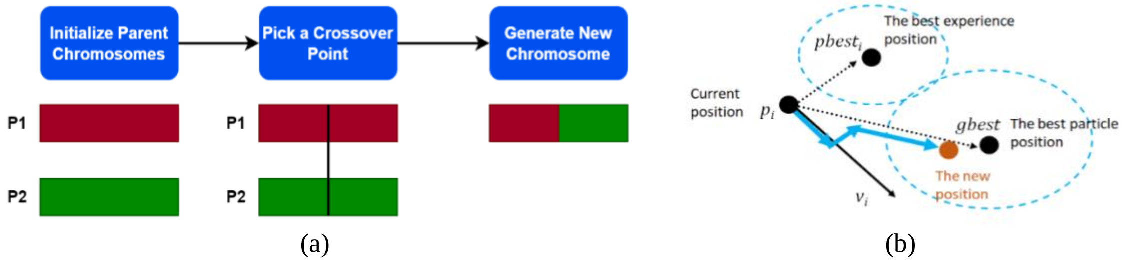


Figure 6. Basic operational principles of two algorithms: (a) major styps for GA and (b) moving particles in PSO

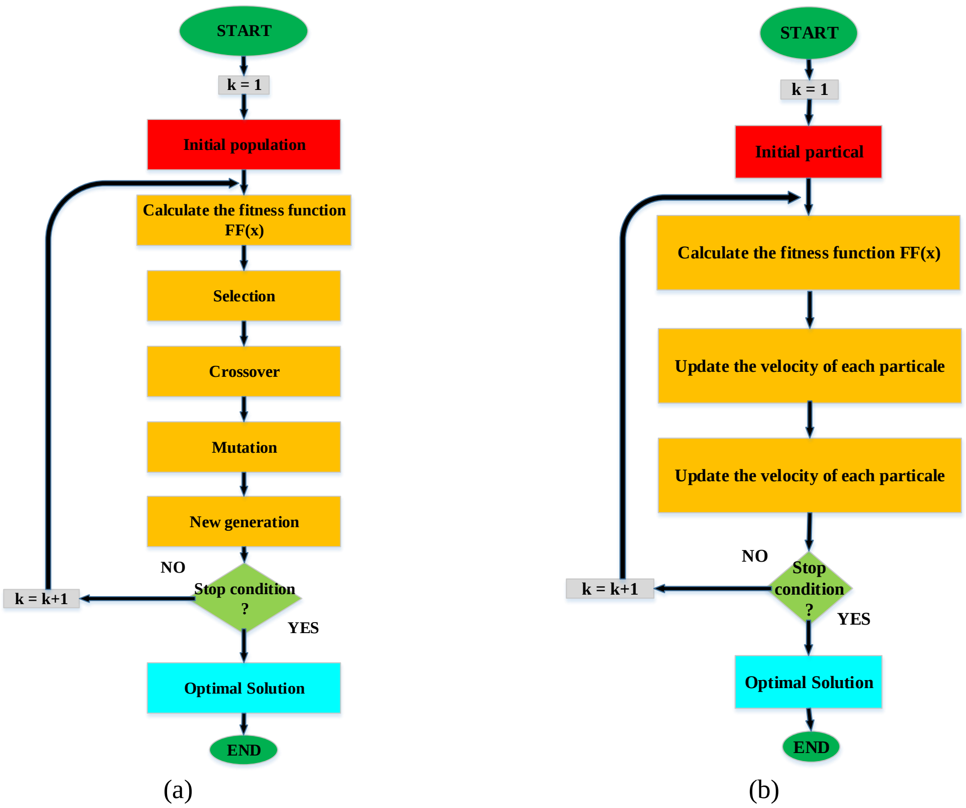


Figure 7. Flowchart of (a) GA and (b) PSO

2.4. Fitness function

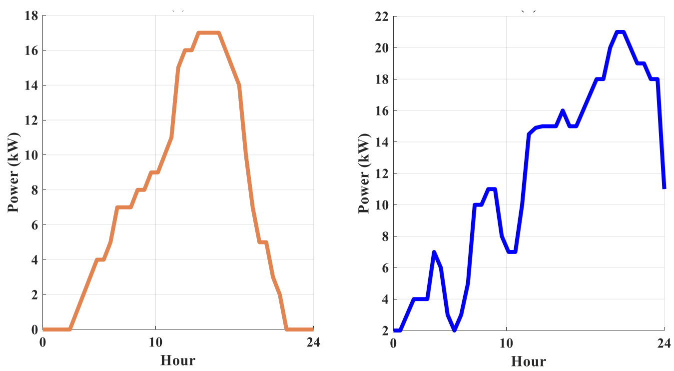
The fitness function employed in this study for both algorithms can be mathematically as (10). In (10), FF(x) denotes the fitnessscore of an individual solution x within the population. For each hour i from 1 to 24, $P_{gen,i}$ represents the total power generated from the PV and Wind sources, while $P_{dem,i}$ signifies the corresponding power demand and ω can be a weight that reflects the importance of matching load consumption. A higher weight places more emphasis on minimizing deviations. This fitness function used to evaluate the quality of solutions generated by the two algorithms GA and PSO. It quantifies the mismatch between power generated by PV and wind sources and the corresponding power demand over a 24-hour period. The fitness score is calculated by summing the absolute differences between power generation and power demand for each hour. Through iterative optimization, the two algorithms seek to minimize this fitness score, leading to energy distribution profiles that efficiently match power generation with demand while minimizing surplus or deficit.

$$FF(x) = \sum_{i=1}^{24} \omega \left| P_{gen,i} - P_{dem,i} \right| \tag{10}$$

3. RESULTS AND DISCUSSION

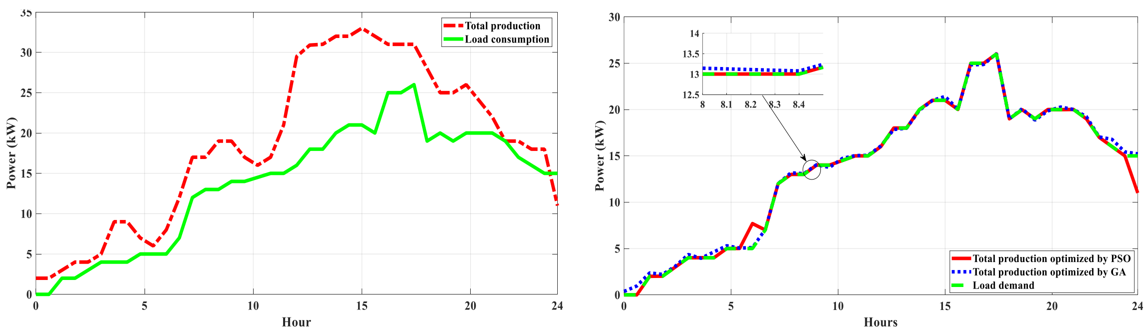
This section offers a thorough analysis of the results derived from our GA-based optimization and approaches. In Figure 8 we begin by presenting the profiles for PV production in Figure 8(a) and wind production in Figure 8(b) over a 24-hour period. It is important to mention that the data utilized to create these profiles are not real; they are only comparable to actual data. Figure 9 illustrates the combined energy production from both PV panels and wind turbine sources in Figure 9(a), along with the load consumption profile over a 24-hour period in Figure 9(b). It is noteworthy that the total energy production often exceeds the load demand, potentially resulting in a wasteful power surplus when the battery is fully charged during that specific hour. Figure 10 examines source utilization in the microgrid, illustrating PV and wind turbine utilization percentages in Figures 10(a) and 10(b) comparing source utilization before and after optimization with studied algorithms.

In Figure 10(a) depicts the utilization percentages of PV and wind power production. Throughout the day, it is evident that wind power constitutes a significantly larger portion, accounting for 62.36%, compared to PV's 37.64%. This difference can indicate an issue related to the balance and efficiency of renewable energy sources in the energy system. Such a scenario may lead to the grid becoming overly reliant on wind energy, potentially causing overproduction during windy periods and underproduction during periods of low wind. In Figure 10(b), the effects of the optimization process are evident. Wind power now constitutes 50,6% of the total energy generated, with solar panels contributing 49,4% in the case of GA. For PSO, 51,81% of the total energy is generated from wind turbine, and 48,19% comes from solar panels. These results indicate that the changes made have helped address the issue of relying too heavily on wind power. This correction is important because it reduces the likelihood of producing excessive energy during windy periods and insufficient energy during periods of low wind. These improvements highlight the importance of finding the right mix of energy sources to maintain a stable and reliable energy system. The optimized approach of PSO and GA has effectively bridged the gap between the power produced by renewable energy sources and the power required by the load. This visual representation validates the success of the energy management strategy by ensuring that energy generation closely aligns with consumption needs. As a result, energy is now being utilized more efficiently and actively avoiding unnecessary waste.



(a) (b)

Figure 8. Profiles of (a) production PV and (b) WIND



(a) (b)

Figure 9. The combined energy production from (a) total production optimized by PSO and GA and (b) total production and load demand

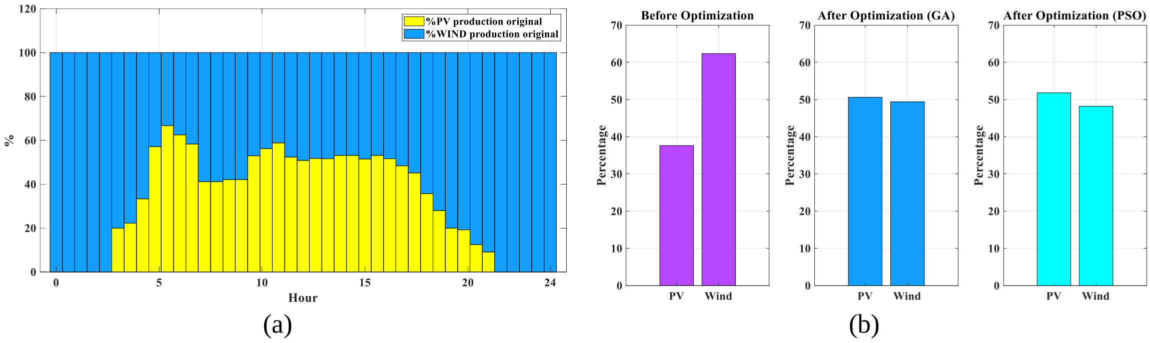


Figure 10. Percentage of (a) use for each source and (b) use for each source

To assess the convergence of each algorithm, a statistical analysis is carried out using the mean absolute percentage error (MAPE) [25]. This can be calculated as the relative error, which is defined as the absolute difference between the output power and the desired value, divided by the output power value, as illustrated in the (11). The comparison results shown in Figure 11, between the mean error values for the GA and PSO provide valuable insights into their respective performance. The mean error of 1.9729 for GA indicates the average deviation between the optimized solutions and the desired outcomes. On the other hand, the mean error of 1.1888 for PSO represents a lower average deviation, suggesting that the PSO approach exhibits a relatively higher accuracy in achieving optimal solutions.

$$\mathrm{MAPE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{t}=\mathrm{t}_0}^{\mathrm{N}}\left|\frac{\mathrm{P_{gen}}-\mathrm{P_{dem}}}{\mathrm{P_{gen}}}\right| \times 100 \tag{11}$$

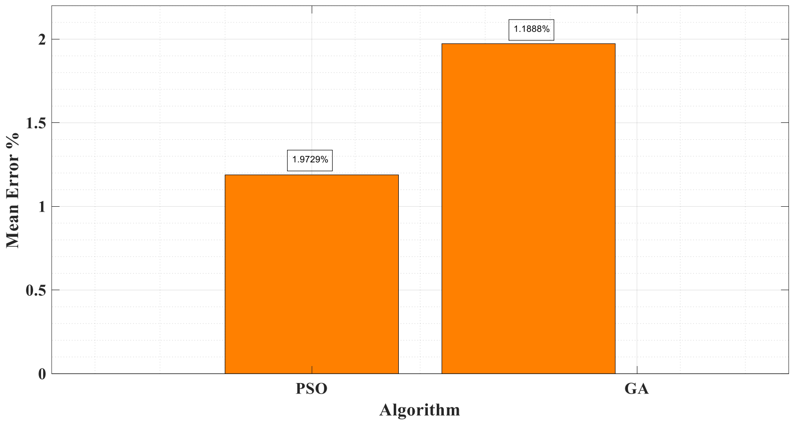


Figure 11. Mean error GA vs PSO

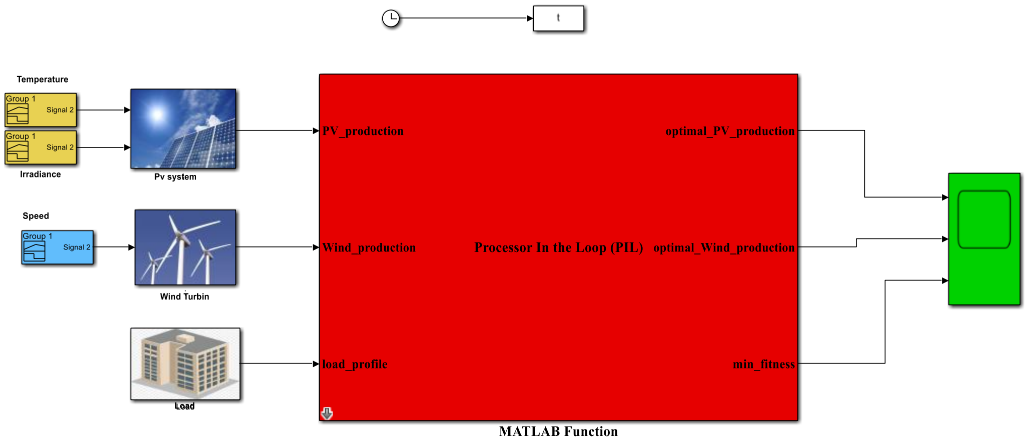
3.1. PIL test using digital signal processor board LaunchPad development kit LAUNCHXL-F28069M

To validate and evaluate the proposed algorithm, a similar testing method called PIL was used, this time with the LaunchPad F28069M board. The PIL test involves developing specific code for the embedded 32-bit microcontroller on the LaunchPad F28069M. This microcontroller possesses distinct features, including 256 Kbyte flash memory, a clock frequency of 90 MHz, a floating-point unit, digital signal processor (DSP) instructions, and 96 Kbytes RAM. Throughout this validation process, a dedicated PIL block was integrated into the control system. This block includes the customized code for the LaunchPad F28069M and seamlessly interfaces with Simulink software.

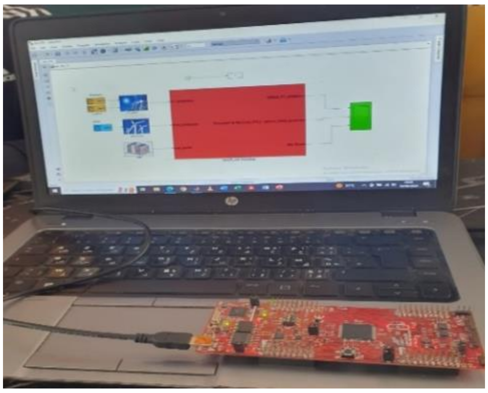
The diagram in Figure 12 illustrates the integration of the PSO algorithm into the processor loop using Matlab/Simulink. The steps to set up and conduct the PIL test using the LaunchPad F28069M board can be understood similarly to the example studied. Only the PSO algorithm is showcased in this co-simulation, as it demonstrates superior performance compared to the GA. Notably, it exhibits a higher level of accuracy in attaining optimal solutions [26]. The main goal of using the PIL method in this study is to establish a direct connection between computer simulations and real-world practical.

Figure 12. The process for setting up a parameterized PIL test using the LaunchPad F28069M

Figure 13 shows the integration of the PSO algorithm onto a DSP platform through PIL testing including a block diagram of the PIL setup in MATLAB Simulink at Figure 13(a) and PIL co-simulation test in Figure 13(b). This study aims to validate the compatibility of simulation results with real-world scenarios. This technique allows researchers to gauge how the algorithm performs, adjust its settings, and ensure it works seamlessly in a near real-time setup. In essence, PIL acts as a link between computer-based simulations and physical hardware, facilitating accurate assessment and refinement of the algorithm's performance for real-world applications [27]. Furthermore, the PSO algorithm implemented on a DSP board using PIL. This implementation involved setting up the algorithm to run in synchronization with the physical hardware, highlighting the concrete advantages of using PSO to improve solar PV and wind power generation in micro grids.



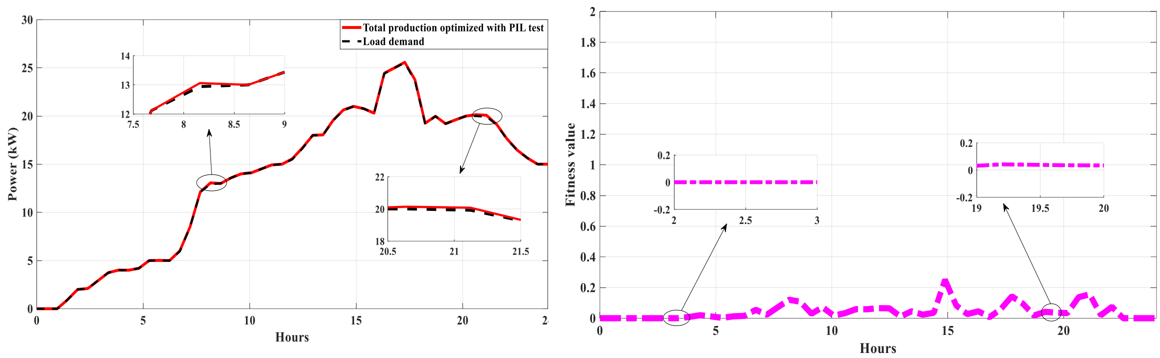
(a)



(b)

Figure 13. The integration of (a) block diagramme of PIL in MATLAB Simulink and (b) PIL co-simulation test

Figure 14 displays results from numerical simulations, presenting performance metrics of the system in Figure 14(a) the optimal total production achieved through PIL, and Figure 14(b) the fitness value obtained through PIL testing. These results closely align with those from the PIL co-simulation test, thus validating the effectiveness of the proposed algorithm. Consequently, the PIL co-simulation process is proven to be a valuable tool for validating hardware implementations of different algorithmic strategies [27].



(a) (b)

Figure 14 displays results from numerical simulations, presenting performance metrics of the system in (a) the optimal total production achieved through PIL and (b) the fitness value obtained through PIL testing

4. CONCLUSION

In conclusion, this paper addresses the optimization of energy allocation in microgrids by using PV panels and wind turbines to match load demands and minimize wastage, highlighting frequent power surpluses and the need for optimization. By applying PSO and GA techniques, we successfully mitigated the disparity between renewable energy production and load requirements, with PSO demonstrating higher accuracy. A practical co-simulation PIL validation on the LaunchPad F28069M board confirmed the algorithms' efficacy and cost-efficiency. Future research should integrate energy storage, explore advanced algorithms and machine learning, utilize real-time data and forecasts, and evaluate economic and environmental impacts to enhance microgrid management and sustainability.

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