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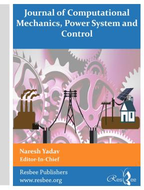

Optimizing Solar-Photovoltaic-Distributed Energy Resources in Power Networks using AI-based Particle Swarm Optimization (PSO) Algorithm

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Abstract: This study was conducted to optimize the integration of solar-photovoltaic-distributed energy resources (SPV-DERs) within the Nigerian power system networks using an AI-based Particle Swarm Optimization (PSO) Algorithm. By employing a mixed research method, primary and secondary data were gathered to calculate flow analysis, NR method's equations, PSO's position update model, particle swarm optimizer algorithm, and application modeling including Solar-PV DER modeling. The AI-based PSO algorithm design was developed for optimizing SPV-DER integration in Nigerian power system networks, and key parameters and variables that needed consideration were identified. The study also established how the performance of the AI-based PSO algorithm could be evaluated and compared with other optimization techniques for SPV-DER integration within Nigerian power system networks. The study's results showed that voltage limits were within acceptable ranges, and solar power contributions were estimated at 880.10MW with 46,718 panels needed. The study concluded and recommended that investing in AI-powered tools for efficient power distribution; monitoring and resource optimization for sustainable energy sources would optimize performance and unleash Nigeria's sustainable energy potential.

Keywords: solar-photovoltaic-distributed energy resources, power system networks, AI-based, Particle Swarm Optimization (PSO), Algorithm

Nomenclature

Abbreviations	Descriptions
SPV-DERs	Solar-Photovoltaic-Distributed Energy Resources
PSO	Particle Swarm Optimization
AI	Artificial Intelligence
NR	Newton-Raphson
MW	MegaWatts
IEEE	Institute of Electrical and Electronics Engineers
kV	KiloVolt
KWh	Kilowatt-hour
AC	Alternating Current
LF	Load Flow
Pbest	Personal Best Position
Gbest	Global Best Position
Hz	Hertz
MVAR	Mega Volt-Ampere Reactive
ODERPON	Optimized Distributed Energy Resource Power Network
ETAP	Electrical Transient Analyzer Program
MVA	Mega Volt-Ampere

1. Introduction

The decentralized generation and distribution of renewable energy sources, known for their erratic and unpredictable nature [28], have raised concerns about their practicality. Nonetheless, solar power presents itself as a promising renewable energy solution due to its reliance on sophisticated technology, such as photovoltaic cells and focusing lenses. Although its efficacy is contingent on the prevailing weather conditions, there is a prevailing sense of optimism that solar power can eventually become self-sustainable; despite setbacks it may encounter [22]. Thus, to maintain a steady energy supply, even in the face of challenges, it is essential to supplement solar energy with other reliable energy sources

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through an integrated approach to ensure that power stations can meet peak demands and secure enough reserves.

Traditional algorithms for handling LF and demand, like the NR algorithm [16], are becoming increasingly ineffective when networks become overwhelmed or receive energy from many entities. It is vital to identify the allocation and management of DERs for optimal performance. Complex and intelligent optimizers are necessary, requiring AI approaches to address the issue [4][18].The PSO is one such approach for power networks [26].

The authors of this study have proposed the use of PSO-Solar-PV-DER for power networks. This application was tested on the IEEE 6-bus and Nigerian 330kV 34-bus power networks. The IEEE 6-bus system is commonly used as a benchmark system in power systems and energy research [30]as it is a condensed representation of a real-world power system with six buses that are interconnected by transmission lines. It is usually scrutinized for various analyses, including power flow, optimal power flow, stability, and control system design. It comprises bus voltage magnitudes, line impedances, and generation/load attributes that can be altered to simulate different situations and their effect on network performance.

Statement of the Problem

The Nigerian power sector is best with innumerable issues that are causing problems with the generation and distribution of electricity. The escalating demand for electric power has exacerbated the situation, leading to overwhelmed generating stations and a deteriorating infrastructure. Electric power stations that are connected to load centers rely on extended transmission lines that are often fragile due to aging. More so, the interconnected power system includes transmission lines, buses, and power stations. Unfortunately, most of these devices are being pushed beyond their capacity, leading to further stress and instability in the system. As a result, there are frequent disruptions in the power supply, hindering the quality of power delivered to the end-users. In light of this, we are determined to take advantage of advanced techniques and equipment to address these problems. We are proposing the integration of AI-enhanced PSO-Solar-PV-DER for power networks to improve the stability and quality of power delivery and meet the increasing demand for electricity in Nigeria.

Aim and Objectives of the Study

This study was aimed at investigating optimizing SPV-DERs in power networks using AI-based PSO algorithms within the Nigerian power system networks. Specifically, the objectives were to:

1. Develop an AI-based PSO algorithm for optimizing the integration of SPV-DERs within the Nigerian power system networks.
2. Determine the key parameters and variables that need to be considered in the AI-based PSO algorithm for optimizing SPV-DER integration within the Nigerian power system networks.
3. Evaluate and compare the performance of the AI-based PSO algorithm with other optimization techniques for SPV-DER integration within the Nigerian power system networks.

Research Questions

1. How can AI-based PSO algorithms be designed for optimizing the integration of SPV-DERs within the Nigerian power system networks?
2. What are the key parameters and variables that need to be considered in the AI-based PSO algorithm for optimizing SPV-DER integration within the Nigerian power system networks?
3. How can the performance of the AI-based PSO algorithm be evaluated and compared with other optimization techniques for SPV-DER integration within the Nigerian power system networks?

The paper is organized as follows: Section 2 covers the literature review. Section 3 details the Materials and Methodology, and 4 emphasizes Solar-PV Distributed Energy Resource (DER) Modeling, Section 5 explains the results and discussion. Section 6 mentions the advantages and disadvantages of the proposed method. The conclusion is recapitulated in Section 7.

2. Literature Review

Solar energy is a well-known fact [19]that has gained popularity over the years. The sun is an ancient source of renewable energy that is eco-friendly and abundant, making it attractive in regions that have suitable weather conditions [13][25]. However, the amount of solar energy received by the earth's surface depends on various factors, such as geographic location [21], time of day[9], season, and local weather conditions[20]. Despite modern solar panels only converting 15-20% of the input power into output power[15][22], space solar cells have become increasingly popular due to their high efficiency[10]and focus on improving photon absorption in the middle cell to increase current [22].

Nigeria, which spans a vast land area of 923,768 sq. Km [29], enjoys abundant sunshine all year round, with an average daily sunshine duration of 6.5 hours and a flux of 5.55KWh per square meter per day. Nigeria's solar energy potential is equivalent to generating 4.851× 〖10〗^12 energy daily [12]when harnessed efficiently. With suitable solar radiation intensity of 3.5 to 7kWh per square meter per day for generating electrical energy, Nigeria still faces challenges such as a national grid with an extensive geographical spread[1], aging infrastructure, and a lack of investment[2][23]. To achieve reliable electricity production and sustainable energy in Nigeria, incorporating AI-based PSO algorithms and DERs [5]is the key. PSO algorithm uses swarm intelligence to simulate the behavior of a group of particles in navigating a multidimensional search space to find optimal solutions [22]. According to [24] PSO optimization is a valuable tool in optimizing SPV-DERs in power networks. The hybrid solution of the AI-based PSO algorithm and DERs has led to a notable improvement in solar energy station efficiency. Additionally, PV cells are preferred as a means of power generation for small-scale solar installations due to their low maintenance cost.

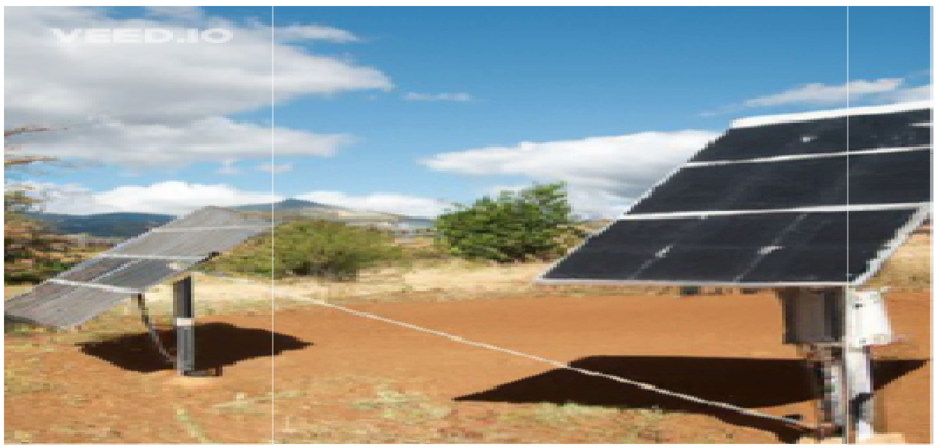

Fig. 1.*Showcasing off-grid and grid-tie PV arrays.*

Source: Adapted from Ok po's conceptualization (2023)

Two setups are available for small PV arrays as shown in Fig. 1 - off-grid and grid-tie systems. The off-grid system includes a charging system and a battery that serves as a backup source of power, while the grid-tie system uses the grid as a backup power source and can be arranged with a smart meter. However, research has shown that they cannot generate AC power in the absence of an inverter, and with the introduction of an inverter, the cost and complexity of the system increase.

2.1Theoretical Framework

James Kennedy and Russell Eberhart [7] [14] proposed the PSO theory in 1995, which suggests that the swarm intelligence of social insects can be mimicked to efficiently solve intricate optimization problems. This theory has been a fundamental aspect in advancing and refining the PSO algorithm, contributing to the field of AI-driven optimization. The PSO algorithm, utilizing solar irradiance, load demand, and operational constraints, offers optimal allocation and utilization of PV systems for Nigerian power networks. In a bid to tackle Nigeria's challenges, including inadequate power generation capacity, transmission losses, and high energy demand. The PSO algorithm incorporates renewable energy sources into the existing power infrastructure by identifying ideal PV installation locations in the network. The algorithm reduces the cost of electricity generation. The PSO algorithm's ability to explore and exploit search spaces makes it ideal for optimizing SPV-DER deployment. It employs intelligent techniques that enable adaptive and dynamic optimization by considering real-time data and system conditions, thus aiding decision-making. The PSO algorithm continuously adjusts configurations based on changes in environmental and network conditions, promising optimal performance, and maximizing energy generation from solar resources.

2. 2 Review Table

Table 1 portrays the objective, methodology, key findings, and contribution of the existing method. We considered eight papers that used a different methodology for Optimizing SPV-DERs in Power Networks. Each method has certain benefits and shortcomings that were explained in detail.

Table 1: *Review Based on Existing Methods*

S/N	Authors	Objective	Methodology	Key Findings	Contribution
1	Wang *et al.*[31]	Dynamic control and optimization of distributed energy resources.	Real-time optimization algorithms and coordinated control strategies.	Improved utilization and performance of distributed energy resources.	Enhanced microgrid operation and integration of renewable energy sources.
2	Wu *et al.*[32]	Distributed coordination for optimizing distributed energy resources.	Distributed optimization framework with consensus algorithms.	Improved system performance and integration of distributed energy resources.	Decentralized control strategy for efficient DER operation in power systems.
3	Banos*et al.*[6]	Optimization methods in renewable and sustainable energy applications.	Review of optimization techniques applied to renewable energy systems.	Assessment of optimization methods in renewable energy application.	Comprehensive review of optimization methods in renewable and sustainable energy research.
4	Jeddi*et al.*[11]	Robust optimization for dynamic planning of distributed energy resources.	Development of a robust optimization framework for DER planning.	Improved planning of dynamic distributed energy resources in distribution networks.	Robust optimization framework for effective dynamic DER planning in distribution networks.
5	Ahmadi*et al.*[3]	Distributed energy resource allocation using multi-objective optimization.	Application of the grasshopper optimization algorithm for DER allocation.	Effective distributed allocation of energy resources using multi-objective optimization	Utilization of the grasshopper optimization algorithm for distributed energy resource allocation.
6	Ma*et al.*[17]	Modeling and operational optimization for complex energy networks with DERs.	Development of modeling and optimization methods based on energy hubs.	Improved modeling and operational optimization for complex energy networks with DERs.	Enhanced modeling and optimization techniques for complex energy networks with distributed energy resources.
7	Saif *et al.*[27]	Optimal allocation of distributed energy resources.	Simulation-based optimization for DER allocation.	Effective allocation of distributed energy resources using simulation-based optimization.	Improved optimization techniques for optimal allocation of distributed energy resources
8	Golsorkhi *et al.*[8]	Distributed control framework for integrated PV-battery-based islanded microgrids.	Microgrids' distributed control framework.	Improved control framework for integrated PV-battery-based islanded microgrids	Enhanced distributed control framework for efficient operation of islanded microgrids.

2. 3 Identified Research Gap

The research gap arises from the need for an optimization method that can effectively handle the complexities of integrating SPV-DERs into Nigerian power networks. Traditional techniques fall short ofcapturing the dynamic characteristics and uncertainties associated with solar energy generation and demand fluctuations. This study fills the gap by utilizing the AI-based PSO algorithm, providing an innovative and efficient approach to optimize SPV-DER integration. The algorithm's ability to handle uncertainties and dynamic changes in solar energy enables improved grid stability, optimal resource utilization, and enhanced energy management. The findings contribute to effective strategies for integrating renewable energy sources into power systems, promoting a sustainable and reliable energy future.

3. Materials and Methods

The study used standard flow techniques, AI LF optimizer, and NR modeling to evaluate renewable energy systems. The PSO technique was utilized for dynamic, global space-level solutions. Hence, the study covered LF analysis, NR method's equations, PSO's position update model, PSO, and application modeling, including Solar-PV DER modeling.

3.1 LF Analysis

The processing of non-linear relations that involve power system energy injections, load bus demands, bus voltages, and associated parameters like line admittance, impedance, and shunt capacitance forms the basis of mathematical modeling for LF problems. The determination of key performance indicators for power system LF is facilitated by these parameters, which in turn helps to compute interconnected network parameters. In model formulations for power mismatches, these are usually taken into consideration.

$$P\_ij = \sum\left(V\_i * V\_j * Y\_ij * cos\left(\delta\_ij - \theta\_i + \theta\_j\right)\right) \tag{1}$$

This equation represents the active power injection (P) at the bus i in the LF analysis. It calculates the sums of the product of voltage magnitudes (V) at bus i and j, line admittance (Y) between buses i and j, and the cosine of the angle difference (δ) between buses i and j. The angles θ represent the phase angles of the buses. This equation helps determine the power mismatch or imbalance in the system.

$$Q\_ij = \sum\left(V\_i * V\_j * Y\_ij * sin\left(\delta\_ij - \theta\_i + \theta\_j\right)\right) \tag{2}$$

This equation represents the reactive power injection (Q) at the bus i in the LF analysis. It calculates the sums of the product of voltage magnitudes (V) at buses i and j, line admittance (Y) between buses i and j, and the sine of the angle difference (δ) between buses i and j. The angles θ represent the phase angles of the buses. This equation helps assess the reactive power imbalance in the system.

$$LFx = PQ \cup PV \tag{3}$$

This equation represents the unknown system vectors in the LF problem. It combines the sets of PQ (active and reactive power) and PV (active power and voltage magnitude) buses to represent the unknowns in the LF problem.

$$s = n + 2n \tag{4}$$

This equation calculates the total number of buses in the system, including PQ and PV buses. It adds the number of PQ buses (n) and twice the number of PV buses (2n) to obtain the total number of buses (s).

$$\Delta PQ \leq \varepsilon max \tag{5}$$

This equation represents the convergence rule for the LF process. It checks whether the power mismatch (ΔPQ) at each bus i is smaller or equal to a specified tolerance (εmax). The LF iteration continues until the power mismatch reaches its maximum within the specified tolerance.

3.2 Equation of the NRMethod

Using the notation earlier presented, we consider a generic nonlinear equation with solution $f(x) = 0$, where, x is an argument of the solution function. Also, consider x^0, as an initial solution estimate of $f(x)$; then $f(x)$ may follow a Taylor series expansion around x^0 as:

$$f(x) \approx f(x\_0) + f'(x\_0) * (x - x\_0) \tag{6}$$

This equation represents the Taylor series expansion of a generic nonlinear equation $f(x) = 0$. It approximates the function $f(x)$ around an initial estimate x_0 by considering the first derivative $(f'(x\_0))$. By neglecting higher-order terms, this equation simplifies the nonlinear equation to a first-order approximation.

$$f(x) \approx f(x\_0) + f'(x\_0) * (x - x\_0) \tag{7}$$

This equation is a simplified version of equation (7), where the higher-order terms on the right-hand side are eliminated, resulting in a first-order model. It provides an estimated value of x based on the initial estimate x_0 and the function $f(x)$.

$$x\_k+1 = x\_k - f(x\_k) / f'(x\_k) \tag{8}$$

This equation represents the update rule for finding a new estimate x in each iteration of the NR method. It uses the current estimate x_k and the function $f(x)$ to calculate the correction term Δx, which is obtained by dividing the function value by its derivative. The new estimate x_k+1 is then obtained by subtracting the correction term from the current estimate. Given k iteration steps, the update step in the NR method can be expressed as:

Equation (9):

$$New\ estimate\ (k+1) = Previous\ estimate\ (k) - Change\ in\ estimate\ (k) \tag{9}$$

The change in the estimate (Δx) in the NR method is calculated as the ratio of the function value $(f(x))$ to its derivative value $(f'(x))$ at the current estimate:

$$Change\ in\ estimate\ (k) = Function\ value\ (k)\ /\ Derivative\ value\ (k) \tag{10}$$

The updated estimate in the NR method is determined by combining the Jacobian matrix $(J(x))$ and the function value $(g(x))$ at the current estimate:

$$\text{New estimate } (k+1) = \text{Previous estimate } (k) - \text{Inverse of Jacobian matrix } (k) \text{ multiplied by Function value } (k) \quad (11)$$

These equations are essential in analyzing power system LF and solving nonlinear equations using the NR method. They help assess power imbalances, optimize the system, and converge to a solution that minimizes the cost function. A typical performance plot of the NR solution process is shown in Fig. 2.

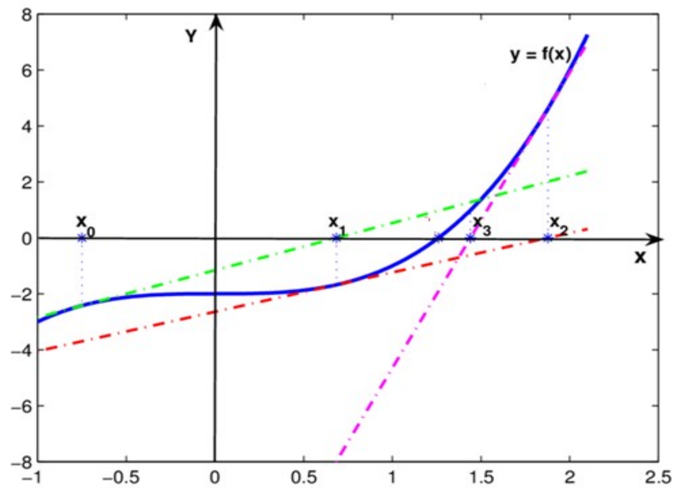

Fig. 2. *Typical Plot of NR Solution Process.*

3.3 Position Update Model of the PSO

PSO involves updating a particle's solution vector (velocity state) randomly. This occurs within a group of particles with randomization influenced by a weighted velocity vector and a random particle position state. It determines how particles in a swarm update their positions in the search space during the optimization process. The PSO algorithm combines the individual experiences of particles to guide the search towards the optimal solution. By iteratively updating the positions and velocities of particles, PSO explores the search space and converges toward the best solution. The equation is used to guide the particles towards the optimal solution. This state is affected by updates of previous best position states, as well as local and global levels. It is modeled as:

$$X(t+1) = X(t) + V(t+1) \quad (12)$$

Where:

- X(t+1) represents the new position of a particle at time t+1.
- X(t) represents the current position of the particle at time t.
- V(t+1) represents the velocity of the particle at time t+1.

The velocity of the particle is calculated using the following equation:

$$V(t+1) = w * V(t) + c1 * r1 * (Pbest - X(t)) + c2 * r2 * (Gbest - X(t)) \quad (13)$$

Where:

- V(t+1) represents the new velocity of the particle at time t+1.
- w is the inertia weight, which controls the impact of the particle's previous velocity on the new velocity.
- V(t) represents the current velocity of the particle at time t.
- c1 and c2 are acceleration coefficients that control the impact of the particle's Pbest and the Gbest on the new velocity.
- r1 and r2 are random numbers between 0 and 1.

The Pbest is the best position the particle has achieved so far, and the Gbest is the best position achieved by any particle in the swarm.

3.4 Step-by-Step Application of the PSO Equation

1. Initialize the swarm of particles with random positions and velocities.
2. Evaluate the fitness of each particle's current position.
3. Update the Pbest of each particle if its current position is better than its previous best position.
4. Update the Gbest by selecting the particle with the best fitness value among all particles.
5. For each particle, calculate the new velocity using the PSO equation mentioned earlier.

6. Update the position of each particle using the new velocity.
7. Repeat steps 2 to 6 until a termination condition is met (e.g., a maximum number of iterations or a desired fitness value is reached).

3.5 Power Mismatch Model for Particle Swarm Optimizer (PSO) Objective Function

The PSO approach can be used to solve power system LFA problems by optimizing power system design variables, including bus voltages and angles, real and reactive powers, and more, through position vectors within an upper/lower bound constraint. The parameters to be solved in this approach involve defining real and reactive power injections from real operation stations and calculating real and reactive powers based on network transmission line parameters. The power mismatch model described in Equations 14to16 is employed to form the PSO objective function, which aims to minimize the objective overall differential summations of power mismatches, ensuring that it remains below a stated permissible error value defined as, ε .

$$\Delta P_i = P^{inj} - \sum_{j-1}^{n} |V_i||V_j||Y_{ij}|\cos(\delta_i - \delta_j - \theta_{ij}) \tag{14}$$

$$\Delta Q_i = Q^{inj} - \sum_{j=1}^{n} |V_i||V_j|\sin(\delta_i - \delta_j - \theta_{ij}) \tag{15}$$

$$obj+ = \min\{|\Delta P_i|, |\Delta Q_i|\} \le \varepsilon \forall i \tag{16}$$

Where:

ΔP_i = active power mismatches at bus i
ΔQ_i = reactive power mismatches at bus i
P^{inj} = injected active power at bus i
Q^{inj} = injected reactive power at bus i
$|V_i|$ = absolute value of the complex voltage at busesi
$|V_j|$ = absolute value of the complex voltage at bus j
$|Y_{ij}|$ = absolute value of the admittance matrix of the ij^th^element
θ_{ij} = admittance angle at bus i, j
δ_i = voltage angle of the busi
δ_j = voltage angle of the bus j
Obj+ =Objective Function
ε = stopping criterion

4. Solar-PV Distributed Energy Resource (DER) Modeling

For the Solar PV used in a DER power network system, the model equations comprised the solar irradiance model; PV module model; power electronics model, and system integration model.

4.1 Solar Irradiance Model Equation

The solar irradiance model equation is used to calculate the amount of solar radiation received at a given location. It is based on the latitude, longitude, and time of the day. It takes into account factors such as the position of the sun, atmospheric conditions, and shading effects. The equation is typically based on physical principles and empirical data. One commonly used solar irradiance model equation is the Perez model. The equation is:

$$SolarIrradiance(W/m^2) = k * cos(latitude) * (1 - e^(0.0034 * (time\_of\_day - 12))) \tag{17}$$

Where

k = 1367 W/m^2 (constant)
$latitude$ = location's latitude
$time\_of\_day$ = time of the day in hours (0 to 24)

Or

$$I = I0 * (DNI * cos(\theta) + DHI) * f1 + I0 * f2 * (1 - f3 * exp(-DHI / f4)) \quad (18)$$

Where:

I represent the total solar irradiance on a horizontal surface (W/m²).

$I0$ is the extraterrestrial solar irradiance on a horizontal surface (W/m²).

DNI is the direct normal irradiance (W/m²).

θ is the solar zenith angle.

DHI is the diffuse horizontal irradiance (W/m²).

$f1, f2, f3, f4$ are coefficients determined from empirical data.

4.2 PV Module Model Equation

The PV module model equation describes the electrical behavior of a photovoltaic (PV) module. It relates the output current and voltage of the module to the solar irradiance and temperature. It can be represented by the following equation:

$$Power\ Output\ (W) = Solar\ Irradiance * PV\ Module\ Efficiency \quad (19)$$

Or

$$I = Iph - I0 * (exp((V + IRs) / (n * VT)) - 1) - (V + IRs) / Rp \quad (20)$$

Where:

I is the output current of the PV module (A).

Iph is the photocurrent generated by the solar irradiance (A).

$I0$ is the diode reverse saturation current (A).

V is the output voltage of the PV module (V).

IRs is the series resistance of the PV module (Ω).

n is the diode ideality factor.

VT is the thermal voltage (V).

Rp is the parallel resistance of the PV module (Ω).

4.3 Power Electronics Model Equation

The power electronics model equation is used to calculate the power losses in the power electronics of a solar PV system. It depends on the power output and the efficiency of the power electronics. This equation represents the relationship between the input and output voltages of the DC-DC boost converter. The equation is:

$$[Vout = \frac{D}{1-D} \times Vin] \quad (21)$$

Where:

V_{out} = Output voltage

V_{in} = Input voltage

D = Duty cycle of the converter.

4.4 System Integration Model Equation

The system integration model equation is used to calculate the total power output of a solar PV system. It depends on the power output of each component and the efficiency of the system integration. This equation takes into account the power outputs of individual components and their overall efficiency to determine the total power output of the integrated solar PV system. The equation is:

$$T = \eta * (P\_module1 + P\_module2 + \ldots + P\_modulen) \quad (22)$$

Where

T is the overall power output of the solar PV system

η is the efficiency of the system integration

$P\_module1, P\_module2, \ldots, P\_modulen$ are the power outputs of each component in the system.

5. Results and Discussions

Answers to Research Questions

Research Question 1: How can an AI-based PSO algorithm be designed for optimizing the integration of SPV-DERs within the Nigerian power system networks?

The design of an AI-powered PSO algorithm follows the structure modeled in Fig. 3. Incorporating the IEEE 6-Bus Power Network Grid's transmission network, the ODERPON leverages ETAP and MATLAB_R2007b tools for design and simulation experiments. The slack-bus generator is presumed to manage the extra power flows in the system. The line and bus data is adapted [27]. Fig 3 represents the Pattern of AI-based PSO algorithm design for optimizing the integration of SPV-DERs within the Nigerian power system networks.

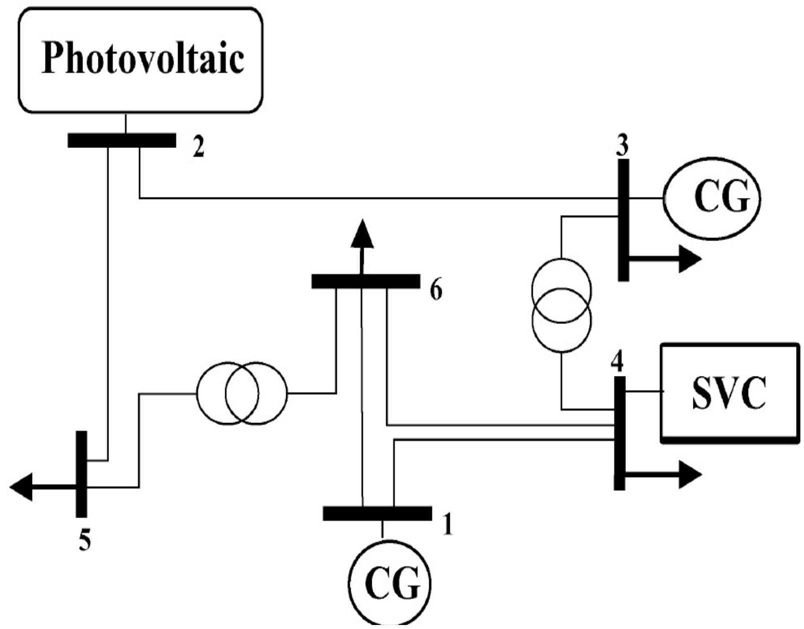

Fig. 3. *Pattern of AI-based PSO algorithm design*

As can be seen from Fig. 3, the conventional power generator source has been replaced with a PV-DER. However, in this study, the DER is added to the existing source; this allows the system to generate sufficient power and in addition save power when the sunshine is at maximum levels. Thus, the idea is to balance the power system requirement of the grid for sustainability purposes.

Research Question 2: What are the key parameters and variables that need to be considered in the AI-based PSO algorithm for optimizing SPV-DER integration within the Nigerian power system networks?

Transmission line parameter (which includes resistances (denoted R), reactances (denoted X), shunt susceptance (denoted B) between the interconnected points in the power network), power system network loading (which includes both generation (Slack and PV) buses and the load (PQ) buses) as well as variables of Bus, line power data for Nigerian 330-kV, 34-Bus and 11-machine system. They are subsequently presented and represented in Tables 2-4and Fig. 4.

Table 2: *Transmission Line Parameters*

From	To	R(p.u)	X(p.u)	B(p.u)	Tap
1	2	0.0122	0.0916	1.2100	1
1	4	0.0016	0.0120	0.3100	1
3	4	0.0002	0.0094	0.0000	1
4	5	0.0048	0.0360	0.0900	1
4	9	0.0021	0.0155	0.0700	1
5	6	0.0019	0.0142	0.3600	1
5	7	0.0003	0.0188	0.0000	1
5	10	0.0019	0.0142	0.3700	1
8	9	0.0054	0.0405	0.3300	1
8	15	0.0053	0.0406	0.4500	1
9	15	0.0065	0.0427	0.5500	1
9	16	0.0099	0.0742	0.9800	1
10	13	0.0090	0.0680	0.5200	1
10	14	0.0077	0.0582	0.7700	1
11	15	0.0021	0.0104	0.3100	1
12	15	0.0041	0.0305	0.4100	1
14	17	0.0104	0.0783	0.0100	1
15	16	0.0110	0.0828	0.0900	1
15	20	0.0004	0.0027	0.0500	1
15	21	0.0055	0.0414	0.3500	1
15	22	0.0012	0.0092	0.2000	1
16	18	0.0064	0.0405	0.1500	1
16	19	0.0038	0.0288	0.7600	1
16	21	0.0055	0.0414	0.5500	1
16	23	0.0054	0.0405	0.3800	1
16	24	0.0010	0.0074	0.1900	1
18	25	0.0010	0.0077	0.1000	1
19	26	0.0005	0.0038	0.3800	1
19	27	0.0006	0.0038	0.4000	1
22	28	0.0005	0.0036	0.3000	1
22	29	0.0003	0.0021	0.2000	1
23	30	0.0038	0.0284	0.3700	1
23	31	0.0049	0.0037	0.0900	1
23	32	0.0061	0.0455	0.0200	1
24	25	0.0025	0.0186	0.2400	1
28	29	0.0035	0.0206	0.3000	1
32	33	0.0010	0.0074	0.0900	1
33	34	0.0005	0.0038	0.3000	1

Table 3: *Line Parameters of the Power Network*

Branch No	From bus	To bus	Branch impedance p.u	Transformer Tap
1	1	6	0.123+ j0.518	1
2	1	4	0.080+ j0.370	1
3	4	6	0.097+ j0.407	1
4	5	2	0.282+ j1.050	1
5	2	3	0.723+ j1.050	1
6	6	5	0.000+ j0.3.300	1.025
7	4	3	0.000+ j0.133	1.100

Table 4: *System Loading (Bus) Data including PV generation and PQ-Loading*

Bus No.	Bus Type	Bus Voltage p.u	Angle degree	Load		Generrator		Shunt injection capacitance Q^C MVAR
				P_L MW	Q_L MVAR	P_G MW	Q_G MVAR	
1	Slack	1.05	0	0	0	0	0	0
2	PU	1.10	0	0	0	50	0	0
3	PQ	1	0	55	13	0	0	0
4	PQ	1	0	0	0	0	0	0
5	PQ	1	0	30	18	0	0	0
6	PQ	1	0	50	5	0	0	0

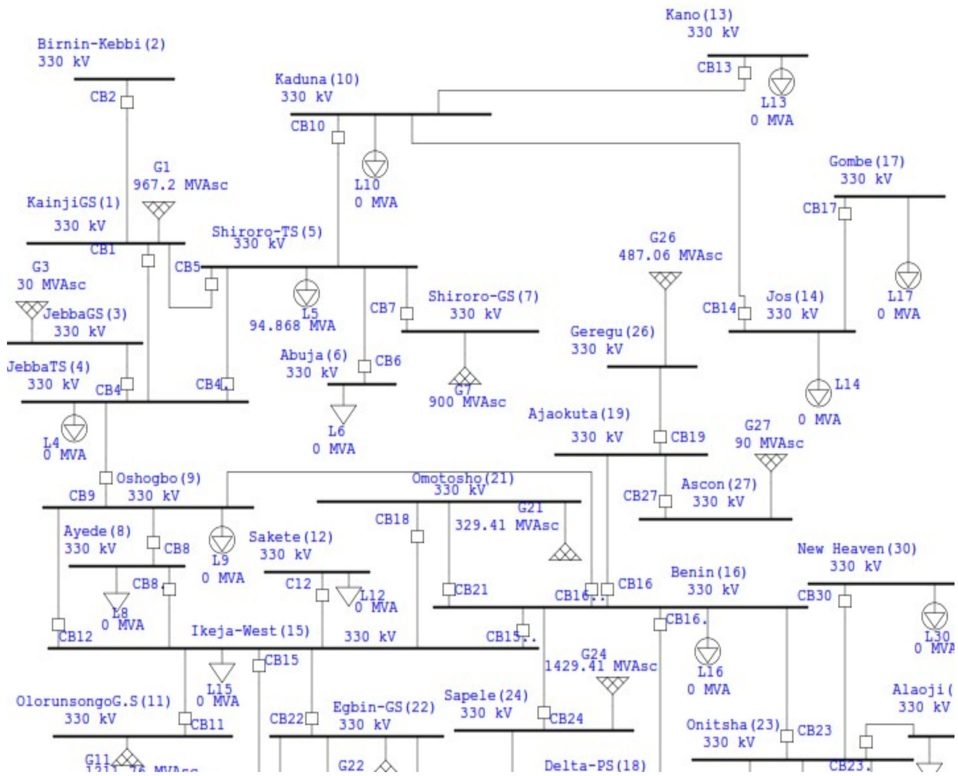

Fig. 4. *Bus, Line Power Data for Nigerian 330-kV, 34-Bus; 11-machine system*

As shown in Fig. 4, the considered Nigerian power system is a 34-bus, 11-machine network. The system is designed to operate at a base frequency of 50Hz and a base MVA of 100MVA. In this study, Kainji-GS (Bus 1) is considered a swing bus. The real power generation of the swing (slack) generator bus is estimated at 520MW at 0.8 power factor (pf). More so, the Tables showed that there are 6 buses out of which the first (Bus 1) is a slack or reference generator bus, the second (Bus 2) is a PV bus and the rest of thebuses are PQ load buses. The power system network loading includes both generation (Slack and PV) buses and load (PQ) buses. Where the bus is a PV or slack, an additional maximum and minimum MVAR limit is specified with the minima in brackets. The conventional LF solver typically defines slack as 0.00MW and MVAR, but it is essential to note that the ODERPON solution requires primary parameter settings for transmission line parameters. In Table 2, the data presented correspond to parameters for the transmission lines used for transmitting electric power between two points. The Table includes resistance, reactance, and line charging, all measured in per unit (p.u.) values. The tap value is set at 1.0, indicating no voltage up or down in all cases. Accurate parameter values are critical when constructing transmission lines as they determine power transmission efficiency and the maximum allowable power transferable via the line. The data in this Table indicate that the lines connecting nodes 1-4, 3-4, and 5-7 have low values of resistance, reactance, and charging. In contrast, the lines between nodes 16-19, 16-23, and 16-21 have a high value of resistance and reactance which may result in significant power losses. Overall, the efficient distribution of electrical power is highly dependent on these transmission line parameters and appropriate calculation is essential in developing electric power systems.

Research Question 3: How can the performance of the AI-based PSO algorithm be evaluated and compared with other optimization techniques for SPV-DER integration within the Nigerian power system networks?

Table 4 presents a comparison of the base results of the NR method with those of the proposed PSO. Fig. 5 shows the fitness profile of PSO regarding power-loss minimization steps against iteration size, with its maximum iteration size and population size set to 50,000 steps and 50 particles respectively. Tables 5to 12 and Fig. 5 to 10 also exhibit the results of DER when utilizing the PSO algorithm.

Table5: *Comparative Bus-voltages and angles of 6-Bus Using NR & PSO Methods*

Bus id	VbusNR (p.u.)	VbusPSO (p.u.)	DbusNR (rad)	DbusPSO (rad)
1	1.0500	1.0500	0.0000	0.0388
2	1.1000	1.1000	-5.6674	0.0199
3	0.8662	0.9962	-13.6677	0.0611
4	0.9644	0.9962	-9.8683	0.0611
5	0.9161	1.0000	-13.2530	0.0042
6	0.9527	1.0000	-12.5687	-6.2790

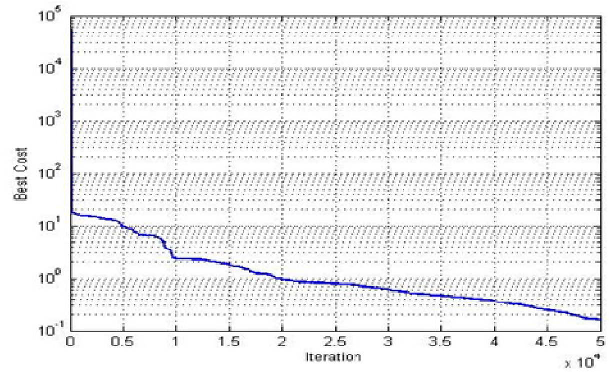

Fig. 5. *Fitness Response Plot of PSO Solution Process (Basic)*

5.1 Results Using Particle Swarm Optimizer Method with DER

The outcome of the PSO approach for the 6 Bus grid with Solar-PV-DER is depicted in Tables6and 7for trials 1 and 2, with identical iteration and population as the validation case. The fitness error responses are displayed in Fig. 6 and 7, while Table 7 contains the Solar-PV-DER power estimates.

Table 6: *Bus-voltages-angles of 6-Bus Using PSO & DER (Trial 1)*

Bus id	Vbus (p.u.)	Dbus (rad)
1	1.05	-1.17
2	1.10	-1.17
3	1.00	-1.17
4	1.00	-1.17
5	1.00	-1.17
6	1.00	5.11

Table 7: *Bus-voltages-angles of 6-Bus Using PSO & DER (Trial 2)*

Bus id	Vbus (p.u.)	Dbus (rad)
1	1.05	-2.02
2	1.10	-2.01
3	1.00	4.24
4	1.00	4.24
5	1.00	4.28
6	1.00	-2.00

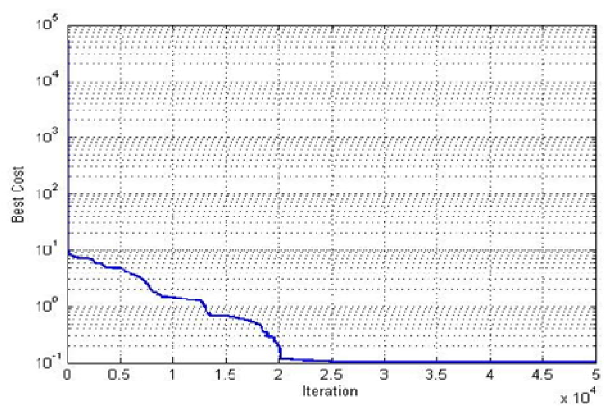

Fig. 6. *Fitness Response Plot of PSO Solution Process with DER (Trial 1)*

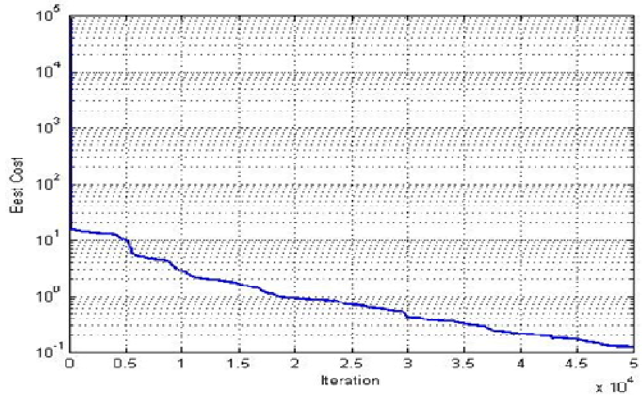

Fig. 7. *Fitness Response Plot of PSO Solution Process with DER (Trial 2)*

Table 7: *Estimated Solar-PV-DER Power Contributions and Sizing*

Trial	Solar-PV-Power Contribution (MW)	No. of Panels (Np)
1	55.00	1460
2	68.17	3618

From the results in Table 7, we see the ability of the proposed optimized Solar-PV-DER solution based on PSO (Solar-PV-DER-PSO) to make reasonable power estimates. In particular, for the second trial run, it is seen that the power contribution of the Solar-PV-DER can exceed the loading requirement of Bus 3.

Table 8: *Bus-voltages-angles of 6-Bus Using PSO & DER (10% Loading)*

Bus id	Vbus (p.u.)	Dbus (rad)
1	1.05	2.28
2	1.10	2.29
3	1.00	8.55
4	1.00	2.27
5	1.00	2.30
6	1.00	2.30

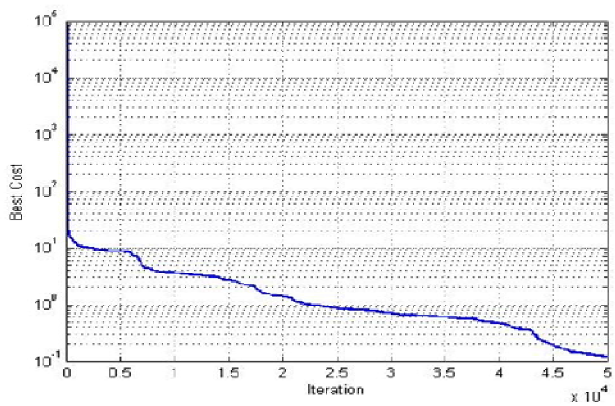

Fig. 8. *Fitness Response Plot of PSO Solution Process with DER (10% loading)*

Table 9: *Bus-voltages-angles of 6-Bus Using PSO & DER (50% Loading)*

Bus id	Vbus (p.u.)	Dbus (rad)
1	1.05	-2.70
2	1.10	-2.70
3	1.00	-2.70
4	1.00	-2.70
5	1.00	3.58
6	1.00	3.58

Table 10: *Bus-voltages-angles of 6-Bus Using PSO & DER (100% Loading)*

Bus id	Vbus (p.u.)	Dbus (rad)
1	1.05	-2.37
2	1.10	-2.37
3	1.00	3.91
4	1.00	-2.37
5	1.00	3.91
6	1.00	3.91

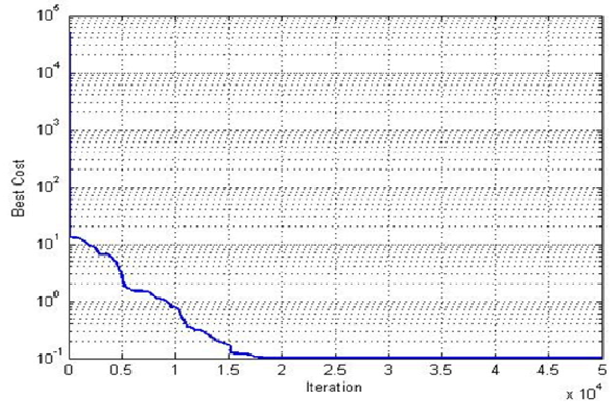

Fig. 9. *Fitness Response Plot of PSO Solution Process with DER (50% loading)*

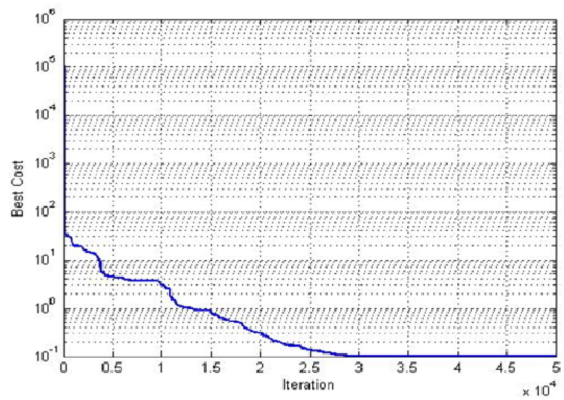

Fig. 10. *Fitness Response Plot of PSO Solution Process with DER (100% loading)*

Table 11: *Estimated Solar-PV-DER Power Contributions and Sizing (Incremental Loading)*

Loading (%)	Solar-PV-Power Contribution (MW)	No. of Panels (Np)
10	61.82	3282
50	42.75	2269
100	25.33	1345

As can be seen from Table 11, increasing the loading at bus 3 leads to a reduction in Solar-PV DER contribution. At the 10% level, the reduction is not significant when compared to the 50% and 100% levels of incremental loading.

Table 12: *Bus-voltages-angles of 34-Bus Using PSO & DER*

Bus id	Vbus (p.u.)	Dbus (rad)
1	1.0600	-1.0610
2	1.0000	5.2222
3	1.0400	-1.0609
4	1.0000	-1.0609
5	1.0000	-1.0608
6	1.0000	-1.0608
7	1.0000	-1.0608
8	1.0000	-1.0613
9	1.0000	-1.0612
10	1.0000	-1.0608
11	1.0200	-7.3446
12	1.0000	-1.0614
13	1.0000	-1.0608
14	1.0000	-7.3439
15	1.0000	-1.0614
16	1.0000	-1.0616
17	1.0000	-1.0607
18	1.0300	-1.0616
19	1.0000	5.2215
20	1.0000	-1.0614
21	1.0000	-1.0615
22	1.0500	5.2218
23	1.0000	5.2214
24	1.0400	-1.0616
25	1.0000	-1.0616
26	1.0100	5.2215
27	1.0300	-1.0617
28	1.0200	-1.0614
29	1.0000	-1.0614
30	1.0000	5.2214
31	1.0300	5.2214
32	1.0000	5.2213
33	1.0400	5.2212
34	1.0200	-1.0620

In Table 12, it is seen that all bus voltages are within tolerable limits after the LF solution. Also, the estimated solar power contribution and panel size were found to be 880.10MW and 46, 718 panels respectively.

6. Advantages and Disadvantages

Advantages

- The proposed method can provide optimal results and maximize energy generation from solar resources.
- The PSO algorithm can be adjusted based on environmental changes and network conditions.
- The use of the IEEE 6-bus system helps to obtain reliable and accurate analysis of network performance.
- This method used real-time data and system changes so, that the system can effectively adapt to changes.

Disadvantages

- This paper only focuses on the sources based on the application and testing of the PSO algorithm for power networks**.**

7. Conclusion and Recommendation

Nigerian power system, with its 34-bus, 11-machine network, requires accurate parameters for its transmission lines to ensure efficient distribution of electrical power. Monitoring power flows, voltage profiles, and stability limits is critical in maintaining the optimal functionality of the network, especially when dealing with fluctuating energy sources. While challenges remain, utilizing AI-enhanced resources to manage distributed energy resources and optimizeperformance has the potential to unlock vast opportunities for sustainable energy sources. Future research can explore the scalability and applicability of PSO-Solar-PV-DER in larger power networks. It also investigates the impact of different weather conditions and solar energy variations on performances.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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