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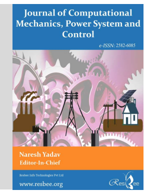

Artificial Neural Network with Crow Search Algorithm for Optimal Sizing of Photovoltaic System

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Abstract: The need for renewable energy sources in addressing global energy demands is growing, especially in Nigeria where electricity demand often exceeds supply. Solar photovoltaic (PV) systems have become a viable solution, with federal universities in Nigeria, as major electricity consumers, recognizing their potential. However, determining the right size of PV systems for individual faculties within these universities is a complex task. This study attempted to simplify this process by introducing an innovative approach to size PV systems in these faculties. The research method used the Extended Kalman Artificial Neural Network (EKF-ANN) and the Crow Search Algorithm (CSA) to enhance the accuracy of PV system sizing. Data was collected on the study site, load demand, weather conditions, system components, and operational control and systems models to establish sizing criteria. The study focused on the optimal size of a solar PV system at the Faculty of Law building, University of Port-Harcourt, and how to improve its accuracy. The results showed that using global solar insolation parameters, EKF-ANN predicted values for global temperature, flock size, and maximal iteration. This optimized system could generate surplus power for effective grid supply. The study found that the optimal size of the series-connected panels for the Faculty of Law building was 96, 83, 73, and 65 units, with corresponding insolation values ranging from 3.737 to 4.368 kW/m². It was concluded that the combination of CSA and EKF-ANN in solar PV sizing is suitable forachieving optimal outcomes for energy storage and grid supply. Nonetheless, the study recommended additional investigation into real-time and grid-connected solutions to enhance the proposed approach's effectiveness.

Keywords: Artificial Intelligence; Artificial Neural Network; Crow Search Algorithm; Solar-PV; Insolation

Nomenclature

Abbreviations	Descriptions
PV	Photovoltaic
AI	Artificial Intelligence
CSA	Crow Search Algorithm
EKF-ANN	Extended Kalman Artificial Neural Network
ANN	Artificial Neural Network
SPM	Solar-PV Module
SCC	Solar Charge Controller
PINV	Power Inverter
BM	Battery Module
RES	Renewable Energy Sources
O&M	Operation and Maintenance
PCON	Power Converter
EKF	Extended Kalman Filtering
POA	Probability of Awareness
LOF	Length of Flight
MATLAB	Matrix Laboratory
DOD	Depth of Discharge
TL	Total Load Demand
PSH	Peak Sunshine Hours
MPPT	Maximum Power Point Tracking
MPC	Model Predictive Control
PSO	Particle Swarm Optimization
RDG	Renewable Distributed Generation
CSA-ADPSO	Crow Search Algorithm/Auto-Drive Particle Swarm Optimization
HRES	Hybrid Renewable Energy Systems

1. Introduction

The utilization of AI techniques has revolutionized many industries, and their deployment in the PV system industry is no different. One of the most popular AI techniques currently in use is the CSA-optimized method[15]. The use of this algorithm as an integrated system is a viable alternative for sizing stand-alone PV systems [24]. Moreover, it also complements ANN[18]. This is especially important in areas with increasing demand for electricity but the poor supply of traditional analytical methods that may not offer the required degree of accuracy[17]. In buying time also, they can minimize investment costs to suit the situation. The sizing of stand-alone PV systems is vital to the effective functioning of PV systems [17]since it plays a significant role in determining the expenses of the PV system.

Notably, AI-based systems,such as the EKF-ANN[36] [2][25]and CSA techniques[32]have revolutionized the way solar cells, panels, and battery storage sizes are accurately determined. Such systems possess the unique ability to learn from examples and process incomplete data thereby enabling quick and reliable predictions and generalizationsnotwithstanding long-term radiation data acquisition remains a challenge in some stand-alone PV systems. The integration of analytical methods and AI-based systems can significantly improve the accuracy of analytical methods while benefiting from the speed and reliability of AI-based systems[13]. That said, the selection of an appropriate sizing regime is highly dependent on the specific application, and it is essential to balance the benefits and drawbacks of each approach. While AI-based systems offer numerous advantages, analytical methods remain the ideal approach for sizing stand-alone PV systems due to their simplicity and accuracy. The blending of AI-based systems and analytical approaches has become increasingly popular as technology continues to evolve[28]. This innovative approach provides a significant opportunity to solve complex issues that were previously insurmountable using traditional problem-solving techniques. The application of this cutting-edge technology in addressing the inadequate power supply in Federal Universities in Nigeria, beginning with the Faculty of Law building at the University of Port Harcourt, is an encouraging step towards paving the way for a more efficient and dependable power supply.

1.1 Statement of the Problem

The issue of providing consistent power supply while simultaneously minimizing unmet loads and storing excess energy plagues faculties in federal universities across Nigeria. Overcoming this challenge has prompted researchers to deploy hybridized and non-hybridized techniques. However, determining the right sizing of PV systems to meet total site loading and excess electricity requirements remains a major obstacle. The multifaceted complexities linked with effectively optimizing the PV systems have led to the start of a research project in the Faculty of Law building at the University of Port Harcourt. The project plans to use a unique optimization algorithm that leverages the integrated behavior of crows and computer systems modeled after the human brain. The project is in its infancy, and the effectiveness of this approach remains to be observed, but the researchers remain resolute in providing a groundbreaking prototype for coping with increasing electricity demands across numerous Nigerian federal university faculties.

1.2 Aim and Objectives of the Study

This study was aimed at investigating an ANN with CSA for optimal sizing of a PV system at the Faculty of Law building, University of Port-Harcourt. Specifically, the objectives were to:

1. Find outhow CSA can be utilized to determine the optimal size of a solar PV system at the Faculty of Law building, University of Port-Harcourt.
2. Establishhow an EKF-ANN can be integrated with the CSA to improve the accuracy of solar PV sizing at the Faculty of Law building, University of Port-Harcourt.

The proposed method combines an ANN with the CSA for optimal sizing of a PV system.The CSA is a metaheuristic-based AI optimizer that uses the concept of crow-searching behavior to find the optimal solution. Initially, the CSA parameters are initialized.Then an initial population of crows is generated and their fitness is evaluatedusing the ANN model.After that, the position of each crow based on the crow searching behavior is updated, and the fitnessof the new positions is calculated using the ANN model.The steps are repeated until it reaches the maximum number of iterationsto find the optimal sizing of a PV system.

The organization of this paper is in this order: Section 2 presents the literature review, and Section 3 explains the materials and methodology. The Results and discussionsare explained in section 4. Section 5 covers the result and discussion, Section 6 explains the advantages and disadvantages, and Section 7 concludes the paper

2. Literature Review

ANN is a computational model inspired by the structure and functioning of the human brain[29]. It consists of interconnected nodes, called artificial neurons, which process and transmit information through weighted connections. ANN is capable of learning from data and making predictions or decisions based on the patterns it recognizes[33]. Similarly, [23] submitted that CSA is a metaheuristic optimization algorithm inspired by the intelligent foraging behavior of crows. It mimics the way crows search for food by dividing the search space into subspaces and iteratively updating the positions of potential solutions to find the optimal solution. More so, [31]remarked that optimal sizing of a PV system refers to determining the appropriate size and configuration of components such as solar panels, batteries, and inverters to maximize the system's performance and efficiency while meeting specific requirements or constraints. In the same vein, different authors [20][34] acknowledged that the combination of ANN with CSA for optimal sizing of PV systems involves utilizing ANN as a predictive model to estimate the optimal sizing parameters for a PV system, while CSA is employed as an optimization algorithm to search for the best combination of these parameters. In this approach, [26] added that ANN is trained using historical data on various factors influencing PV system sizing, such as solar irradiance, temperature, load demand, and battery capacity.

According to [26],the trained ANN can then predict the optimal sizing parameters based on new input data. On the part of CSA, research has shown that it is used to optimize these predicted parameters by iteratively updating their values within predefined ranges[9]. The algorithm mimics the intelligent search behavior of crows to explore different combinations of sizing parameters and converge towards the optimal solution[7]. By combining ANN's predictive capabilities with CSA's optimization abilities, this approach aims to find the most efficient and cost-effective sizing configuration for a PV system[8][20], considering factors such as energy generation, storage capacity, and system reliability. This integrated approach has been applied in various studies related to PV system design and optimization [5]. For example, [3] utilized an ANN with CSA to optimize the algorithm on a smart microgrid, considering factors such as solar irradiance, load demand, and battery capacity. The results showed that the proposed approach outperformed traditional sizing methods in terms of system performance and cost-effectiveness. Another study [22] applied the combination of optimization of hybrid renewable energy involving predictive AI and CSA for high-rise residential buildings. The approach considered factors such as energy demand, solar resource availability, and battery capacity. The results demonstrated that the integrated approach could effectively determine the optimal sizing parameters, leading to improved system performance and reduced costs.

2.1 Theoretical Framework

The author [14] elucidates the theory behind the ANN and their applicability for optimizing the capacity of a PV system[4]. ANN is a computational model that emulates biological neural networks.It is an interconnected amalgam of artificial neurons that process and transmit data. With the help of historical data concerning solar radiation, temperature, and other pertinent factors. ANN can be trained to predict the most fitting dimensions of a PV system for amassing maximum energy production. Incorporating this approach can lead to better sizing decisions which can ultimately improve performance and cost-effectiveness. In contrast, the CSA represents a metaheuristic optimization technique that mimics the intelligent foraging behavior of crows. [30] introduced CSA to solve optimization problems in three phases - initialization, exploration, and exploitation. During the initialization phase, crows standing for potential solutions are randomly generated. In the exploration phase, each crow seeks to find a solution by assessing its fitness through an objective function. In the exploitation phase, the best solutions dictate the flight paths of other crows. To apply CSA to optimize solar PV systems, [10] extended the CSA by incorporating improved flower pollination to enhance its search capability and speed of convergence. CSA can identify the optimal system parameters by establishing an objective function incorporating factors such as solar irradiance, temperature, load demand, and cost. The algorithm proceeds to iteratively search for a combination of parameters that yields the best results.

2.2 Review

Table 1 portrays the objective, methodology, key findings, and contribution of the existing method. We considered eight papers that used a different methodology for the Optimal Sizing of PV Systems. Each method has certain benefits and shortcomings that were explained in detail**.**

Table 1. *Review Based on Existing Methods*

Authors	Year	Objective	Methodology	Key Findings	Contribution
Cortés-Caicedo ,*et al* [11]	2022	To solve the problem of optimally locating and sizing PV generation units in electrical networks.	Master–slave methodology	Achieved cost reductions in the total annual operating costs by optimizing the location and sizing of PV generation units in electrical. networks.	Application of the CSA for optimizing the location and sizing of PV generation units in electrical networks to reduce operating costs.
Ahmed, *et al* [1]	2020	To present a comparative review ofMPPT techniques based on MPC.	Comparative review methodology	Extended Kalman filter was found to be an effective algorithm in achieving accurate tracking of the maximum power point for PV systems using a single voltage. sensor.	Comparative review of MPPT techniques based on MPC.
Farh,*et al* [14]	2020	To propose a CSA auto-drive PSO for optimal allocation and sizing of renewable distributed generation.	Mixed research design	The algorithm effectively determined the optimal locations and sizes of RDG units, leading to improved system performance and reduced power losses.	Solving the problem of optimal allocation and sizing of RDG in power systems through the combination of the CSA-ADPSO algorithm.
Javad-Aliabad iand Radmehr [19]	2021	To optimizeHRES in radial distribution networks while considering uncertainties using the CSA.	CSA algorithm	The proposed approach considered uncertainties, leading to more reliable and robust solutions for integrating RES into distribution networks.	Novel application of the CSA algorithm for optimizing HRES in RDS.
Gurubel,*et al* [16]	2016	Creating smarter energy systems with grid-connected storage.	Neural forecasting techniques and optimization methods.	Accurate forecasting, and optimal sizing of hybrid renewable energy with storage.	The study provided a novel approach for forecasting and sizing HRES with a grid-connected storage system using neural forecasting techniques.
Docimo, *et al* [12]	2017	Estimate the PV module's temperature and irradiation with EKF for MPPT.	EKF	The algorithm was found to be effective in estimating the temperature and irradiation for the MPPT of a PV module.	It highlighted the potential of using EKF for MPPT in solar energy systems.
Villegas-Mier, *et al* [35]	2021	To review the use of ANNs in MPPT algorithms for optimizing PV power systems.	Comprehensive reviewusing pre-selected data from the PV system.	ANNs offer advantages such as adaptability, robustness, and accuracy in tracking the maximum power point.	It highlighted the potential of ANNs for optimizing the performance of solar energy systems.
Boulmrharj, *et al* [6]	2018	To propose an approach for dimensioning stand-alone PV systems, considering factors such as load demand, solar irradiation, and battery capacity.	The study developed an approach for dimensioning stand-alone PV systems based on load demand analysis, solar irradiation data, and battery capacity requirements. The proposed approach was validated through simulations and case studies.	The approach was found to be effective in facilitating the installation and enhancing the behavior of stand-alone PV systems.	It provided a systematic method for determining the optimal configuration of such systems, considering various factors that impact their performance and reliability.

2.3 Identified Research Gap

While there are studies on the use of ANN and CSA for optimal sizing of PV systems, specific research focusing on the Faculty of Law building, University of Port-Harcourt is lacking. This presents a research gap as the unique geographical, climatic, and architectural characteristics of this location may influence the performance and optimization of PV systems. Furthermore, most existing studies do not integrate ANN with CSA in their methodologies, which could potentially enhance the accuracy and efficiency of PV system sizing. Another gap lies in the lack of comparative studies between this combined approach and other optimization techniques. Therefore, research is needed to explore the effectiveness of ANN and CSA in this specific context and to compare their performance with other methods. This could provide valuable insights for the design and implementation of PV systems in similar environments.

3. Materials and Methodology

To evaluate renewable energy systems effectively, choosing the right site requires consideration of specific criteria. These include solar PV, battery, neural, and optimization models. Others are:

i. Study site and available load demand
ii. Metrological data.
iii. System components.
iv. Mathematical modeling description.
v. Operational Control and Systems Model.

3.1 Specifications of Selected Location and Load Demand Data

Accurately determining a building's energy demands is crucial when designing a RES. Thermal modeling of the home is utilized to achieve this goal. As a case study, the University of Port Harcourt's Faculty of Law building was chosen. Since the building is intended for faculty use, electricity is not used for cooking and heating purposes, resulting in insignificant load demand.

3.2 The Metrological Data

Solar radiation and ambient temperature significantly impact the PV output power. The following points describe solar irradiance and temperature at the selected building, obtained from the University of Port Harcourt.

Solar radiation: The annual average and the maximum value of solar irradiance are 5.15kWh/m^2/day and 7.61kWh/m^2/day respectively. University of Port Harcourt receives a noticeable volume of solar irradiance which confirms that solar power plant is a significant energy source.

***Ambient temperature*:** Ambient temperature plays an essential role in the PV panels' performance. Hence, a correct evaluation of ambient temperature data is crucially important. For the purported site, the ambient temperature was found to vary between 26^{o}C and 32^{o}C during sunshine hours.

3.3 System Components

A stand-alone solar system typically consists of two core components: the SPM and BM. Other necessary components include converter electronics like the SCC and PINV, These are described in the following sub-sections.

***Solar-PV module*:** Solar energy requirements can be fulfilled by arranging some PV modules in series and parallel. Various PV modules of different sizes from 60W to 170W are commercially available. For this research project, the Suniva ART245-60 modules from Suniva® Inc. were utilized since they are highly efficient monocrystalline cells with rated output, designed optimally for high-power applications such as grid-tied systems. Table 1 demonstrates the features of Suniva ART245-60's solar module under standard test conditions.

Battery module: The BM plays animportant role as an energy storage medium during cloudy weather periods of abysmally low solar insolation. For this research work, the Rolls Flooded Deep Cycle Batteries (Type-6CS25P) manufactured by Surrette Battery Company® Inc. are used. It has a maximum ampere-hour (A-h) capacity of 1156A-h and 279A-h.

Table 2: *Characteristics of Suniva ART245-60 solar module*

Parameter	Symbol/Unit	Rated Value
Maximum Power	Pmax (W)	240
Voltage @ Maximum Power	Vmp (V)	30.65
Current @ Maximum Power	Imp (A)	7.82
Open Circuit Voltage	Voc (V)	37.08
Short Circuit Current	Isc (A)	8.33
Voltage-derating factor	β,Voc (%/°C)	-0.332
Current-derating factor	α,Isc (%/°C)	+0.035
Power-derating factor	γ,Voc (%/°C)	-0.465
Cell per Module	N	60
Module Dimension		1657x987mm
Module Thickness (Depth)		42mm
Approximate Weight		19kg
Max. System Voltage	Vdc	1000
Operating Module Temperature	°C	-40 to +90
Module Efficiency		14.9%
Fill Factor		77.6%
Irradiance		1000w/m²
Normal Operating Cell Temperature	NOCT	45°C
Base Temperature		25°C
Type of Solar Cell	Monocrystalline cells of 156 x 156 mm	
Frame	Silver anodized aluminum alloy	
Glass	Low-iron & tempered with anti-reflective coating	
Junction Box	IP67 rated; with internal bypass diodes	
Cable	4 mm² cable length approximately 1m	
Connection	MC4 Connector	

3.4 Mathematical ModelingDescription

The Solar-PV power system calculations were factored in the SPM and BM models, including charge controller and inverter efficiency parameters as per standard procedure. The economic analysis also includesthe O&M costs of the converter, battery, and solar PV module. Additionally, the mathematical models for ANN and CSA were outlined.

Solar-PV power modeling:For a given PV module, the solar generation may be computed considering the peak sunshine periods, and the peak Solar-PV power including the charge controller and inverter efficiencies [27].

$$P_{pv(pk)} = \frac{TL}{PSH * n_{cr} * n_{inv}} \tag{1}$$

Where,

TL = The total load demand

PSH= Peak Sunshine Hours

n_{cr} = SCC efficiency

n_{inv} = PINV efficiency

Using the peak powers, the actual continually generated PV powers can be computed accordingly [27][37] [38] [39]

$$P_{pv} = P_{pv(pk)} * \left(N_s * N_p * I_{sc} * V_{oc} * FF\right) \tag{2}$$

Where,

N_s = number of PV modules connected in series

N_p = number of PV modules connected in parallel

V_{oc} = open circuit voltage of single PV module at standard test conditions

I_{sc} = short-circuit current of single PV module at standard test conditions

FF = Fill factor of PV module

The open circuit and short-circuit parameters Voc and Isc are computed as follows:

$$V_{oc} = V_{oc(stc)} - K_v T_c \tag{3}$$

$$I_{sc} = \left(I_{sc(stc)} + K_i (T_c - 25)\right) G \tag{4}$$

Where,

K_v = PV module open-circuit voltage temperature coefficient correction factor, $V/^oK$

K_i = PV module short-circuit current temperature coefficient correction factor, $A/^oK$

G = Global solar irradiance, $kW\text{-}hr/m^2/day$

T_c = PV cell temperature, ^{o}

The cell temperature T_c is influenced by ambient conditions and can be precisely estimated using EKF-ANN.

$$T_c = T_{amb} + (0.0256 \times G) \tag{5}$$

Where,

T_{amb} = ambient temperature, ^oK

BMmodeling: The primary consideration when modeling the BM is its size in Ampere-hour (A-h). The BM A-h capacity determines how much current can be delivered per hour by the battery. Following the model presented in [27], BM A-h capacity can be estimated as:

$$C_{Ah} = \frac{\left(\frac{TL}{ninv}\right) * A_{days}}{DOD * n_{BAh} * N_s * N_p * V_B} \tag{6}$$

Where,

V_B = BM voltage

n_{BAh} = Battery efficiency

Techno-economics modeling design: The economics of the solar PV system considers the O&M costs for the PCON as suggested [40] and the BM and SPM costs as suggested in [41].
The costs are implemented as an objective (fitness-cost) function including as in equation (7):

$$C = C_{pv} * (N_p + N_s) + C_{bat} * N_{bat} + C_{inv} * N_{conv} \tag{7}$$

Where,

N_{conv} = Number of converters

C_{pv} = Solar-PV cost per module

C_{bat} = Battery cost per module

C_{inv} = Inverter cost per module

EKF-ANNmodeling design: While the ANN used a standard learning algorithm based on back-propagation, it was further optimized by the method of EKF as described in [21].

***Crow search algorithm*:** The CSA is a greedy and ruthless approach tofinding optimal solutions. Solutions are ranked using thievery and hiding tactics based on LOF and POA. Depending on the lof value and a reference state of 1, crows may find local (<1) or global (>1) optima. CSA follows a two-step procedure, as shown in the key search equations:

Consider a follower crow state value say, i, and another hider crow state value say, j.Also, consider a set of follower flocks say, x, and correspondingly another crow set called the hider-set say, m, with iterations set at $iter$, where $iter$ = 1, 2, 3, …, $iter_{max}$. The follower flocks are represented as a set of d-dimensional vectors:

$$x^{i,iter} = [x_1^{i,iter}, x_2^{i,iter}, \ldots, x_d^{i,iter}] \tag{8}$$

Also, assuming the crow state value, j correspondingly is at position say, m^j_{iter}, which represents a hiding place.

Then:

For State 1: Crow j is unaware that Crow i follows it; hence, Crow i approaches a solution point in space at iteration step, $iter$, to Crow j food hideout, with a Crow j awareness probability of $AP^{i,iter}$. This can be described by equation (9) as follows:

$$x^{i,iter+1} = x^{i,iter} + r_i \times fl^{i,iter} \times \left(m^{i,iter} - x^{i,iter}\right) \qquad r_j < AP^{i,iter} \tag{9}$$

For State 2: Crow j is aware that Crow i follows it; hence, Crow j deceives Crow i to approach a random point away from its food hideout, with an awareness probability of $AP^{i,iter}$.

$$x^{i,iter+1} = r_i \qquad r_j \geq AP^{i,iter} \tag{10}$$

To guarantee that good memory positions are attained basedon equations (9) and (10), a memory update fitness functional rule is employed as shown in equation (11):

$$m^{i,iter+1} = \begin{cases} x^{i,iter+1} & f\left(x^{i,iter+1}\right) > m^{i,iter} \\ m^{i,iter}, & \text{otherwise} \end{cases} \tag{11}$$

It is important to note that the value of $AP^{i,iter}$ should be chosen such that it permits the process of diversification and intensification, a key attribute for metaheuristic-based artificial intelligent optimizers.

4. Results and Discussions

Research Questions

1. How can the CSA be utilized to determine the optimal size of a solar PV system at the Faculty of Law building, University of Port-Harcourt?
2. How can an EKF-ANN be integrated with the CSA to improve the accuracy of solar PV sizing at the Faculty of Law building, University of Port-Harcourt?

Results detailing how the CSA can be utilized to determine the optimal size of a solar PV system at the Faculty of Law building, University of Port-Harcourt (Research question 1) and how EKF-ANN can be integrated with the CSA to improve the accuracy of solar PV sizing at the Faculty of Law building, University of Port-Harcourt (Research question 2) were revealed.The results were obtained through neural network training and testing, as well as the CSA's performance in predicting optimum Solar PV installation sizing, monthly ambient temperature, and the impact of various search strategies on the prediction of monthly solar irradiation.

4.1 Simulation Details

The simulations were performed using the MATLAB® software installed on a suitable PC. The key parameters for the Solar PV optimization including boundary constraints using CSA are provided in Table 2. The key CSA and EKF-ANN parameter values are also specified in Table 3 and Table 4 respectively.

Table2. *CSA boundary optimization constraints*

Parameter	Parameter Symbol/Unit	Upper Bound	Lower Bound
Number of Series Connected Panels	Ns	100	1
Solar Insolation	G (kWh/m^2 day)	5:1	5:1
Ambient Temperature	T_a(mm)	Estimated from, G	Estimated from, G

Table3. *CSA Parameters*

Parameter	Default Parameter Value
LOF	2
POA	0.1
flock size, f_z	20
maximal iteration time step, t_{max}	5000

Table4. *EKF-ANN Parameters*

Parameter	Default Parameter Value
Percent Train, P_T (%)	90
Number of hidden neurons	60
Activation Function	Tanh

In Table 3, the first two parameters are intuition-based while the last two are population-based parameters. The parameter P_T, in Table 4, is needed for determining the number of samples used by the EKF-ANN for training

4.2 Solar PV Ambient Temperature Estimation Results

Accurate ambient temperature estimation is crucial for efficient modeling of solar power generation from PV panels. Monthly solar insolation-temperature data and an EKF-ANN estimator can be used effectively to estimate the temperature. After multiple trial runs, the best neural prediction error results were 0.0848^{o}C and 0.0799^{o}C for the training and test sets. Fig.2 provides EKF-ANN's training and test prediction response.

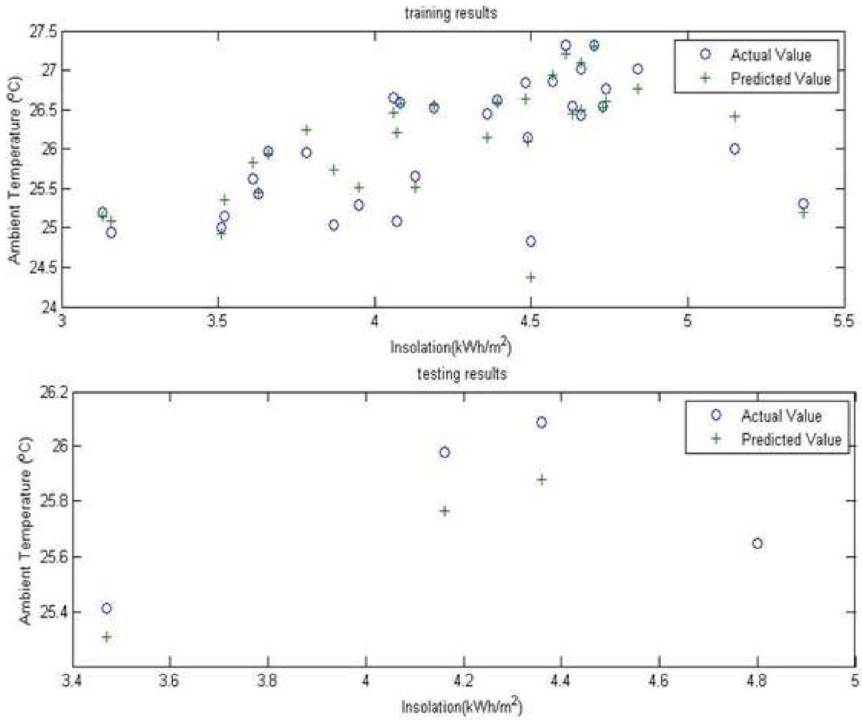

Fig.2. *Neural Prediction Response (90% Training data)*

Fig.2. shows that EKF-ANN's training and test responses track each other closely, with a few deviations between their predicted and actual values. The small error values and lower test error than training error indicate that the neural model is not overfitting to the input data. Therefore, the EKF-ANN model can be considered an effective estimator of ambient temperature based on solar insolation in the proposed case study site.

4.3 Solar PV System Optimization

Considering the developed EKF-ANN ambient temperature estimator model, numerical optimization using the CSA optimizer was performed to determine the optimal state parameters for citing a Solar PV in the case study sites. The optimizations were performed considering the default CSA parameter setting and also a variation of the flock size parameter, *N*. The fitness power mismatch error response (Best Cost vs. iteration) is shown in Fig.3 while corresponding simulation results for various flock sizes areshown in Fig.4.

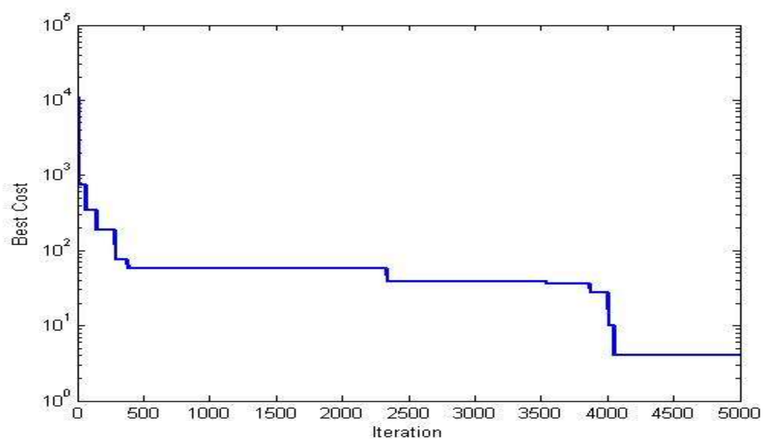

Fig.3. *Fitness power-mismatch error responses for default CSA parameter setting*

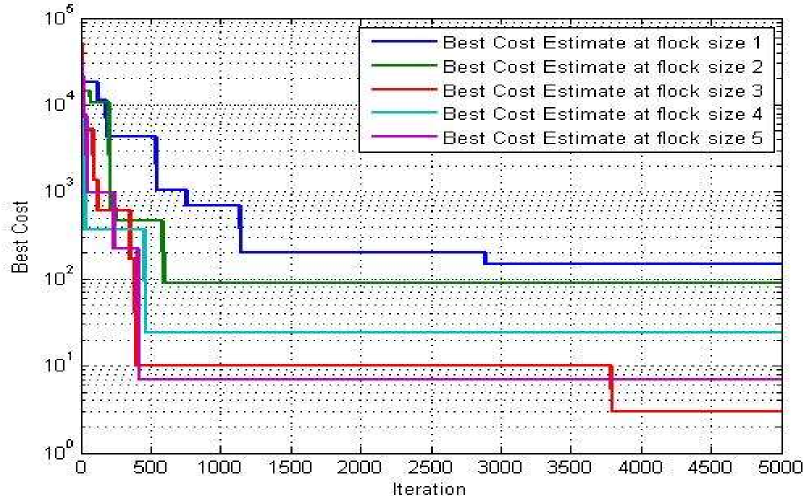

Fig.4. *Fitness power-mismatch error responses for various flock sizes*

From Fig. 3, it can be seen that the CSA responds to the Solar PV parameter optimization by a minimization operation over some sample iterations. These Best Cost through the first 500 iterations (iters) follows a graded somewhat staggered decrease and then begin to roughly stabilize from about the 500th iteration to the 4000th one for which a graded sharp drop in cost error (Best Cost) is observed. From the 4000th iteration to the 5000th iteration, no significant drop in Best Cost is observed; this implies a possible final solution is found at the 4000th iteration and further increases in maximal iteration time step parameter, t_{max}, may not benecessary. A similar fitness response profile can be observed in Fig. 4 as t_{max} is increased. In particular, it can be seen that while theBest Cost estimate was found earlier at a flock size, fz = 5 (500th to about 4000th iteration), a much better solution was found later at a flock size, fz = 3 (about 4000th iteration to 5000thiteration). The earlier solution is a special case of sub-optimality which was avoided by increasing the range of t_{max}.

4.4 Optimized Parameter and Excess Power Estimates

The Solar PV estimates consider the optimization parameter at the different insolations. For this study, the insolations are captured by a set of 20 linearly spaced data values from 1 to 5kW/m^2 (see Table 5). Using a developed MATLAB CSA program routine, the optimized states are shown in Table 5.

Table 5. *Numerical optimized parameter and excess power results*

sample	*G (kW/m2)*	*N_s(opt)*	*G_{opt}(kW/m2)*	*$T_{a(opt)(}$ (^{o}C)*	*P_{excess}(kW)*
1	1.0000	80.0694	0.0010	1.0000	-31.16084101
2	1.2105	96.8582	0.0010	1.0000	-24.10409626
3	1.4211	82.7175	0.0010	1.0000	-30.04779547
4	1.6316	98.4269	0.0010	1.0000	-23.44475182
5	1.8421	78.0208	0.0010	1.0000	-32.02193775
6	2.0526	99.4848	0.0010	1.0000	-23.00010978
7	2.2632	90.4480	0.0010	1.0000	-26.79848025
8	2.4737	76.3237	0.0010	1.0000	-32.73526325
9	2.6842	96.2771	0.0010	1.0000	-24.34837478
10	2.8947	95.9562	0.0010	1.0000	-24.48322886
11	3.1053	86.1510	0.0010	1.0000	-28.60459562
12	3.3158	100.0000	3.3160	25.0000	-29.09434317
13	3.5263	100.0000	3.5260	25.0000	-29.63840012
14	3.7368	96.0000	3.7370	26.0000	30.56046829
15	3.9474	83.0000	3.9470	26.0000	20.20831123
16	4.1579	73.0000	4.1580	26.0000	12.22971653
17	4.3684	65.0000	4.3680	26.0000	5.793837237
18	4.5789	58.0000	4.5790	26.0000	-0.010473096
19	4.7895	52.0000	4.7890	26.0000	-5.1085036
20	5.0000	47.0000	5.0000	26.0000	-9.391129345

From Table 5, the optimal parameter state values *(N_s(opt),G_{opt}(kW/m2)* and $T_{a(opt)(}$ (^{o}C). However, the feasible optimal states to support gridconnectivity are obtained at sample insolation points 14 to 17 (see table section in bold). Thus, it will be more beneficial to operate the Solar PV system as an effective energy storage unit or in grid-connected mode at these points.

5. Advantages and Disadvantages of Adopting ANN with CSA for Optimal Sizing of PV System

Advantages:

i) **Enhanced Accuracy**: The combination of ANN and CSA can provide more accurate results in sizing PV systems due to their ability to learn and adapt from data.

ii) **Efficiency**: CSA being a swarm intelligence-based algorithm, can efficiently search for the optimal solution, reducing the time and computational resources required.

iii) **Adaptability**: ANN's ability to learn and adapt makes the system more flexible to changes in environmental conditions and system parameters.

iv) **Scalability**: The ANN and CSA approach can be scaled up or down easily, making it suitable for both small and large PV systems.

v) **Robustness**: The combination of ANN and CSA can handle complex and non-linear problems, making it robust against uncertainties and variations in the system.

Disadvantages:

i) **Overfitting:** ANN models can sometimes overfit the training data, leading to poor generalization performance on newunseen data.

ii) **Complexity:** The combination of ANN and CSA can be complex to implement and require a deep understanding of both techniques.

iii) **Computational Cost:** Although CSA is efficient, the training process of ANN can be computationally expensive, especially for large and complex systems.

6. Conclusions and Recommendations

A new and innovative approach to optimizing solar PV system sizing has been discovered through a groundbreaking study at the University of Port-Harcourt. This approach uses a combination of the CSA and the EKF-ANN to achieve optimal results. The CSA is responsible for finding the ideal installation size for Solar PV panels, while the EKF-ANN analyzes various parameters such as search strategy, ambient temperature, insolation constraints, and objectives such as matching excess energy or powerload. The study has shown that by using specific panel sizes and considering insolation levels, it is possible to generate energy storage or supply to the grid. However, additional research is necessary to explore real-time Solar PV systems, intelligent-based linear solar PV, and Grid-connected solutions/technologies.

Compliance with Ethical Standards

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

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

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