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An Optimization Tool for a Standalone Photovoltaic System

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ABSTRACT

Stand-alone photovoltaic systems (SAPV) are often used in remote areas where access to grid electricity is limited. This system depends on solar energy. However, Photovoltaic (PV) systems need a greater initial investment than conventional sources of energy, and their effectiveness is reliant on a number of environmental conditions such as the unpredictable solar radiation. One step in reducing the investment cost of a PV system is determining the optimal size of solar PV components that minimize costs. This paper presents a Particle Swarm based optimization tool for sizing Stand-alone PV systems. The optimization tool selects the optimal Levelized Cost of Energy (LCOE) of the PV system during its entire lifespan while maintaining its reliability. The Particle Swarm Algorithm was implemented in order to solve the optimization problem. The Loss of Power Supply Probability (LSPS) is considered as the reliability index for this optimization. A design example in Serengeti, Tanzania is used to validate the proposed method. With an average daily load consumption of 94.3kWh, an optimal size of 30kW of Solar PV, 82kWh of Li-ion battery and 13kW of inverter was obtained at a LCOE of 0.22114 $/kWh. The Power simulation for this system was also carried out based on the mathematical models. The proposed method is investigated by simulation with several meteorological data, and the effectiveness is validated by using a similar tool which utilizes the mixed integer linear programming method.

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INTRODUCTION

Population growth results in an increase in electricity demand. The majority of this demand is satisfied by the usage of fossil fuels. According to (Agency, 2022), The production of oil, coal, and other fossil fuels accounts for 66% of the energy consumed by consumers. The downsides of fossil fuels are their scarcity and environmental issues, which are the primary source of global warming, acid rains, and air pollution. Renewable energy sources (RESs) are superior alternatives to fossil fuels (Kåberger, 2018). The benefits of RES include its environmental friendliness and global availability. Further, consumption does not diminish RES. Considering these benefits, several nations are being encouraged to use RES over fossil fuels (Algarni et al., 2023).

Due to the fact that photovoltaic (PV) systems are a clean, ecologically friendly,

and secure energy source, their installation has played a vital role on a global scale (Tawalbeh et al., 2021). However, PV systems need a greater initial investment than conventional sources of energy, and their effectiveness is reliant on a various environmental factors, including the unpredictable nature of solar radiation and variable weather patterns that includes temperature fluctuations, and different forms of precipitation such as rain and snow (Mwakitalima et al., 2021). Lately, storage batteries and super capacitors have been increasingly utilized to enhance reliability of PV systems (Balducci et al., 2021).
Stand-alone photovoltaic systems are often used in remote areas where there is limited access to grid electricity (Idoniboyeobu et al., 2017). These systems consist of a solar PV system and a battery bank to enable power supply during low sun conditions. A major problem associated with Photovoltaic (PV) system consisting of a solar panel and a battery, is how to determine the optimal size of each system components to reliably meet load demands (Seedahmed et al., 2022). Sub optimal size would result in enormous investment costs that could be avoided, inefficient exploitation of energy sources, and decreased power reliability, all of which would severely affect the community that the system is intended to serve (Kapilan et al., 2022).

The development of efficient and cost-effective PV systems is crucial for the widespread adoption of renewable energy source. The optimal sizing of standalone PV systems remains a significant challenge in the field (Khatib & Muhsen, 2020). To this end, various approaches have been used in literature for optimal sizing. Gradient-based methods use differential calculus to find the best solutions for differentiable and continuous functions. These techniques are broadly categorized as Linear programming model (LPM), dynamic programming (DP), and nonlinear programming (NLP) and have been widely utilized in hybrid systems size (Mekontso et al., 2019). However the random nature of natural resources, the nonlinear change in power output from PV arrays, the choice of component type, orientation, and the economic model of the cost of energy produced by PV systems all make the optimization problem of these systems very difficult to be done by classical methods (Memon & Patel, 2021). This fact has led researchers to develop several approaches and strategies for optimizing PV systems, including heuristic methodologies.
Heuristics are computational methods that repeatedly improve candidate solutions to find an optimal solution based on a given measure of quality. (Wang & Chen, 2013). Despite meta-heuristic methods being superior to traditional approaches, its usage in power system problems is still low (Memon & Patel, 2021).It has been observed that the Genetic Algorithm (GA), Particle Swarm Algorithm (PSO), and their derivatives have been the most prevalent meta-heuristics utilized in prior literature. Makhloufi determined the dimensions of the PV array and the storage battery for a PV lighting system application in Adrar, Algeria using a GA. The GA technique was compared to the worst month method and the ***Loss of Power Supply Probability*** (LPSP) method, both of which are traditional approaches. The results revealed that the GA technique outperformed the other two approaches (Makhloufi, 2015).

The authors in (Yoza et al., 2014) used the Tabu Search (TS) approach to improve PV/battery combo in a Japanese smart house. By implementing the optimization issue in two portions, consideration was given to optimal appliance scheduling based on lowest operational cost and expansion planning based on least total system cost. The economic factor that was incorporated into the optimization function for the two halves of this study may not precisely correspond to the technical factor.

The authors in (Aziz et al., 2014) proposed Evolutionary Programming (EP) for the sizing of the SAPV system in a rural

Malaysian village located in Tawau, Sabah. As a technical evaluation of the system, performance ratio (PR) was used. The classical evolutionary programming (CEP) and fast evolutionary programming (FEP) methods were used to size the SAPV system and were evaluated in comparison with the iterative-based sizing algorithm (ISA) with and without the Maximum Power Point Tracker (MPPT). However, monthly meteorological data, daily load demand, and a simple battery model were used, which could impact the generated power output.

In the field of Computational Intelligence PSO is a relatively recent approach that has been employed with great success. PSO involves social engagement in problem solving where it imitates social behavior of the bird flocking and fish schooling (Amer et al., 2013). PSO algorithm was originally proposed by Kennedy and Eberhart in 1995(Kennedy & Eberhart, 1995). In PSO, the coordinates of each particle represent a possible solution referred to as particles with a location and velocity vector. In each iteration, particles in a physical-dimensional search space get closer to the optimal solution by displaying their velocity, the best solution they have attained at that time, and the best solution acquired by all particles

Using PSO, Amer, Namaane and M'Sirdi, presented a basic strategy for optimum power generation from several sources in Hybrid Renewable Energy System (HRES) to lower the Levelized Cost of Energy (LCOE). In addressing such optimization problems, the PSO showed its heightened sensitivity and intensity (Amer et al., 2013). On the other hand, Djidimbélé (Djidimbélé et al., 2022) proposed a method for estimating and reducing power losses of a Hybrid Photovoltaic and Wind System (HPWS) in a Radial Distribution Network (RDN) using PSO. The constraints on objective function allowed to size the photovoltaic generator, wind turbine, and total production cost. The proposed system configuration (PSC) increased voltage and minimized power losses in the radial network.

In this paper, an optimization tool for sizing a SAPV is presented. The tool suggests the optimal PV, battery, and inverter sizes to satisfy a given power demand at the lowest possible cost. The cost minimization is implemented using the Particle Swarm Optimization (PSO). The performance of the presented SAPV system is evaluated by using 15min meteorological and typical load demand data. The rest of the paper is organized as follows. Section 2 presents the steps of modelling the SAPV systems, proposed optimal sizing algorithm using PSO and the design example. Section 3 presents the results and discussions. Finally, Section 4 concludes the work and suggests future directions.

METHODS AND MATERIALS

Modelling of a Standalone PV System

The stand-alone PV systems consists of the Solar PV panel, a storage device and its controller that regulates and controls the output from solar array in order to meet the load power requirements (Onar & Khaligh, 2015). The storage device supplies the difference between PV panel power and load bus power. The PV panel supplies load power and charge the storage device when its power exceeds demand. Figure 1 shows a basic PV panel/battery architecture**.**

PV Model

Equation (1) is used to estimate the output power of a PV module based on the solar irradiation at time *t* (Vinod et al., 2018)

$$P_{PV}(t) = N_{PV} \cdot (\frac{G_{(t)}}{G_{stc}}) \cdot ([1 + \alpha(T_C - T_{STC})] \quad (1)$$

where, N_{PV} is the rated PV size, $G(t)$ is the total solar irradiance (W/m^2) at given time instant t, G_{stc} is the solar irradiance (W/m^2) at Standard Test Condition (STC) (1kW/m^2), T_C is the cell temperature, T_{STC} is the PV cell temperature at STC, α is the temperature coefficient of the PV cell.

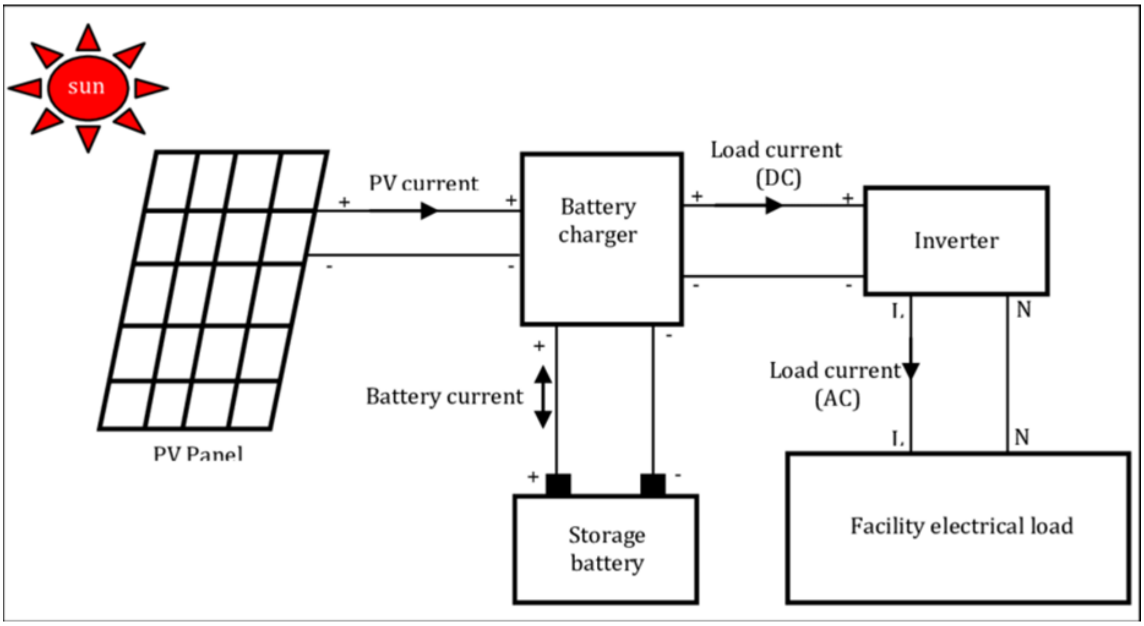

Figure 1: Standalone PV System with battery (Onar & Khaligh, 2015).

The temperature of the cell can be calculated in (2) (Vinod et al., 2018)

$$T_c = T_a + \left[\frac{T_{OC}-20}{800}\right].G(t) \quad (2)$$

T_a is the ambient temperature in degrees Celsius, whereas T_{OC} is the nominal operating cell temperature.

Battery Model

The battery can both serve the load during a power loss (discharge) and store extra power (charge) when generated power exceeds load demand, depending on its state of charge (SOC) (Chen et al., 2020). Equations (3) and (4), respectively, can be used to calculate the battery's discharging and charging energies at time t (Traoré et al., 2018) .

$$E_{bd}(t) = E_{b,(t-1)} - [(P_L(t) - P_{PV}(t)) \cdot \Delta t] / \eta_d \quad (3)$$

$$E_{bc}(t) = E_{b,(t-1)} + [(P_{PV}(t) - P_L(t))\Delta t].\eta_c \quad (4)$$

Here $E_{b,t-1}$ is the battery energy at time $t-1$ in (kWh), E_{bc} is the energy charged into the battery, E_{bd} is the energy discharged by the battery P_{PV} is the power from PV, P_L is the load demand power, η_c and η_d are the charging and discharging battery efficiency respectively. The battery's state of charge is expressed as equation 5 (Traoré et al., 2018) .

$$SOC_{(t+1)} = SOC(t) + \frac{E_{bc}(t).\eta_c}{E_{b(t)}} - \frac{E_{bd}(t)}{E_{b(t)}.\eta_d} \quad (5)$$

where $SOC(t)$ and SOC_{t+1} is the battery state of charge at time t and $t+1$ respectively, $E_{b(t)}$ is the battery energy which during charging is equal to $E_{bc}(t)$ and during discharging is equal to $E_{bd}(t)$. The battery management is designed such that at times when the power produced by the Solar PV is more than the power required, the excess energy is used to charge the battery. But at times when the power from the solar PV is insufficient to meet the load, the battery discharges to supply power to the load. The Battery's Charge-Discharge energy management pseudo-code algorithm is shown in Figure 2 below.

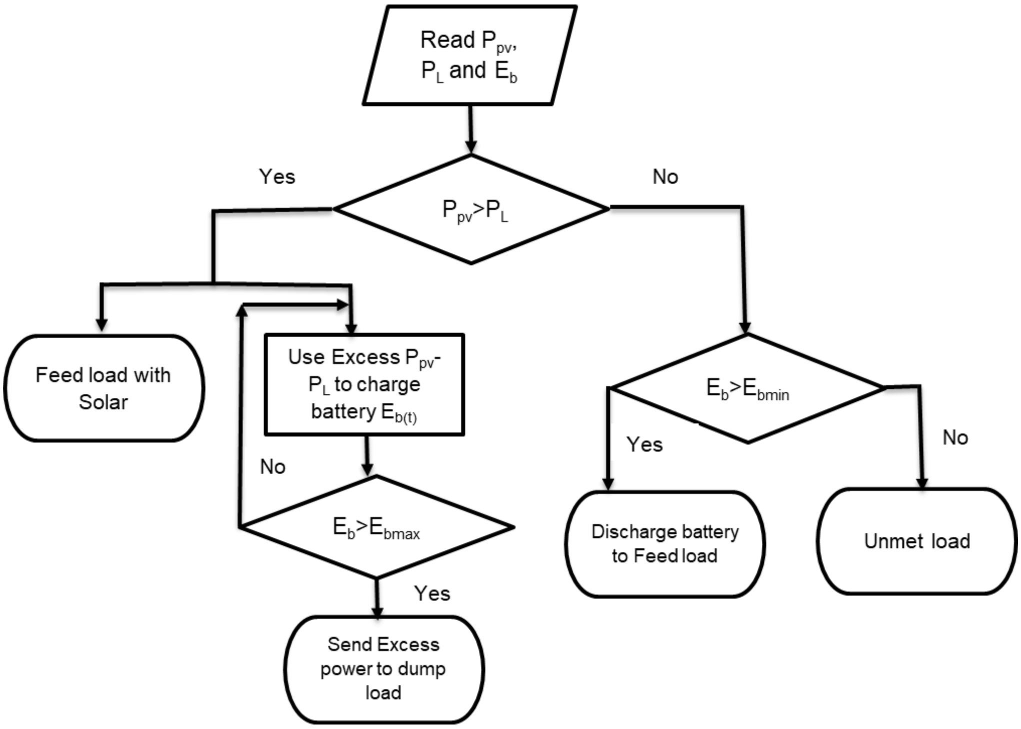

Figure 2: Operating strategy of the battery model.

Inverter model

In single phase inverter, power output is what defines its efficiency. (Arefifar et al., 2017). This is expressed by the following relationship

$$P_{inv} = \frac{P_L}{\eta_{inv}} \quad (6)$$

where P_{inv} is the Inverter Power, P_L is the load demand and η_{inv} is the efficiency of the inverter.

Reliability Model

The power system enters a Loss of Power Supply scenario when load demand exceeds PV and battery energy for hour *t* ($P_{supplied}(t) < P_{needed}(t)$), which is expressed from equation (7) (Traoré et al., 2018),

$$P_{loss}(t) = P_L(t) - [P_{PV}(t) + P_{bd}(t)] \cdot \eta_{inv} \quad (7)$$

where P_{bd} is the power discharged by the battery.

The LPSP is the term used to express the possibility of having a power outage during a given time period *T*. It is expressed as a percentage or a fraction. It is calculated by the following equation (Ganbasha & Ayop, 2022)

$$LPSP = \frac{\sum_{t=0}^{T} P_{loss}(t)}{\sum_{t=0}^{T} P_L(t)} \quad (8)$$

where $\sum_{t=0}^{T} P_L(t) \neq 0$

and P_{loss} is the difference between power needed and power supplied

Optimization of Solar PV system

Objective function and Design parameters

In this section, the levelized Cost of Energy (LCOE) is considered as the objective function. The problem is formulated as follows:

$$\min\{F\} \quad (9)$$

where *F* is the LCOE which is the function of Total Annual Cost (TAC) expressed as equation (10):

$$F = \frac{TAC}{\sum_{t=1}^{T} E_L(t)} \quad (10)$$

Here E_L here represents the electrical load served by the PV system

TAC includes the capital cost of equipment including PV panels, batteries and the inverter as well as the maintenance cost, and can be written as:

$$TAC = aC_{in} + C_m \quad (11)$$

where

$$C_{in} = N_{pv}C_{PV} + E_bC_b + P_{inv}C_{inv} \quad (12)$$

$$C_m = N_{pv}C_{PV,m} \quad (13)$$

Here, N_{PV}, E_b and P_{inv} are rated PV size in kW, Battery storage capacity in kWh and Inverter size in kW respectively, while C_{PV}, C_b and C_{inv} are unit cost of the PV panels, batteries, and the inverters, respectively. Also, $C_{PV,m}$ is the unit costs of maintenance for the PV panels and a denotes the annual cost coefficient, defined in equation 14 (Samuel, Mwaniki and Funsho Akorede, 2019):

$$a = \frac{i(1+i)^{n}}{i(1+i)^n - 1} \quad (14)$$

Here *i* is the interest rate and *n* is the system life period. The interest rate in Tanzania of 5% was used based on (Mbowe et al., 2020) Some equipment in the SAPV system needs to be replaced several times during the project lifetime. Here, the battery lifetime considered here is of Lithium ion that has an average of 10 years at 10% Depth of Discharge (DOD) (Mallon et al., 2017). Using the single payment present value factor, the present value of battery C_b can be expressed as follows:

$$C_b = P_b\left(1 + \frac{1}{(1+i)^{10}}\right) \quad (15)$$

where P_b is the price of the battery. Also, the lifetime of the inverter is considered here to be 10 years, so the present worth of inverter C_{inv} can be expressed using the single payment present value factor as follows:

$$C_{inv} = P_{inv}\left(1 + \frac{1}{(1+i)^{10}}\right) \quad (16)$$

where P_{inv} is the inverter price. The rated PV size, battery storage capacity and inverter size are considered as design parameters.

Constraints

The following constraints must be met:

- Reliability:

$$LPSP \leq LPSP_{set} \quad (17)$$

- PV power limits:

$$N_{PV\,min} \leq N_{PV} \leq N_{PV\,max} \quad (18)$$

- Battery stored energy:

$$E_{bmin} \leq E_b \leq E_{bmax} \quad (19)$$

where the maximum charge quantity of the battery bank takes on the value of the nominal capacity of the battery bank and the minimum charge quantity of the battery bank is obtained by maximum depth of discharge which can be calculated as:

$$E_{bmin} = (1 - DOD) \cdot E_{bmax} \quad (20)$$

For this optimization DOD was considered to be 0.1 which is equivalent to 10% for lithium ion batteries (Mallon et al., 2017).

- Inverter number:

$$N_{inv} \geq 0. \quad (21)$$

Proposed optimal sizing algorithm using PSO

PSO is a powerful optimization technique inspired by the social behavior of birds and fish. In the context of this research, PSO was employed to optimize a SAPV system, aiming to find the optimal combination of PV size,battery size and inverter capacity while satisfying various constraints, including the LPSP.

The PSO algorithm begins with the initialization of a key parameters. These parameters includes the population Size (N_{pop}), maximum Iterations ($\text{Max\_}it$), Convergence Tolerance (C_t), Inertia Weight (w), Personal learning coefficient (C_1), Global Learning Coefficient (C_2). Particle positions are constrained within specified lower (L_B) and upper (U_B) bounds. The algorithm then generates an initial swarm of N_{POP} particles based on equation (22) below, each representing a potential solution.

$$x_Z = Rand(L_B, U_B) \quad (22)$$

where $Rand$ is a uniformly distributed random function

These particles are assigned random positions and velocities within the defined bounds. The cost of each particle's position is calculated equation (10). Importantly, constraints including LPSP are checked during initialization to ensure that the solutions are feasible from the outset.

Particle velocities and positions are iteratively updated based on the equation (17) and equation (18) incorporating the inertia weight (w), personal learning coefficient (C_1), and global learning coefficient (C_2). The positions are constrained to stay within the specified bounds. Equation (17) and equation (18) are used to quantitatively represent the alteration of the particle's velocity and position respectively:(Amer et al., 2013):

$$v_i(t) = wv_i(t-1) + c_1r_1(P_1 - x_1(t - 1) + c_2r_2(G - x_1(t-1) \quad (23)$$

$$x_i(t) = x_i(t-1) + v_i(t) \quad (24)$$

where $v_i(t)$ is the velocity of agent i at iteration t, $x_i(t)$ is the current location of agent i at iteration t, w is the inertia weight, r is a uniformly distributed random number between 0 and 1, c is the weighting factor, P_1 is the best position of particle i previously visited during the current stage and G is the global best position

The algorithm continuously checks for convergence by monitoring the difference in cost between consecutive iterations. When the convergence criterion is met i.e. when the cost change is less than convergence tolerance for all particles, the optimization terminates early. Alternatively, if the maximum iteration limit is reached, the algorithm concludes. Upon termination, the PSO algorithm provides the optimal solution. The proposed algorithm is illustrated in Figure 3 while system parameters are indicated in Table 1.

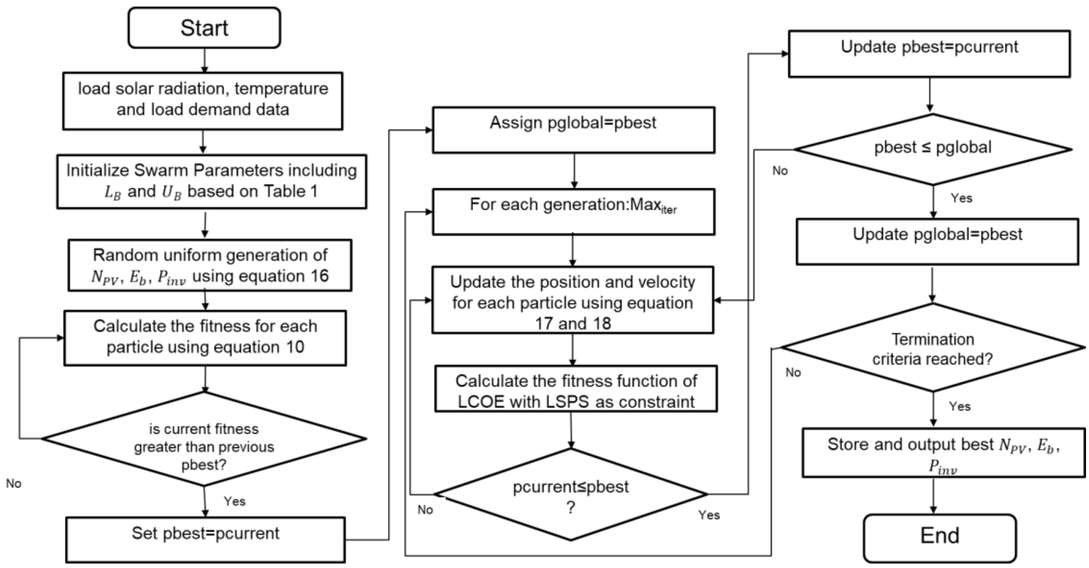

Figure 3: Flow chart of the proposed optimization algorithm.

Table 1: System parameters defined and optimized using PSO algorithm

Parameters	**Value**
Population Size (N_{pop})	30
Maximum Iterations (Max_it)	100
Convergence Tolerance (C_t)	1e-6
Inertia Weight (w)	0.7288
Personal learning coefficient (C_1),	1.4962
Global Learning Coefficient (C_2)	1.4962
$N_{PV\ min}$, $N_{PV\ max}$	0,1000
E_{bmin} , E_{bmax}	0,2000

Cost Parameters
The cost parameters used in this study were obtained from (*Power Providers Tanzania*, 2023) are highlighted in Table 2.

Table 1 Cost Parameter Used (Power Providers Tanzania, 2023)

Component	Capital cost (C_{in})	O&M costs (C_m)	Component life (years)
PV	\$750/kW	\$15/kW/year	25
Li-ion Battery	\$455/kWh)	\$10/kW/year	10
Inverter Capital cost	\$500/kW	\$10/kW/year	10

Case Study based on Serengeti Meteorological data

To demonstrate the capability of the optimization tool, two different installed standalone photovoltaic (PV) system with high and low irradiance were used. The first case study is a Camp hotel in the Serengeti region of Tanzania and the second is the camp hotel near Lepo national park in Gabon representing high and low irradiance respectively. In order to size using the proposed method, it is necessary to gather data pertaining to solar irradiation, ambient temperature, and load demand specific to the site.

Solar Irradiance and Temperature Meteorological Data

In order to model the power output from the Solar PV, the solar irradiation and temperature data is needed. Meteorological data, encompassing solar irradiance and ambient temperature, was obtained from the soDa website for the calendar year 2022. (*SoDa*, 2022). The solar irradiance are 15min interval data for the whole 2022. This data was converted to hourly data in order to match with the collected hourly demand profile for the camp hotel. The hourly variation of solar radiation and ambient temperature for the two studied climates including Serengeti and Lepo in gabon representing high irradiance and low irradiance respectively are displayed in Figure 4 and Figure 5 respectively. The figures indicate that the solar irradiance in Serengeti reaches a maximum of 1100W/m2 and has an average daily solar irradiance of 5763W/m^2/day. In comparison, Lepo Camp Hotel experiences a peak solar irradiance of 910W/m2 and an average daily solar irradiance of 3922W/m^2/day, which is comparatively lower than Serengeti. The average ambient temperature for Serengeti is 23.2°C during the day compared to Gabon's average temperature of 27.5°C during the day.

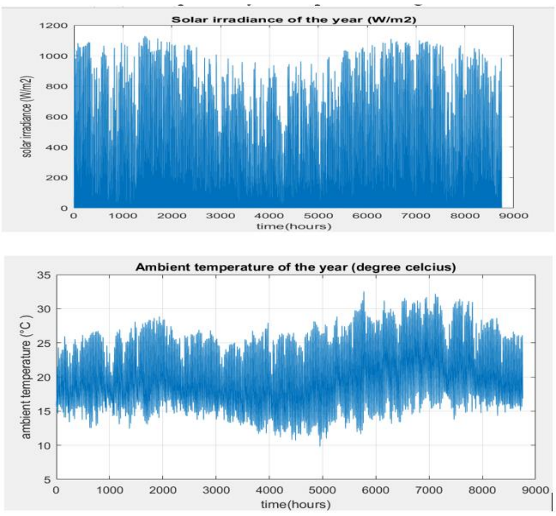

Figure 4: Hourly Solar irradiance and Temperature variation for Serengeti

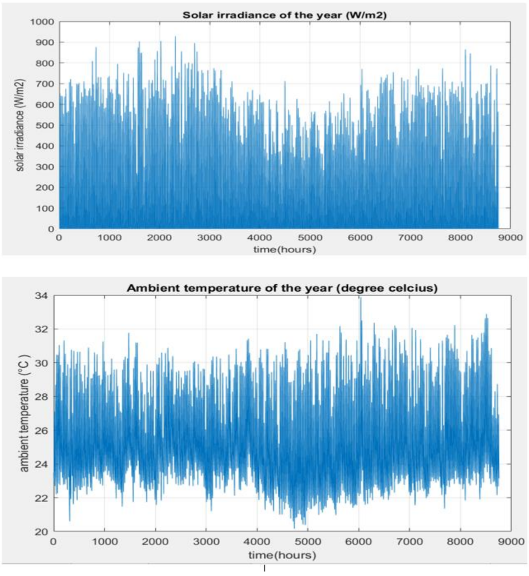

Figure 5: Hourly Solar irradiance and Temperature variation for Lepo in Gabon.

Load demand Data

As input for optimization, the hourly load demand for the camp hotel in Serengeti in 2022 was used. The same load profile was used for both case studies to compare the capabilities of the proposed optimization tool in obtaining an optimal solution for areas with both high and low irradiance. Figure 6 shows portion of the hourly load demand for a year, with a peak load of about 11.9 kW, an average load of about 4 kW. The average energy in kWh per day is 94.3 kWh/day. The night energy use is observed to be high compared to the day amounting to 66 kWh of the daily energy consumption. This is due to the lights being on during night and higher occupancy rate of the hotel camp during the night compared to day time.

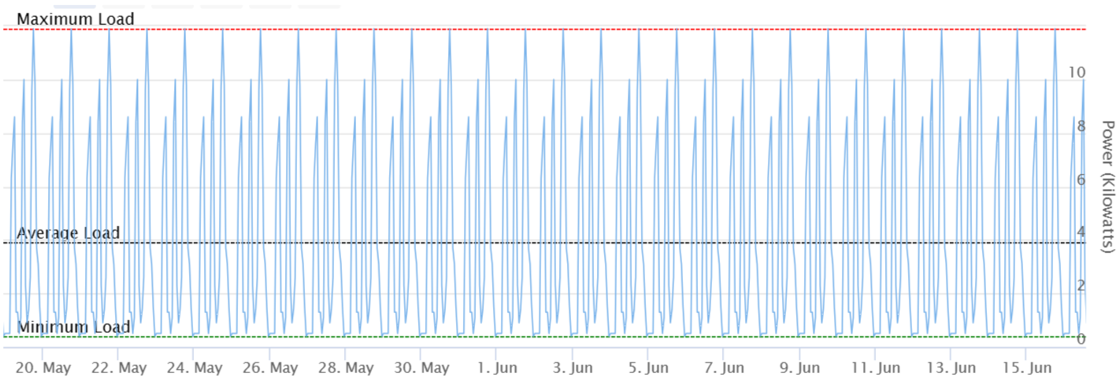

Figure 6: Hourly load demand profile of a camp hotel in Serengeti.

RESULTS AND DISCUSSIONS

Optimum Sizing Results using PSO Algorithm

The PSO Algorithm was implemented in MATLAB R2020a on a computer with a 2.40 GHz Intel Processor, 8GB RAM, and a 64-bit operating system. The PSO parameters were set according to Table 1, and the LSPS was set at 0.005. The optimal results for the LCOE and corresponding values of the design parameters for each case studied are provided in Table 2. These optimal sizes ensure that the PV system can meet 100% of the load. The LCOE of Serengeti is lower than that of Gabon due to the higher irradiance in Serengeti. It was observed that the required Solar PV size for Gabon is larger compared to Serengeti, while the battery sizes are almost similar. The inverter size is the same for both case studies since it depends only on the load and not the irradiance levels.

Table 2: Optimal sizing results using PSO

Case Study	Solar PV	Li-ion Battery	Inverter	LCOE

Serengeti	30 kW	82 kWh	13 kW	0.22114 $/kWh
Gabon	47 kW	79 kWh	13 kW	0.24459 $/kWh

The convergence rate of the PSO algorithm for the two case studies are shown in Figure 7. From the convergence plot in Figure 7 the optimization process terminated at 30th iteration despite number of iterations being set to 100 due to the fact that there was no more convergence in COE.

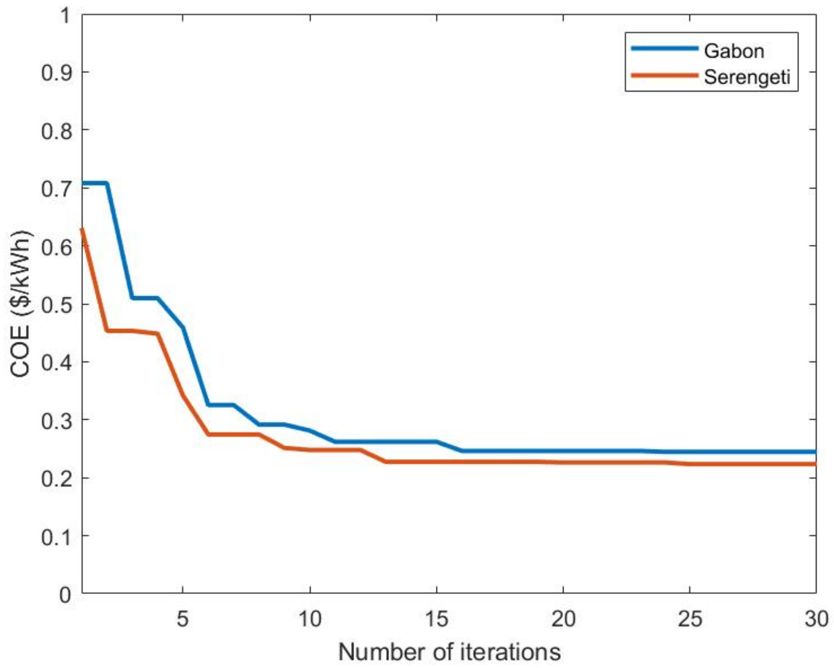

Figure 7: Optimal Sizing Convergence graph.

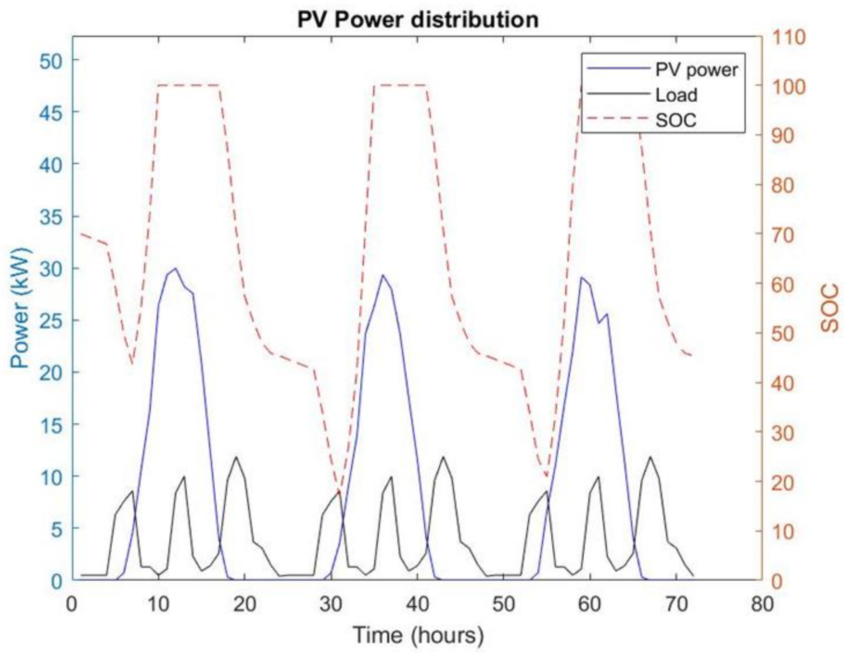

Figure 8: Hourly variation of the SPV system under best optimal configuration for Serengeti.

Power Distribution Simulation Output

To obtain a good insight into the hourly variation of power supply by PV, load demand, and battery charging and discharging, variations of these parameters at the optimal configuration for the two studied cases are shown in Figures 8–9. Note that the variation is shown for the first three days of the year.

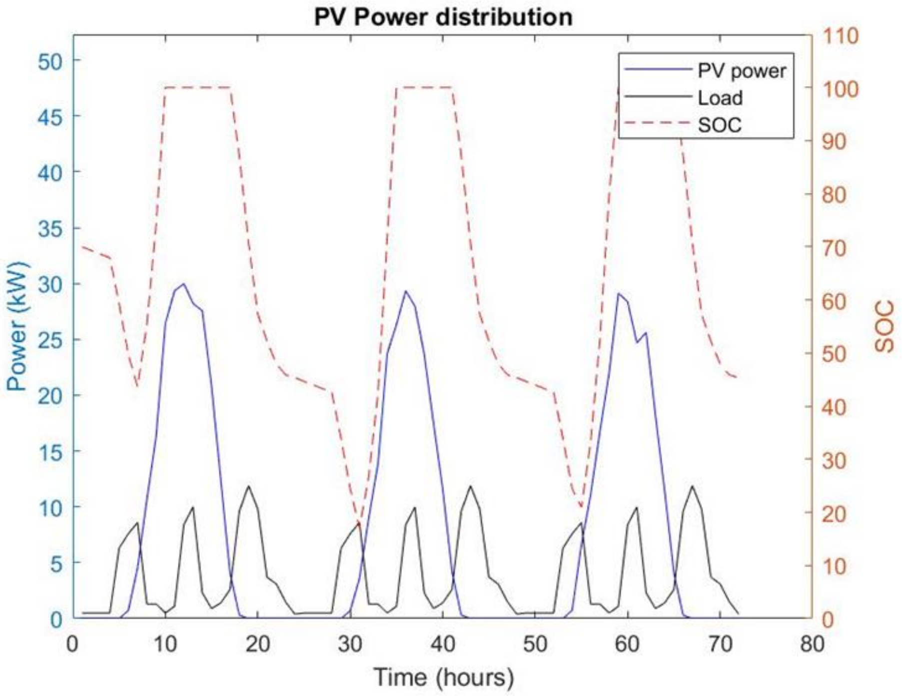

Figure 9: Hourly variation of the SPV system under best optimal configuration for Gabon.

During periods when the solar photovoltaic (PV) system generates an excess of power beyond the required load, the surplus energy is utilized to charge the battery until it reaches its maximum capacity of 100% state of charge. (iii) An area with low radiation requires a PV generator of larger size in order to supply the same load that may be supplied by a smaller PV generator in a region with high irradiance and (iv) The discharge curve is identical for both case studies, since they both utilized the same night profile. In this profile, the batteries were fully charged at the end of the day and began discharging as the sun set.

Figure 8 illustrates the monthly average of photovoltaic (PV) electricity generated across the whole year. The data reveals that the month of July had the lowest power generation, whilst the month of March demonstrated the highest power output, which is attributed to the varying levels of solar radiation throughout these periods.

Comparison and Validation

To validate the proposed method, Renewable energy Integration and Optimization (REopt) tool was used to perform the same optimization task with the same meteorological data, load demand and system specifications. The REopt is a techno-economic decision support platform used by NREL researchers to optimize energy systems for buildings, campuses, communities, micro grids, and more (Simpkins et al., 2014). Formulated as a mixed integer linear program, REopt recommends an optimally sized mix of renewable and distributed energy, conventional generation, and energy storage technologies (Simpkins et al., 2014). The results show very close similarities in output generated by both methods as shown in Table 3 below.

Table 3: Comparison of Optimal sizing results with REopt

Parameter	Proposed Algorithm	REopt tool
Solar PV	30 kW	37 kW
Lion Battery	82 kWh	78 kWh
Inverter	13kW	13kW
COE	0.22114 $/kWh	0.201 $/kWh
Total Cost	105,000 $	93,000$
Computation time	36s	20s

The proposed Algorithm shows a slight reduction in the PV size required, accompanied by an increase in the size storage capacity required. In terms of power output, the solar PV size obtained from the PSO algorithm is 19% lower than that obtained from REopt, the inverter size obtained from two methods were exactly the same, while battery size obtained from applying the PSO algorithm optimization showed a 3.7% increase in size when compared to the results obtained from REopt.

Analysis in terms of computation time (in seconds), the optimal sizing using the proposed algorithm took 36 seconds while the same sizing took 26 seconds using the REopt optimizer, this shows a 10 seconds time increase. Moreover, analysis in terms of cost of energy, the Proposed Algorithm offered an overall cost of energy (COE) increase of about 0.02 $/kWh which represents a 9.8% increase, when compared to the cost of energy obtained from REopt. This is due to the fact REopt considers 30% incentives given as a percentage of capital costs. The federal percentage based incentive is treated as tax-based incentive to promote the use of renewable energy in America (Qadir et al., 2021). If 30% incentives would not be considered, then REopt would result to 0.241 $/kWh which is higher than LCOE for the Proposed method

CONCLUSION

This study proposed a PSO based optimal sizing tool for a Stand-alone PV system containing solar PV, Inverter and battery energy Storage. The Stand-alone PV system is designed to supply cost effective, reliable and clean power to load in which it is intended to serve. The LSPS is considered as reliability index for this optimization. A design example in Serengeti, Tanzania is done to show the capabilities of the proposed method. With an average daily load consumption of 94.3kWh, an optimal size of 30kW of Solar PV, 82kWh of Li-ion battery and 13kW of inverter was obtained at a LCOE of 0.221$/kWh. The Power simulation for this system was also carried out based on the mathematical models. The proposed method was investigated here in with a different meteorological data that has low average solar radiation to show the capabilities of this method in low irradiance regions. This investigation showed that the proposed method can be used to perform design task for any region and it is not site specific. To validate the proposed method, REopt tool was used to perform the same optimization task with the same meteorological data, load demand and system specifications. The comparison showed very close similarities in output generated by both methods.

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