SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V12I5P108

Volume 12 Issue 5, 77-90, May 2025

Original Article

Optimal Sizing of Photovoltaic and Battery Energy Storage Systems Incorporating Constant Current and Constant Power Load Models

Gauri Mandar Karve[1*], Mangesh S. Thakare[1], Geetanjali A. Vaidya[2]

[1]*Department of Electrical Engineering, PVG's COET & GKPIOM, Pune, Savitribai Phule Pune Vidyapeeth, Maharashtra, India.*
[2]*SAS Powertech Pvt. Ltd, Baner, Pune, Maharashtra, India.*

[*]*Corresponding Author : gmk_elect@pvgcoet.ac.in*

Received: 03 March 2025 Revised: 08 April 2025 Accepted: 22 April 2025 Published: 31 May 2025

Abstract - *Load modelling is critical in power system analysis, significantly affecting voltage stability, power flow, and the sizing and placement of Distributed Generators (DGs). Current research has primarily focused on optimal sizing methodologies for DGs and battery energy storage systems, predominantly utilizing constant load models. This approach fails to capture the dynamic and non-linear characteristics of actual load behaviour, which affects the voltage stability. The practical loads are composed of ZIP loads (Constant Impedance Load -CIL-'Z', Constant Current Load- CCL-'I' and Constant Power Load-CPL-'P'). In this context, this research evaluates the effect of CCL and CPL modelling on the optimal sizing of system components, particularly in light of the growing prevalence of battery-operated loads. The study proposes an optimal system size designed to accommodate the diverse load demands represented by ZIP loads affecting system voltage across various applications, including residential, industrial, commercial, and agricultural settings. The analysis is conducted using the Improved Particle Swarm Optimization technique with consideration of a ±5% variation in the system's rated voltage. The present study evaluated the minimum total annual cost over a twenty-year timeframe, utilizing actual site data. The results indicate a maximum number of system components in the agricultural load due to the dominating CPL. The results also propose the inclusion of 10% CCL in residential, industrial, and commercial loads due to the increasing reliance on battery-operated systems: electric vehicles and hybrid electric vehicles.*

Keywords - *Battery Energy Storage, Constant current load model, Improved Particle Swarm Optimization, Optimal sizing, Photovoltaic system.*

1. Introduction

Battery Energy Storage System (BESS) plays a multifaceted role within the power system, encompassing functions such as load levelling, frequency and voltage regulation, power quality enhancement, and integrating Renewable Energy Sources (RESs) to establish a microgrid. Consequently, the demand for BESS is experiencing exponential growth, with forecasts indicating an annual increase of 25%, ultimately reaching 2,600 GWh by the year 2030.

Incorporating BESS into the Distribution Systems (DSs) to yield significant technical, economic, and environmental advantages is evaluated in [1]. The benefits of BESS for optimizing the energy efficiency of the DSs are thoroughly studied by Das et al. through the co-optimization of the size, location, and charge/discharge profiles of batteries within specified DSs [2].

Therefore, to improve the performance of the DSs, the efficiency of its components, such as RESs and BESS and their compatibility with respect to load variation need to be studied and analyzed. The penetration of RESs and the application of electronic power devices highlights the need for accurate load modelling to address the new challenges that are evolving in power system operation, control, and stability studies [3]. For this, it is necessary to understand the behaviour of various types of loads, such as load modelling with respect to RESs and BESS. The operation and sizing of BESS are affected by four main factors: State of Charge (SOC), temperature, cyclic life and charging-discharging rates of the battery. All these four factors are highly dependent on each other and are decided by the discharging rates of the battery, which is greatly affected by the type of load to which the battery is discharged. There are various kinds of loads in electrical power systems, such as heating loads, air-conditioning loads, refrigerators, lighting loads, pumps, induction motors, etc. Each load has stochastic, weather-dependent, and time-varying behaviours, diverse components, and a lack of precise load composition information, which makes load modelling a challenging one [4]. Though load modelling is challenging, its impact on the operation of RES and BESS in the case of microgrids is required to be studied as compared to conventional power systems due to the reduced distance between power generation and load [5].

Various categories of load models, static, dynamic, and composite load models, their sub-classifications and their estimation techniques were reviewed in detail [3, 4, 6]. The authors described the use of the Improved Particle Swarm Optimization (IPSO) technique to determine the parameters of the load model by comparing its performance with the Genetic Algorithm (GA) [7]. In [8], an automatic load modelling system for predicting parameters of induction motor and ZIP load models by means of power quality monitoring data on an industrial site is presented. The authors proposed a measurement-based novel technique for building an equivalence of a DS using a recurrent neural network [9]. The dynamic simulations of large power systems based on measurement data for an aggregated load model using the vector fitting technique are discussed by Papadopoulos et al. [10]. A similar study was carried out by Yiqi Zhang et al., who applied least squares, optimization, and neural network methods [11].

In [12], the authors considered an exponential dynamic load model and identified its real-time parameters using an unscented Kalman filter. The use of GA for measurement-based modelling of composite load models in the power system is proposed by Jahromi et al. [13]. The authors reviewed techniques and approaches for load modelling, from conventional methods to novel ones, along with the research gaps in the literature [3].

Out of the various load models discussed so far in the literature, the ZIP model is discussed in this paper in detail, which is the combination of the Constant Impedance Load (CIL-Z) model, the Constant Current Load (CCL-I) model and the Constant Power Load (CPL-P) model. But CPL rules over the other two types of ZIP load category due to the proliferation of power electronics which is explained in [14, 15]. Abbas et al. provided an example of a ballast. The previous form of ballast, known as magnetic ballast, was designated as CIL, whereas the current version, identified as electronic ballast, is classified as CPL [14]. The significant transformation in load composition over the past decade is largely due to the increased utilization of power electronics in numerous household applications, including LED and LCD televisions and heating and lighting systems. This shift has been comprehensively presented, along with the experimental determination of the ZIP coefficients of modern loads under changing voltage scenarios [15]. Similar to CPL, CCL is also increasing due to chargers for Electric Vehicles (EVs), Hybrid Electric Vehicles (EVs), laptops and mobile devices. Therefore, the effect of increasing CPL and CCL in the ZIP load in DSs should be analyzed.

The impact of ZIP load modelling on the Optimal Placement and Sizing of Distributed Generators (OPSDGs) in distribution systems is evaluated with different test systems [16-20]. In [16], the authors used Monte Carlo simulation to find the optimal size of the Photovoltaic (PV)-DG system by minimizing the system losses. The impact of the ZIP load model on OPSDG is discussed in [18]. The results are assessed using standard IEEE 15-bus (radial) and IEEE 30-bus (mesh) systems with the Butterfly-PSO technique and confirmed by comparing them with GA and standard PSO. Similar work is also carried out in [18, 19]. In [18], Zonkoly et al. presented the results using IEEE 38-bus (radial) and IEEE 30-bus (ring) systems with PSO algorithm, while in [19], the authors compared the analytical approach with the classical grid search algorithm for OPSDGs on radial feeders for distinct load models. Ravi Teja et al. [20] proposed an optimal method to find the OPSDG for loss reduction in 25-bus DS. The study considered the impact of seasonal load variations with the ZIP load model consisting of Residential, Industrial and Commercial (RIC) types.

In [21], various static load models are checked out for maximum bus loading capacity for the IEEE 14-bus system using the 'node elimination technique' for ZIP load models. This study indicates that the CCL model demonstrates superior voltage stability limits in comparison to the CIL model.

From the previous study, it is observed that the impact of voltage variations in conjunction with ZIP loads on the optimal sizing of system components has been examined less. Table 1 presents a comparison of previous studies on ZIP load modelling and the proposed approach.

Table 1. Comparison of various studies for ZIP load modelling

Sr. No.	Paper	Test System	MOF	Optimization Techniques	Load Models/ DG size
1	Mazhar Abbas [15]	Not mentioned	-	Not mentioned	Expo. Load models.
2	[17] Hengsriawat	51-bus, DS in Thailand	minimize APL THDv	Monte Carlo simulation	The probabilistic approach to find the optimal size of PV-DG.
3	Bohre, A [18]	15-bus radial	Minimize APL,	BF-PSO, GA,	Expo. Load models with R, I,

		and 30-bus mesh system	RPL, VDI	PSO	A loads. DG size and location change with load type.
4	El-Zonkoly [19]	38-bus RDS, IEEE 30-bus meshed system	APL, RPL voltage profile, line loading	PSO	Expo. load models.
5	Gozel, T. [20]		minimize APL	analytical + classical grid search algorithm	Expo. load models.
6	Ravi Teja [21]	25-bus unbalanced RDS	APL, RPL	Not mentioned	ZIP load models. R, I, A, loads. DG size -location changes with load type.
7	J. N. S. Mrudveeka [22]	IEEE 14 bus system	assessing maximum bus loadability	New Algorithms used	Expo, Poly load models. Voltage stability limit – CCL > CIL model.
8	**Proposed Work**	**PV-BES Islanded Microgrid**	**TAC and Voltage variations**	**IPSO**	**Expo. and Poly. Load models with R, I, C, A loads. Optimum system components for ZIP load in R, I, C, and A loads.**

Exponential, Poly: Polynomial, APL: Active Power Loss, RPL: Reactive Power Loss, VDI: Voltage Deviation Index, PSO: Particle Swarm Optimization, BF-PSO: Butterfly-PSO, IPSO: Improved PSO,
GA: Genetic Algorithm, Distributed Generation: DG, TAC: Total Annual Cost, R: Residential, I: Industrial, C: Commercial, A: Agricultural, Expo: RDS: Radial Distribution System, THDv: Total Harmonic Voltage Distortion.

Table 1 indicates that the optimal sizing of DGs and BESSs is primarily determined for various objectives based on active power load demands. Furthermore, existing studies have generally focused on either ZIP load characteristics or specific sectoral loads, such as residential, industrial, commercial, or agricultural, but have not comprehensively addressed the optimization for a combination of these diverse load types with voltage variations. Very few studies are based on the impact of ZIP load modelling on the optimal sizing of PV and BESS with system voltage variations.

This study aims to determine the optimal sizing of BESSs and associated systems in the context of complex power load demands. It evaluates the impact of ZIP (CIL, CCL and CPL) type loads across residential, industrial, commercial, and agricultural sectors. Additionally, it addresses the effects of system voltage variations on system components, which have previously received insufficient attention. The study justifies the attention due to the increasing demand associated with CCL and CPL, which have arisen from the integration of battery-based systems and the proliferation of power electronics in modern applications.

The key contributions of this paper are stated as follows:

- The paper evaluates the minimum Total Annual Cost (TAC) of the system over a period of twenty years by optimizing the sizing of BESS, PV panels, and inverters. This assessment incorporates ZIP-type load models and analyzes their impact on residential, industrial, commercial, and agricultural sectors, utilizing the IPSO algorithm for enhanced efficiency. The optimal system components are determined by considering ZIP load modelling by polynomial and exponential expressions. The results are identical for both modelling approaches.
- This paper investigates the practical variations in system voltage, specifically within a range of 415V ± 5%. When the system voltage decreases to 395V, which is below the nominal value of 415V, it has been determined that the optimal battery sizing designed for CPL is greater than that established for CCL and CIL. Conversely, when the system voltage rises to 435V, exceeding the nominal level of 415V, the optimal battery sizing for CIL exceeds that for CCL and CPL. It appears that the rated system voltage of 415V has minimal impact on overall system sizing; however, fluctuations in voltage conditions significantly influence the design of the system.
- Implementing a 10% CCL for residential, industrial, and commercial sectors is proposed. This measure takes into account the growing prevalence of battery-operated loads, including EVs and HEVs, within microgrid systems. Thus, this work emphasizes the impact of CCL on the optimum sizing of BESS and the system components, considering system voltage variations.

The rest of the paper is distributed as follows: Section 2 defines the problem statement, while Section 3 presents the system under consideration and the mathematical modelling of system components. Section 4 describes the IPSO algorithm to determine the optimum system components. Section 5 defines the objective function with constraints. Outcomes are presented in Section 6, and Section 7 concludes the paper.

2. Problem Statement

Upon reviewing the existing literature, it has become apparent that the influence of ZIP load modelling and its repercussions on residential, industrial, commercial, and agricultural loads with respect to battery sizing while considering voltage variations within the system has received insufficient attention.

Consequently, this paper aims to identify the optimal sizing of system components by considering the impact of ZIP load modelling for minimizing Total Annual Cost (TAC) amidst variations in voltage. The issue of battery sizing is of significant importance, particularly in light of the rapid global deployment of BESS, which is increasing exponentially.

Even minor adjustments in battery sizing can result in considerable financial implications. This highlights the necessity for optimal battery sizing in relation to load modelling, underscoring its critical role in effective energy management solutions.

3. System Under Study and Mathematical Modelling of System Components

Figure 1 schematically represents the system configuration under study. The system components are a solar PV system, inverters, and BESS connected to the ZIP type of load for Residential, Industrial, Commercial, and Agricultural (RICA) loads. The mathematical modelling of system components is described in the next section.

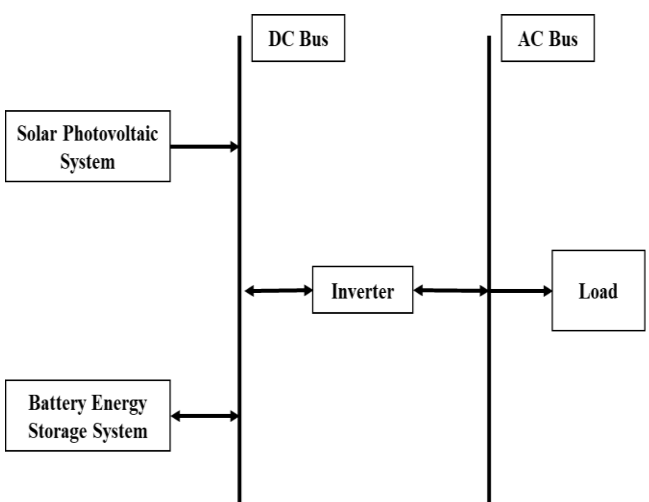


Fig. 1 Schematic of the system under study

3.1. Solar PV System

Figure 2 depicts the profile of solar irradiance for a specific location, Rafsanjan, in W/m^2 [22]. The solar irradiance for a year is averaged out as monthly solar irradiance, which is further averaged out as weekly solar irradiance and then averaged out as daily (24-hour) solar irradiance.

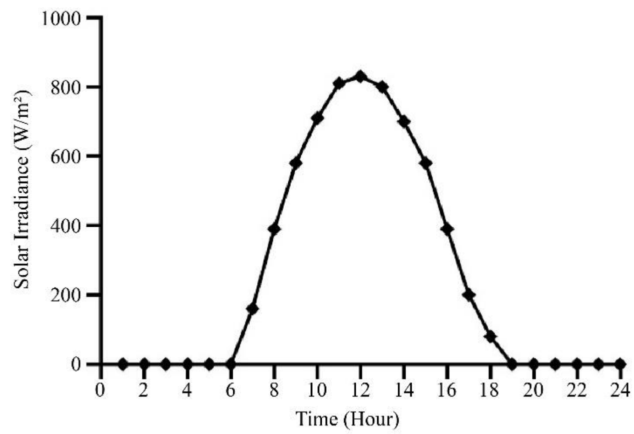


Fig. 2 Solar irradiance profile

The power output from each PV panel and that of the complete PV system are calculated using Equations (1) and (2), respectively [22, 23].

$$p_{PV} = \begin{cases} \left(\frac{P_R.r^2}{R_{SR}.R_C}\right) & \text{if } 0 \leqslant r \leqslant R_C \\ \left(\frac{P_R.r}{R_{SR}}\right) & \text{if } R_C \leqslant r \leqslant R_{SR} \\ P_R & \text{if } R_{SR} \leqslant r \end{cases} \quad (1)$$

$$P_{pv} = p_{pv} \text{ X } N_{pv} \quad (2)$$

Where,

P_R : Rated PV power (W);
r : Solar irradiance (W/m^2);
R_{SR} : Solar irradiance under the standard environment as 1000 W/m^2;
R_C : Certain solar irradiance point (W/m^2);
$P_{PV\text{-}Each}$: Power rating of a PV panel (W);
N_{PV} : Number of PV panels;
P_{PV} : Total power output of all PV panels (W)

3.2. Battery Energy Storage System

BESS is integrated into the microgrid system to compensate for the shortfall of power when RESs (solar PV panels) are unable to satisfy the load demand. The output power of the PV system determines the SOC of the battery. While determining the SOC of BESS, constraints based on the minimum (SOC_{min}) and maximum SOC (SOC_{max}) must be satisfied, which are -

$$SOC_{min} \leqslant SOC \leqslant SOC_{max}$$

Values of SOC_{min} and SOC_{max} are decided by the battery technology. In this paper, lithium-ion batteries are considered; therefore, the ranges of SOC are - SOC_{min}= 20% and SOC_{max}=100%. The battery tries to serve 100% supply reliability to the system by storing the excess renewable energy from the PV system after fulfilling the load demand.

While the battery will discharge when load demand exceeds the PV power. This emphasizes the need for the battery system to be sized optimum. The charging-discharging battery modes are mathematically expressed as [22, 23] -

Charging Mode:

$$E_{Batt}(t) = E_{Batt}(t-1) \times (1-\alpha) + \left[E_{pv}(t) - \frac{E_{load}(t)}{n_{inv}}\right] n_{BC} \quad (3)$$

Discharging Mode:

$$E_{Batt}(t) = E_{Batt}(t-1) \times (1-\alpha) - \left[\frac{E_{load}(t)}{n_{inv}} - E_{pv}(t)\right] n_{BD} \quad (4)$$

Where,

$E_{Batt}(t)$ and $E_{Batt}(t-1)$: Energy stored in a battery at time (t) and (t-1);
$E_{pv}(t)$: Energy generated by PV (kWh);
$E_{load}(t)$: Energy required by load demand (kWh);
α : Self-discharge rate per hour of battery;
n_{inv} : Inverter efficiency;
n_{BC} : Battery's energy efficiency during charging;
n_{BD} : Battery's energy efficiency during discharging

3.3. Load Model

3.3.1. ZIP Model [4, 14]

The load model is mathematically expressed as voltage - power relation, where the voltage (magnitude and/or frequency) is input to the model, while the power (active or reactive) is the output of the model, and this model can be used in steady-state as well as in dynamic studies.

The ZIP model describes the voltage-power relation in a polynomial form, which combines the CIL, CCL and CPL. The graphical representation of the ZIP load model is shown in Figure 3 and explained as follows,

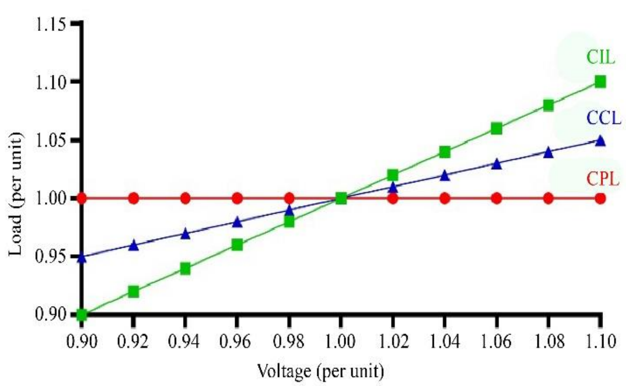


Fig. 3 Characteristics of ZIP loads

Constant Impedance Load (CIL) Model

In this model, if the voltage decreases, the current will decrease with the same ratio and then the power changes at the square of the voltage. Resistive loads and heating loads are examples of CIL.

$$Z = \frac{V}{I} = \left(\frac{\Delta V}{\Delta I}\right) = \left(\frac{\Delta V^2}{\Delta P}\right)$$

$(\Delta V)\ \alpha\ (\Delta I)$
$(\Delta P)\ \alpha\ \Delta V^2$

Constant Current Load (CCL) Model

In this model, the power will decrease by the same ratio if the voltage decreases. Arc furnaces, welding transformers, and battery chargers for EVs and HEV are a few examples of CCL.

As P=VI, for CCL model, (P) α (V) or ΔP=ΔV.

Constant Power Load (CPL) Model

In this model, the current will increase if the voltage decreases. Induction motors and inverter-based power electronic loads are examples of CPL. As P = VI, for the CPL model, ΔV= (1/Δ I) or change in voltage is inversely affecting change in current, i.e. ΔI= (1/ΔV).

There are two ways of representing the load model mathematically as below [4, 14] -

3.3.2. Polynomial Load Modelling

In this type, active power is expressed by Equation (5)

$$P = P_0\left[a_0 + a_1\left(\frac{V_a}{V_0}\right) + a_2\left(\frac{V_a}{V_0}\right)^2\right] \text{ Watt} \quad (5)$$

Reactive power is expressed by Equation (6)

$$Q = Q_0\left[b_0 + b_1\left(\frac{V_a}{V_0}\right) + b_2\left(\frac{V_a}{V_0}\right)^2\right] \text{ VAR} \quad (6)$$

Where,

P_0 : Active power load demand (kW), considering real-time data from the actual site
a_0 and b_0 : ZIP coefficients for CPL;
a_1 and b_1 : ZIP coefficients for CCL;
a_2 and b_2 : ZIP coefficients for CIL;
V_a : Actual system voltage (volts);
V_0 : Rated or nominal system voltage (volts)

3.3.3. Exponential Load Modelling

In this type, active power is expressed by Equation (7)

$$P = P_0\left[\left(\frac{V_a}{V_0}\right)^{np}\right] \text{ watt} \quad (7)$$

Reactive power is expressed by Equation (8)

$$Q = Q_0 \left[\left(\frac{V_a}{V_0}\right)^{nq}\right] \quad \text{VAR} \tag{8}$$

Where,

P_0 : Active power load demand (kW);

np and nq : ZIP coefficients for CPL, CCL and CIL with values 0, 1, 2 respectively;

V_a : Actual system voltage (volts);

V_0 : Rated or nominal system voltage (volts)

3.3.4. Load Profile

Figure 4 depicts the load demand profile of a particular area [22]. The load demand for a year is averaged out into a monthly load demand, which is further averaged out as a weekly load demand and then averaged out as a daily (24-hour) load demand.

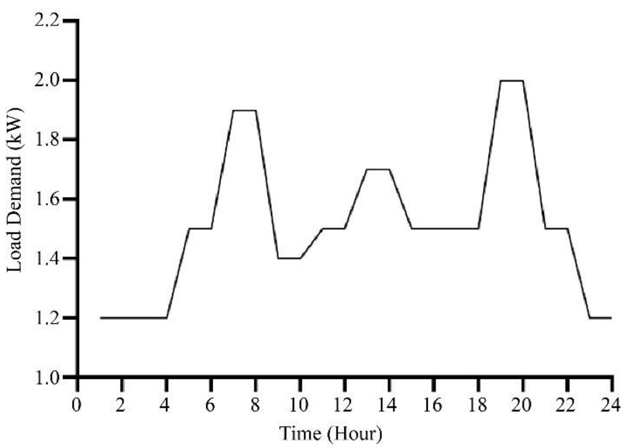


Fig. 4 Profile of load demand [22]

In this work, optimal sizing of system components is found using the polynomial and exponential ZIP load modelling techniques. The results of both techniques are found to be identical.

4. Methodology for Optimizing System Components for ZIP Load

This section describes the optimum sizing of system components employing the IPSO algorithm.

The non-linear, non-convex optimization problems involve a high level of complication and computational efforts, which can be handled by nature-inspired optimization methods. These methods, Particle Swarm Optimization (PSO), GA, Ant Bee Colony, etc, analyze complex optimization problems in electrical power systems effectively and efficiently. Various types of PSO algorithms are applied to find the capacity size and placement of sectionalizes, designing power system controllers, optimal placement of phasor measurement units, optimal power flow, economic dispatch, optimal DG location, optimal placement of wind turbines, the optimal location of FACTS devices etc. [24].

In this study, the improved PSO (IPSO) is employed to determine the optimum sizing of the system components, with minimum TAC being a non-linear optimization problem. IPSO is suitable for such a type of optimization problem [24-26] due to its ability to converge quickly without getting stuck at local minima.

It is executed to determine the optimum size of system components (N_{PV}, N_{Batt}, N_i) for a minimum TAC. The following steps describe the procedure to determine optimum sizes of N_{PV}, N_{Batt} and N_i for ZIP load in RICA loads with voltage variations.

4.1. Algorithm for Optimization of System Components

1. Read input data as solar irradiance and active power load demand (P_0) from the load curve for 24 hours [22].
2. Assume rated voltage of system (V_0) = 415V, actual voltage due to load (Va) =$V_0 \pm$ 5%=395V and 435V.
3. Consider Case 1: V_0=415V, Va=395V and the load demand of 1st hour (P_0)=1400kW.
4. 4. Use polynomial /exponential load model equations for active power as- $P = P_0[a_0 + a_1(V_a/V_0) + a_2(V_a/V_0)^{2]}$ Or $P = P_0\,(Va/V_0)^{np}$ ...watt.
5. Put np= 0,1, 2 for CPL, CCL, CIL.
6. Find active power (Pz) in kW for CIL for 1st hour.
7. Similarly, obtain active power for 24 hours P_z(CIL).
8. Put np=1 for CCL and np=0 for CPL. Calculate active power for CCL P_i(CCL) and CPL P_p(CPL) for 24 hours.
9. Determine line currents for each type of ZIP load $(I_L)_{CIL}$, $(I_L)_{CCL}$, $(I_L)_{CPL}$ by assuming a suitable power factor ($\cos\phi$). For residential load, determine line current for 24 hours using $P_{3\phi}$= 1.732 x V_L x I_L x $\cos\phi$ --- watt.
10. Find 3-phase reactive power using $Q_{3\phi}$=1.732 x V_L x I_L x $\sin\phi$ ---VAR.
11. Find complex power for each type of ZIP load. For the residential load for 1st hour, as $(S_z)_{CIL}$=(P+jQ) kVA.
12. Find complex power for residential load for 24 hours.
13. Calculate the percentage of ZIP load in residential load [27] as - (30% CIL + 70% CPL).
14. Propose a 10% CCL in ZIP load to incorporate increased battery-operated loads in residential loads. Therefore, the new residential load is = (20% CIL + 10% CCL + 70% CPL).
15. Repeat the procedure to find complex power for industrial, commercial and agricultural loads by assuming suitable power factors.
16. Use the complex power data of RICA loads in the MATLAB programme as load data.
17. Use the IPSO algorithm to optimize the system components, such as the number of PV panels (N_{PV}), batteries (N_{Batt}), and inverters (N_i) for minimum TAC. Display and summarize the results of the best particles,

such as NPV, NBESS, and Ni, and the cost of the system for RICA types of load.

Steps 1 to 16 are repeated for RICA types of loads considering V_0 = Va= 415V (Case 2) and V_0 = 415V, Va=435V (Case 3) with polynomial ZIP load equations.

The flow chart for determining the optimum sizing of system components for ZIP in RICA loads considering voltage variations using the IPSO algorithm is given in Figure 5.

IPSO algorithm has been configured with 50 populations and 100 iterations. Through optimization over 10 runs, the system has been refined to yield consistent and dependable results.

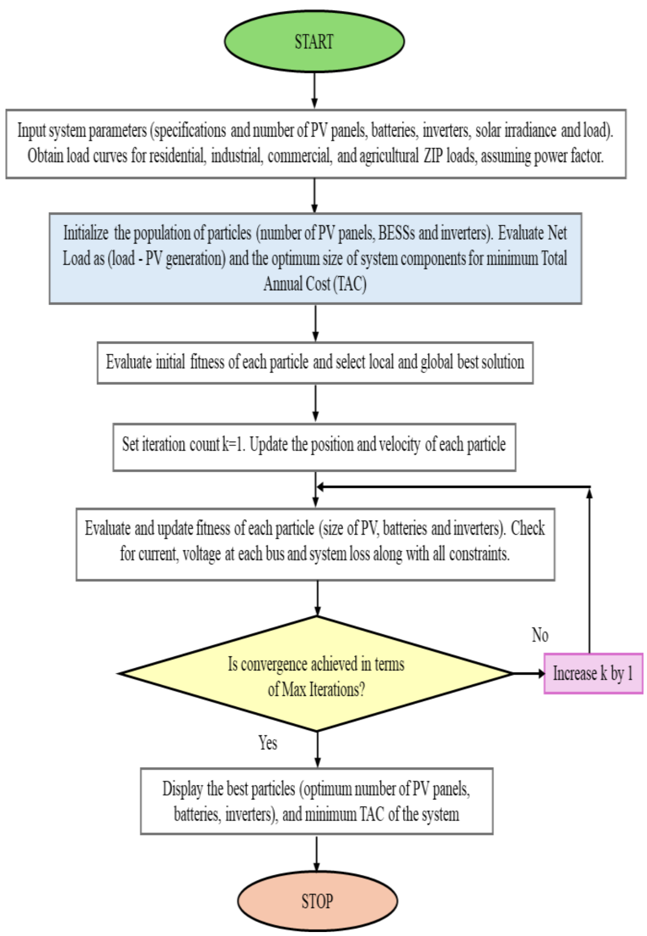


Fig. 5 Flow chart of IPSO algorithm for determining optimum sizing of system components

The outcomes of the study are presented in tabular and graphical forms in the results and discussion section.

5. Objective Function

The primary objective is the optimum sizing of the system components by minimizing the TAC of the system, considering ZIP load in RICA loads. The optimum TAC is accomplished with minimum capital cost (C_{Cpt}), maintenance cost (C_{Mtn}) and replacement cost of all system components for twenty years.

The capital cost is incurred only at the beginning of the project, while the maintenance cost and replacement cost occur during the project's life.

The system's TAC is minimized by the optimum selection of capacity size and number of system components such as PV panels, inverters, and BESSs using Equations (9) to (12).

5.1. Objective function

For minimization of TAC –

$$\text{Minimization of TAC} = \sum_{n=1}^{20} \left(C_{Cpt} + C_{Mtn}\right) \qquad (9)$$

Where,

C_{Cap} : Capital Cost of solar PV system, inverters and battery;

C_{Mtn} : Maintenance Cost of solar PV system, inverters and battery

$$C_{Cap} = \left[N_{PV} \times C_{PV} + N_{Batt} \times C_{Batt} + N_{Inv} \times C_{\frac{Conv}{Inv}}\right] \qquad (10)$$

$$C_{Mtn} = \left[C_{PV} + C_{Batt} + C_{Inv}\right] \qquad (11)$$

5.2. Constraints

The equality and inequality constraints are as below - $\Delta P = (P_{Gen} - P_{Load}) \geqslant 0$. With - inequality constraint as – $\Delta P \geqslant 0$

$\Delta P = [P_{Gen}(t) - P_{Load}(t)]$ --- for t = 1 to 24 hours

$0 \leqslant N_{pv} \leqslant (N_{pv})_{max}$

$0 \leqslant N_{batt} \leqslant (N_{Batt})_{max}$

$0 \leqslant N_{ci} \leqslant (N_{ci})_{max}$

The initial capital cost (P) can be converted to the annual capital cost (A) using the Capital Recovery Factor (CRF), expressed by Equation (12), [22, 23]:-

$$CRF = \frac{A}{P} = \frac{[j(1+j)^n]}{[(1+j)^n - 1]} \qquad (12)$$

Where,

n : Life span;

j : Rate of interest.

A few components of the PV-BES system require replacement multiple times over the lifespan of the project, which is assumed to be 20 years, and the battery life is 5 years. So, a single payment present worth factor for the battery can be calculated using Equation (13) as [22, 23].

$$C_{Batt} = P_{Batt}(1 + \frac{1}{(1+i)^5} + \frac{1}{(1+i)^{10}} + \frac{1}{(1+i)^{15}}) \quad (13)$$

Where,
C_{Batt} : Present worth of Battery;
P_{Batt} : Price of Battery ($)

The minimum TAC of system components can be calculated by using the specifications from Table 2.

Table 2. Specifications of system components [23]

System Parameters	Value
Rated power of single solar PV panel (P_R)	260 W
Price of single solar PV panel (Ppr)	200 $
Installation cost of solar PV panel (P_{inst})	0.5 x Ppr
Annual operation and maintenance cost of solar PV panels	12 $ / Year
Life of solar PV panel	20 Years
Efficiency of PV panel	15.8%
Area of PV system	1.64 m^2
Rating of a single battery	2.1 kWh
Price of a single battery (P_{Batt})	310 $
Annual operation and maintenance cost of battery	10 $ / Year
Battery's charging efficiency	85%
Battery's discharging efficiency	100%
Hourly self-discharge rate of battery (α)	0.02%
Battery's life span	5 years
Rating of single inverter	3 kW
Price of single inverter (Pi_{nv})	1583 $
Operation and maintenance cost of inverter	15 $ / Year
Inverter's efficiency	95%
Inverter's lifespan	10 Years
Interest rate (j)	10%
The life span of the project (n)	20 Years

The outcomes of the study are presented in tabular and graphical forms in the following section.

6. Results And Discussion

The impact of ZIP load modelling on the optimal sizing of battery and system components, considering voltage variation, is analyzed in this section.

The number of solar PV panels (N_{PV}), Number of Batteries (N_{Batt}) and Number of Inverters (N_i) are determined for three cases (Case 1 to Case 3) of microgrid systems with voltages as 415V± 5%, i.e. 395V, 415V and 435V and its effect in RICA loads [27].

The study examines the impact of variations in CPL on RICA loads. Furthermore, the analysis advocates for a 10% CCL in residential, industrial, and commercial sectors, attributed to the rise in battery-operated loads.

6.1. Effect of Variations in CPL on Optimum Sizing of System Components

The study considered the percentage of CIL and CPL without CCL in RICA loads, as shown in Table 3. [27].

Table 3. Percentage of CIL and CPL without CCL in various loads [27], and power factors [15]

Case	% CIL	% CCL	% CPL	cosϕ
Residential	30	0	70	0.95
Industrial	20	0	80	1
Commercial	50	0	50	0.85
Agricultural	0	0	100	0.9

The load curves are modified considering the % of CIL and CPL in ZIP load for RICA loads and are shown in Figure 6.

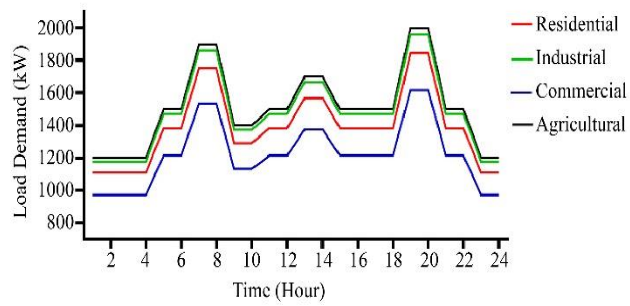


Fig. 6 Load Curves without CCL

From the load curves shown in Figure 6, the number of PV panels, batteries, and inverters are determined for 395V, 415V, and 435V without considering CCL. The size of system components is presented in Table 4. From Figure 6, it is seen that the load curve for the commercial category is the lowest. Therefore, the system components for that load type are also the lowest. On the contrary, the load curve for the agricultural category is the highest. Therefore, the system components for that load type are also the highest.

Table 4. Number of PV panels, batteries, and inverters for (a) 395V, (b) 415V, and (c) 435V without CCL.

Case	N_{PV}	N_{Batt}	N_i	Cost (M$)
Case 1: V_0 = 415V, V_a = 395V				
Residential	25	17	3	20.73
Industrial	26	18	3	23.619
Commercial	24	16	3	16.773
Agricultural	30	22	3	26.662

Case 2: V_0 = 415V, V_a = 415V				
Residential	25	18	3	21.83
Industrial	26	18	3	23.619
Commercial	25	17	3	20.73
Agricultural	30	22	3	26.662
Case 3: V_0 = 415V, V_a = 435V				
Residential	26	18	3	23.619
Industrial	27	18	3	24.15
Commercial	25	17	3	20.73
Agricultural	30	22	3	26.662

6.2. Effect of Inclusion of 10% CCL on Optimum Sizing of System Components

The study proposed 10% of CCL in residential, industrial, and commercial loads, as shown in Table 5. The 10% CCL does not apply to agricultural loads, as these loads predominantly consist of induction motor-pumping systems, which are classified as CPL.

Table 5. Percentage of CIL and CPL with proposed 10% of CCL in various loads

Case	%CIL	% CCL	% CPL
Residential	20	10	70
Industrial	10	10	80
Commercial	40	10	50
Agricultural	0	0	100

The load curves are modified considering the percentage of CIL, CCL, and CPL in the ZIP load for RICA loads, as shown in Figure 7.

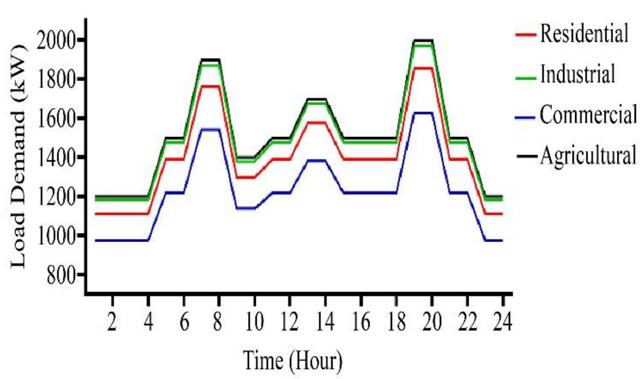


Fig. 7 Load curves with 10% CCL

The results obtained are presented in tabular and graphical forms. Table 6 shows the number of system components for (a) 395V, (b) 415V, and (c) 435V with 10% CCL for three cases (Case 1 to Case 3).

Table 6. Number of PV panels, batteries, inverters for (a) 395V, (b) 415V, and (c) 435V with 10% CCL.

Case	N_{PV}	N_{Batt}	N_i	Cost (M$)
Case 1: V_0 = 415V, V_a = 395V				
Residential	25	18	3	21.83
Industrial	26	19	3	24.219
Commercial	24	17	3	17.971
Agricultural	30	22	3	26.662
Case 2: V_0 = 415V, V_a = 415V				
Residential	25	19	3	22.746
Industrial	26	19	3	24.219
Commercial	25	18	3	21.83
Agricultural	30	22	3	26.662
Case 3: V_0 = 415V, V_a = 435V				
Residential	26	19	3	24.219
Industrial	27	19	3	25.02
Commercial	25	18	3	21.83
Agricultural	30	22	3	26.662

These numbers in Table 6 illustrate the quantity of solar PV panels (N_{PV}), batteries (N_{Batt}), and inverters (N_i) required for the ZIP load type across residential, industrial, commercial, and agricultural sectors, considering three system voltages: 395V, 415V, and 435V. It is evident from these figures that the highest demand for system components arises from the agricultural load category, attributed to its classification as 100% CPL.

Furthermore, it is observed that as the system voltage increases from 395V to 415V and subsequently to 435V, the optimal number of solar PV panels, batteries, and inverters also escalates for residential, industrial, and commercial applications. However, the quantity of system components required remains constant and is significantly higher for the agricultural load, which is classified as 100% CPL. Additionally, it is noteworthy that the agricultural load, being 100% CPL, does not contribute to an increase in CCL-type load. The results obtained are also presented graphically in Figures 8 and 9.

It is important to note that the variation in system voltage, specifically the range of 415V ± 5% (i.e., between 395V and 435V), plays a vital role in the optimal system sizing. These variations are commonplace, as fluctuations in load can lead to changes in system voltage.

In this context, the necessary adjustment to achieve optimal component sizing can amount to 8% to 10% of the total number of components required. Therefore, addressing this aspect can lead to substantial savings in the system's TAC, particularly in systems operating at megawatt (MW) or gigawatt (GW) scales.

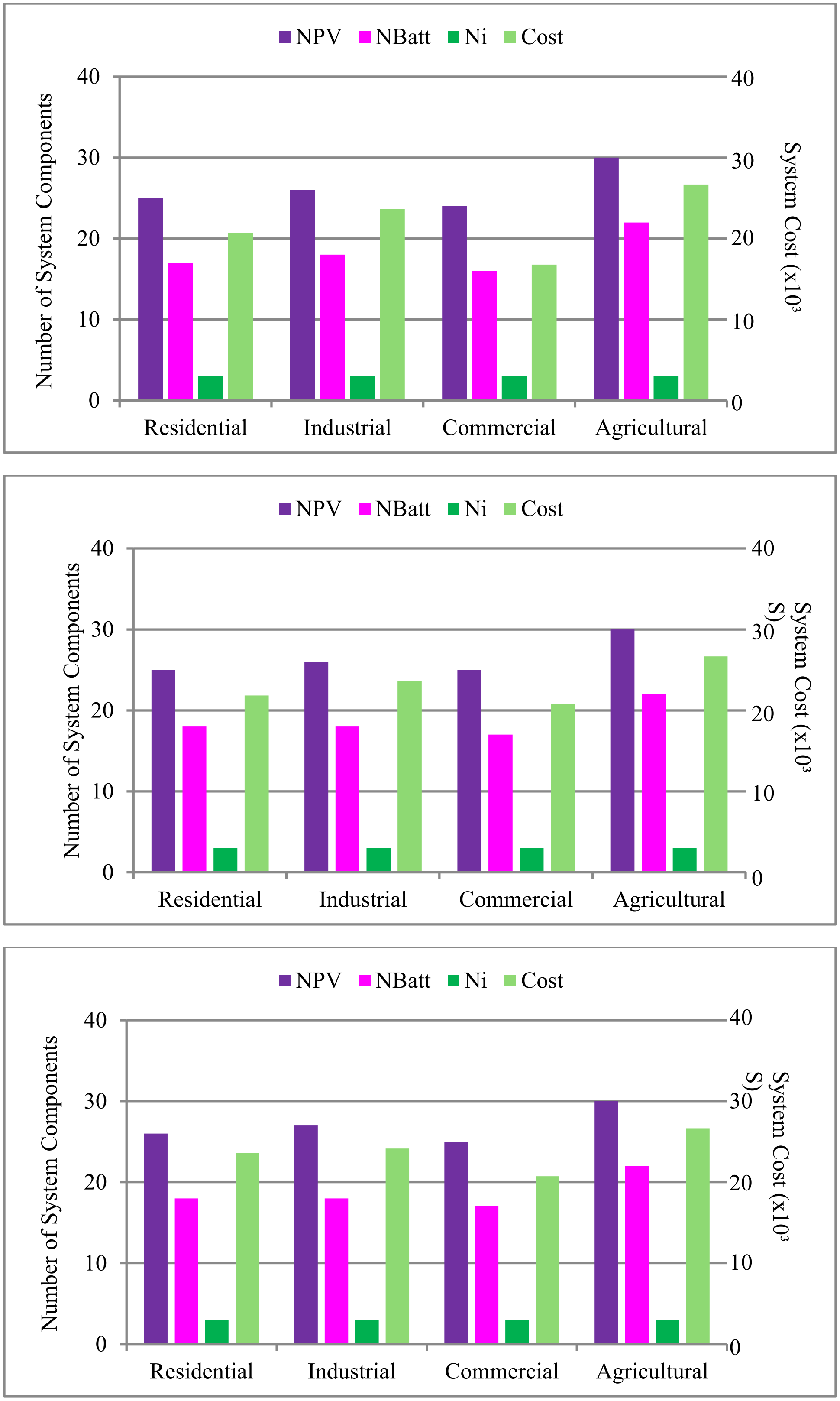
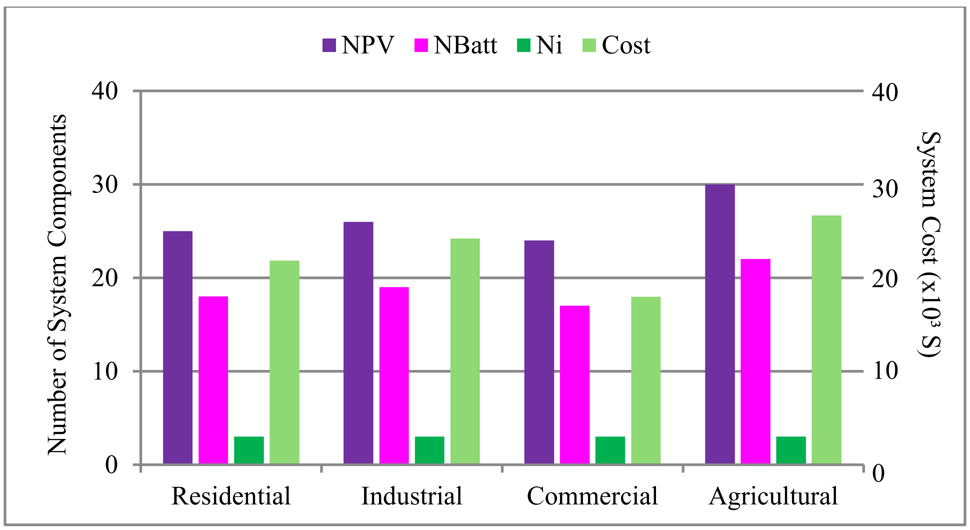
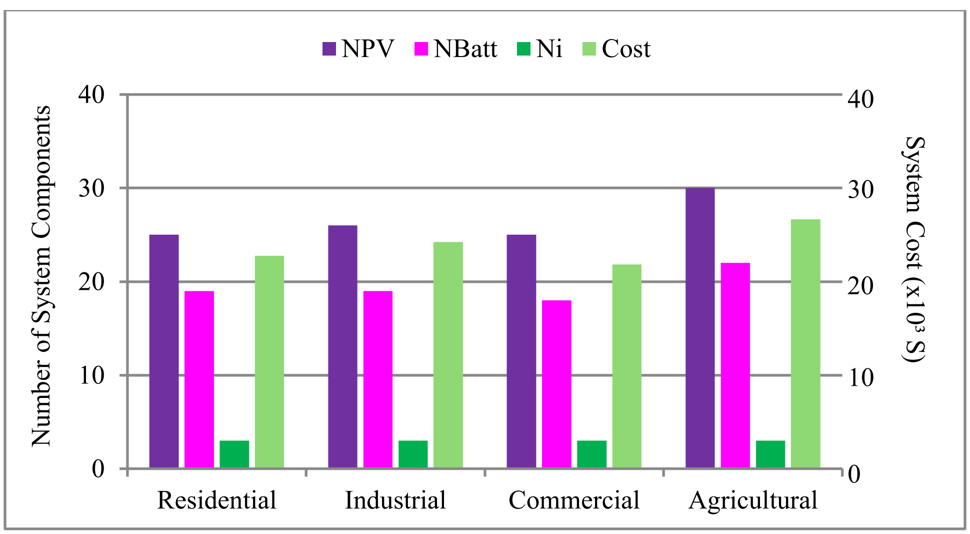


Fig. 8 Number of PV panels, batteries, and inverters for (a) 395V, (b) 415V, and (c) 435V without CCL.

As the system voltage is increased from 395V to 435V, the optimum N_{Batt} determined also escalates for RIC types loads, while the N_{Batt} remains the same for agricultural loads, being 100 % CPL. It can be summarized that optimum battery capacity sizing determined for system voltage as 415V± 5% is highest for the ZIP model for agricultural loads than that of optimum battery capacity sizing determined for the ZIP model for RIC loads due to the percentage of CPL in agricultural load is 100% while for RIC loads, CPL percentages are 70%, 80%, and 50% respectively. The results indicate that the number of batteries (N_{Batt}) required for the system with and without CCL are changing by just one number, but this change will be significant if the system or battery sizing will be in megawatt (MW) or gigawatt (GW) capacities. However, this change is applicable only for RIC loads. The findings indicate that the optimal number of batteries necessary for a ZIP load exhibits only minor variations, typically limited to one or two units. However, this adjustment accounts for approximately 8-10% of the maximum battery capacity required by the system, particularly for agricultural loads. This refinement can lead to significant cost savings for projects, especially those operating at megawatt or gigawatt capacities. The relevance of this study is underscored by the projected exponential increase in global battery demand, which is expected to reach 2,600 GWh by 2030.The TAC for the system at voltage levels of 395V, 415V, and 435V is illustrated in the accompanying figures. Analysis of these figures indicates that the TAC for residential loads is considerably lower when compared to that of industrial, commercial, and agricultural loads across all specified voltage levels. This distinction is primarily due to residential loads being classified as the lowest type of CPL. In contrast, the TAC for agricultural loads is the highest among these categories, reflecting that agricultural loads are classified as the highest CPL type relative to residential, industrial, and commercial loads.





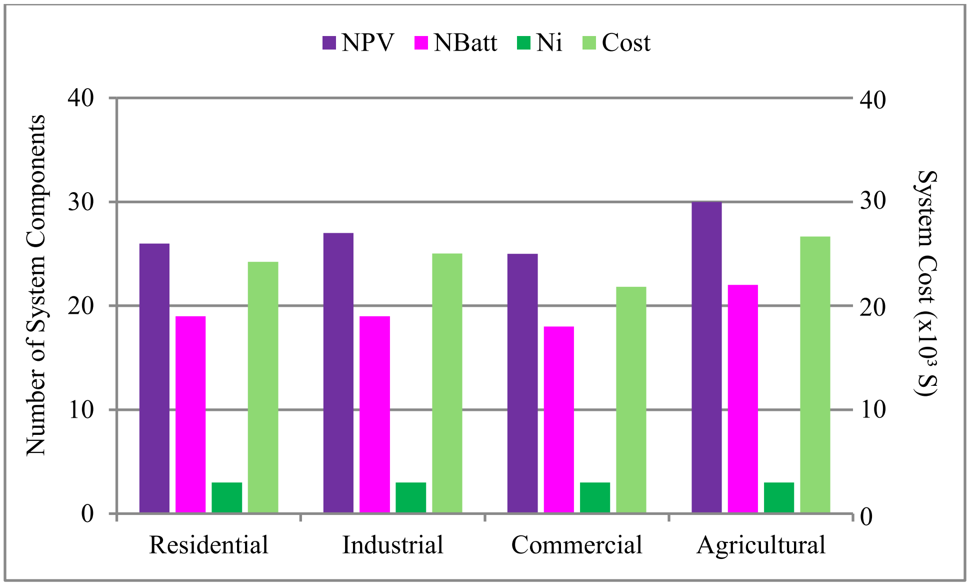


Fig. 9 Number of PV panels, batteries, and inverters for (a) 395V, (b) 415V, and (c) 435V with CCL.

The increase in battery-operated loads, such as EVs and HEVs, will lead to an increase in CCL. This study has assumed a 10% rise in CCL in RIC loads. This increase has not been considered for the agricultural load, which is 100% CPL in nature. The IPSO algorithm's convergence curves for the system's minimum TAC across various categories of RICA loads can be illustrated for three distinct voltage levels. Figure 10 presents a specific instance depicting the system voltage for agricultural loads.

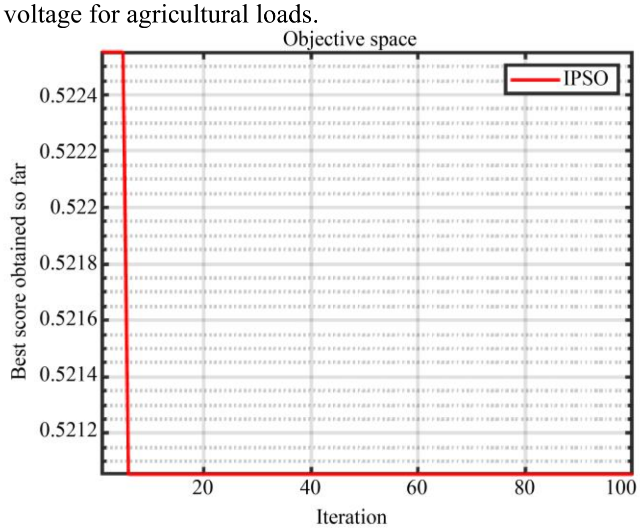


Fig. 10 Convergence curve of IPSO for agricultural load

7. Conclusion

This research investigates the optimal capacity sizing of BESS and associated system components, focusing on ZIP (CIL, CCL, CPL) load models accommodating voltage variations. Using the IPSO algorithm, the study assesses the effects of ZIP loads on residential, industrial, commercial, and agricultural loads. The findings reveal that the number of solar PV panels, batteries and inverters is the highest for agricultural loads across all voltage deviations - 395V, 415V, and 435V due to a complete reliance (100%) on CPL in this category.

The system under examination observed an 8-10% variation in the maximum number of components required for agricultural loads due to a higher percentage of CPL. In contrast, for systems with capacities of megawatts (MW) or gigawatts (GW), optimizing the number of components can lead to substantial reductions in the total annual costs.

In view of anticipatory battery charging requirements for EVs and HEVs in the coming days of modern power systems, this work proposes adding a 10% CCL in residential, industrial, and commercial loads. This study underscores the significance of load modelling and its influence on the optimal sizing of BESS and its components while also considering the effects of voltage fluctuations. This work is of significant importance due to the increasing power electronics load in modern applications.

Author Contributions

Gauri M. Karve: Conceptualization, Methodology, Software, Data curation, Writing Original draft, Mangesh S. Thakare: Reviewing, Editing, Visualization, Supervision, Geetanjali A. Vaidya: Reviewing, Editing, Visualization, Supervision

Funding Source

This work was funded by the University Research Grant Scheme, Board of College and University Development, Savitribai Phule Pune University, under grant number 15ENG001815.

Nomenclature

P_R	Rated PV power (kW)
R	Solar irradiance (kW/m^2)
R_{SR}	Solar radiation under the standard environment (kW/m^2)
R_C	Certain solar irradiance (kW/m^2)
$P_{pv\text{-}Each}$	Power rating of each PV panel (kW)
N_{PV}	Number of PV panels
P_{pv}	Total power output of all PV panels (kW)
A	Area of PV panel (m^2)
η_{pv}	Efficiency of PV panel (%)
A	Self-discharge rate per hour of BESS
$E_{PV}(t)$	Energy generated by PV (kWh)
$E_{load}(t)$	Energy required by load (kWh)
$E_{BESS}(t)$	Energy stored in Battery/BESS (kWh)
n_{BC}	Energy efficiency of battery during charging (%)
n_{BD}	Energy efficiency of battery during discharging (%)
n_{inv}	Efficiency of Inverter (%)
CRF	Capital Recovery Factor

Abbreviations	Full Form
Batt / BESS	Battery / Battery Energy Storage System
RESs	Renewable Energy Sources
DSs	Distribution Systems
RIC	Residential, Industrial and Commercial
RICA	Residential, Industrial, Commercial and Agricultural
SOC	State of Charge
IPSO	Improved Particle Swarm Optimization
GA	Genetic Algorithm
CIL	Constant Impedance Load (Z)
CCL	Constant Current Load (I)
CPL	Constant Power Load (P)
ZIP	CIL (Z), CCL(I), CPL(P)
DGs	Distributed Generators
PV	Photovoltaic
MOD	Modes of Discharge
TAC	Total Annual Cost
EVs	Electric Vehicles
HEVs	Hybrid Electric Vehicles

References

[1] Shohana Rahman Deeba et al., "Evaluation of Technical and Financial Benefits of Battery-Based Energy Storage Systems in Distribution Networks," *IET Renewable Power Generation*, vol. 10, no. 8, pp. 1149-1160, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[2] Choton K. Das et al., "Overview of Energy Storage Systems in Distribution Networks: Placement, Sizing, Operation, and Power Quality," *Renewable and Sustainable Energy Reviews*, vol. 91, pp. 1205-1230, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[3] Musa Mohammed et al., "Load Modeling Techniques in Distribution Networks: A Review," *Journal of Applied Materials and Technology*, vol. 1, no. 2, pp. 63-70, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[4] Anmar Arif et al., "Load Modeling-A Review," *IEEE Transactions on Smart Grid*, vol. 9, no. 6, pp. 5986-5999, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[5] B.J. Seshaprasad, and D. Mikkelsen, "Load Models for Power System Stability Studies," *IEEE Transactions on Power Systems*, pp. 166-172, 2000. [Google Scholar]

[6] Prabha S. Kundur, and Om P. Malik, *Power System Stability and Control*, 2nd ed., McGraw Hill, United States, 2022. [Google Scholar] [Publisher Link]

[7] P. Regulski et al., "Estimation of Composite Load Model Parameters Using an Improved Particle Swarm Optimization Method," *IEEE Transactions on Power Delivery*, vol. 30, no. 2, pp. 553-560, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[8] Sangwook Han et al., "Development of the Automatic Load Modelling System using PQM Data on Industry Site," *Journal of International Council on Electrical Engineering*, vol. 7, no. 1, pp. 51-57, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[9] Chao Zheng et al., "A Novel RNN based Load Modelling Method with Measurement Data in Active Distribution System," *Electric Power Systems Research*, vol. 166, pp. 112-124, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[10] Eleftherios O. Kontis et al., "Measurement-Based Dynamic Load Modeling Using the Vector Fitting Technique," *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 338-351, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[11] Yiqi Zhang et al., "ZIP Load Modeling for Single and Aggregate Loads and CVR Factor Estimation," *International Journal of Emerging Electric Power Systems*, vol. 23, no. 6, pp. 839-858, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[12] Alireza Rouhani, and Ali Abur, "Real-Time Dynamic Parameter Estimation for an Exponential Dynamic Load Model," *IEEE Transactions on Smart Grid*, vol. 7, no. 3, pp. 1530-1536, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[13] Mansour Eshragh-Niay Jahromi, and Mohammad Taghi Ameli, "Measurement-Based Modelling of Composite Load using Genetic Algorithm," *Electric Power Systems Research*, vol. 158, pp. 82-91, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[14] Mazhar Abbas et al., "Comparative Analysis of Battery Behavior with Different Modes of Discharge for Optimal Capacity Sizing and BMS Operation," *Energies*, vol. 9, no. 10, pp. 1-19, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[15] Abdullah Bokhari et al., "Experimental Determination of the ZIP Coefficients for Modern Residential, Commercial, and Industrial Loads," *IEEE Transactions on Power Delivery*, vol. 29, no. 3, pp. 1372-1381, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[16] Vichakorn Hengsritawat, and Thavatchai Tayjasanant, "Impacts of Load Models and Power Factor Control on Optimal Sizing of Photovoltaic Distributed Generators in a Distribution System," *IEEJ Transactions on Electrical and Electronic Engineering*, vol. 7, no. 6, pp. 567-573, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[17] Aashish Kumar Bohre et al., "Impacts of the Load Models on Optimal Planning of Distributed Generation in Distribution System," *Advances in Artificial Intelligence*, vol. 2015, no. 1, pp. 1-10, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[18] A.M. El-Zonkoly, "Optimal Placement of Multi-Distributed Generation Units Including Different Load Models using Particle Swarm Optimisation," *Swarm and Evolutionary Computation*, vol. 5, no. 7, pp. 760-771, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[19] T. Gozel et al., "Optimal Placement and Sizing of Distributed Generation on Radial Feeder with Different Static Load Models, *2005 International Conference on Future Power Systems*, Amsterdam, Netherlands, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[20] Ravi Teja Bhimarasetti, and Ashwani Kumar, "Distributed Generation Placement in Unbalanced Distribution System with Seasonal Load Variation," *2014 Eighteenth National Power Systems Conference (NPSC)*, Guwahati, India, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[21] J.N.S. Mrudveeka, S.V.N.L. Lalitha, and M. Ramamoorty, "Analysis of Maximum Loadability of a Bus for Different Load Models using New Algorithms," *Indian Journal of Science and Technology*, vol. 9, no. 23, pp. 1-8, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[22] Akbar Maleki, Mehran Ameri, and Farshid Keynia, "Scrutiny of Multifarious Particle Swarm Optimization for Finding the Optimal Size of a PV/Wind/Battery Hybrid System," *Renewable Energy*, vol. 80, pp. 552-563, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[23] Akbar Maleki, "Optimization based on Modified Swarm Intelligence Techniques for a Stand-Alone Hybrid Photovoltaic/Diesel/Battery System," *Sustainable Energy Technologies and Assessments*, vol. 51, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[24] J. Kennedy, and R. Eberhart, "Particle Swarm Optimization," *Proceedings of ICNN'95 - International Conference on Neural Networks*, Perth, WA, Australia, vol. 4, pp. 1942-1948, 1995. [CrossRef] [Google Scholar] [Publisher Link]

[25] Répélé Djidimbélé et al., "Optimal Sizing of Hybrid Systems for Power Loss Reduction and Voltage Improvement using PSO Algorithm: Case Study of Guissia Rural Grid," *Energy Reports*, vol. 8, no. Sup 9, pp. 86-95, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[26] Latifa El Boujdaini et al., "Sizing of a Stand-Alone PV-Wind-Battery-Diesel Hybrid Energy System and Optimal Combination using a Particle Swarm Optimization Algorithm," *Electrical Engineering*, vol. 104, no. 5, pp. 3339-3359, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[27] H. Lee Willis, *Spatial Electric Load Forecasting*, 2nd ed., Boca Raton, CRC Press, 2002. [CrossRef] [Google Scholar] [Publisher Link]