

Article

A Multi-Objective Optimized Approach to Photovoltaic-Battery Systems Constrained by Transformer Capacity for Existing Buildings

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Abstract

As urban populations grow and energy demands escalate, it is increasingly challenging for existing building electrical infrastructure in densely populated areas to meet contemporary energy requirements. Traditional grid expansion methods often impose prohibitive economic costs and environmental impacts. Photovoltaic-battery (PVB) systems emerge as a sustainable alternative to enhance building energy self-sufficiency while addressing transformer capacity constraints. This study develops a multi-objective optimization methodology for PVB system configuration in retrofit applications, introducing the transmission limit ratio (*TLR*) metric to quantify grid interaction capacity. Taking a residential building as a case study, the constraints on configuration variables under insufficient transformer capacity are obtained through simulation. Applying the NSGA-II algorithm, optimal configurations are identified for economic and environmental scenarios. In terms of configuration, a PVB system, 0.743 PV penetration, 205 kWh battery is the best optimal configuration for an economic operation scenario, while 1.356 PV penetration and 201 kWh battery is the best for an environmental operation scenario, when the *TLR* is 0.8. The analysis demonstrates PV penetration's critical role in scenario transition, while battery capacity primarily ensures system stability across *TLR* variations. This methodology provides practical insights for engineers in optimizing sustainable energy systems within existing infrastructure constraints, particularly relevant for high-density urban environments.



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Keywords: existing building retrofit; PV-battery system; capacity configuration; transformer capacity constraints; multi-objective optimization

1. Introduction

Due to rapid population growth and urbanization [1], the energy crisis has become increasingly severe, with energy demand reaching unprecedented levels [2]. Consequently, increased energy consumption has amplified carbon emissions, creating urgent challenges for sustainable urban development [3]. The 2024 Statistical Review of World Energy reports that energy-related emissions exceeded the 40 GtCO₂e level, with emissions from direct use of energy reaching 35 GtCO₂e for the first time ever [4]. The building sector plays a pivotal role in this dilemma, due to its high energy usage and environmental impact [5,6].

Notably, energy consumption in this sector accounts for 36% of the global energy demand and contributes to 39% of global CO₂ emissions [7,8].

To address these challenges, it is crucial to decrease fossil fuel dependence and actively stimulate the transition to renewable energy sources [9]. This transition holds particular significance for the cities where rapid urbanization coincides with evolving energy infrastructure. Renewable energy has immense significance in enhancing energy structures, safeguarding the ecological environment, combating the repercussions of climate change, and fostering sustainable socioeconomic development [10]. Considering the physical characteristics of buildings, both roofs and façades present ample opportunities for the integration of distributed photovoltaics (PVs). Consequently, PV stands as the most prevalent renewable energy technology within the building sector, with the aim of reducing dependence on the power supply from the utility grid and decreasing carbon emissions during operation [11,12].

PV constitutes a vital means of solar energy exploitation, enabling direct electricity generation, transmission, and utilization [13]. Nevertheless, the PV power generation is intermittent and cannot match the load curve in a time sequence. To this end, a battery energy storage system (BESS) can be configured for load shifting to deal with this problem [14]. BESS not only effectively regulates renewable energy and load demand, but also significantly reduces the power peak-to-valley difference [15]. Recent studies highlight critical cost considerations: shared energy storage models demonstrate that cost allocation strategies must balance fairness and actual usage to achieve economic viability [16], while inadequate compensation mechanisms directly prolong energy storage cost recovery periods [17]. This is compounded by findings that distributed storage topologies can mitigate installation costs compared to centralized systems [18], underscoring that in BESS configuration, energy storage capacity should not be too large, as this would result in a substantial increase in investment cost [19,20]. Conversely, a smaller energy storage capacity would provide limited enhancement to the operational efficiency of the system [21,22]. Hence, BESS size configuration is of vital importance in building energy systems [23].

Several scholars have discussed the configuration of BESS in buildings. Tahir Hira et al. [24] identified characteristic days tailored for BESS capacity optimization to manage ramp rates in microgrids. Ref. [25] introduces a BESS capacity sizing method grounded in reliable output power analysis. This approach formulates a model to establish the relationship between power capacity and wind energy loss. Following this, Ref. [26] details an optimized energy storage configuration strategy for PV plants, based on calculated indices of power and capacity satisfaction. It further analyzes power forecast errors across various weather conditions, employing an energy storage system for error compensation. Zhang Liang et al. [27] developed a method for optimal source-storage capacity allocation incorporating the integrated demand response (IDR). Their methodology establishes a bi-level optimization model that jointly addresses capacity allocation and operational optimization, aiming to minimize both system investment and operating costs. Finally, Ref. [28] presents an evaluation of a grid-connected system integrating PV, battery storage, and electric vehicles (EVs) within gymnasium buildings, demonstrating that the primary electricity demand of such facilities can be effectively met through appropriately sized PV installations and battery capacities. Tan et al. [29] proposed a stochastic approach to optimize the battery size in distribution grids with PVs. However, these approaches neglect the consideration of transmission capacity between buildings and the utility grid. In fact, buildings have a maximum power supply limit from the grid due to transformer configurations, known as the rated power of the transformer [30,31].

While significant research exists on transformer-aware optimization for grid-level distributed energy resources, studies specifically addressing building energy systems remain

limited, with prior work mainly focused on buildings-to-distribution-network integration frameworks [32] and transformer lifetime extension [33,34]. Recent advances demonstrate growing interest in this domain, including coordinated transformer-distributed energy storage planning to reduce costs and improve grid utilization [35], dynamic thermal rating techniques for enhancing PV hosting capacity under varying conditions [36], comprehensive reviews of load capability assessment for renewable-integrated transformers [37], and distributed optimization methods using transformer-assisted deep reinforcement learning in related contexts [38]. Unlike multiagent cooperative frameworks focusing on profit allocation among diverse stakeholders (e.g., wind/hydrogen/buildings via asymmetric Nash bargaining) [39], this study addresses single-building PV-battery optimization under hard transformer constraints through multi-objective physical configuration. Furthermore, while protection schemes like pole differential current relaying ensure HVDC transmission security [40], our work focuses proactively on preventing transformer overloads via TLR-constrained design rather than post-fault responses.

Nevertheless, at the building level, transformer capacity configurations are typically designed to satisfy conventional power demands. However, with the increasing power demand from users, there is a growing presence of large-scale electrical equipment within buildings, such as air conditioners, electric water heaters, ovens, and bathtubs. Consequently, the original transmission capacity between buildings and the utility grid may not be able to accommodate the new peak load, resulting in frequent power outages. This challenge is particularly pronounced in existing residential buildings, where equipment and facilities have aged significantly after prolonged operation. Furthermore, the lack of management and maintenance further exacerbates this situation [41]. Therefore, these aforementioned issues significantly impact residents' quality of life.

In general, the expansion of transmission capacity between buildings and the utility grid becomes necessary when the distribution system experiences frequent overload [42]. However, the reconstruction of power systems, particularly in existing buildings, presents significant challenges. The early construction of these buildings has resulted in disorganized facilities and chaotic lines, making planning difficult. Moreover, the reconstruction of an upper-level transformer substation requires the construction of power corridors. Consequently, all of these factors contribute to a substantial economic burden, as shown in Figure 1.

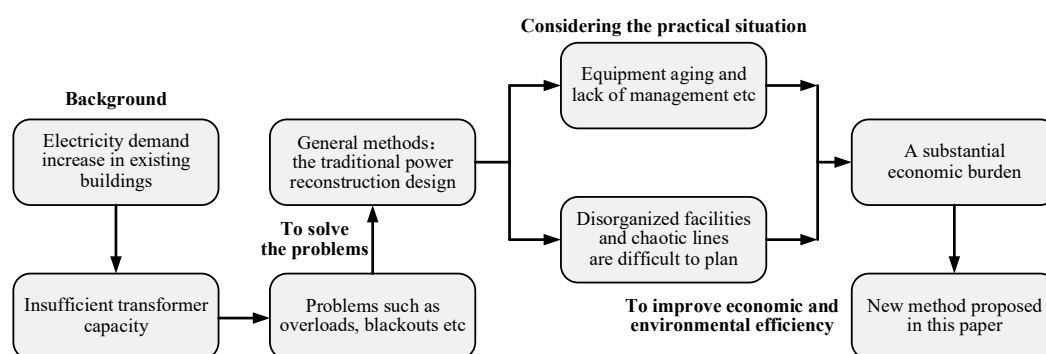


Figure 1. The background of the new method.

Therefore, for existing buildings that face challenges in power capacity expansion and have poor economic benefits, it is feasible to retain their original power systems (including transformer configurations) and reduce their reliance on the public grid by implementing a hybrid AC/DC PV-battery (PVB) system. This can be achieved by effectively controlling the energy flow within the system, thereby ensuring that the electric power drawn from the utility grid stays within the transformer's rated power range. The configuration method of

the PVB system, including PV capacity allocation and energy storage capacity allocation, is precisely the focus of this study.

The flowchart of the optimization procedure is illustrated in Figure 2. A residential building in Shanghai and local meteorological data were selected as the simulation object. As the problem of insufficient capacity mainly occurs during the peak usage time in summer due to heightened cooling demands that drive the annual extreme transformer loading, 24 h of a typical summer day was taken as the research object. This approach captures the most severe grid stress scenario, ensuring safe operation throughout the year by addressing the extreme day balance while aligning with the optimization methodology's focus on critical infrastructure constraints.

PVB system size ranges (PV, battery size) and other parameters serve as input for the models, along with weather data, load data, transformer capacity, and system constraints obtained through domain analysis. The NSGA-II optimization algorithm optimizes the configuration of the energy system with the objective of minimizing the two optimization objectives under the aforementioned constraints. NSGA-II is applied to determine the Pareto front sets. Then, two objective functions are weighted for two scenarios that emphasize the economy and environment, respectively. Finally, the optimal system configuration is obtained for the corresponding scenarios, and a sensitivity analysis is conducted on the configuration variables.

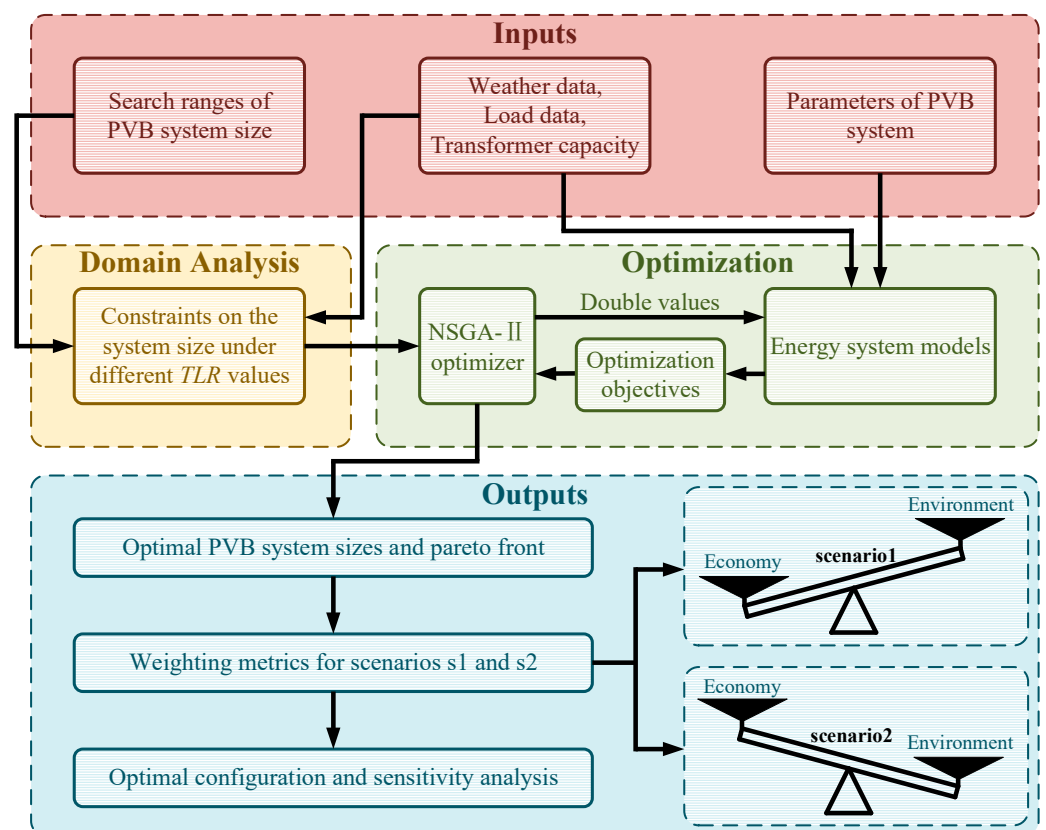


Figure 2. Flowchart of the optimization procedure.

Consequently, based on the aforementioned technical approach, this study focuses on the following issues:

1. The potential for buildings to largely maintain the current power system, while considering distributed generation on the demand side to offset the impact of loads on transmission capacity.

2. Minimum required battery energy storage capacity for different PV penetration under transformer capacity constraints.
3. Proposal of a multi-objective optimized approach to PVB system, based on building load power and transmission capacity, with economic and environmental performance as evaluation criteria.
4. Discussion of the effects of configuration variable modifications on system performance, serving as a reference for practical engineering applications.

The paper organization is as follows. Section 2 details the system layout and optimization objectives and elaborates on the simulation models and operational strategy. In Section 3, the constraints on the system configuration range under an insufficient transformer capacity are discussed through simulations. The Pareto front solution set is obtained under the constraint by NSGA-II, and the weights of the objective functions are allocated based on the requirements of the two scenarios to calculate the optimal configuration. In Section 4, the mechanism by which the variables impact the system under the optimization method is examined. Finally, Section 5 provides the relevant conclusions.

2. Methodology

2.1. System Framework

Figure 3 presents a schematic of the conventional AC distribution system found in existing buildings, which delivers electricity to users through a transformer and AC bus. Therefore, the transmission capacity is constrained by the performance of the transformer and AC bus, and can be influenced by emerging loads.

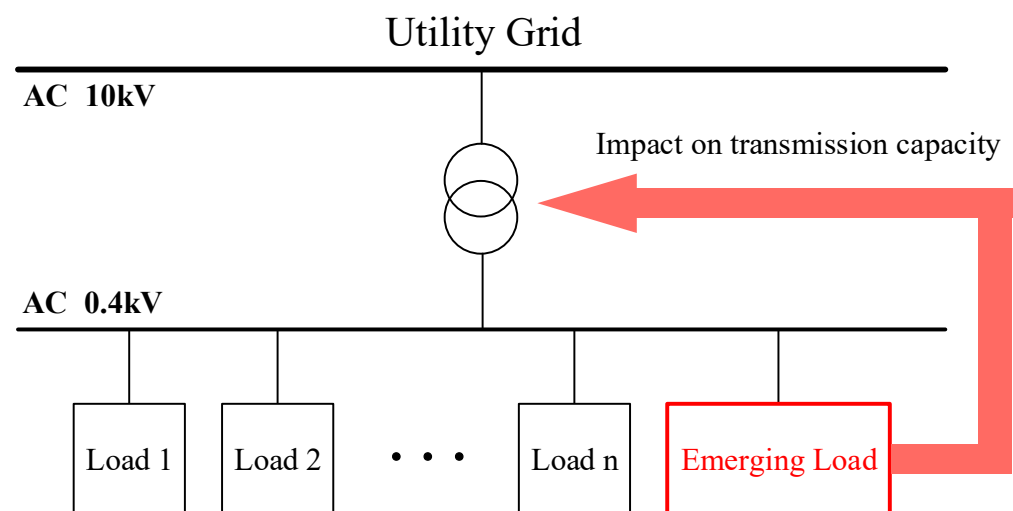


Figure 3. Topology of the conventional AC distribution system.

Advancements in technology have led to a surge in the adoption of DC devices, posing challenges for AC distribution systems. Frequent conversion between AC and DC reduces the energy efficiency of the distribution system. To address this issue, Figure 4 shows the proposed AC/DC hybrid PVB system for buildings. The bidirectional AC/DC converter enables simultaneous operation of the AC and DC buses. In contrast to the conventional AC distribution system, the AC/DC hybrid PVB system incorporates the concept of zoning and sub-modules to effectively differentiate between the AC and DC components, while utilizing renewable energy resources.

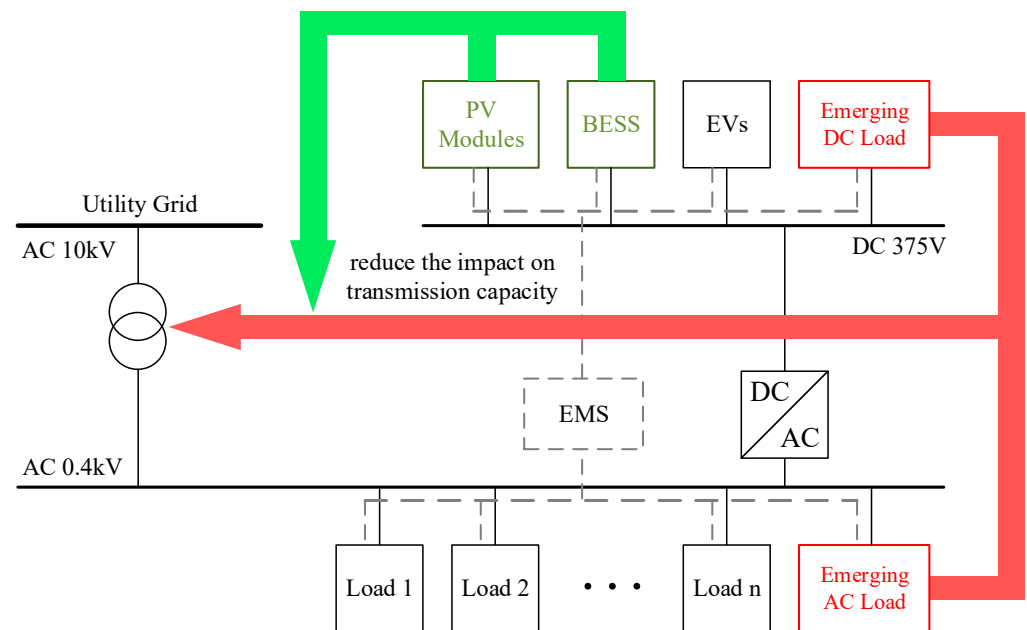


Figure 4. Topology of the AC/DC hybrid PVB system.

The energy generated by the PV modules is supplied to both the building load and the battery, where surplus PV power is curtailed. During PV power shortages, the battery is discharged and additional energy is imported from the utility grid to ensure continuous power delivery to the PVB system. Combined PV and BESS operation enables a reduction in the load rate on the transformer and mitigates the impact on the transmission capacity. Additionally, an energy management system (EMS) is implemented using the Internet of Things (IoT) technology, featuring a multi-load data architecture and a multi-node distributed access system (refer to Figure 5). The EMS can monitor devices and their energy data in real time, facilitating optimal control of the entire PVB system.

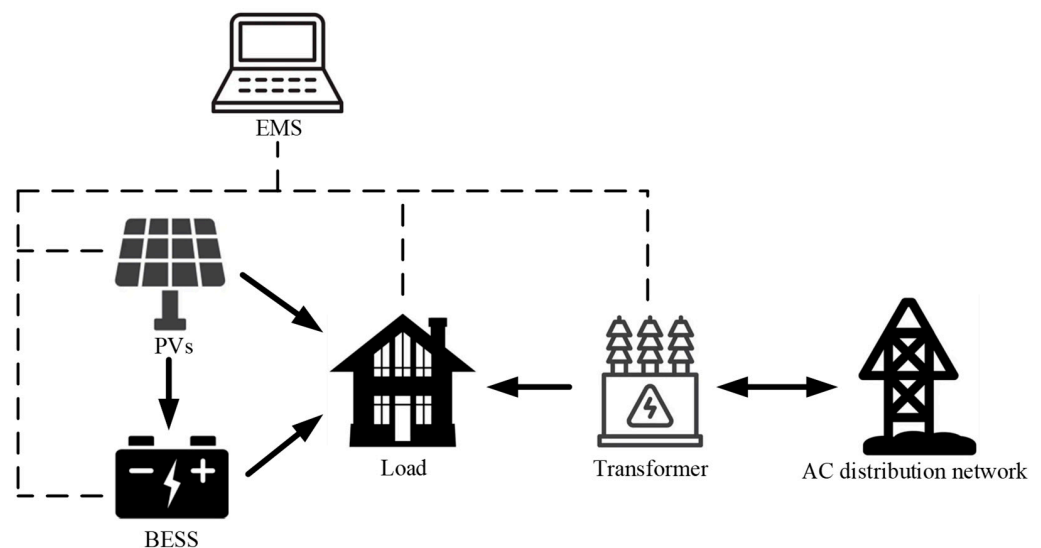


Figure 5. The energy flow in the PVB system.

2.2. Optimization Objectives

This research utilizes the Diurnal Total Cost (*DTC*) as the model's economic optimization criterion to gauge the financial feasibility of system investment and operational expenditures [43,44]. *DTC* comprises four components, (1) diurnal investment expenditure (*DIN*), (2) operation cost (*OPE*), (3) variable maintenance cost (*VM*), (4) fixed maintenance

cost (FM), as shown in Equation (1). Equation (2) to Equation (5) enable the calculation of parts (1)–(4). Furthermore, varying operational scenarios allow for adjustments to the system configuration in each design solution. Consequently, subscript k is utilized to distinguish indicators, such as DTC , DIN , OPE , in calculations, reflecting variations across different operational scenarios. Parameters for different equipment in the system, such as C and φ , are differentiated using the subscript i .

$$DTC_k = DIN_k + OPE_k + VM_k + FM_k, \forall k \in K = \{s_1, s_2\} \quad (1)$$

$$DIN_k = \frac{1}{365} \sum_i (CRF_i \cdot C_i \cdot \varphi_i), \forall k \in K, \forall i \in I = \{pv, bat\} \quad (2)$$

$$OPE_k = \sum_{t=1}^{24} (E_{grid,k,t} \cdot c_{buy,t}^{ele}), \forall k \in K \quad (3)$$

$$VM_k = \sum_{t=1}^{24} \sum_i (E_{i,k,t} \cdot \varphi_{var,i}), \forall k \in K, \forall i \in I \quad (4)$$

$$FM_k = \sum_i (C_i \cdot \varphi_{fix,i}), \forall i \in I \quad (5)$$

$$CRF_i = \frac{m(1+m)^{n_i}}{(1+m)^{n_i} - 1}, \forall i \in I \quad (6)$$

In these equations, s_1 and s_2 represent the economic and environmental operation scenarios, respectively. CRF , the capital recovery factor, is utilized to determine the present value of an annuity (a consistent stream of equal yearly cash flows). The annual real interest rate (8%) is denoted by m , while n signifies the system's lifespan in years. Equipment i 's capacity is represented as C_i . The unit price of equipment i is denoted by φ_i , and its variable and fixed maintenance cost coefficients are, respectively, given by $\varphi_{var,i}$ and $\varphi_{fix,i}$. The quantity of electricity procured from the grid at time t is $E_{grid,k,t}$, and the corresponding purchase price per unit is $c_{buy,t}^{ele}$.

The environmental optimization objective of the model is represented by the diurnal carbon emission (DCE) of the system [45]. The investigated system's carbon emissions mainly originate from grid electricity purchases. In this study, the emission factor method [46] is used to calculate the DCE , as shown in Equation (7). Similarly, the DCE index also uses the subscript k to distinguish the different operation scenarios.

Diurnal carbon emission (DCE) serves as the model's environmental optimization objective [45]. For the system under investigation, grid-purchased electricity constitutes the primary source of carbon emissions. Calculation of the DCE follows the emission factor method [46], detailed in Equation (7). Additionally, the DCE index incorporates the subscript k to differentiate among various operational scenarios. The term ξ^{ele} denotes grid emission factor.

$$DCE_k = \sum_{t=1}^{24} (\xi^{ele} \cdot E_{grid,k,t}), \forall k \in K \quad (7)$$

Using the NSGA-II algorithm, the two designated objectives are optimized to generate the Pareto fronts. Therefore, a composite optimization objective function F can be defined by weighting the system's optimization objectives, applicable to various operating scenarios, as indicated in Equation (8).

$$F = \omega_{DTC} \cdot \underbrace{\frac{DTC_k - DTC_{min}}{DTC_{max} - DTC_{min}} \times 100\%}_{DTC_k^{nor}} + \omega_{DCE} \cdot \underbrace{\frac{DCE_k - DCE_{min}}{DCE_{max} - DCE_{min}} \times 100\%}_{DCE_k^{nor}}, \forall k \in K \quad (8)$$

In Equation (8), the symbols ω_{DTC} and ω_{DCE} denote the decision weights assigned to the economic and environmental objectives, respectively. The terms $DTC_{\min}$ and $DCE_{\min}$ correspond to the minimum achievable values (or ideal targets) for economic and environmental objectives. Conversely, $DTC_{\max}$ and $DCE_{\max}$ represent their maximum possible values, which signify the worst-case scenario expectations for each objective. Correspondingly, DTC_k^{nor} and DCE_k^{nor} denote the DTC_k and DCE_k after normalization, respectively.

2.3. System Model

2.3.1. PV Generator Model

PV modules have nonlinear characteristics, and their output power is significantly dependent on solar radiation and ambient temperature. For a specific location, the power generation of a PV system is modeled through the following calculation [47,48]:

$$\begin{cases} P_{pv} = \eta_{pv} A_{pv} G_{\beta} \\ \eta_{pv} = \eta_{\gamma} \eta_{pc} [1 - \beta(T_c - T_{cref})] \\ T_c = T_a + [(NOCT - 20)/800] G_{\beta} \end{cases} \quad (9)$$

The actual power output of the PV modules, denoted by P_{pv} , is calculated using several parameters: η_{pv} (PV generator efficiency), A_{pv} (PV panel area in m^2), and G_{β} (solar radiation incident on the tilted plane in W/m^2). The modules are tilted at an angle equal to the site latitude. Additional factors include η_{γ} (reference module efficiency), η_{pc} (power conditioning efficiency, set to 1 when Maximum Power Point Tracking (MPPT) is used [49]), and β (the temperature coefficient for generator efficiency). Temperatures involved are T_{cref} (reference cell temperature in $^{\circ}C$) and T_c (cell temperature in $^{\circ}C$), the latter being estimable from ambient temperature T_a ($^{\circ}C$) and solar radiation G_{β} . The nominal operating cell temperature ($NOCT$) is a standard value of $45^{\circ}C$ [50]. Crucially, parameters A_{pv} , η_{pc} , β , and $NOCT$ vary depending on the specific PV module type and are usually supplied by the module manufacturers.

2.3.2. Battery Energy Storage System Model

During any hour, the excess power generated by the PV generators can be utilized for battery charging, while the stored energy can be discharged when power generation falls short. Therefore, the difference between the energy generated and the load demand determines whether the battery is in a charging or discharging state. The state of charge (SOC) is commonly used to describe the charging and discharging state of batteries, and is defined as the ratio of the energy content of the battery (E_{bat}) to its rated capacity (C_{bat}) in Equation (10).

Within each hour, surplus energy from the PV units can charge the batteries. Conversely, stored energy is discharged when generation cannot meet demand. Consequently, the net energy balance (generation minus load demand) dictates the battery's operating mode: charging or discharging. The battery's state of charge (SOC), a standard indicator for its energy level, is expressed as the proportion of its current stored energy (E_{bat}) to its rated capacity (C_{bat}), as defined in Equation (10).

$$SOC = \frac{E_{bat}}{C_{bat}} \quad (10)$$

The battery's functioning status comprises two primary phases: charging and discharging. During the operation of the battery, SOC can be expressed as follows [51]:

$$\begin{cases} P_{bat} = \alpha P_{bat,ch} + (1 - \alpha) P_{bat,dis} \\ SOC(t + \Delta t) = SOC(t) + \alpha \frac{\eta_{ch} P_{bat,ch} \Delta t}{C_{bat}} + (1 - \alpha) \frac{P_{bat,dis} \Delta t}{\eta_{dis} C_{bat}} \end{cases} \quad (11)$$

where P_{bat} indicates the actual operating power of the battery, $P_{bat,ch}$ and $P_{bat,dis}$ correspond to the charging power ($P_{bat,ch} > 0$) and discharging power of the battery ($P_{bat,dis} < 0$), respectively. In addition, α is a binary number, where 1 represents the battery charging state and 0 represents the battery discharging state. η_{ch} and η_{dis} denote the efficacy rates for battery charging and discharging, respectively. Δt signifies the discrete temporal interval for simulation, which is taken as 1 s in this study.

At any time t , the charged quantity and the operating power of the battery are governed by the following constraints:

$$\begin{cases} SOC_{min} \leq SOC(t) \leq SOC_{max} \\ P_{bat,dis}^{max} \leq P_{bat} \leq P_{bat,ch}^{max} \end{cases} \quad (12)$$

where SOC_{max} signifies the battery's maximum charge capacity, while SOC_{min} denotes its minimum charge capacity; and $P_{bat,ch}^{max}$ and $P_{bat,dis}^{max}$ are the maximum charging power and maximum discharging power, respectively.

2.4. System Operation Strategy

To gain complete insight into operation strategy, it is imperative to establish the parameters for different simulation scenarios. PV penetration (R_{pv}) is typically expressed as the quotient between the total photovoltaic generation (E_{pv}) and the building load (E_{load}) [52]. To quantify the transmission capacity between buildings and the utility grid, this study defines the transmission limit ratio (TLR) as the ratio between the maximum transmission power (P_{trans}^{max}) and the building load's peak power (P_{load}^{max}). R_{pv} and TLR are important dimensionless variables in this study, and their expressions are shown in Equation (13).

$$\begin{cases} R_{pv} = \frac{E_{pv}}{E_{load}} \\ TLR = \frac{P_{trans}^{max}}{P_{load}^{max}} \end{cases} \quad (13)$$

This study aims to configure the BESS optimally and reduce DTC and DCE , subject to the constraints imposed by the existing building's transmission capacity. The charging or discharging state of the battery is governed by the disparity between generated PV energy and load energy demand. Therefore, based on the difference between P_{pv} and P_{load} , the operational state of the system can be classified into four modes, as illustrated in Figure 6.

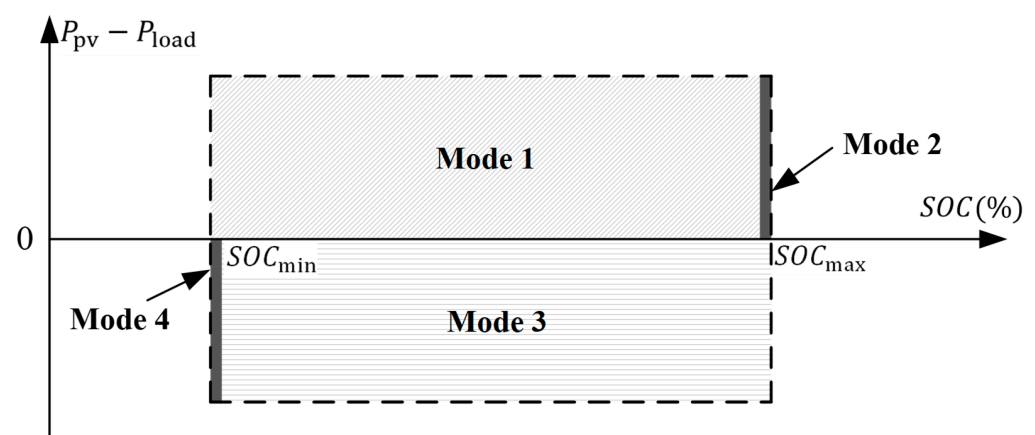


Figure 6. Operation mode division diagram.

Based on the classification of modes, an appropriate operation strategy was formulated to effectively manage the energy flow within the PVB system. Figure 7 depicts the system's operational strategy. The battery stores energy during intervals of excess PV generation and discharges power when PV output is inadequate to satisfy the building's demand.

Crucially, if P_{load} exceeds P_{pv} , the PVB system gives precedence to procuring electricity from the power grid. Should the net load (defined as P_{load} minus P_{pv}) surpass $P_{\text{trans}}^{\text{max}}$, the battery supplies the additional power requirement. From an energy balance perspective, the power constraint is given by the following equation:

$$P_{\text{pv}} + P_{\text{grid}} = P_{\text{load}} + P_{\text{bat}} \quad (14)$$

To clearly express the control effect, the net load ($P_{\text{load}}^{\text{net}}$) is introduced (as shown in Equation (15)), which is defined as the difference between P_{load} and P_{pv} . The three power curves are plotted in Figure 8. To further illustrate the relationship between the energy flows, the available surplus PV output and the net load exceeding the maximum transmission power are represented by $E_{\text{pv}}^{\text{ex}}$ and $E_{\text{load}}^{\text{ex}}$, respectively (as shown in the green and red areas). Obviously, the blue and green areas have the same area, both representing $E_{\text{pv}}^{\text{ex}}$. The main objective of the control strategy is to store $E_{\text{pv}}^{\text{ex}}$ through BESS to supply power to $E_{\text{load}}^{\text{ex}}$, while ensuring that the power supply from the grid does not exceed $P_{\text{trans}}^{\text{max}}$, as depicted in Figure 9. $E_{\text{pv}}^{\text{ex}}$ and $E_{\text{load}}^{\text{ex}}$ can also be calculated using the following formulas.

$$\begin{cases} P_{\text{load}}^{\text{net}} = P_{\text{load}} - P_{\text{pv}} \\ E_{\text{pv}}^{\text{ex}} = \int_{t=0}^{24} \max(P_{\text{pv}} - P_{\text{load}}, 0) dt = \int_{t=0}^{24} \max(-P_{\text{load}}^{\text{net}}, 0) dt \\ E_{\text{load}}^{\text{ex}} = \int_{t=0}^{24} \max(P_{\text{load}}^{\text{net}} - P_{\text{trans}}^{\text{max}}, 0) dt \end{cases} \quad (15)$$

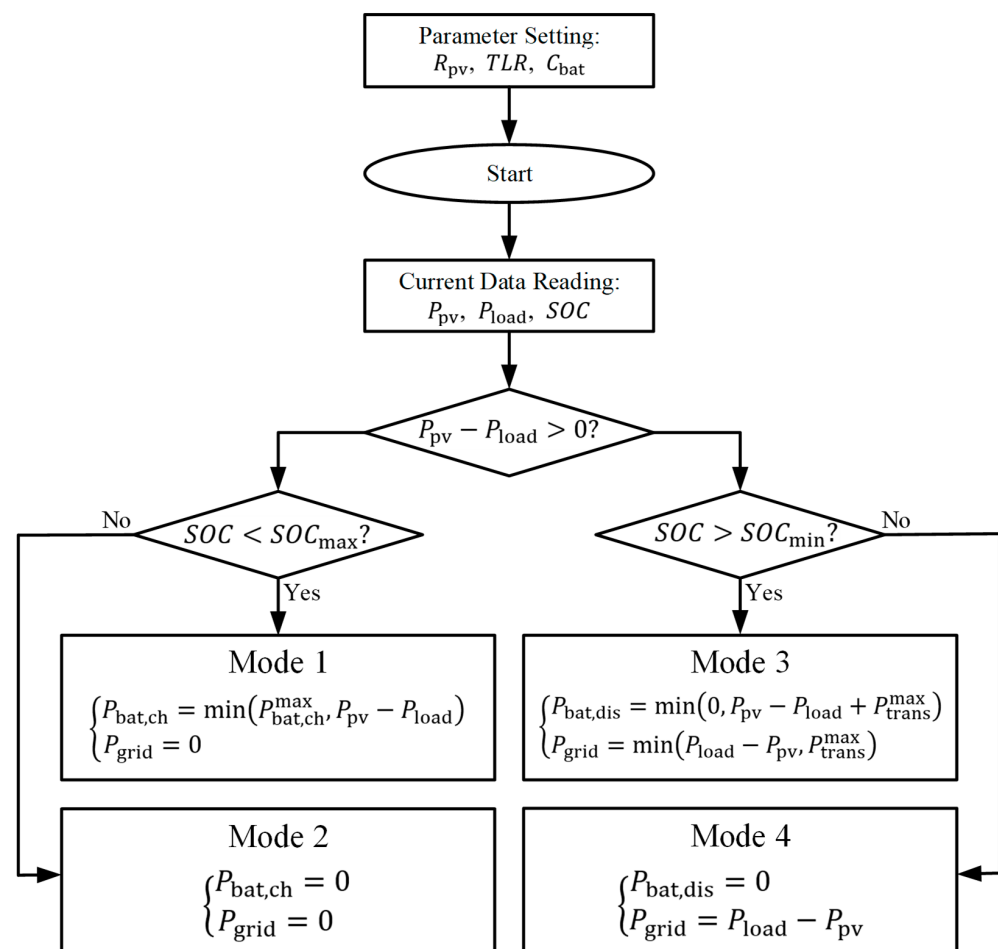


Figure 7. Flow chart of the system operation strategy.

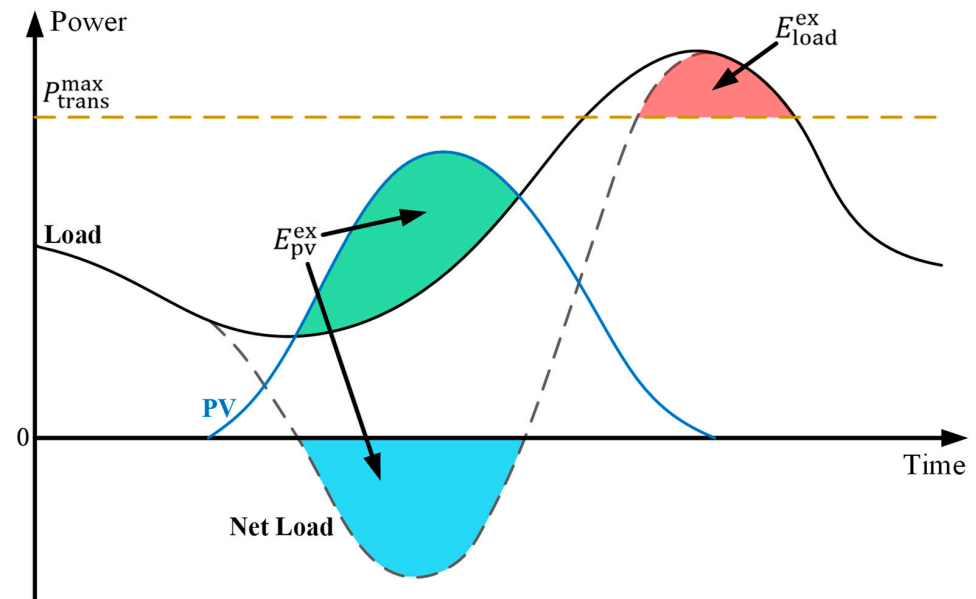


Figure 8. Schematic diagram of control effect.

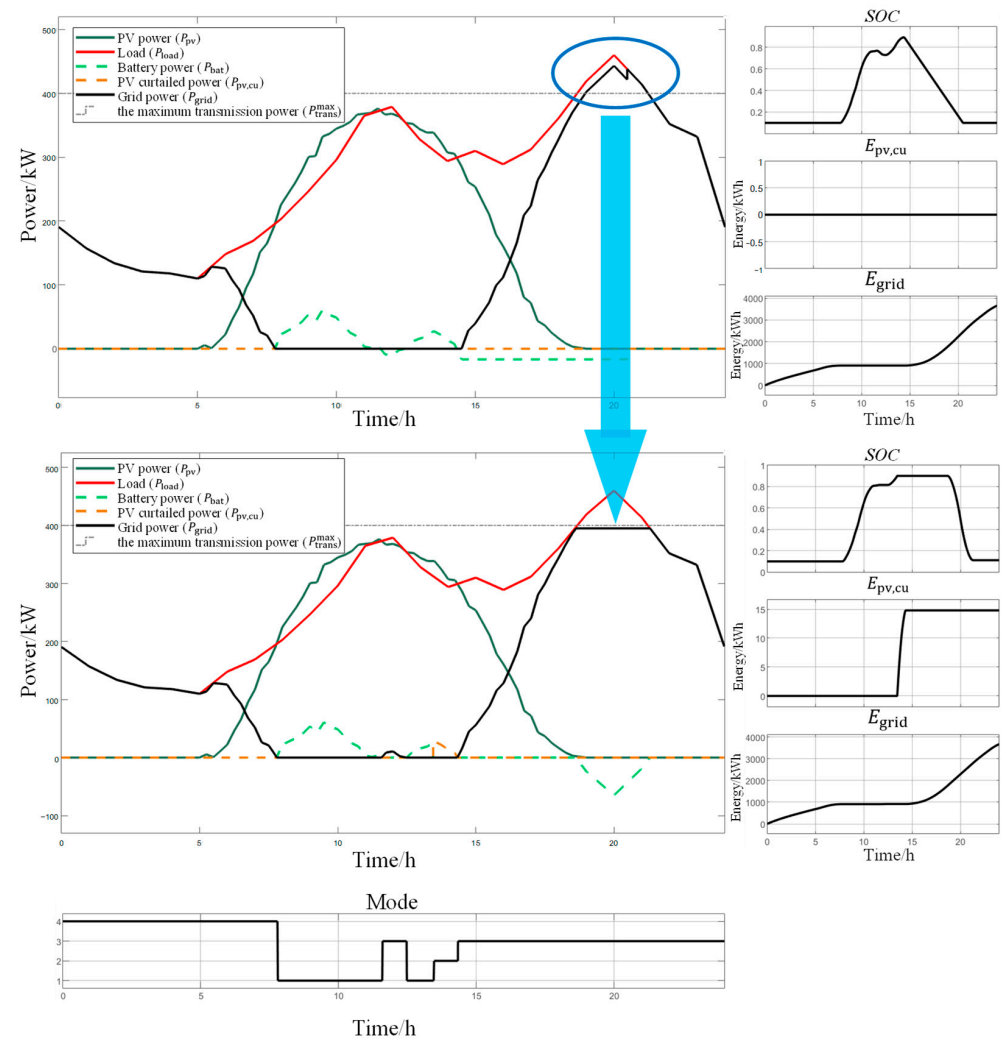


Figure 9. Schematic diagram of simulated diurnal operation.

3. Case Study and Results

First, the typical daily load of a residential building in Shanghai is selected as the research object of this study, with a summer day chosen due to its load profile, dominated by peak cooling consumption, exhibiting the annual maximum transformer stress. This makes it a conservative benchmark for capacity constraints under extreme conditions. As shown in Figure 10, for ease of description, the peak load value above P_{trans}^{max} is defined as $P_{load,D}^{max}$, which can be determined as follows:

$$P_{load,D}^{max} = P_{load}^{max} - P_{trans}^{max} \quad (16)$$

Because this study mainly focuses on the situation where P_{trans}^{max} is less than P_{load}^{max} , $P_{load,D}^{max}$ must be greater than 0, and similarly, TLR must be less than 1. According to the definition of $P_{load,D}^{max}$, the maximum net load curve exceeding P_{trans}^{max} is calculated as follows:

$$P_{load,D}^{net,max} = P_{load}^{net,max} - P_{trans}^{max} \quad (17)$$

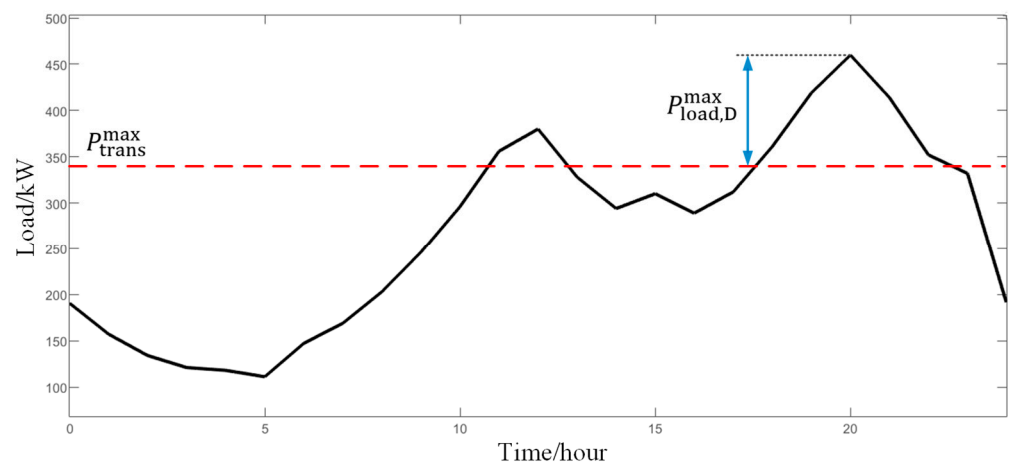


Figure 10. The typical diurnal load curve.

Table 1 details the battery parameters used for this research.

Table 1. Battery parameters.

Parameters	Value	Unit
SOC_{max}/SOC_{min}	0.95/0.10	/
Charging/discharging rate	0.5	C
η_{ch}/η_{dis}	95%	/
Cycle times	6000	times
Service life	15	years

The parameters of optimization objectives can be found in Table 2.

Table 2. The parameter settings of the optimization objectives.

Parameters	Value	Unit
φ_{pv} [53]	726	USD/kW
φ_{bat} [54,55]	500	USD/kWh
$\varphi_{var,pv}$	0.001	USD/kWh
$\varphi_{var,bat}$	0.002	USD/kWh
$\varphi_{fix,pv}$	0.001	USD/kWh
$\varphi_{fix,bat}$	0.001	USD/kWh

Table 2. Cont.

Parameters	Value	Unit
m	8	%
n_{pv}	20	years
n_{bat}	15	years

In the case study, a time-of-use electricity pricing scheme was employed for Shanghai residential electricity tariffs ($c_{buy,t}^{ele}$), as detailed in Table 3. Electricity rates are higher during the high-demand hours (6:00 AM to 10:00 PM) at 0.0897 USD per kWh. Conversely, the lower rate of 0.0446 USD per kWh applies during off-peak periods, which run from midnight to 6:00 AM and 10:00 PM to midnight.

Table 3. Shanghai residential time-of-use electricity pricing schedule.

Time Period	Period Type	Electricity Price (USD/kWh)
00:00–06:00	Off-peak	0.0446
06:00–22:00	Peak	0.0897
22:00–24:00	Off-peak	0.0446

3.1. Domain Analysis of the System

Considering the limitations of transformer capacity, there should exist a minimum storage capacity (C_{bat}^{min}) under each TLR value and R_{pv} , which can meet the minimum requirements for the normal operation of the system. The C_{bat}^{min} , along with the corresponding R_{pv} and TLR values, can provide constraints for the search range in subsequent multi-objective optimizations. Therefore, before optimizing the system configuration, it is necessary to simulate the above constraints to obtain an effective region within the independent variable domain.

A Cartesian coordinate system is established featuring R_{pv} on the x-axis, with TLR assigned to the y-axis. To obtain universally applicable research results, the range of R_{pv} is set from 0 to 1.5, while the range of TLR values is limited to 0 to 1. Figure 11 presents the results from simulating the boundary conditions. It is obvious that not every point in the coordinate system has a corresponding C_{bat}^{min} . Overall, the coordinate system can be divided into four regions by using three lines.

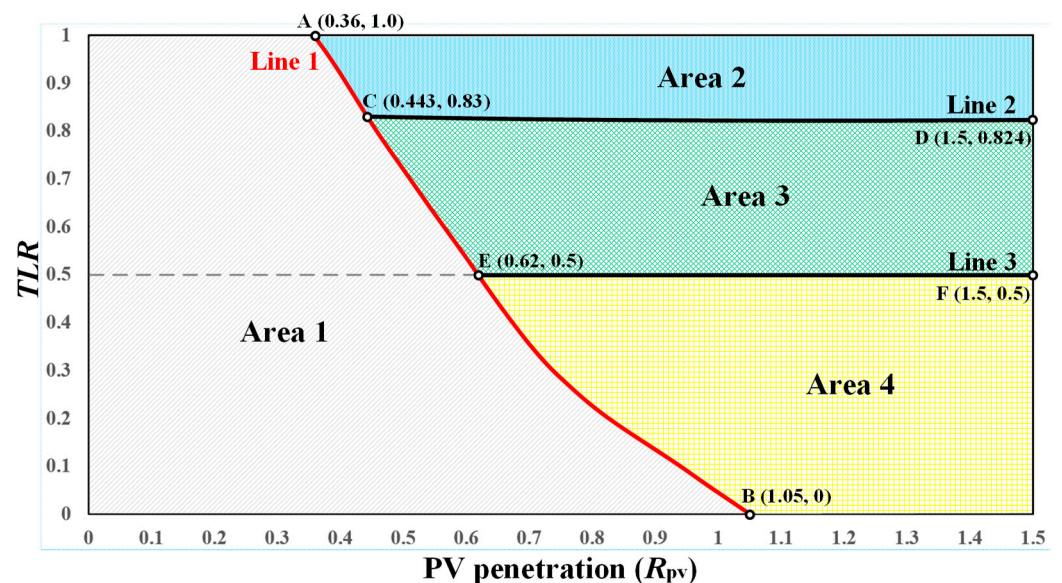


Figure 11. System domain diagram.

Based on the energy relationship in Figure 8, it is evident that to guarantee standard daily operation of the system, E_{pv}^{ex} must be greater than E_{load}^{ex} . Considering the energy loss resulting from battery charge/discharge cycles, Line 1 can be derived through simulation, as shown by the red line in Figure 11. It is apparent that as R_{pv} increases, TLR gradually decreases, with the rate of decrease diminishing. This can be attributed to higher R_{pv} leading to greater availability of photovoltaic power generation, thereby reducing the demand for transmission capacity from the grid (i.e., TLR value). From an energy perspective, C_{bat}^{min} does not theoretically exist in Area 1, so this paper will not further discuss this area.

To better illustrate the physical meaning of Line 1, line segment AA1 is constructed perpendicular to the y-axis passing through point A, intersecting the y-axis at point A1. Point B extends to the right along the x-axis to point B1. The moving points X, Y, and Z are located on segments AA1, AB, and BB1, respectively (excluding the two endpoints of each segment). The system analysis corresponding to these points is shown in Figure 12.

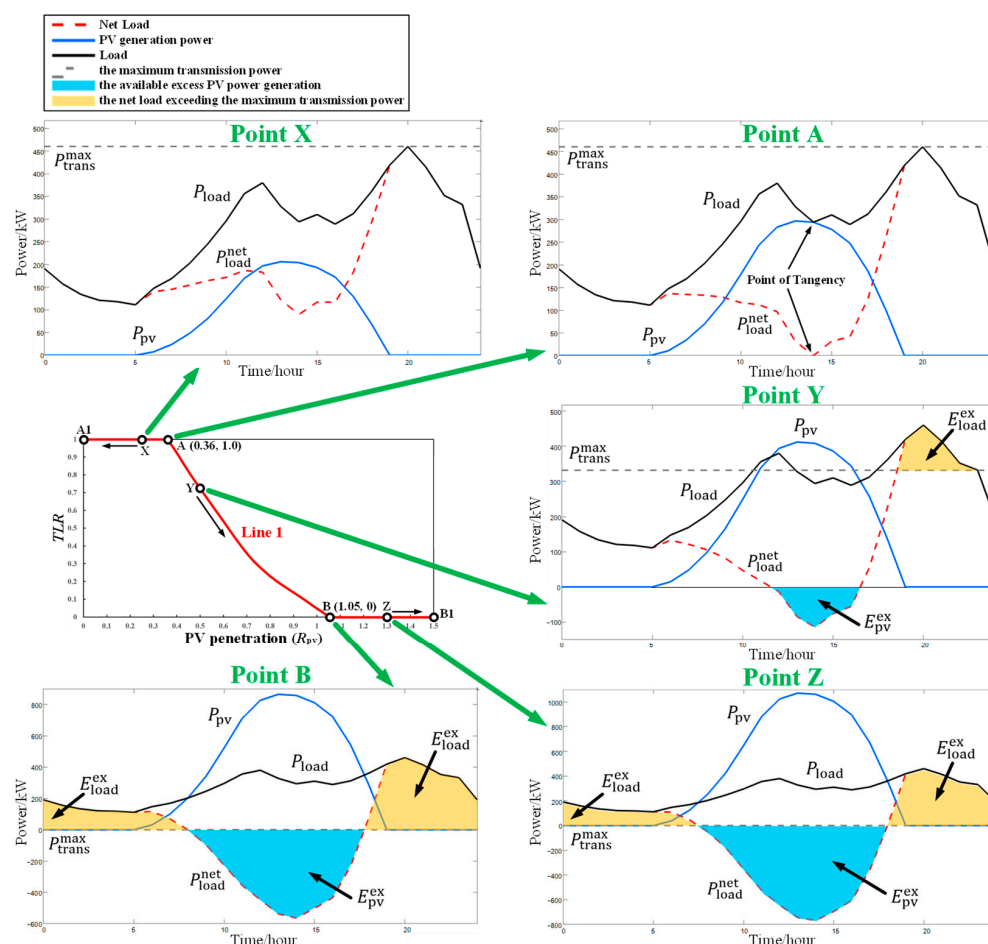


Figure 12. System analysis of each point on Line 1.

The R_{pv} at point X is extremely low, resulting in P_{load}^{net} always being greater than 0. This implies that the PV output curve is consistently below the load curve, leading to the absence of E_{pv}^{ex} in this situation. As the R_{pv} increases, the critical point (point A) reaches 0.36. At point A, a tangent point is formed between the PV output curve and load curve. Correspondingly, the net load curve is tangent to the X-axis, where E_{pv}^{ex} is equal to zero. Along line AB, both E_{pv}^{ex} and E_{load}^{ex} increase simultaneously with the increase in R_{pv} . However, E_{pv}^{ex} remains equal to E_{load}^{ex} after energy loss. As R_{pv} continues to increase, a new critical point (point B) is reached. At point B, the TLR has dropped to 0, while E_{pv}^{ex} after energy loss remains equal to E_{load}^{ex} . This indicates that the system no longer

requires electricity from the grid and can utilize effective energy flow planning to fulfill the complete daily energy requirements solely with PV generation, thereby achieving a fully self-sufficient power supply mode. On segment BB1, as R_{pv} further increases, E_{load}^{ex} decreases while E_{pv}^{ex} increases, as shown at point Z. Excess PV power generation can be curtailed or transmitted to the utility grid. A summary of the system analysis corresponding to the relevant points in Line 1 is shown in Table 4.

Table 4. System analysis corresponding to each point.

Point	TLR	PV Penetration (R_{pv})	Relationship Between E_{pv}^{ex} and E_{load}^{ex}
X	1	0~0.36	E_{pv}^{ex} is non-existent while $E_{load}^{ex} = 0$
A	1	0.36	$E_{pv}^{ex} = E_{load}^{ex} = 0$ (critical point)
Y	0~1	0.36~1.05	E_{pv}^{ex} after energy loss is equal to E_{load}^{ex}
B	0	1.05	E_{pv}^{ex} after energy loss is equal to E_{load}^{ex}
Z	0	1.05~1.5	E_{pv}^{ex} after energy loss is greater than E_{load}^{ex}

Under the premise of the energy relationship (on the right side of Line 1), the configuration of the energy storage capacity (C_{bat}^{min}) cannot be based solely on E_{load}^{ex} . Due to the high-power demands of peak loads on the battery, the necessary capacity may exceed the minimum value theoretically required based on energy needs alone, when accounting for charge–discharge rate limitations. To determine the critical point of this relationship, Line 2 is derived through simulation, as shown in Figure 11. However, Line 2 appears as an approximately straight line in Figure 11 and lacks clear features. Therefore, it is magnified and presented in Figure 13.

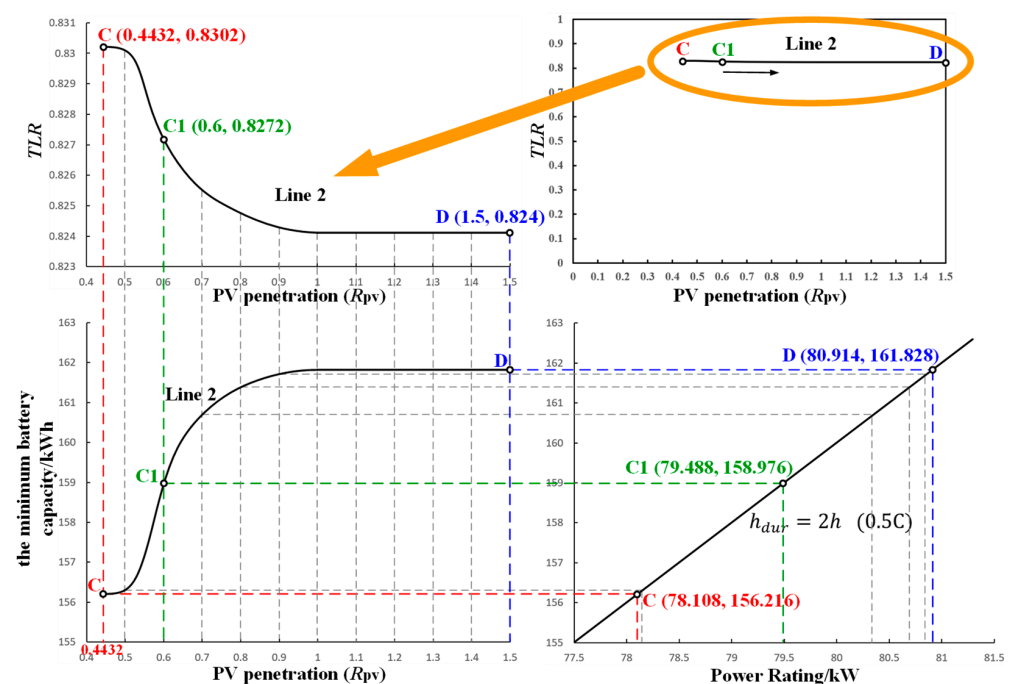


Figure 13. Line 2 and corresponding energy storage capacity.

The characteristic curves demonstrate that as R_{pv} increases, TLR gradually decreases and eventually stabilizes at 0.824. Similarly, as R_{pv} increases, C_{bat}^{min} gradually increases and then stabilizes at 161.828 kWh. This is because a higher R_{pv} implies a lower E_{load}^{ex} under the same TLR condition. Therefore, TLR can be further reduced to achieve a larger E_{load}^{ex} until E_{load}^{ex} under each R_{pv} exhibits the same multiple relationship with $P_{load,D}^{net,max}$, resulting in a higher required C_{bat}^{min} . Furthermore, in the lower right portion of Figure 13, the C_{bat}^{min}

and maximum battery discharge power required for each point on Line 2 are located on the previously defined battery characteristic line, with a maximum charging/discharging rate of 0.5 C.

To further analyze the situation at each point on Line 2, point C1 (with a R_{pv} of 0.6) is selected, and a line chart illustrating the corresponding E_{load}^{ex} (black axis) and C_{bat}^{min} (orange axis) values for its TLR (0.8272) is presented in Figure 14. $P_{load,D}^{net,max}$ is selected as the y-axis in the figure to facilitate the description of the energy and power relationship.

In Figure 14, the E_{load}^{ex} corresponding to $P_{load,D}^{net,max}$ is represented by the black solid line, while the battery characteristics are depicted by the orange dashed line. Along the OC1 line, the C_{bat}^{min} is determined by the energy storage capacity corresponding to the battery characteristics at the same $P_{load,D}^{net,max}$ value, as indicated by the orange arrow. Beyond point C1, the corresponding C_{bat}^{min} can be directly determined based on the E_{load}^{ex} curve, as shown by the grey arrow. Point C1 serves as a critical point on the line where the R_{pv} is 0.6. Furthermore, Line 2 is formed by connecting the critical points at different R_{pv} values. In Area 2 above Line 2, the value of C_{bat}^{min} is selected based on the battery characteristics (orange dashed line). In the area below Line 2, the value of C_{bat}^{min} is calculated based on the energy relationship (black solid line).

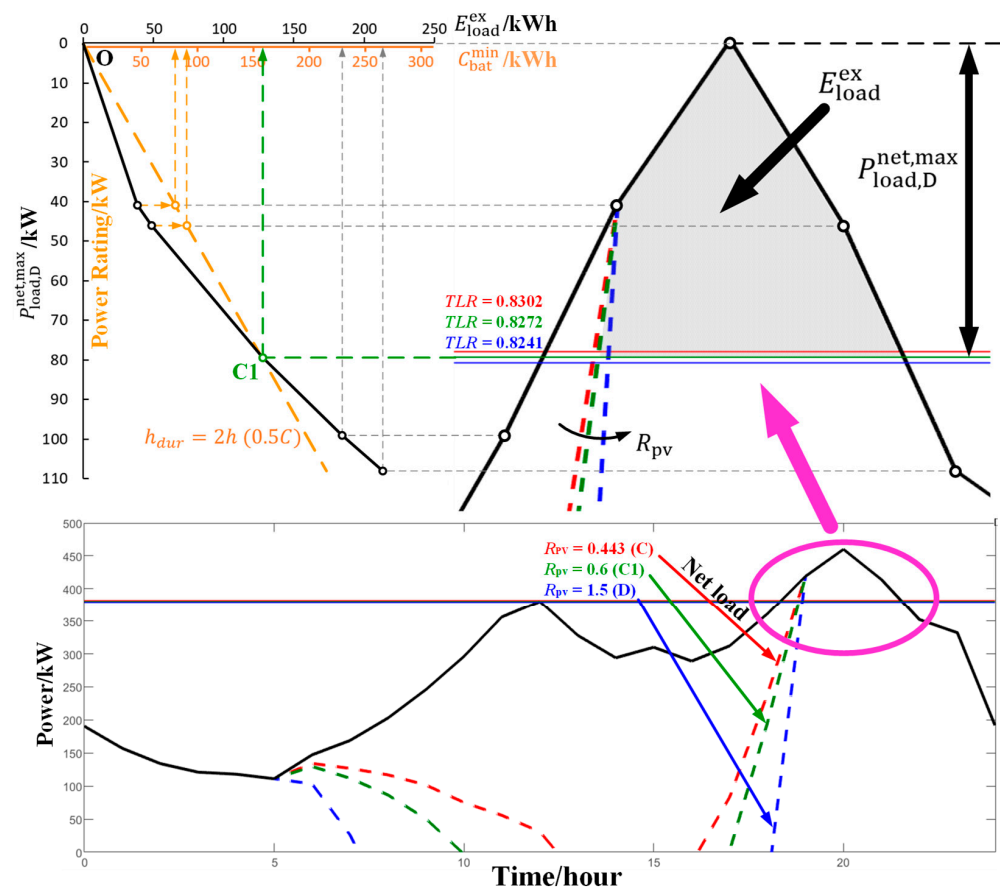


Figure 14. Energy and power curve at point C1.

Line 3 in Figure 11 is a straight line with a TLR value of 0.5. Area 4 below Line 3 is characterized by a low transmission capacity of the power grid, making it more suitable for traditional power expansion methods. Therefore, this study does not delve into the discussion in Area 4. This study mainly focuses on Areas 2 and 3.

3.2. Capacity Analysis of Energy Storage System

The results of the battery capacity configuration after the simulation within the domain of R_{pv} and TLR are shown in Figure 15. It can be observed that C_{bat}^{min} is negatively correlated with the R_{pv} and positively correlated with the TLR value. Additionally, the growth rate of C_{bat}^{min} with increasing TLR is comparatively moderate in Area 2, while in Area 3, the increase in C_{bat}^{min} with TLR is more pronounced.

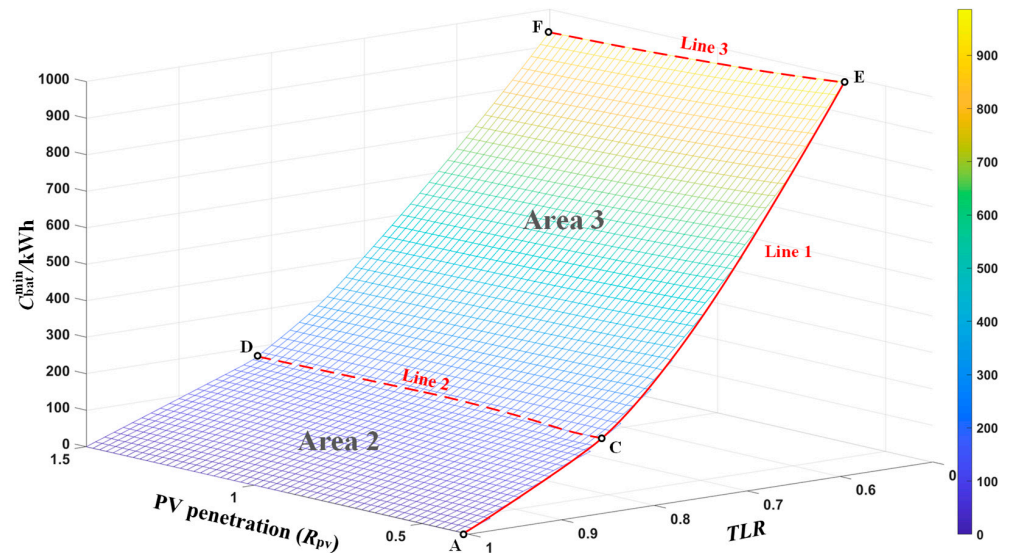


Figure 15. C_{bat}^{min} distribution diagram.

To more thoroughly examine how variables influence C_{bat}^{min} , the relationship curves between C_{bat}^{min} and R_{pv} , as well as TLR values, are shown in Figure 16. Analysis shows that TLR values have a significant influence on C_{bat}^{min} . A decreasing TLR value indicates a more severe system power capacity shortage, necessitating greater renewable energy integration and larger associated storage capacity. In contrast, the impact of R_{pv} on C_{bat}^{min} is relatively small. As the R_{pv} increases, the required storage capacity of the system gradually decreases.

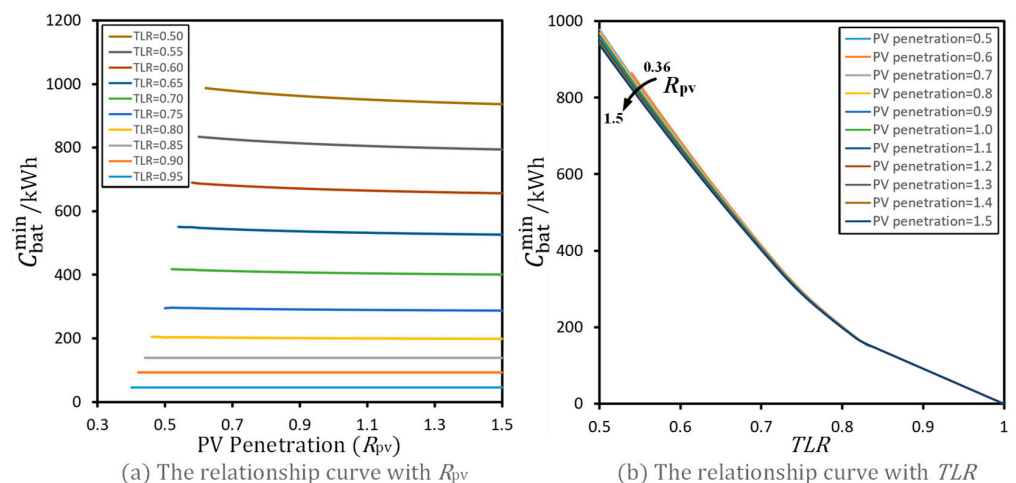


Figure 16. The relationship curves of C_{bat}^{min} .

3.3. Optimization Results and Analysis

Based on domain analysis in Section 3.1 and the storage capacity analysis in Section 3.2, system configuration optimization needs to be conducted under the following constraints:

$$\begin{cases} (R_{pv}, TLR) \in A, A \in (\text{Area2} \cup \text{Area3}) \\ C_{bat}(R_{pv}, TLR) \geq C_{bat}^{\min}(R_{pv}, TLR) \end{cases} \quad (18)$$

In Equation (18), A represents the effective definition domain of R_{pv} and TLR , that is, the union set of Areas 2 and 3 in Figure 11.

The Pareto front generated by NSGA-II is shown in Figure 17. In Figure 17a, the blue points are the designed Pareto front solution sets corresponding to the TLR values. The Pareto front of these points is represented by the red dashed line, that is, the Pareto-optimal sets of the PVB system. However, it should be taken into account that in practical engineering applications, TLR is a fixed value and not a variable that can be optimized and adjusted. Therefore, in Figure 17b, the design Pareto front sets of the system under specific TLR values are shown separately. Each curve represents the optimal solution set for the PVB system design stage under the current TLR value.

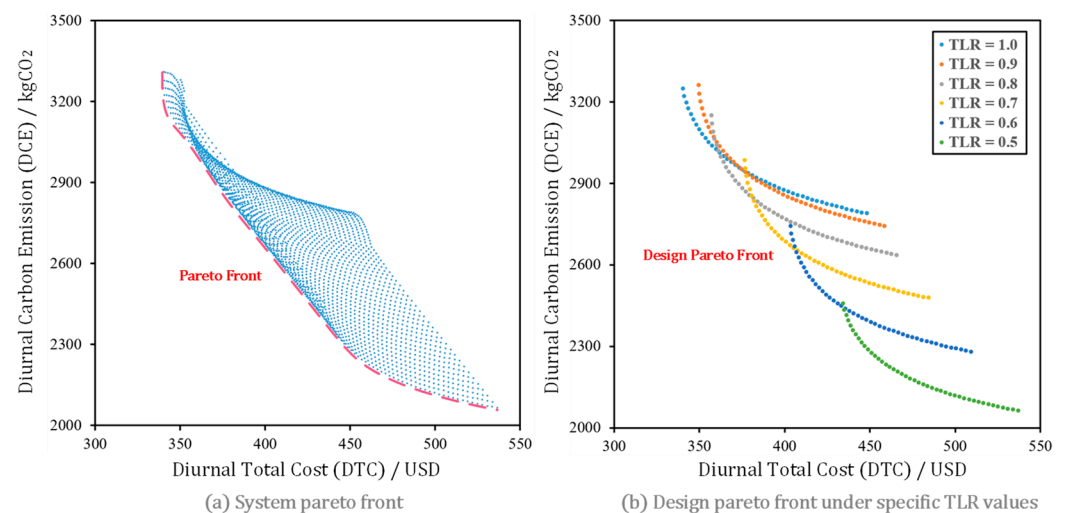


Figure 17. The pareto-optimal sets of PVB system.

Figure 18 shows the distribution of the battery capacity configuration, DTC , and DCE across the optimized solution groups at different TLR levels. The chart shows that smaller TLR values require larger storage capacity. When TLR is 0.9, a 100kWh battery is configured, while when TLR is 0.5, a battery with a capacity of up to approximately 1000 kWh needs to be configured to meet optimization. High-capacity storage equipment incurs higher costs, which increases the DTC . Correspondingly, high-capacity storage equipment can effectively reduce DCE and is more environmentally friendly.

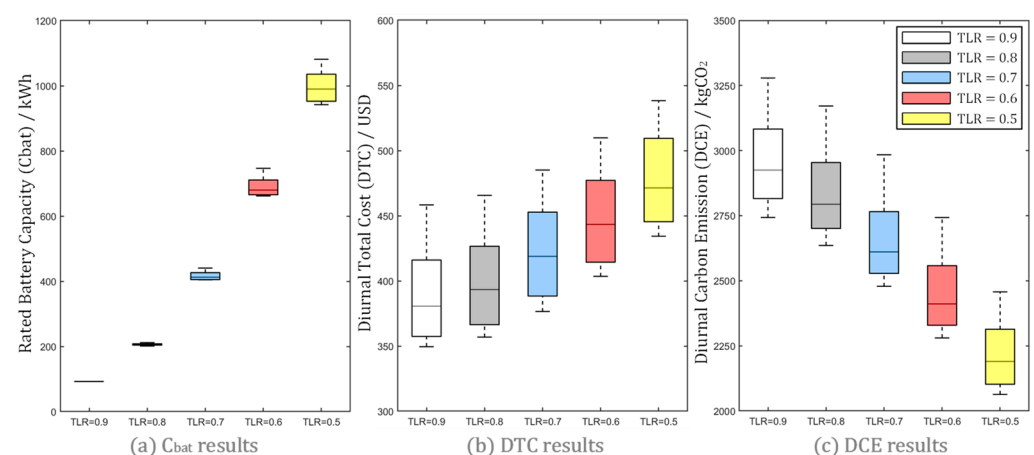


Figure 18. Analysis of configuration and optimization objectives under different TLR values.

After obtaining the optimal solution sets for each *TLR* value, another step is to assign decision weights to each objective based on the two scenarios. Table 5 is a pairwise comparison matrix constructed based on the scores given by the experts for each objective. Scores range from 1 to 9, where a score of 1 indicates two equally important objectives, and a score of 9 indicates that one objective is much more important than the other [56]. To validate the acceptability of the subjective scoring matrix, the decision matrix's consistency ratio should remain below 0.1 [57]. Given that stakeholders assign differing priorities to each objective, this research incorporates two distinct sets of decision weights for stakeholders with varying emphases, presented in Table 5.

Table 5. Decision matrix of scenarios s_1 and s_2 .

s_1 : Economic Operation Scenario			s_2 : Environmental Operation Scenario		
	<i>DTC</i>	<i>DCE</i>		<i>DTC</i>	<i>DCE</i>
<i>DTC</i>	2	1	<i>DTC</i>	3	1
<i>DCE</i>	1	1/2	<i>DCE</i>	1	1/3
Weight	0.67	0.33	Weight	0.25	0.75

Based on the weights in Table 5, the optimal configurations corresponding to different *TLR* values for scenarios s_1 and s_2 can be calculated, as shown in Table 6 and Figure 19. In both scenarios, as *TLR* decreases, the required configuration capacities for both PV and energy storage increase. The demand for increased energy storage capacity is significantly higher than that for increased PV capacity. This is because increasing energy storage capacity to address peak loads is more economical compared to increasing PV configuration capacity. Additionally, equipment capacity expansion is necessary to accommodate the growing user load, which implies an increase in *DTC*. This increased economic investment yields favorable environmental benefits, namely a reduction in the value of *DCE*.

Table 6. The optimal configurations for scenarios s_1 and s_2 .

s_1 : Economic Operation Scenario					s_2 : Environmental Operation Scenario				
<i>TLR</i>	R_{pv}	C_{bat} (kWh)	<i>DTC</i> (USD)	<i>DCE</i> (kgCO ₂)	<i>TLR</i>	R_{pv}	C_{bat} (kWh)	<i>DTC</i> (USD)	<i>DCE</i> (kgCO ₂)
0.9	0.732	94.32	359.48	3060	0.9	1.358	92.46	437.75	2774
0.8	0.743	205.16	367.72	2940	0.8	1.356	201.07	444.74	2667
0.7	0.752	424.92	387.75	2771	0.7	1.383	404.42	467.49	2503
0.6	0.762	709.90	414.58	2556	0.6	1.400	661.96	495.05	2300
0.5	0.785	1034.30	445.68	2311	0.5	1.461	942.93	531.68	2070

Comparing the two scenarios, under the same *TLR* value, the difference between R_{pv} in scenario s_1 and s_2 is large, while the difference between C_{bat} is small. Between different *TLR* values in the same scenario, the difference between R_{pv} is small, while the change in C_{bat} is large. Therefore, it can be considered that R_{pv} is the key factor that distinguishes between the two scenarios, while C_{bat} mainly distinguishes different *TLR* values. The size of R_{pv} can be adjusted to achieve the conversion between economic scenarios and environmental scenarios, while the size of C_{bat} is mainly used to meet the safe operation of the system under different *TLR* values (i.e., the C_{bat} is to some extent higher than the C_{bat}^{min} in the corresponding case).

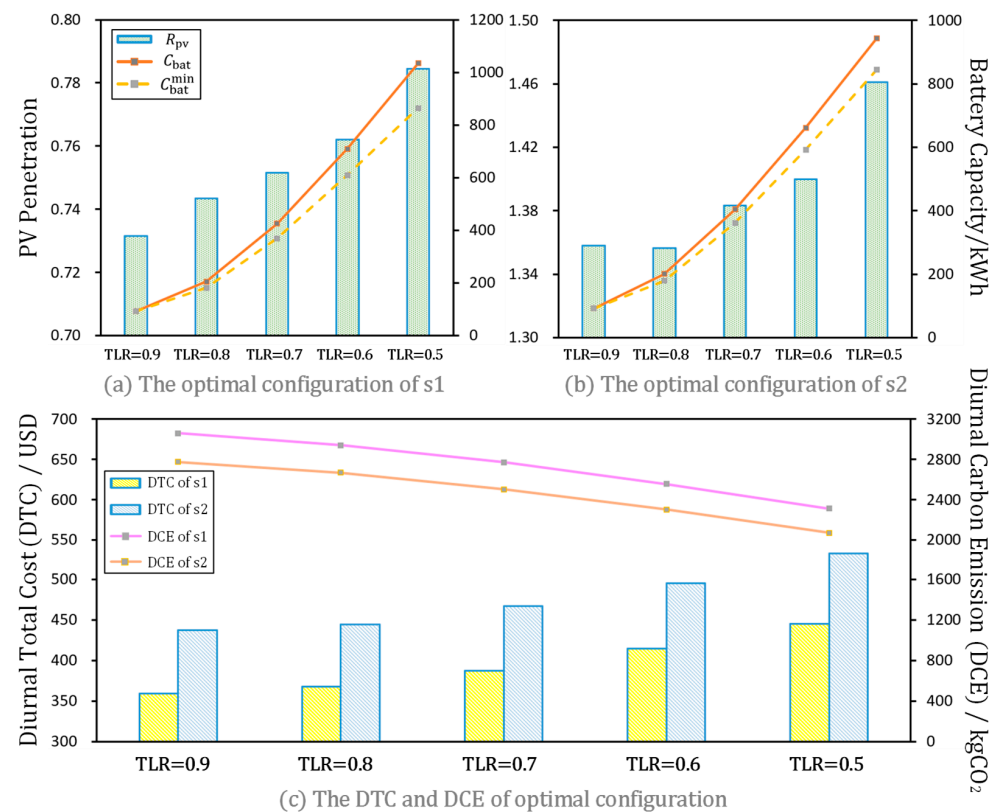


Figure 19. Analysis of the optimal configurations for scenarios s_1 and s_2 .

4. Discussion

The domain analysis in Section 3.1 determines which combinations (i.e., the corresponding areas in the domain) will have feasible system configuration solutions, thus guaranteeing secure system functioning during scenarios of inadequate transformer capacity. In Section 3.2, battery storage capacity analysis calculates the minimum storage capacity (C_{bat}^{min}) corresponding to each point within the feasible domain (i.e., Areas 2 and 3). Therefore, the conclusions of Sections 3.1 and 3.2 provide constraint conditions for the variable values from the perspective of system safe operation for the multi-objective optimization in Section 3.3.

Section 3.3 employs the NSGA-II algorithm with two objective functions to derive the optimal system configuration solution set, presenting tailored optimal configurations for distinct scenarios. Next, this section discusses the impact mechanism of the variables (i.e., A and B under a fixed TLR) on the system in the optimization method, and explores the limitations of the current study.

4.1. Analysis of Changes in Independent Variables

In Figure 20, the influence of variable changes on the objective functions (DTC and DCE) is illustrated. The images on the left describe the impact of R_{pv} changes on the objective functions. The images on the right describe the impact of C_{bat} changes on the objective functions. DTC and DCE changes are represented by yellow and blue, respectively, while scenario 1 and scenario 2 are distinguished by solid and dashed lines, respectively.

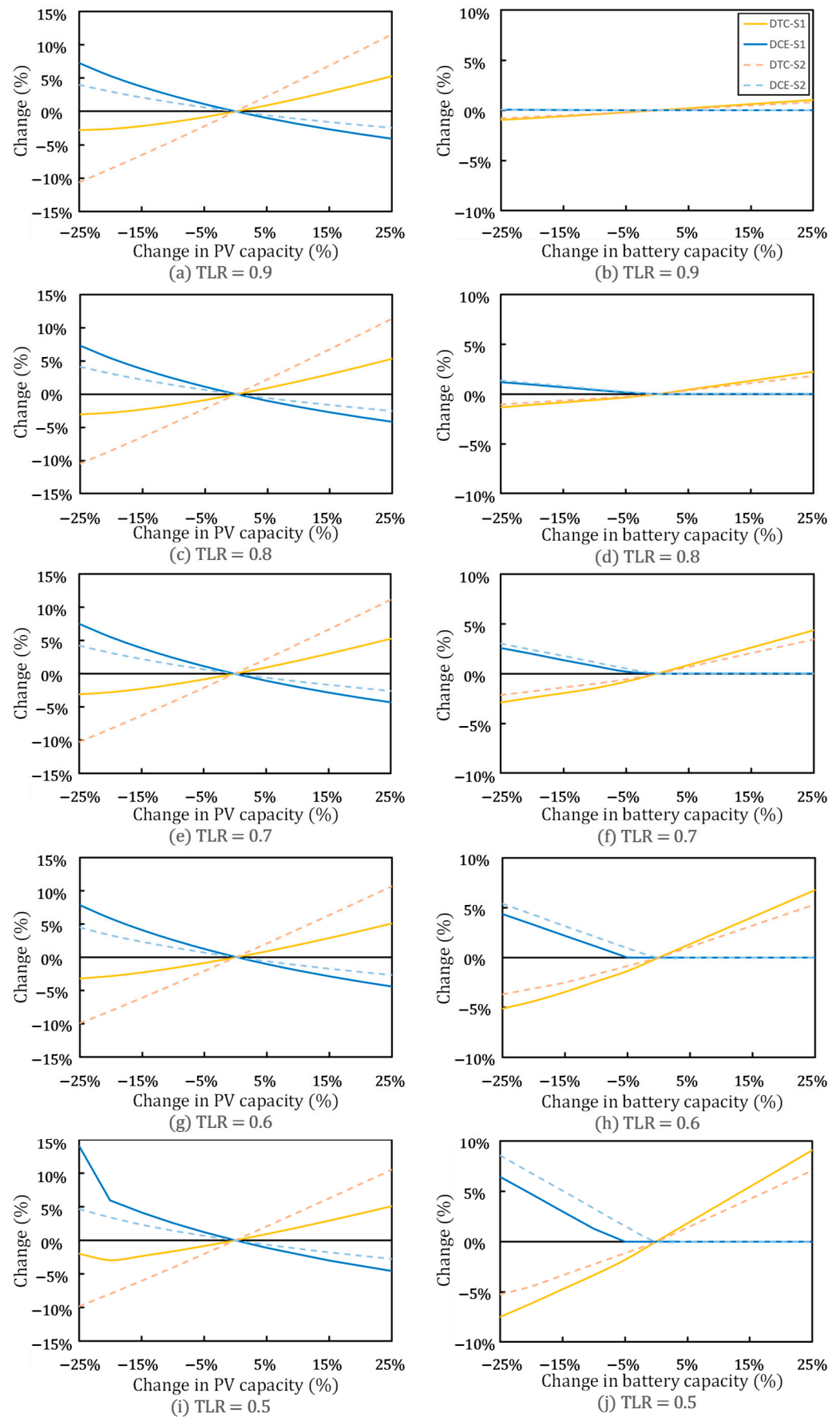


Figure 20. Effect of change in PV and battery capacity on DTC and DCE.

The system configuration at the origin for s_1 is derived from the optimal configuration in Table 6 for s_1 , and the data for s_2 are similarly derived. Considering that in some configuration cases, the C_{bat} reduced by 25% would be lower than the corresponding C_{bat}^{min} , causing the system to be unable to operate safely. Therefore, in this case, insufficient power is assumed to be provided by temporary power supply devices to clearly demonstrate the trend of the changes. Based on Figure 20, the following conclusions can be made:

1. The sensitivity curves of R_{pv} for different TLR values are almost identical. The sensitivity curves of C_{bat} are significantly affected by the TLR value; the lower the TLR , the greater the impact on DTC and DCE . When the TLR is high, R_{pv} exerts a stronger influence than C_{bat} on the system's economic and environmental performance. When the TLR is low (values of 0.6 and 0.5), R_{pv} and C_{bat} have a comparable influence on the system's performance. Therefore, in practical engineering, when the TLR value is high, the PV configuration is more effective than BESS in improving the performance of the system. When the TLR value is low, the BESS has the same importance as the PV in improving the system performance.
2. As shown in Figure 20b,d,f,h,j further increasing the value of C_{bat} will not further reduce DCE . This is because it has already reached the optimal point in terms of energy matching between PV output and power demand. Further increasing C_{bat} will not reduce the power input from the grid to reduce carbon emissions, but will only increase the investment amount. Therefore, in practical engineering, C_{bat} should be configured according to the actual TLR , and to a certain extent, it should be larger than C_{bat}^{min} to secure the system's operational safety, but avoid excessive capacity that causes unnecessary waste.

4.2. Limitations

The study has the following limitations: First, power line loss is not considered in the simulation of the PVB system. This simplification was made to establish a uniform configuration method, but it inevitably introduces a gap between the simulation and reality. Future work should incorporate power line loss to enhance model fidelity. Second, the PVB system was simulated using a predetermined operating strategy. Given that various commonly used strategies exist, each potentially influencing the results, it is imperative to investigate the robustness of the conclusions under different operating strategies.

Finally, while this study successfully demonstrates the multi-objective optimization approach using existing residential buildings as a case study, its applicability to other building types warrants careful consideration. Here, we note that different building types (e.g., offices, shopping malls, restaurants) exhibit distinct load characteristics. The approach, relying on distinct peak and valley load patterns driven by user behavior, is inherently adaptable for scenarios like offices where similar temporal load variations exist (though peak/valley timing may differ) by adjusting model parameters accordingly. However, its effectiveness may be limited for buildings with fundamentally different load profiles, such as industrial facilities characterized by continuous operation and less pronounced demand fluctuations. Therefore, extending and validating the configuration method for diverse building types, including complexes and large industrial parks, represents a necessary direction for future research.

5. Conclusions

PV systems integrated with battery storage are essential for enhancing electrical flexibility in existing urban built environments, particularly in densely populated cities where aging infrastructure and transformer capacity constraints challenge sustainable energy transitions. This study develops a multi-objective optimization approach for PVB systems

specifically adapted to existing buildings, effectively balancing energy self-sufficiency improvements while avoiding costly electrical capacity expansions, a critical advantage for rapidly urbanizing regions. The analysis further reveals how capacity allocation decisions directly influence both economic feasibility and environmental outcomes, providing practical guidance for architectural and engineering professionals engaged in building retrofitting projects constrained by grid limitations. By addressing the dual priorities of technical adaptability and sustainability in energy-upgrading existing urban infrastructure, this study contributes actionable strategies to advance decarbonization goals while respecting the operational realities of high-density built environments. The main conclusions are as follows:

1. This study employed a residential building in Shanghai as a case study and constructed a mathematical model for the PVB system. The system is operated according to a formulated operational strategy. The *TLR* is used to express the proportion of P_{trans}^{max} to P_{load}^{max} . The simulation results facilitate the analysis of the system domain in a Cartesian coordinate system, where the x-axis represents PV penetration and the y-axis represents *TLR*. Areas 2 and 3 represent theoretically feasible areas for the PVB system configuration.
2. In the domain, the minimum storage capacity (C_{bat}) corresponding to each point is calculated, providing constraint conditions for the variable values from the perspective of system safe operation for multi-objective optimization. *TLR* values have a significant influence on C_{bat}^{min} . The lower the *TLR* value, the larger is the corresponding storage capacity required. In contrast, the effect of R_{pv} on C_{bat}^{min} is relatively small. As the R_{pv} increases, the required storage capacity of the system gradually decreases.
3. The Pareto optimal set is acquired through the application of the NSGA-II algorithm, with the Diurnal Total Cost (*DTC*) and Diurnal Carbon Emission (*DCE*) as the optimization objectives. The weights of the optimization objectives are set based on two scenarios, focusing on economic and environmental performance, respectively, to calculate the optimal configurations for both scenarios. For instance, 0.743 PV penetration and 205 kWh battery are the optimal configurations for economic operation scenarios with the *DTC* and *DCE* equal to 367.72 \$ and 2940 kgCO₂, respectively, when the *TLR* value is 0.8. For the environmental operation scenario, 1.356 PV penetration, 201 kWh battery is the best optimal configuration with *DTC* and *DCE* equal to 444.74 \$ and 2667 kgCO₂, respectively.
4. The impact mechanism of the variables (i.e., *A* and *B* under a fixed *TLR*) on the system in the optimization method is discussed. When the *TLR* value is high, the PV configuration is more effective than the BESS in enhancing the system performance. When the *TLR* value is low, both the PV and BESS have the same importance in improving the system performance. In practical engineering, to guarantee system security, C_{bat} should be configured according to the actual *TLR*, and to a certain extent, it should be larger than C_{bat}^{min} , but avoid excessive capacity that causes unnecessary expenses.

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Abbreviations

Acronym:

BESS	Battery energy storage system
EV	Electric vehicle
NSGA-II	Non-dominated Sorting Genetic Algorithm II
PV	Photovoltaic
PVB	Photovoltaic battery
s_1	Scenario 1: economic operation scenario
s_2	Scenario 2: environmental operation scenario

List of symbols:

C_{bat}	Rated battery capacity (kWh)
C_{bat}^{min}	minimum battery capacity required (kWh)
CRF	Capital recovery factor (dimensionless)
DTC	Diurnal total cost (USD)
DCE	Diurnal carbon emission (kgCO ₂)
E_{load}	Electricity consumption of the building load (kWh)
E_{load}^{ex}	Net load exceeding P_{trans}^{max} (kWh)
E_{grid}	Electricity imported from the utility grid (kWh)
E_{pv}	Electricity generated by the PV modules (kWh)
$E_{pv,cu}$	Curtailed electricity generated by the PV modules (kWh)
E_{pv}^{ex}	Available excess PV power generation (kWh)
P_{bat}	Operating power of the battery (kW)
P_{load}	Electric power of the building load (kW)
P_{load}^{max}	Maximum load power (kW)
$P_{load,net,max}$	Maximum net load power (kW)
$P_{load,D}^{max}$	Maximum value of the load curve exceeding P_{trans}^{max} (kW)
$P_{load,D,net,max}$	Maximum value of the net load curve exceeding P_{trans}^{max} (kW)
$P_{load,net}$	Electric power of the net load (kW)
P_{grid}	Electric power imported from the utility grid (kW)
P_{trans}^{max}	Maximum transmission power (kW)
P_{pv}	Generation power of the PV modules (kW)
$P_{pv,cu}$	Curtailed PV power (kW)
R_{pv}	PV penetration (dimensionless)
SOC	State of charge (%)
TLR	Transmission limit ratio (dimensionless)
φ_{pv}	Unit price of PV (USD/kW)
φ_{bat}	Unit price of BESS (USD/kWh)
φ_{var}	Variable maintenance cost coefficient (USD/kWh)
φ_{fix}	Fixed maintenance cost coefficient (USD/kWh)
ζ_{ele}	Emission factor of the grid (kg/kWh)

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