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Research Article

An integrated framework for techno-enviro-economic assessment in nanogrids

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Abstract. This paper presents an integrated framework designed for capacity planning of grid-connected nanogrid, a small solar and energy storage system that can provide kilowatt-level services to individual buildings. This framework comprehensively evaluates nanogrid cost-effectiveness, sustainability, and reliability, employing a multi-faceted techno-enviro-economic assessment approach. Traditional nanogrid capacity planning often prioritizes peak load requirements, which may lack optimality owing to occasional peak load occurrences. Conversely, optimizing solely for base load requirements might also fall short of effectiveness, compromising reliability and sustainability objectives. The proposed framework employs a three-step, integrated process for nanogrid (NG) capacity planning. Firstly, the Planner module identifies optimal asset sizing considering a two-day look-ahead logic. Then, the Operator module serves as a digital twin for the system, conducting hourly calculations over a short-term horizon. Lastly, the Evaluator module evaluates technical, environmental, and economic metrics for each solution, assessing the effectiveness of asset-sizing decisions. A simulated case study has demonstrated the effectiveness of the proposed framework. The technical assessment revealed that a PV size of 24 kW and a storage capacity of 91 kWh led to the most reliable solution, with a probability of local sufficiency of 95 percent. Furthermore, the environmental assessment showcased a renewable fraction of 94% with a PV size of 26 kW and a storage of 85 kWh. Economically, the analysis identified that a PV size of 12 kW and a storage size of 24 kWh led to the minimum total cost. In contrast, a PV size of 26 kW and a storage size of 85 kWh yielded a total operating savings of $4,801.

Keywords: Nano-grid, capacity planning, energy dispatch, sustainability, framework

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1. Introduction

The aging electrical power system infrastructure suffers from several challenges, leading to high power losses and eventually decreasing efficiency (Elsayed *et al.*, 2019). The cost of rebuilding infrastructure is so high that non-traditional approaches to address the challenges are needed (Afzal *et al.*, 2020). Therefore, distributed generation (DG) emerges as a promising concept. DG involves setting up smaller generators near consumers, offering benefits for the environment, economy, and technology, especially within distribution networks (Nguyen *et al.*, 2018). Furthermore, utilities can control these generators for better operational reliability (Kanakadhurga & Prabaharan, 2022). This control enables quick adaptations to fluctuations in demand or supply, strengthening the grid's dependability.

Incorporating DG into consumer premises signifies the emergence of a novel power system paradigm known as a microgrid (MG). According to the International Council on Large Electric Systems (CIGRE) (Marnay *et al.*, 2015), the microgrid is an electrical distribution system with interconnected loads and distributed energy sources, such as DG, that function as a single controllable entity. It can operate in grid-connected or isolated mode (Jiayi *et al.*, 2008). In the grid-connected mode, bi-directional energy exchanges between the microgrid and the utility become feasible, allowing the microgrid's power output to deviate from local demand requirements. Conversely, during islanded operation, wherein the microgrid operates independently from the utility grid, local power generation and Battery Energy Storage Systems (BESS) must sufficiently meet the demand, given the unavailability of the utility grid. (Lagouir *et al.*, 2021) . Microgrids encompass diverse hybrid energy resources, particularly renewables like solar PV and wind, and distributed generation, such as diesel generators and energy storage (Khamharnphol *et al.,* 2023).

The scale of assets within a microgrid fluctuates according to the specific application, encompassing settings ranging from a campus or village to the expansive dimensions of an island or urban municipality. (Bhagavathy & Pillai, 2018; Bin *et al.*, 2022; Obara *et al.,* 2018). However, the smallest microgrid, NG , is a single building at the kW level and can operate either in grid-connected or isolated mode by following the local energy demand and generation availability (Kempener *et al.*, 2015). NGs, commonly situated in residential dwellings, rural locales, or small-scale industrial settings, manage loads below 20 kW. They primarily leverage clean energy sources, including fuel cells, solar arrays, and wind turbines (Sayed *et al.*, 2023; Teleke *et al.,* 2014) .

As per the Lawrence Berkeley National Laboratory, an NG must include at least one load or sink of power—which could be

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energy storage—and at least one external connection point (Nordman *et al.*, 2012). An NG, in comparison to a microgrid, encounters fewer technical and regulatory obstacles, contributing to their substantial deployment (Werth *et al.*, 2015).

To enhance the sustainability of energy generation and to provide flexibility for the next generation of power system infrastructure, renewable energy resources (Ahmed & Demirci, 2022; Khalid *et al.*, 2016) and energy storage (Denholm & Hand, 2011) are considered the assets in an NG. Renewable energy sources enhance sustainability; however, due to their intermittency and variability, they pose reliability challenges, and thus, a trade-off between sustainability and reliability should be navigated.

The optimization of asset sizing for a reliable and sustainable NG assumes paramount importance in achieving optimal self-sufficiency, offering grid relief, and ensuring cost-effectiveness. Consequently, potential challenges arising from integrating renewables can be mitigated (Ahmed, 2023; Bandyopadhyay *et al.*, 2020). In the design procedure of a PV-based microgrid or an NG, the optimal sizing of their components ensures the optimal utilization of the available solar energy and associated storage devices (Mathew *et al.,* 2022). Optimal BESS sizing improves reliability and resilience (Xie *et al.*, 2019). An optimal hybrid sizing can be considered in profitability analysis for off-grid microgrids, such as in the mining industry (Ellabban & Alassi, 2021).

Several papers have studied the microgrid and NG from technical and operational (Dali *et al.*, 2010; Mahmoodi *et al.*, 2013), environmental (Gildenhuys et al., 2019; Zachar et al., 2014), and economic (Jha *et al.*, 2016; Nayak *et al.*, 2019) perspectives. The authors (Babacan *et al.*, 2017) presented a convex optimization-based ESS scheduling algorithm that minimizes the monthly bills. In addition, a new concept of a supply charge is introduced to encourage consumers to store the surplus solar energy that can potentially cause reverse power flow in the grid. Notably, (Bouchekara *et al.,* 2021) introduced a design for hybrid NG for a camp located in Saudi Arabia's Western region. The method considers two conflicting objectives in the optimization problem: the loss of power supply probability and energy cost. Using four variants of Particle Swarm Optimization (PSO), four algorithms are combined for various NG elements, achieving a solution that balances cost-effectiveness and reliability. A techno-economic approach is proposed by the authors (Dahiru and Tan, 2020) to optimize NG size in tropical regions of the Amazon. The method considers multiple renewables to achieve lower levelized energy costs, net present costs, and low per capita energy consumption. The authors (Ban *et al.*, 2019) modeled off-grid NG sizing by Mixed Integer Linear Programming (MILP) and solved it using robust optimization. The optimization model minimizes investment costs of solar PV and battery systems in the NG. The reliability is ensured by energy storage from periods of high PV output and utilizing it in periods of power shortage.

Most microgrid/NG planning and operations studies have concentrated on singular dimensions such as technical feasibility, economic viability, or environmental sustainability. The contribution of this paper; however, is to adopt an integrated framework that combines technical, environmental, and financial considerations. By incorporating sustainability, cost-effectiveness, and reliability elements, this study provides a holistic understanding of NG within a comprehensive landscape, departing from the limited scope of prior research endeavors. The framework is composed of three essential modules: Planner, Operator, and Evaluator, collectively interact to offer a comprehensive techno-enviro-economic assessment. A comprehensive list of technical, economic, and environmental metrics is also given for other researchers to follow.

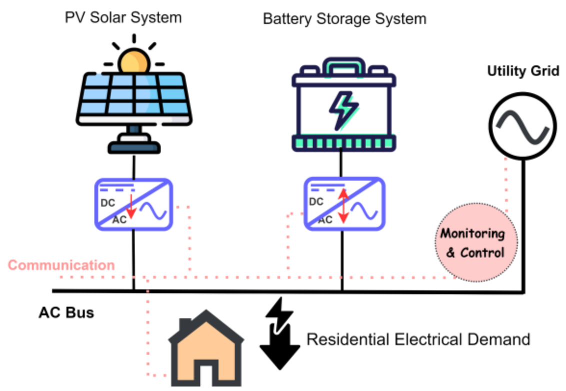

Fig 1. Proposed Nanogrid Architecture

2. Methodology

The proposed methodology for capacity planning of NGs comprises a three-step framework acting as a multi-level program. These three modules are the Planner, Operator, and Evaluator. The three steps form a comprehensive decision support framework, ensuring a balanced consideration of technical, environmental, and financial metrics.

- Planner: This module calculates the daily optimal capacities of the BESS and PV system, considering a 2-day look-ahead. After running this for a year, we get 365 daily optimal capacity solutions.
- Operator: This module takes each of the 365 daily optimal capacity solutions from the Planner module, assumes it as the fixed capacity for the entire year, and calculates the optimal dispatch of BESS and PV based on the annual data.
- Evaluator: This module evaluates each of the 365 solutions from the Operator module based on 15 different metrics, which cover technical, environmental, and financial factors. It does not provide a single best solution but presents the results for each metric for every solution. The customer can then select the solution that best meets their specific requirements.

The proposed methodology presents a systematic and adaptable framework for NG capacity planning. While it might not guarantee a single optimal solution, it offers a robust and practical approach tailored to the complexities of several real-world scenarios. This methodology will undergo testing using an AC NG architecture, as depicted in Figure 1, similar to the AC NG architecture introduced by (Santoro *et al.*, 2023).

As shown in Fig 2, the methodology starts with importing input data and assumptions. Input data include energy prices, demand, solar PV generation profile, BESS and solar PV asset parameters. The Planner is a linear programming problem that finds the optimal sizes of BESS in MWh and solar PV in KWp. Later, the Operator is a mixed-integer programming problem that finds the hourly optimal dispatch of the assets. In the last phase, the Evaluator uses the outputs of previous modules and calculates several technical, economic, and financial metrics. The resultant metrics are a decision support mechanism for the desirable NG capacity.

2.1 Planner module

The Planner module operates as the first stage of the proposed decision support framework. The Planner module aims to calculate the daily optimal capacities of the BESS and PV system for each day of the year. To maintain the simplicity and clarity of the module, the time value of money and costs related to managing and sustaining the investment over the

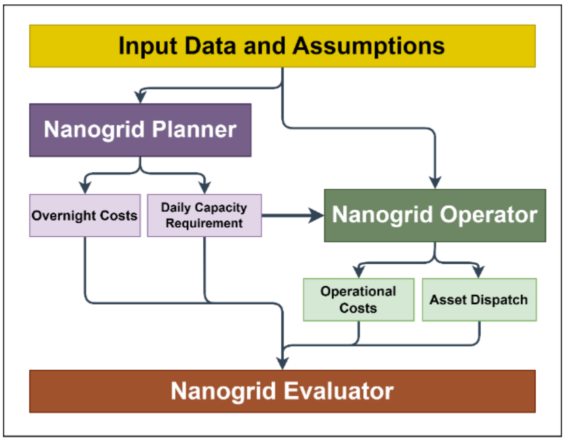

Fig 3. Nanogrid Capacity Sizing Strategy

project's lifetime have not been considered. The planning modules typically minimize the cost of purchasing (fixed cost) and operating (variable cost) the assets while still meeting the supply and demand balance. To do this, an LP problem is developed to determine the optimal size of the PV panels and BESS for a given load profile and set of constraints. Capacity optimization problems inspire the proposed model, but it contains differences. One of the differences is the optimization window of the problem. Generally, capacity optimization problems consider an hourly demand profile for a year to find the optimal sizes; however, the Planner module searches for the optimal size of assets for each day in a year while considering the look-ahead logic. Look-ahead logic is a strategy that allows the model to consider not only the conditions of the current day but also anticipate the general trends for the next two days. This is done by considering 72 hours of data for each iteration: 24 hours for the current day and 48 hours for the next two days. This means that when determining the optimal capacities for the current day, the model already knows the conditions expected for the next two days, as shown in Fig 3. This will enable the BESS to be optimized to handle future events.

The second difference is in how the overnight cost of assets is considered in the Planner module. Generally, the annuity of investment is used in capacity optimization models in the literature; however, due to the daily basis approach adopted in this study, the overnight cost of assets is assumed to be in per diem for a given expected lifetime of the asset.

The Planner module is developed in the standard form of linear programming (LP). Once the optimal capacities for the current day are determined, the model rolls forward to the next day, bringing in new data for the look-ahead period and repeating the optimization process. This sequence is carried out for an entire year, resulting in a set of 365 daily optimal capacity solutions, as shown in Figure 4, which illustrates the flowchart of the Planner.

The LP program minimizes the per diem total cost, comprised of BESS overnight cost, PV overnight cost, and import cost (generally the cost of energy received from the grid)

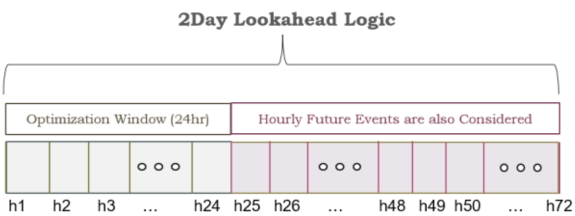

Fig 4. 2-Day Lookahead Logic Concept

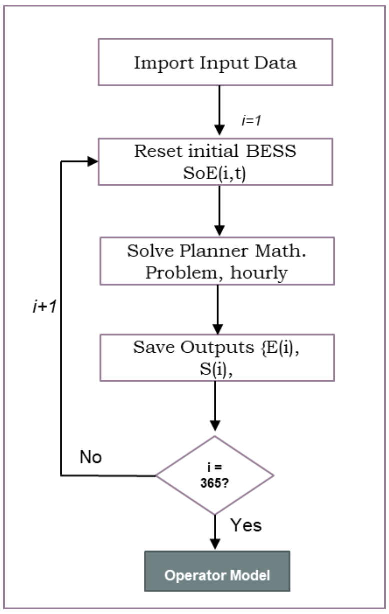

Fig 2. Flow Chart of the Planner Module

as in Equation (1). In addition, a set of constraints must be satisfied on an hourly interval. Equation (2) initializes the state of energy (SoE) in BESS as a β percent of its entire energy capacity. Equation (3) maintains the supply-demand balance on an hourly basis throughout the optimization horizon (24 hours plus look-ahead). Solar production, battery discharge, and imported power from the grid on the left-hand side of the equation should be balanced with the sum of the demand and the BESS charging energy. The SoE is defined in Equation (4) as a difference equation by accumulating the energy charged at time t on top of the SoE at time t-1 and subtracting discharge energy at time t. Equation (5) is a box constraint to limit the SoE so that it does not exceed the total BESS energy capacity. Equations (6) and (7) limit the BESS charging power so that it does not exceed the available empty capacity in BESS and the maximum charging capacity assumed by the user. Similarly, the BESS discharge capability is limited in Equations (8) and (9) to not exceed the available energy already accumulated in BESS and to respect the maximum discharging capacity assumed by the user. Finally, Equation (10) ensures that the hourly import energy from the grid does not exceed the grid import capability assumed by the user (generally the contract capacity).

$$\text{Minimize } ((E * OC^e) * \alpha^E) + ((S * OC^S)) * \alpha^S) + \sum_t \rho_t * g_t * \Delta t \qquad (1)$$

subject to

$$e_t = \beta * E \qquad ,t = 1 \qquad (2)$$
$$s_t + d_t + g_t = l_t + c_t \qquad ,\forall t \in \{1, \dots, T\} \qquad (3)$$
$$e_t = e_{t-1} + \mu_c . c_t . \Delta t - \frac{d_t}{\mu_d} . \Delta t \qquad ,\forall t \in \{2, \dots, T\} \qquad (4)$$
$$0 \le e_t \le E \qquad ,\forall t \in \{1, \dots, T\} \qquad (5)$$
$$0 \le c_t \le E - e_{t-1} \qquad ,\forall t \in \{2, \dots, T\} \qquad (6)$$
$$0 \le c_t \le \gamma * E \qquad ,\forall t \in \{1, \dots, T\} \qquad (7)$$
$$0 \le d_t \le e_{t-1} \qquad ,\forall t \in \{2, \dots, T\} \qquad (8)$$
$$0 \le d_t \le \gamma * E \qquad ,\forall t \in \{1, \dots, T\} \qquad (9)$$
$$0 \le g_t \le G \qquad ,\forall t \in \{1, \dots, T\} \qquad (10)$$

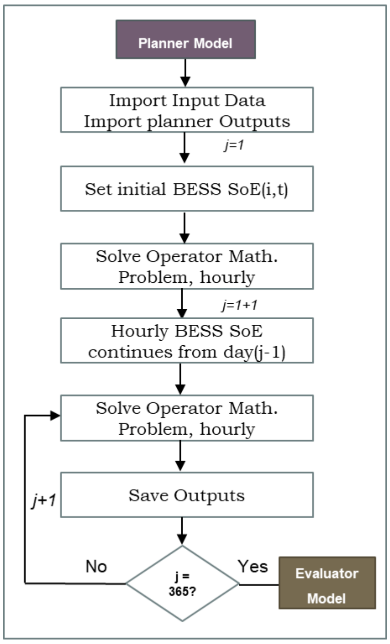

Fig 5. The Operator Process Flow Chart

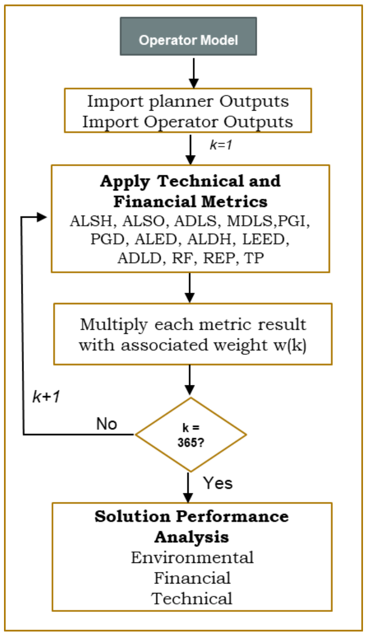

Fig 6. The Evaluator Process Flow Chart

2.2 Operator Module

In the second step, the Operator module takes each of the 365 daily optimal capacity solutions provided by the Planner module and treats them as fixed capacities for the entire year. Using the annual data, the Operator module calculates the optimal dispatch of BESS and PV for each solution while minimizing the total energy cost purchased from the grid. The problem is formulated as a mixed-integer linear programming (MILP) problem, solved hourly over a 72-hour planning horizon (24 hours as an optimization window with a 2-day look-ahead logic).

The inputs to the Operator module are the capacity solutions for the BESS and PV, as shown in Figure 5, and the load profile for the NG. The model considers factors such as the energy storage system's efficiency, the energy cost from the grid, and limits on the charging and discharging rates of the battery. The state of energy (SoE) maintains its continuity from day to day throughout the horizon, in which the initial hour dispatch of each day depends on the previous day's last hour SoE. The algorithm runs for 365 different capacity cases and provides hourly dispatch results for annual operations.

The Operator module minimizes the import cost while respecting a set of constraints. The objective function is the minimization of the energy cost from the grid as given in Eq. (11). Equations (2-6), (8), and (10), as discussed in the Planner module above, are included. Additionally, Equations (12) and (13) are included to limit the charging and discharging capabilities and to prevent simultaneous charging/discharging occurrences.

$$\textbf{\textit{Minimize}} \sum_t \rho_t * g_t \qquad (11)$$

$$subject\ to$$

$$(2-6), (8), (10)$$

$$0 \le c_t \le \gamma * E * u_t \quad ,\forall t \qquad (12)$$

$$0 \le d_t \le \gamma * E * (1-u_t) \quad ,\forall t \qquad (13)$$

2.3 Evaluator module

Technical, economic, and financial evaluations are also crucial for an informed decision leading to a plausible capacity-sizing solution. The Evaluator calculates a series of metrics, inspired by Refs (Wang *et al.*, 2013) and (Sambaiah, 2018) to evaluate the performance of each solution. The flowchart of the Evaluator is presented in Fig 6.

The definition, unit, and mathematical formula of these metrics are elaborated in Table 1. The NG Evaluation process explained above leads to the optimal NG capacity planning and operation solutions, provides a multi-perspective analysis of any NG capacity solution, and decides on the optimal size that fulfils the reliability, cost-effectiveness, renewable integration, self-sustainability, and many other requirements. Each metric can be given a certain weight to identify its importance from the user's perspective, and the performance comparison between the solutions can be conducted accordingly. Metrics used in the NG Evaluator are of different weights and can be adjusted by the user to prioritize specific metrics and ignore others if needed.

3. Case Study

The proposed modules were simulated in MATLAB using YALMIP (Löfberg, 2004) and CPLEX. Hourly data on demand, solar profile, and time of use electricity prices were extracted (Energieökonomik, 2020; Every *et al.*, 2017; Pfenninger &

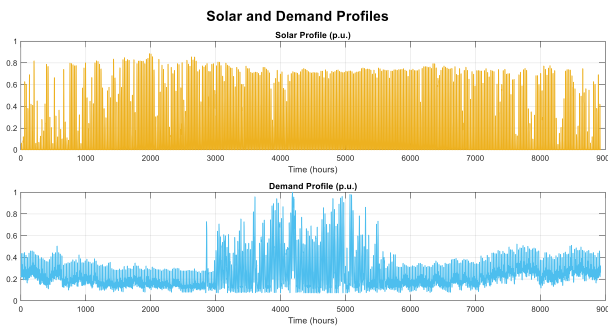

Fig 7. Hourly demand and solar generation profiles

Table 1
Technical, Economic, and Environmental Metrics Applied in the Evaluator Modules

Index	Name	Unit	Category	Formula	Description
ALSH	Annual Local-Sufficiency Hours	hour	Technical	$\sum_{t=1}^{T} LSH_t$ $LSH_t = \begin{cases} 1 & if g_t = 0 \\ 0 & otherwise \end{cases}$ g_t is import energy at hour t	The total annual number of hours the NG obtains local sufficiency to cover hourly demand.
ALSO	Annual Local-Sufficiency Occurrences	Occurrence	Technical	$\sum_{t=1}^{T} LSO_t$ $LSO_t = \begin{cases} 1 & only\ 1st\ LSH_t = 0\ in\ successive\ ev \\ 0 & otherwise, \end{cases}$	The total annual number of occurrences that the NG obtains local sufficiency regardless of the duration
ADLS	Average Duration of Local Sufficiency	hour	Technical	$\frac{\sum_{so} DLS_{so}}{ALSO}$ DLS: Duration of Local Sufficiency so : Local Sufficiency Occurrence	The annual average duration of Local Sufficiency where the NG uses only local resources to maintain supply-demand balance.
MDLS	Maximum Duration of Local Sufficiency	hour	Technical	$\max(DLS_o)$	The annual Maximum duration of Local Sufficiency
PGI	Percentage of Grid Independence	p.u	Technical	$\frac{ALSH}{T}$	The fraction of time that the NG operates in local sufficiency mode throughout the horizon of operations
PGD	Percentage of Grid Dependency	p.u	Technical	$1 - PGI$	The fraction of time that the NG depends on the grid import fully or partially to cover hourly demand
ALED	Annual Local Energy Deficiency	kWh /yr	Technical	$\sum_{t=1}^{T} D_t - G_t$ Where D_t is demand at time t and G_t is the total generation at time t	The total annual energy that needs to be imported from the grid to cover the required demand or to be cut in an off-grid application
ALDH	Annual Local-Deficiency Hours	hour	Technical	$\sum_{t=1}^{T} LDH_t$ $LDH_t = \begin{cases} 0 & if g_t = 0 \\ 1 & otherwise \end{cases}$	The total annual number of hours the NG cannot obtain local sufficiency.
LEED	Local Expected Energy Deficiency	kWh	Technical	$LEED = \frac{ALED}{ALDH}$	The average expected energy deficiency per hour.
ADLD	Average Duration of Local Deficiency	hour	Technical	$\frac{\sum_{do} DLD_{do}}{ALDO}$ DLS: Duration of Local Deficiency do : Local Deficiency Occurrence	The annual average duration of Local Deficiency.
RF	Renewable Fraction	p.u	Environmental	$RF = \frac{\sum_{t=1}^{T}(A_t - C_t) * 100}{\sum_{t=1}^{T} D_t}$ where A_t is available solar at time t, C_t is the curtailed solar at time t and D_t is the demand at time t	The annual renewable production output over total demand
REP	Renewable Energy Penetration	p.u	Environmental	$REP = \frac{\max((A_t - C_t)) * 100}{Max(D_t)}$	The maximum solar production capacity over the maximum demand power.
REC	Renewable Energy Curtailment	kWh	Environmental	$REC = \sum_{t=1}^{T}(A_t - U_t)$ Where U_t is utilized solar at times t	The excess annual renewable production is to be curtailed.
TOS	Total Operational Savings	$	Economic	$TOS = \sum_{t=1}^{T}(G_t - I_t) * a_t$ Where G_t is the total generation, I_t is the imported energy from the grid, and a_t are TOU prices	The total Savings that the NG can achieve on an annual basis
TC	Total Cost	$	Economic	TC = $OC^e + OC^s$+ IC PV Overnight Cost BESS Overnight Cost Import Cost	Annual total cost

Staffell, 2016), respectively and shown in Fig 7. TOU rates change within a day, but they repeat their pattern daily. The demand profile in kW shows higher amplitudes in summer than in winter months. The solar profile is the hourly solar generation in kWh. Additionally, the technical and financial parameters for the case studies are listed in **Error! Reference source not found.**.

In Operator implementation, the Initial SoE on the first day is chosen to be 60% of the BESS capacity at the beginning of operations. The SoE at the end of each day of operation is used

Table 2
Technical and Financial Assumptions

Definition	Symbol	Value	Unit
Solar PV Overnight Cost	OC^S	550	$/kW
Solar PV Lifetime	LT^S	25	Years
PV Per Diem factor	α^S	$\frac{1}{LT^S * 365}$	p.u
BESS Overnight Cost	OC^e	450	$/kWh
BESS Lifetime	LT^e	15	Years
BESS Duration	BSDU	4	Hours
Charging/discharging maximum ratio	γ	$\frac{1}{BSDU}$	p.u (Ratio Of E)
BESS Per Diem factor	α^e	$\frac{1}{LT^e * 365}$	p.u
Maximum power drawn from the grid (kW)	G	10	kW

as the initial SoE of the next day to achieve a continuous BESS operation throughout the year.

4. Simulation Results and Discussion

4.1 Planner Simulations

The Planner module runs for 365 days on an hourly basis for the given inputs with an optimization window of 24 hours and a look-ahead logic of 2 days. In every figure below, the x-axis denotes the identification number of a given day, beginning with 1, symbolizing January 1st, and culminating at 365, representing December 31st. Fig 8 illustrates the fluctuating trends of optimal BESS and PV sizes over a year, revealing distinct seasonal patterns. The optimal BESS size escalates during summer months due to higher solar generation levels that permit the BESS to charge more energy and be ready for dispatch during high-price periods. Similarly, the requirements for PV size also surge in the summer due to high energy demand. Additionally, there are notable spikes in the winter months of December and January. They are strategic provisions to ensure adequate PV capacity during periods of reduced solar availability. The reasoning would be to maximize solar energy utilization and minimize reliance on grid imports even during less sunny winter days. The objective cost, on the other hand, largely shadows the trends of BESS and PV sizing. During winter days, despite the BESS size not being as high as on summer days, the objective function still shows an increase due to more significant imports from the grid where solar PV generation is not sufficiently available.

A mixed illustration is given in Fig 9 to explain the changes in BESS and solar PV capacities throughout the year. The BESS energy capacity and solar PV capacity are shown using purple and yellow circles, respectively. The size of each circle directly corresponds to the capacity of the respective energy source: a larger circle indicates a higher capacity. As observed in the figure, the planner module has provided insights into the day-to-day optimal capacities of the BESS and solar PV, considering the changing demand and solar availability throughout the year. However, the optimal capacities suggested for summer days might be less effective during winter and vice versa. The Operator module will serve a critical role in this regard. It evaluates the impact of operating the system under a "fixed" capacity, as determined by the Planner module for each day over the entire year. Essentially, it answers the question: "What if we had this fixed capacity of BESS and solar PV for an entire year?". Therefore, combining the Planner and Operator modules will provide a more comprehensive decision-making tool that bridges the gap between daily optimal solutions and their long-term implications.

4.2 Operator Simulations

The Operator module is simulated where the Initial SoE on the first day is chosen to be 60% of the BESS capacity at the beginning of operations. The SoE at the end of each day of operation is used as the initial SoE of the next day to achieve a continuous BESS operation throughout the year. The algorithm runs for 365 different capacity cases released by the Planner and provides hourly dispatch results for annual operations.

One capacity case, comprising a PV size of 12 kW and a BESS size of 24 kWh, was chosen to present operational results. The asset dispatch decisions for four consecutive days are illustrated in Fig 10 (a) and (b) for winter and summer, respectively. Throughout the year, the primary objective of the NG is to achieve local energy self-sufficiency. This is managed by harnessing solar power whenever it is plentiful or utilizing energy stored in the BESS when solar production is insufficient to meet the demand. Excess solar energy is stored in the BESS during high solar production and low demand. This stored energy is dispatched during high demand and low solar production periods, effectively shifting renewable energy usage to align better with demand patterns. However, once the BESS reaches its maximum state of charge (SoC) at 100%, additional solar production is inevitably curtailed, highlighting the trade-off between storage capacity and renewable energy utilization. During periods of high demand where solar production and stored energy in the BESS are inadequate, the NG turns to grid imports to meet its energy requirements.

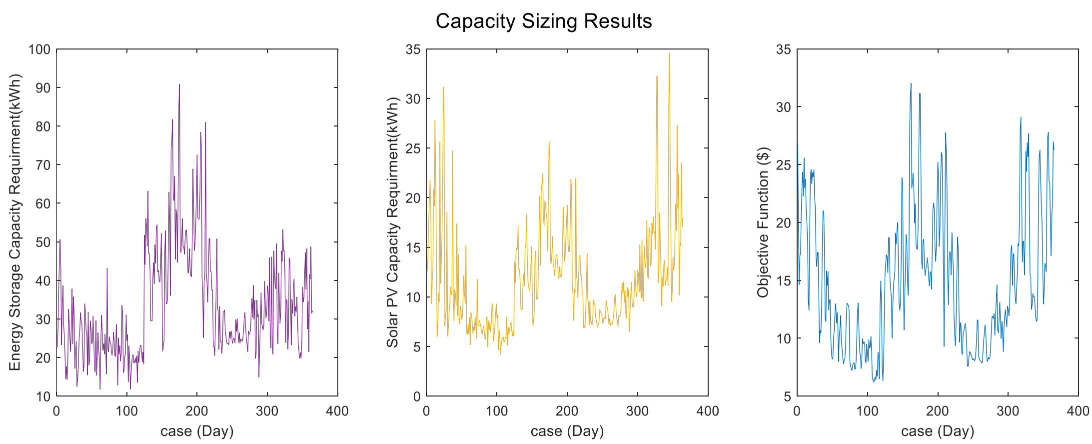

Fig 8. The 365 NG Capacity Sizing Solutions

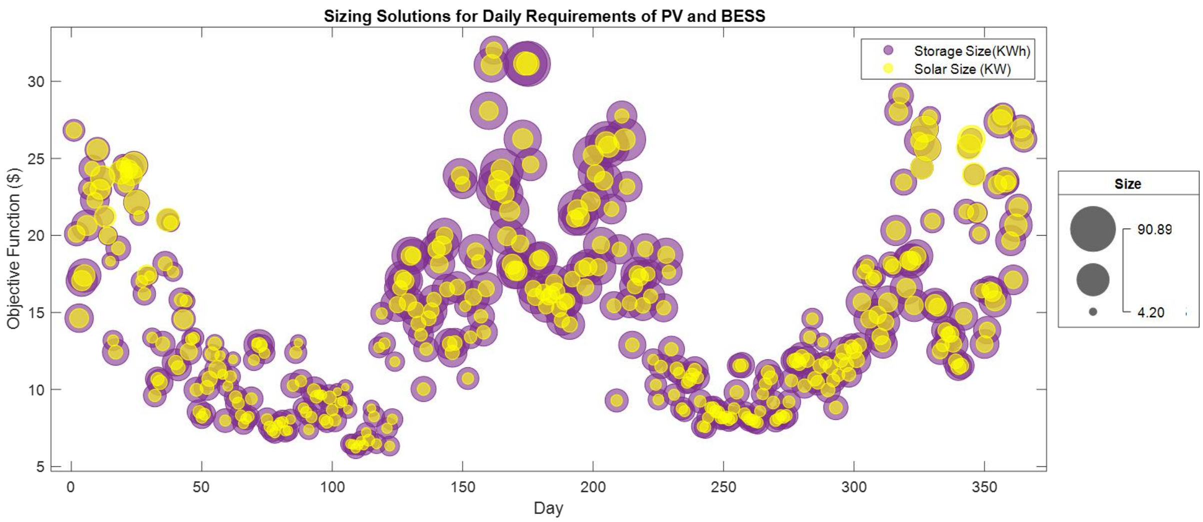

Fig 9. PV and BESS Size Comparison Based on Objective Solution

Fig 11 illustrates the operation cost savings by the 365 sizing solutions received from the Planner. The cost savings differ between the annual utility bill with and without the NG. As a result, the higher the BESS and PV capacity, the higher the cost savings. From the annual cost savings perspective, the highest cost savings of ~$4,801 are achieved with the capacity solutions of ~26kW PV and ~85kWh BESS.

Executing the Operator module enabled a comprehensive understanding of how each 365 daily solution would perform over the entire year. However, with such a multitude of potential optimal solutions, determining the final system configuration necessitates an informed decision-making criterion. The transition from the Operator module to the Evaluator module addresses this need. The Evaluator module significantly refines decision-making, offering a multi-dimensional analysis of each potential solution. Instead of favoring any metric, it provides a diverse set of metrics to evaluate the performance of each solution from different perspectives.

4.3 Evaluator Simulations

After the Planner and the Operator modules, the results of the Evaluator module are presented in this section. To put a perspective on two opposite sides of metrics, one for sufficiency-related metrics and one for deficiency-related metrics are examined. Figure 12 reports the correlations between the proposed sufficiency metrics (TOS, RF, PGI) for different cases. For example, Fig 12 (a) shows that as the NG supplies more demand from the local generation (while PGI is increasing), the import from the grid decreases; therefore, the TOS increases. A similar correlation is observed between the

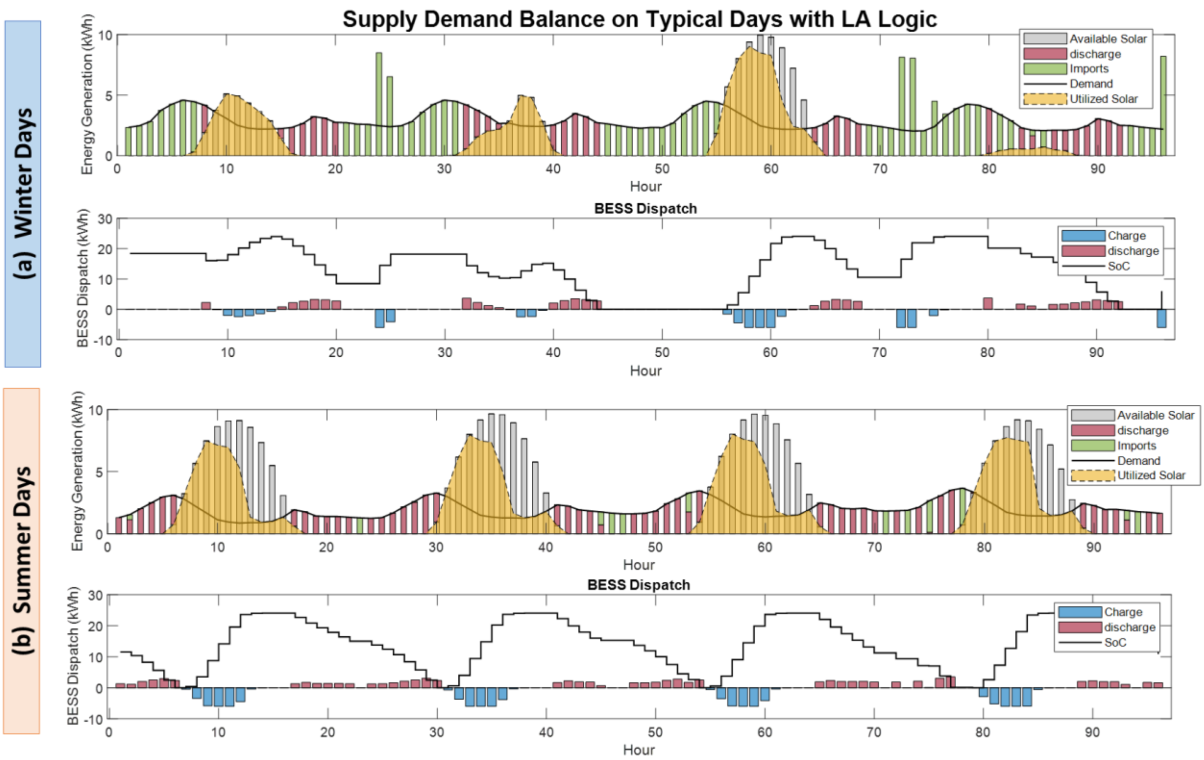

Fig 10. Winter and Summer NG operational dispatch for four consecutive days

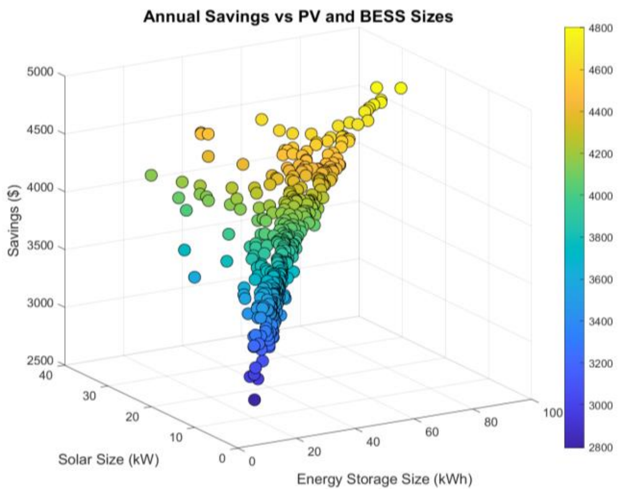

Fig 11. Cost savings versus solar size vs BESS size

PGI and RF in Fig 12 (b). A hundred percent of PGI means no import from the grid to NG; hence, renewable generation has only satisfied the annual demand, leading to 100% RF. Finally, Figures 12 (c) and (d) show the NG sizes versus the RF; as the PV and BESS sizes increase, the RF increases exponentially. However, in some cases, especially in Figure 12 (c), some outliners that do not follow the general relationship are observed. For example, four cases have a PV size greater than 30 kW, and three have a corresponding RF value of 90%. However, the fourth case gives relatively less RF (only %75) even though it is associated with the largest PV size. This outliner can be justified by the size of the BESS of this particular case since it is 40% less than that in the other 3 cases.

On the other hand, the correlations between deficiency metrics (LEED, PGD) are depicted in Fig 13. The inverse proportionality between LEED and TOS is observed in Fig 13 (a). It is also interesting to notice that even a minor LEED increase significantly reduces TOS. Fig 13 (b) states that as the average hourly expected energy deficiency increases (related to the NG size), the NG becomes more dependent on the grid to cover the load, increasing PGD exponentially. In contrast to sufficiency metrics, the PGD decreases exponentially concerning the increase in PV and BESS sizes, as shown in Figures 13 (c) and (d). Additionally, it is observed that the change in RF and PGD is more sensitive to the change in PV size than the change in BESS size. The consumers can determine the size of PV and BESS that meets their comfort by weighing each metric concerning its importance.

4.4 Technical Assessment

In assessing 365 distinct sizing solutions based on the technical metrics proposed within this study, the primary objective was to evaluate each solution's capability to operate independently from the main power grid. One sizing solution was recorded as the best representation of local sufficiency, featuring a photovoltaic (PV) size of 24 kW and a BESS capacity of 91 kWh. This solution recorded a total annual cost of $3,570. Notably, the critical technical metrics associated with this solution are presented in Table 3. The analysis reveals a total annual local sufficiency duration of 8,293 hours and occurred 130 times throughout the year. This means that the probability of local sufficiency is up to 95 percent. Moreover, the average

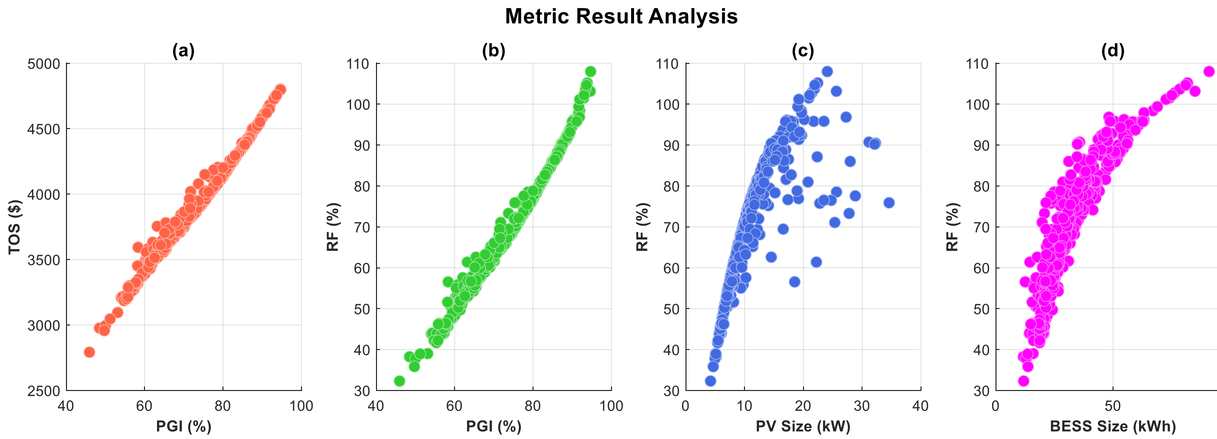

Fig 12. Correlations between Local Sufficiency Metrics

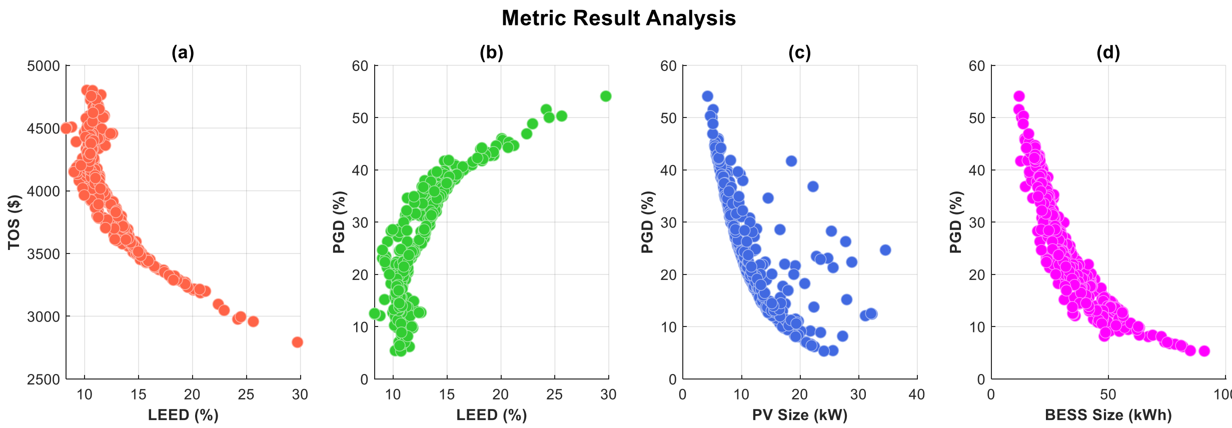

Fig 13. Correlations between Local Deficiency Metrics

Table 3
Main Technical Metric Values

Metric	Value	PV Size	BESS Size	Total Cost
ALSH	8,293 (hours)			
ALSO	130 (Occurrences)			
ADLS	64 (hours)	24 (kW)	91 (kWh)	3,570 ($)
MDLS	2,918 (hours)			
PGI	95 (Percentage)			

duration of local sufficiency was 64 hours, with an exceptional maximum duration of 2,918 hours. In contexts such as rural areas, where continuous electricity supply may not be guaranteed, there is a need to rely on local resources to mitigate the impacts of blackouts. This solution is the most viable option for ensuring reliability in such circumstances.

4.5 Environmental Assessment

Considering environmental metrics and interests, the two relevant metrics are renewable fraction and renewable energy penetration, as shown in Table 4. In the context of the optimized sizing solution with the most favorable environmental metrics, the PV size is 26 kW, the BESS size is 85 kWh, and the total cost is $3,430. This sizing solution achieves an RF of 94%, indicating a high proportion of renewable energy sources utilized, while the REP is 224 percent. These metrics underscore the environmental sustainability of the proposed solution, enhancing renewable energy adoption.

4.6 Economic Assessment

When assessing the economic aspects, the primary metrics used are the total cost and Total Operating Savings shown in Table 5. Among the presented sizing solutions, one stands out economically, featuring a Total Cost of $2,085, with a PV size of 12 kW and a BESS size of 24 kWh. This solution demonstrates a lower total cost compared to others. Conversely, while the solution with a PV size of 26 kW and a BESS size of 85 kWh has a higher Total Cost of $3,430, it yields substantial Total Operating Savings of $4,801. It indicates minimal energy purchasing was achieved, with a prevalence of renewable resources known for cost-effectiveness. These economic metrics offer valuable insights into the cost-effectiveness of each solution, assisting stakeholders in the NG planning process.

Table 4
Main Environmental Metric Values

Metric	Value	PV Size	BESS Size	Total Cost
RF	94 (%)	26 (kW)	85 (kWh)	3,430 ($)
REP	224 (%)			

Table 5
Main Economic Metric Values

Metric	Value	PV Size	BESS Size	Total Cost
TC	2,085 ($)	12 (kW)	24 (kWh)	2085 ($)
TOS	4,801 ($)	26 (kW)	85 (kWh)	3,430 ($)

5. Conclusion

This work has proposed a comprehensive, three-step framework acting as a multi-level program for optimizing capacity planning of grid-connected NG. The framework incorporates a lookahead logic-based approach with a short optimization window, enabling effective utilization of renewable energy resources and achieving local energy self-sufficiency. The Planner module calculates the optimal sizes of the BESS and PV system, with higher values observed during summer due to increased demand and solar potential. On the other hand, the Operator module imports each of the 365 daily optimal capacity solutions from the Planner module, assumes it as the fixed capacity for the entire year, and calculates the optimal dispatch of BESS and PV for each capacity solution. One of the key benefits of the proposed strategy is the ability to shift renewable energy from high solar-low demand periods to low solar-high demand periods, resulting in a more efficient use of energy resources. By storing excess PV energy in the BESS, the system can avoid importing energy from the grid during high-price periods, leading to significant cost savings. The Evaluator module considers various metrics related to reliability, environmental impact, and the microgrid's or NG's financial viability. These metrics include Annual Local-Sufficiency, Renewable Fraction, Total Profit, and others. This multi-perspective evaluation ensures that the sizing solutions provided by the strategy can be reliably adopted, taking into account various essential aspects. Furthermore, the proposed framework is scalable and can be applied to larger microgrid capacities beyond the kW range. It can be extended to analyze microgrids with capacities reaching several MWs or even more, making it a valuable tool for decision-makers and planners in the energy sector. This research fills a critical gap in NG sizing and operation under realistic conditions by proposing a comprehensive framework that optimizes capacity planning. The strategy's lookahead logic, combined with the multilevel optimization approach, allows for advanced planning and dispatch up to 2 days in advance, resulting in cost savings, increased self-sufficiency, and more efficient use of renewable energy resources. The wide range of evaluation criteria ensures that the strategy's sizing solutions are reliable and can be applied in real-world scenarios. Ultimately, the proposed strategy has the potential to contribute to the global transition towards 100% renewable targets, decentralized energy networks, and enhanced reliability in the electricity sector.

As a future work, incorporating the physical network into NG assessment offers a more comprehensive analysis, enabling insights on optimal NG placement. The implications of NG placement, such as network losses, voltage regulation, and interaction with the central grid, were not within the scope of the current research. However, they hold significant promise for future investigations.

Nomenclature

Parameters

t	: Time in hour
β	: BESS's minimum SoE ratio
s_t	: Hourly solar generation (kW)
l_t	: Hourly Demand load (kW)
μ_c, μ_c	: Charging and Discharging efficiencies.
G	: Maximum power drawn from the grid (kW)
γ	: Charging and discharging maximum ratio
ρ_t	: Hourly time of use Energy Prices
α^E	: Per Diem factors for BESS considering lifetime
α^S	: Per Diem factors for PV, considering lifetime
OC^e	: Total overnight cost for BESS
OC^S	: Total overnight cost for PV
E	: Energy Storage Size of Operator model in kWh
S	: Solar PV Size of Planner Operator in kW

Variables

g_t	: Hourly energy imported from the grid in kWh
e_t	: BESS state of energy (kWh)
d_t	: Hourly BESS discharge power (kW)
c_t	: Hourly BESS charge power (kW)
u_t	: Binary variable, one if the battery is charging, and zero otherwise
E^p	: Energy Storage Size for Planner model (kWh)
S^p	: Solar PV size for planner model (kW)

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