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Analysing the impact of the different pricing policies on PV-battery systems: A Dutch case study of a residential microgrid☆

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ABSTRACT

This study investigates the techno-economic impacts of various pricing policies on a photovoltaic (PV) system combined with battery energy storage (BES) as a single integrated system within a Dutch residential building. With the increasing adoption of PV systems, managing reverse power flow and grid stability becomes crucial. The study evaluates different scenarios, including net metering, feed-in tariffs (FiT) with time-of-use (TOU), RTP pricing, and subsidised BES. Using a multi-objective genetic algorithm, the optimal size and charging/discharging patterns of the PV-BES system were determined. The optimisation simultaneously minimises the Net Present Cost (NPC) and maximises the Self-Consumption Rate (SCR), to determine the PV-BES size that achieves an optimal balance between economic and technical performance. Results indicate that RTP pricing significantly enhances SCR. While the levelised cost of electricity (LCOE) and payback periods (PBP) are initially higher in the RTP pricing scenario, subsidising BES can mitigate these disadvantages. Additionally, incorporating price limit control variables into the energy management system (EMS) optimises the charging/discharging cycles, extending BES lifetimes and potentially increasing future revenues. These findings provide insights for policymakers to balance economic benefits and grid technical requirements through effective PV-BES integration.

1. Introduction

Recently, the adoption of photovoltaic (PV) systems has grown at an unprecedented rate worldwide. The International Energy Agency (IEA) projects that in 2050, solar and wind energy together could account for roughly 70% of global electricity generation (Energy Agency, 2050). However, the surge in PV adoption results in substantial reverse power flow into the grid, posing technical challenges for electricity systems. This includes congestion issues in distribution systems due to a mismatch between demand and the peak of PV generation (Hafiz et al., 2020).

A potential strategy to tackle these challenges is integrating battery energy storage (BES) with PV operations within the distribution systems (Li, 2019). If regulatory frameworks allow, Distribution System Operators (DSOs) can leverage the continued installation of PV-BES systems in residential microgrids. The benefits of these systems include peak demand shaving, power quality enhancement, and voltage and frequency stability improvements. Furthermore, the widespread adoption of PV-BES systems could delay the necessity for comprehensive power system reinforcement, thereby providing economic benefits and technical advantages (Zakeri et al., 2021).

From a consumer's perspective, PV-BES systems can lower electricity bills and minimise PV curtailment. Despite this, the relatively high initial cost remains a significant barrier to the broader adoption of BES (Mulleriyawage and Shen, 2020). Nonetheless, the gradual decrease in BES prices makes installing PV-BES systems increasingly justifiable. Furthermore, the presence of subsidy schemes enhances the economic viability of BES (Balcombe et al., 2015).

From the perspective of DSOs, integrating Renewable Energy Sources (RESs) on a large scale imposes significant costs on distribution grids. Traditional distribution systems are not designed to handle substantial bidirectional power flows, necessitating major upgrades to distribution system assets, such as transformers and cables, to accommodate these

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Nomenclature

EMS	Energy Management System	$NPC_{cj}(t)$	Component cost over time (€)
FiT	Feed-in Tariff (€/kWh)	$NPC_e(t)$	Net present cost of electricity (€)
LCOE	Levelized Cost of Energy (€/kWh)	$P_{b,\max}$	Max charge/discharge rate (kW)
NPC	Net Present Cost (€)	$P_{b,\text{in}}(t)$	Available input power to BES (kW)
PBP	Payback Period (years)	$P_{b,\text{out}}(t)$	Available output power from BES (kW)
PV	Photovoltaic	$P_e(t)$	Power exported to the grid (kW)
RTP	Real-Time Pricing	$P_i(t)$	Power imported from the grid (kW)
SCR	Self-Consumption Ratio (%)	$P_l(t)$	Load demand at time t (kW)
SOC	State of Charge (%)	$P_{\text{char}}(t)$	BES charging power (kW)
TOU	Time of Use	$P_{\text{dis}}(t)$	BES discharging power (kW)
$B(t)$	Buying price at time t (€/kWh)	$P_{\text{pv}}(t)$	PV power generation at time t (kW)
C_{mj}	Annual maintenance cost of component j (€)	$P_{\text{pv,dir}}(t)$	Direct PV consumption (kW)
C_{rj}	Replacement cost (€)	$S(t)$	Selling price at time t (€/kWh)
C_{bat}	Battery capacity (kWh)	$SOC_{\max}$	Maximum state of charge (%)
$C_e(t)$	Annual electricity cost (€)	$SOC_{\min}$	Minimum state of charge (%)
CF_i	Cycles to failure	$T_c(t)$	PV cell temperature (°C)
CF_t	Cash flow in year (€)	$T_{\text{amb}}(t)$	Ambient temperature (°C)
$G(t)$	Solar irradiance (W/m^2)	T_{cof}	Temperature coefficient (1/°C)
G_{ref}	Reference irradiance (W/m^2)	T_{NOCT}	Nominal Operating Cell Temperature (°C)
I	Initial investment (€)	T_{ref}	Reference temperature (°C)
J	Objective function value	X_1	Charging price limit (€/kWh)
L_{BES}	BES system lifetime (years)	X_2	Discharging price limit (€/kWh)
M_j	Lifetime of component j (years)	y	Project lifetime (years)
N_j	Number of replacements of component j	Δt	Time step

changes (Pimm et al., 2018). Consequently, while consumers and DSOs recognise the value of deploying PV-BES systems, their objectives often diverge. Consumers focus on reducing electricity bills and increasing energy independence, while DSOs aim to maintain grid stability and minimise operational costs (Aniello et al., 2021). Therefore, achieving optimal performance from Energy Management Systems (EMSs) is crucial to ensure that economic benefits are maximised for all stakeholders, balancing the distinct goals of consumers and DSOs (Hafiz et al., 2020).

Effective EMS design depends on factors such as battery and PV system costs, system size, load consumption patterns, consumer selling tariffs, and electricity pricing regulations (Mulder et al., 2013). Additionally, for DSOs, the economic viability of EMS deployment hinges on the optimal use of BES for peak shaving, which can significantly reduce the need for distribution system reinforcement and associated costs (Mehrjerdi et al., 2020).

The optimal design of EMSs for PV-BES has been extensively researched, with abundant literature addressing various aspects. Numerous studies, such as those by Beck et al. (2016), have evaluated the economic value of PV-BES, focusing on enhancing self-consumption through optimal PV-BES sizing. Zhou et al. (2018) explored how pricing mechanisms influence BES sizing decisions. Since BES sizing is influenced by the formulation of the optimisation function and pricing policies, the findings of Cerino Abdin and Noussan (2018) suggest that BES is not an economically viable option when assessed solely based on financial metrics such as payback time and net present value (NPV).

In Hossain et al. (2024), optimal PV-BES sizing is integrated with a peak shaving control strategy to enhance system efficiency. Additionally, Bandyopadhyay et al. (2020) examined the impact of meteorological conditions on PV-BES sizing, highlighting the influence of climate variability on system performance. In the realm of microgrids, Quynh et al. (2021) propose a novel optimisation technique aimed at maximising the utilisation of RESs while reducing reliance on fossil fuels. Shifting the focus to DSOs, Uddin et al. (2020) developed an algorithm for peak shaving using BES, incorporating varying investment costs to assess economic feasibility.

With respect to EMS design, a rule-based approach (Hossain et al., 2023) is widely used due to its simplicity and suitability for industrial-scale applications (Sun et al., 2020) when compared to more complex techniques such as predictive control (Al-Quraan and Al-Mhairat, 2024) and adaptive controls (Chankaya et al., 2022). Rule-based methods offer clear and interpretable logic, making them practical for real-time implementation. However, rule-based EMSs may lack adaptability to dynamically changing grid conditions compared to more advanced approaches like ML-based EMSs (Hannan et al., 2021).

To overcome this limitation, an optimisation approach can be combined with heuristic techniques such as tabu search (Xu et al., 2022), particle swarm optimisation (PSO) (Medghalchi and Taylan, 2023), and genetic algorithm (GA) (Torkan et al., 2022) to enhance performance in specific applications. For instance, in Manojkumar et al. (2022), a rule-based EMS is integrated with demand response optimisation, considering energy import and export prices. Additionally, rule-based EMSs are applicable for power quality improvement. For example, reactive power support is incorporated into an EMS in Chakraborty et al. (2023).

Despite extensive literature on PV-BES systems, a significant gap remains in understanding the impact of changing pricing policies on primary stakeholders, namely consumers and DSOs. While DSOs view BES as a tool to reduce network utilisation and defer grid expansion costs, consumers focus on maximising economic benefits (Benalcazar et al., 2024). Bridging these differing objectives necessitates a well-structured and balanced pricing policy (Zakeri et al., 2021).

This study thoroughly examines the effects of various pricing policies on the optimal sizing and performance of a PV-BES using a rule-based EMS, chosen for its suitability in achieving the study‘s objectives of cost minimisation and increased self-consumption, while balancing the needs of both DSOs and consumers. This work provides a detailed comparison of pricing policies, highlighting their strengths and shortcomings. Additionally, the research investigates the impact of pricing structures on the lifecycle of BES. Specifically, unsuitable charging and discharging price limits can accelerate BES degradation, leading to higher replacement costs and reducing overall economic viability. Furthermore, this study explores the potential for subsidising BES to offset its high initial investment and replacement costs, integrating subsidies or financial incentives into the optimisation process. To achieve these objectives, a rule-based EMS is combined with an optimisation approach to solve a multi-objective problem. GA is applied to this optimisation problem due to its flexibility in handling multi-objective optimisation and adaptability to nonlinear and complex constraints, making it particularly effective in scenarios with multiple conflicting objectives (Hannan et al., 2021).

This study addresses the question: "How will different pricing policies impact the techno-economic potential of PV-BES in the Netherlands?" To achieve this, the research analyses the optimal size and performance of EMSs within a designated microgrid under various policy scenarios. The primary focus is minimising the microgrid's annual net payment requirements and decreasing network utilisation. In comparison to prior research, this study provides the following contributions:

1. A multi-objective optimisation using a GA is conducted and integrated into a rule-based EMS to determine the optimal PV-BES sizing and BES charging/discharging patterns, aiming to minimise system costs and network utilisation by applying real-world data from the Netherlands to the assumed microgrid.
2. The designed integrated optimisation with a rule-based EMS is applied to the assumed pricing scenarios, and a comparative analysis is presented.
3. The impact of charging/discharging cycles on BES degradation is assessed by estimating the system's lifespan under each pricing scenario. Additionally, price constraints are incorporated into the optimisation to identify optimal pricing strategies that prevent excessive BES usage, thereby mitigating degradation and extending system longevity.
4. A sensitivity analysis is conducted to investigate the effects of variations in load demand, BES pricing, and electricity prices on each pricing scenario. Furthermore, a cash flow analysis is performed, accounting for both initial and replacement costs across all pricing scenarios.
5. An analysis is presented on the implications of future pricing policies for the efficient integration of BES, accompanied by recommendations for improved regulations.

The paper is structured as follows: Section 2 defines the experimental system and the research scope and provides an overview of the real-world parameters associated with the case study. Section 3 presents the EMS and control strategy. Following this, Section 4 outlines the optimisation model. In Section 5, techno-economic findings are elaborated. Section 6 discusses the implications of various pricing scenarios. Finally, the general conclusion and policy implications are presented in Section 7.

2. System configuration and economical parameters

The focus of the study is a microgrid in a residential area in a given city in the Netherlands, given the significant increase in solar PV adoption in the country and the government's ongoing experiments with alternative energy pricing strategies (Londo et al., 2020). Evaluating the implications of these pricing changes is vital, as similar techno-economic shifts are likely to occur in countries with comparable socio-technical characteristics (Zakeri et al., 2021). Fig. 1 illustrates the assumed microgrid case study, consisting of a residential building with 20 households that share a single integrated PV-BES system for generation and storage. This assumption is based on the definition of a microgrid provided in IEEE Power and Energy Society (2017) as 'a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid and can connect and disconnect from the grid to enable it to operate in both grid-connected and island modes.' In this setup, the electricity generated from PV primarily addresses the aggregated load. Any surplus PV generation can be sold back to the grid or stored in the BES. If the PV generation and battery discharging are insufficient to meet the demand, electricity must be purchased from the grid. The assumed system aims to be economically viable.

The EMS of the microgrid should ensure a balanced electrical energy flow while minimising operational costs. Optimal performance relies on pricing signals, real-time PV generation, load profiles, and the BES State of Charge (SOC) (Chakir et al., 2020). As BES lifetime is affected by charging/discharging cycles, the EMS should be designed to reduce BES replacement costs and enhance self-consumption. This is particularly crucial when analysing future regulatory scenarios, as the number of cycles can vary based on pricing signals (Dufo-López, 2015).

2.1. Pricing policies

Regulatory frameworks and business models should be considered when analysing the performance of PV-BES. Various settings can be assumed regarding the business model, including the location of BES, ownership and operation, value proposition, channels for selling the BES value based on the market environment, technology, and related costs of the BES (Mir Mohammadi Kooshknow and Davis, 2018).

This study assumes that end-users own the BES, which is installed 'behind the metre'. Consequently, end-users cannot participate in the wholesale electricity market. Their revenue stream is generated through bilateral contracts with energy suppliers, who can participate in the wholesale market based on the products they wish to buy from end-users.

Various electricity pricing scenarios for the assumed microgrid can be considered in relation to the regulatory framework. The Dutch government plans to phase out the current net-metering policy starting in 2025 (Central government, 2020). This decision is driven by the significant growth in installed PV capacity, which reached 6,900 MW by the end of 2019, marking a 51% increase (Statistics Netherlands , cbs). This significant growth substantially threatens grid congestion (Emilano Bellini, 2019). The congestion issue is particularly severe in areas where the existing network capacity is insufficient. For instance, in the northern regions of the Netherlands, at certain points in time, the network capacity reaches its maximum (Braat et al., 2021). Moreover, excessive export of PV power can lead to voltage regulation problems. These issues may cause frequent tripping of protective devices (e.g., voltage regulating devices), which reduces the lifespan of these devices. In addition, problems related to power quality, grid reliability, stability, and network protection have been widely reported (Hartvigsson et al., 2021; Bayer et al., 2018).

Currently, the net-metering system in the Netherlands calculates the annual difference between electricity consumption and generation, disregarding the time of consumption and generation. This undermines the Time-Of-Use (TOU) pricing scheme, differentiating price rates for peak and off-peak periods (Mir Mohammadi Kooshknow and Davis, 2018). The Dutch government has outlined steps to transition to a feed-in tariff (FiT) scheme. Until 2025, end-users can sell back the energy produced from their PV systems at the same price. Starting in 2025, the allowable percentage for net metering will gradually be reduced, with complete elimination by 2031 (Central government, 2020).

The following factors are considered when defining regulatory scenarios in this study. By implementing a FiT policy instead of net metering, consumers lose the ability to sell excess energy at the purchasing price (Londo et al., 2020). Additionally, the TOU scheme does not accurately reflect the true cost of electricity (Breukers and Mourik, 2013). Hence, hourly adjustments of electricity prices based on actual costs could more effectively promote self-consumption among end-users and encourage BES adoption (Klaassen et al., 2016). Finally, while supportive schemes for developing BES in the Netherlands exist, such as grants and funding for demonstration and R&D projects (e.g., (Rijksdienst voor Ondernemend Nederland (RVO), 2016)), no specific subsidies are available for residential customers (Potau et al., 2018).

Given the existing regulatory conditions, this study assumes four possible scenarios. Table 1 explains these policy scenarios. The first

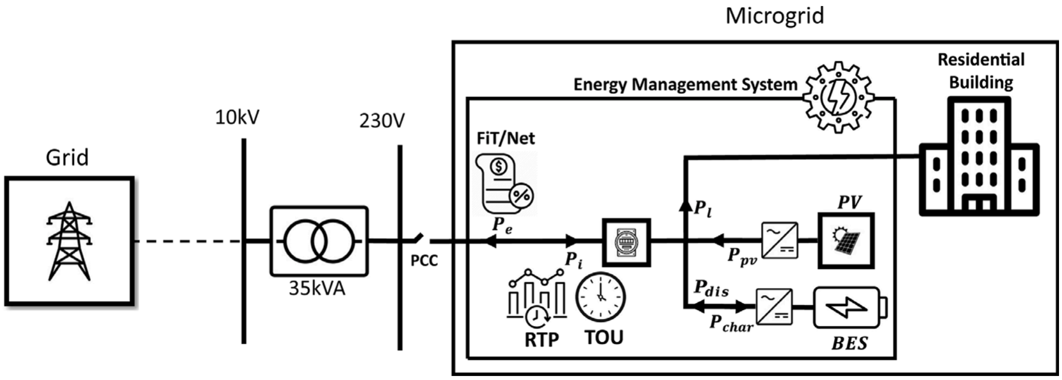


Fig. 1. Microgrid architecture incorporating a PV-BES system.

Table 1
Overview of regulatory scenarios for the techno-economical analysis.

Scenario	Name	Explanation
A	Net metering	Under the net metering policy, customers can reduce their electricity costs by exporting surplus energy generated from their PV systems to the grid, with the exported energy credited against their grid consumption to lower their overall electricity bill (Virtič and Kovačič Lukman, 2019). This study extends the analysis by considering not only the net metering scheme but also the timing of energy production and consumption, which influences the financial and operational effectiveness of the system.
B	FiT with TOU	Under the FiT policy, consumers can export surplus electricity generated from PV systems to the grid and receive compensation from their energy supplier. The compensation rate is typically predetermined and guaranteed for a specific duration (Londo et al., 2020). This study assumes the abolition of net metering in 2021, with prosumers compensated at 0.10 €/kWh for surplus power fed back into the grid, and consumption prices based on TOU rates.
C	RTP	Under RTP, consumers are invoiced or compensated based on hourly day-ahead prices, which are typically published 24 hours in advance. This RTP pricing model aligns retail electricity rates with wholesale market fluctuations, encouraging consumers to adjust their energy usage in response to price signals. (Zakeri et al., 2021).
D	Subsidised BES	Due to high investment costs, BES is currently not profitable (van der Stelt et al., 2018). Therefore, a scenario is considered to implement a 30% investment subsidy for BES combined with RTP.

scenario is smart metering, which accounts for consumption and production times, addressing the current TOU's lack of incentives for self-consumption, which can enhance grid capacity and local power quality (Elkholy, 2019). In the second scenario, net metering is fully phased out, but end-users with PV receive financial compensation for electricity supplied, assumed at 0.1 €/kWh for this study (Central Government, 2020). The third scenario considers dynamic pricing, anticipated for future implementation (Freier and von Loessl, 2022). In this scenario, electricity prices can fluctuate hourly based on the wholesale market, enabling electricity users to manage their power consumption more flexibly and economically. Therefore, this scenario can be considered as real-time pricing (RTP), where the prices for upcoming hours are communicated to end-users in advance (Balakumar et al., 2022). The final scenario combines the third scenario with BES subsidies to explore the necessity of such schemes for BES adoption (Andrey et al., 2020).

2.2. Economic parameters

In the Netherlands, energy suppliers offer varying prices for RTP pricing and TOU schemes (Bart Koenraadt, 2023). Fig. 2(a) presents a box plot of hourly RTP pricing for 2021, with an average value of 0.62 €/kWh used to ensure consistent comparisons. RTP pricing data, sourced from Entose (2021), may include negative values during periods of high renewable energy generation. As shown in Fig. 2(b), TOU pricing exhibits higher electricity prices during peak hours (7:00 to 23:00), while lower prices are applied during off-peak hours and weekends. Table 2 details the pricing signals and other economic parameters used in the analysis.

2.3. Load profile

The electricity load profile for an assumed microgrid with a sizable residential building in Delft, Netherlands, is derived from MFF (2021). Fig. 3(a) illustrates the daily load consumption of 20 households throughout the year. The peak power is 14.8 kW, with an average load consumption of 6.62 kW. The daily mean energy consumption is 158.88 kWh, resulting in an annual energy consumption of 57,999.97 kWh.

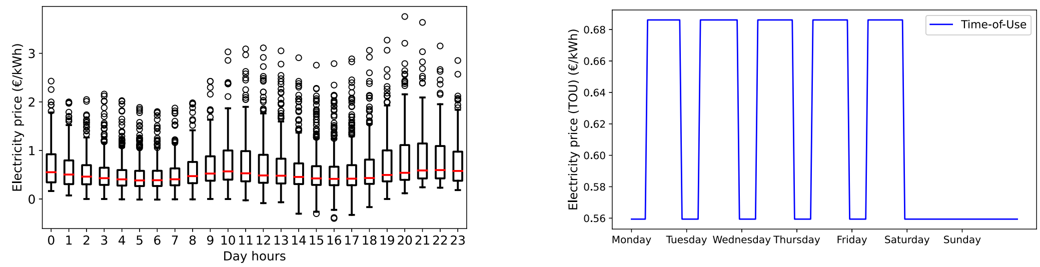
2.4. PV profile simulation

To estimate the annual PV profile, hourly data was retrieved from Royal Netherlands Meteorological Institute (KNMI) (2021). In 2021, the ambient temperature in Delft ($T^{amb}(t)$) was 10.02 °C, and the daily average solar insolation was 2.95 kWh/m^2/day. Using this data, a mathematical model was deployed to generate the power output of a given PV module (P_{pv}) as described in Lan et al. (2015).

$$P_{pv}(t) = N_{pv} \times P_{pv}^{r}(G(t)/G^{ref})[1 + T^{cof}(T^{c}(t) - T^{ref})] \tag{1}$$

$$T^{c}(t) = T^{amb}(t) + ((T^{noct} - 20)/800 \times G(t)) \tag{2}$$

In Eq. (1), N_{pv} denotes the total number of PV modules used in the building, while P_{pv}^{r} represents the rated power output. Solar insolation is denoted by G and expressed in (W/m^2). The solar insolation reference, G^{ref}, has a value of 1000 (W/m^2). For this study, the temperature coefficient T^{cof} is given a value of -3.8×10^{-3} ($1/°C$). T^{ref} represents



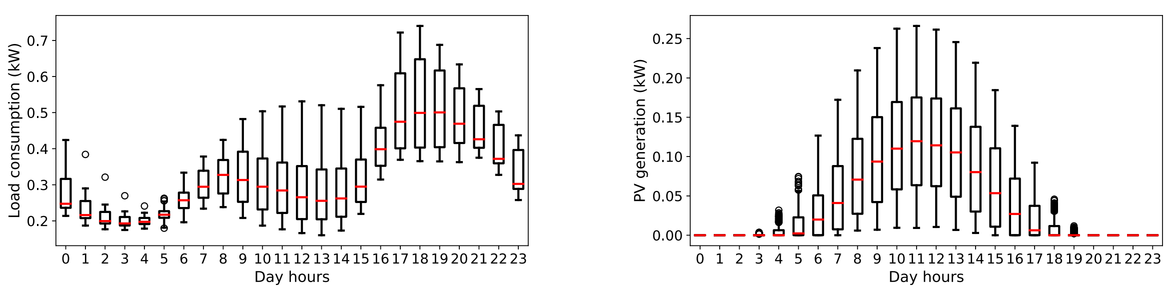
(a) Box plot of RTP pricing.

(b) TOU pricing for weekdays and weekends.

Fig. 2. Real-time and Time-of-use electricity prices.

Table 2
PV-BES economic parameters.

	Details	Value
PV module EnergyPal (2024) Shivam et al. (2021)	Capital & mounting costs Maintenance cost	400 €/kWp 40 €/kW/year
BES BloombergNEF (2021) Randall (2021)	Capital cost BES inverter cost Replacement cost Operation & maintenance costs	700 €/kWh 75 €/kWh 400 €/kWh 0.5% of capital cost/year
Electricity rates and financing Statistics Neterlands (cbs) (2021) Statistcis Neterlands (2021)	TOU (average) TOU (peak) TOU (off-peak) RTP pricing (average) RTP pricing (max) RTP pricing (min) FiT Annual interest rate Project lifetime	0.62 €/kWh 0.69 €/kWh 0.56 €/kWh 0.62 €/kWh 3.75 €/kWh −0.4 €/kWh 0.2 €/kWh 2.8% 20 years



(a) Load box plot for the residential building.

(b) PV generation box plot for a single PV module.

Fig. 3. Daily load and PV generation in the assumed microgrid for 2021.

the standard temperature for solar cells, set at 25 °C (Cotfas et al., 2018).

In Eq. (2), T^c is a function of ambient temperature (T^{amb}), solar insolation, and nominal operating cell temperature (T^{noct}). To simulate PV power output, The IM72CB-330 photovoltaic module was selected for this study due to its affordability and suitability for home application (EnergyPal, 2024). This module comprises 72 multi-crystalline solar cells connected in series, generating a maximum power of 330 Wp. The daily average electricity generation from a single IM72CB-330 module is 0.96 kWh. Fig. 3(b) illustrates the daily PV generation in Delft city for the assumed microgrid.

3. Energy management system

The proposed microgrid in Fig. 1 aims to maximise economic and technical benefits. Fig. 4 illustrates an Energy Management System (EMS) combined with an optimisation method to meet system requirements. Power can be sold to or purchased from the grid based on PV generation$P_v(t)$ and load power $P_l(t)$. When $P_v(t)$ exceeds $P_l(t)$, the BES will be charged at the rate of $P_{char}(t)$ within SOC limit, and any excess power will be sold to the grid. However, the export power is limited by the grid's maximum export capacity $P_{e,max}$. Conversely, the BES will be discharged at the rate of $P_{dis}(t)$ within the SOC limit if PV generation is less than load power. If a power deficit persists, additional power will be imported from the grid. In addition, pricing conditions are incorporated through the use of $X1$ and $X2$ price limit values to ensure the economic feasibility of charging and discharging the BES. These price limit variables are outlined in Section 4.3. The export power $P_e(t)$ and import power $P_i(t)$ can be calculated using Eqs. (3) and (4).

$$P_e(t) = \begin{cases} \min\{P_{e,\max}, P_{pv}(t) - P_l(t) - P_{char}(t)\} & \text{if } P_{pv}(t) \geq P_l(t) \\ & \quad \text{and } P_{pv}(t) - P_l(t) \geq P_{b,\mathrm{in}}(t) \\ & \quad \text{and Price}(t) \geq X_2 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

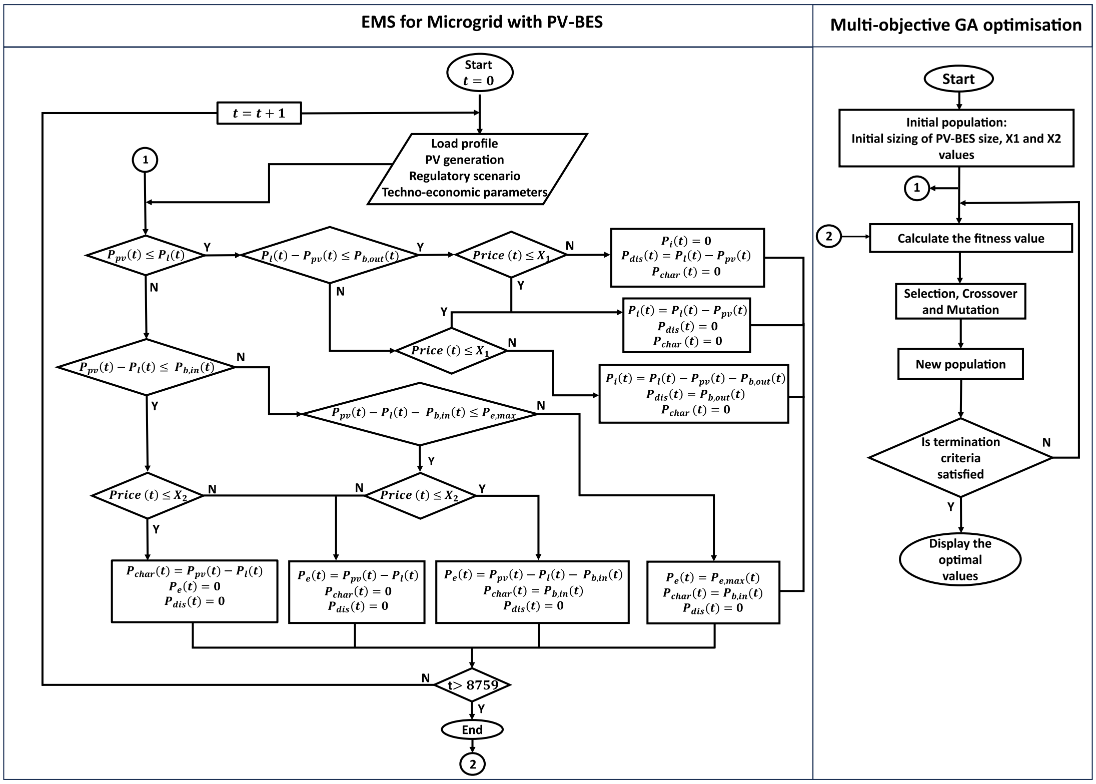


Fig. 4. Integrated EMS-optimisation model.

$$P_i(t) = \begin{cases} & \text{if } P_l(t) \ge P_{pv}(t) \\ P_l(t) - P_{pv}(t) - P_{dis}(t) & \text{and } P_l(t) - P_{pv}(t) \ge P_{b,\text{out}}(t) \\ & \text{and Price}(t) \le X_1 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The available output power $P_{b,out}$ and input power $P_{b,in}$ of the BES for each timestep Δt can be calculated using Eq. (5) and (6). Here, $P_{b,max}$ represents the maximum allowable power of BES and C_{bat} denotes the BES capacity (Javadi et al., 2020).

$$P_{b,out}(t) = \min\{P_{b,max}, (C_{bat}/\Delta t) \cdot (SOC(t) - SOC_{\min})\} \tag{5}$$

$$P_{b,in}(t) = \min\{P_{b,max}, (C_{bat}/\Delta t) \cdot (SOC_{\max} - SOC(t))\} \tag{6}$$

The SOC of the battery in each hour is calculated using Eq. (7).

$$SOC(t+1) = SOC(t) + \frac{P_{char}(t) \cdot \eta_{char} - P_{dis}(t)/\eta_{dis}}{C_{bat}/\Delta t} \tag{7}$$

Where the efficiencies of the charging and discharging processes are denoted by η_{char} and η_{dis}, respectively (Zhang et al., 2020) (see Fig. 4).

4. Optimisation process

This study employs a multi-objective genetic algorithm, an evolutionary algorithm based on the principle of survival of the fittest (Kramer, 2017). The optimisation model aims to minimise the net present cost (NPC) and maximise self-consumption. Section 4 illustrates the optimisation process, where the proposed EMS integrates with the algorithm to determine the optimal size of the PV-BES in different regulatory scenarios. To ensure an optimal global solution, the population size is set to 200 and the number of generations to 500. The mutation rate is 0.1, with a tournament size of 3 for selection and a simple average method used for crossover (Torkan et al., 2022).

4.1. Objective function

The goal of optimisation is to minimise the net present cost (NPC) of the microgrid, which includes the NPC of electricity cost (NPC_e) and the NPC of all components, represented as the sum of the NPC of each component ($\sum_j NPC_{c_j}$). Additionally, import from and imports to the grid should be minimised to maximise self-consumption. Therefore, the objective function, denoted by J, is calculated as

$$J = \min \sum_{t=0}^{8759} \left(NPC_e(t) + \sum_j NPC_{c_j}(t) \right) + \min \sum_{t=0}^{8759} \left(P_i(t) + P_e(t) \right) \tag{8}$$

For comparison purposes across different policy scenarios, it is assumed that 1 kWh of grid utilisation is equivalent to 1 € in Eq. (8). However, different weighting factors can be applied to reflect various trade-offs between NPC and SCR in the objective function, depending on the specific system settings.

The system's NPC_e is calculated by

$$NPC_e(t) = C_e(t).\frac{(1+i)^y - 1}{i(1+i)^y} \tag{9}$$

where i denotes the interest rate and y represents the project lifetime in years (Górnowicz and Castro, 2020), while $C_e(t)$ is the annual cost of electricity, calculated using Eq. (10).

$$C_e(t) = \sum_{t=0}^{8759} B(t).P_i(t).\Delta t - \sum_{t=0}^{8759} S(t).P_e(t).\Delta t \tag{10}$$

where $B(t)$ and $S(t)$ represent the buying and selling price at each timestep (Khezri et al., 2020). The NPC_{c_j} encompasses capital costs, maintenance expenses, and replacement costs of components as (Ali et al., 2023)

$$NPC_{c_j}(t) = NPC_{cap_j} + NPC_{m_j}(t) + NPC_{r_j}(t) \tag{11}$$

where the subscript j represents each component. The subscripts cap, m, and r denote capital, maintenance, and replacement costs,

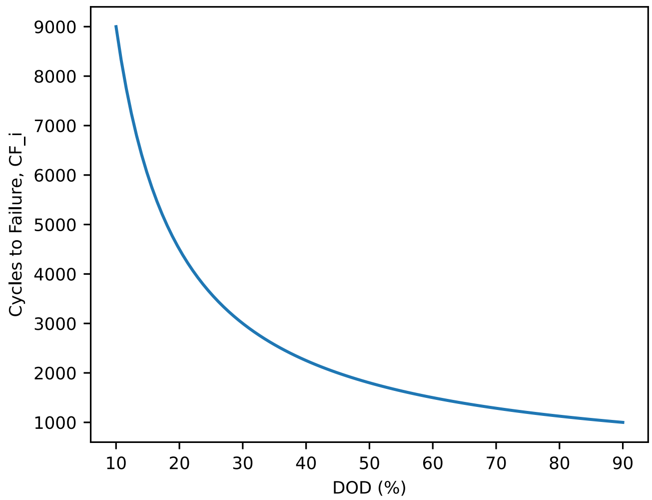


Fig. 5. Cycles to failure vs. DOD for a typical battery.

respectively (Górnowicz and Castro, 2020). The maintenance cost of a component during the lifetime of the system is calculated by

$$NPC_{m_j} = Cm_j . \frac{(1+i)^{(M_j)} - 1}{i(1+i)^{(M_j)}} \tag{12}$$

where Cm_j is annual maintenance cost of the component j, and M_j denotes the lifetime of the component j in years (Singh and Kumar, 2023).

The replacement costs of a component over the system's lifetime is calculated as (Bahramara et al., 2023)

$$NPC_{r_j} = C_{r_j} . \sum_{t=0}^{N_j} \frac{1}{(1+i)^{t.M_j}} \tag{13}$$

where C_{r_j} denotes the replacement cost of component j, and N_j represents the number of times component j is replaced over the system's lifetime, calculated as (Dufo-López, 2015)

$$N_j = \left\lfloor \frac{y}{M_j} \right\rfloor \tag{14}$$

4.2. BES lifetime

The replacement cost for PV-BES systems is primarily influenced by the BES lifetime. The lifetime of the BES is indirectly determined since it depends on the number of charging cycles, which vary based on the BES application and the designed EMS (Yang et al., 2022). Although factors such as operational temperature and corrosion are included in battery aging models, the most significant factor is degradation due to the energy cycle (Vermeer et al., 2022).

This study applies the cycle counting method to estimate the battery's lifetime. This method counts the number of charging cycles N_i per year. The cycle numbers are calculated based on the SOC data for the entire year (Lee and Won, 2023). Additionally, each cycle's Depth of Discharge (DOD) is tracked, ranging from 10% to 90%. Based on the DOD range, the corresponding Cycles to Failure (CFi) can be determined using the CFi vs. DOD curve provided by the battery manufacturer (Tucker, 2010). Fig. 5 illustrates a typical battery's CFi vs. DOD relationship. The battery duration is calculated using Eq. (15) when the DOD is divided into m ranges (Dufo-López, 2015).

$$Life_{BES} = \sum_{t=i}^{m} \frac{N_i}{CF_i} \tag{15}$$

4.3. Charging and discharging price limits

Given the significant impact of the battery's capital and replacement costs on the NPC, it is crucial to consider the effect of pricing on BES aging under various scenarios. Therefore, the optimisation process incorporates the sizing and optimal timing for charging and discharging the BES. To optimise BES operation, the price limits X_1 and X_2 are introduced into the EMS, representing the charging price limit and discharging price limit, respectively. Fig. 6 illustrates these price limits.

In dynamic pricing scenarios, electricity prices change hourly, leading to multiple charging cycles and a reduced battery lifetime (Mayyas et al., 2022). To mitigate this, the charging and discharging price limits are set to balance the reduction in annual charging cycles while maximising arbitrage benefits. The charging price limit (X_1) determines that discharging is preferred when prices exceed this threshold, while power is imported from the grid when prices fall below it. Conversely, the discharging price limit (X_2) suggests that charging is economically advantageous when prices fall below this threshold, and exporting power to the grid is preferred when prices exceed it.

4.4. System constraints

The objective function in Eq. (8) is subject to the following constraints (Wu et al., 2022).

$$P_{pv}(t) + P_{dis}(t) - P_{char}(t) - P_e(t) + P_i(t) = P_l(t) \tag{16}$$

$$0 \le P_e(t) \le P_{e,max} \tag{17}$$

$$0 \le P_{pv}(t) \le P_{pv,max} \tag{18}$$

$$0 \le P_{cha}(t) \le P_{cha,max} \tag{19}$$

$$-P_{dis,max} \le P_{dis}(t) \le 0 \tag{20}$$

$$SOC_{min} \le SOC \le SOC_{max} \tag{21}$$

$$Price_{min} \le X_1, X_2 \le Price_{max} \tag{22}$$

The power balance constraint is expressed in Eqs. (16), and (17) is the constraint of the exported power to the grid. Output power constraints of the PV-BES system are represented in Eqs. (18), (19), and (20). Eq. (21) shows the SOC constraint of the BES. Eq. (22) presents the X_1 and X_2 price limits for charging and discharging.

4.5. Evaluation criteria

Considering the optimisation goals, the levelised cost of electricity (LCOE) and payback period (PBP) can be used as metrics to measure end-user benefits (Blok and Nieuwlaar, 2016). The LCOE is calculated as the system's net present cost (NPC) divided by the total annual energy consumed over the project's lifetime (Zahari et al., 2024).

$$LCOE = \frac{NPC}{\left(\sum_{t=0}^{8759} P_l(t)\right) \cdot y} \tag{23}$$

The PBP metric indicates the time required to recover the initial investment and is calculated by dividing the initial investment cost by the annual cash flow (Han et al., 2022).

$$PBP = \frac{I}{CF_t} \tag{24}$$

In Eq. (24), I is the initial investment. The CF_t represents the cash flow for the year t. It is defined as the difference between the energy savings resulting from the PV-BES and the associated maintenance and replacement costs as (Han et al., 2022)

$$CF_t = C_{e,without,t} - C_{e,t} - C_{m\&r,t} \tag{25}$$

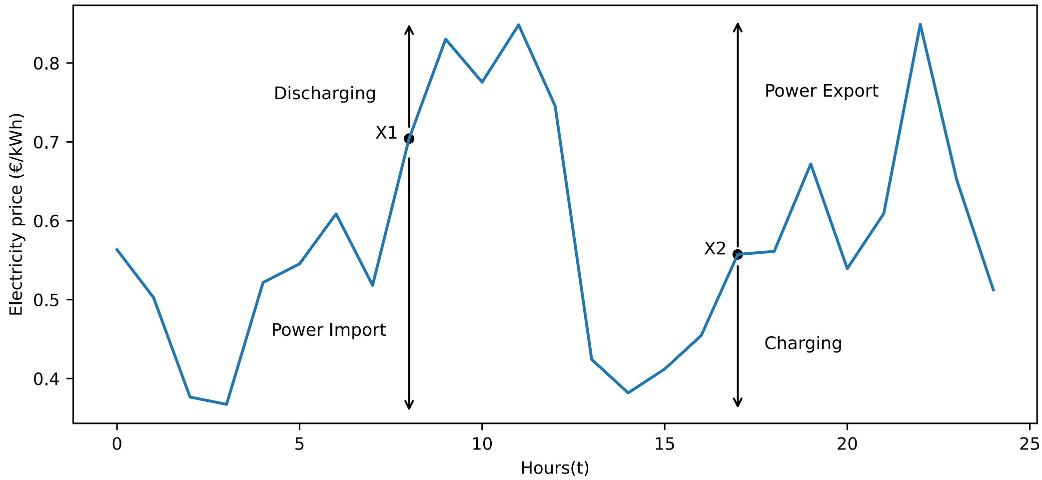


Fig. 6. Exemplifying the application of X_1 and X_2 price limits on a daily basis.

Table 3
Optimisation results for the PV-BES system in the assumed microgrid, with percentage changes shown relative to the Net Metering scenario as the baseline.

Scenario	PV (kWp)	BES (kWh)	X_1 (€)	X_2 (€)	$Life_{BES}$ (year)	LCOE (€/kWh)	PBP (year)	SCR (%)
Net metering	49.5	30.9	–	–	7.50	0.12	2.80	36
FiT with TOU	49.5	76.8	–	–	8.50 (+13.3%)	0.41 (−241.7%)	3.60 (−28.6%)	62 (+72.2%)
Dynamic pricing without X_1 and X_2 limits	49.5	49.6	–	–	5.20 (−30.7%)	0.36 (−200.0%)	3.50 (−25.0%)	57 (+58.3%)
Subsidised BES without X_1 and X_2 limits	49.5	61.3	–	–	5.50 (−26.7%)	0.29 (−141.7%)	3.40 (−21.4%)	58 (+61.1%)
Dynamic pricing with X_1 and X_2 limits	49.5	87.5	1.21	0.23	9.30 (+24.0%)	0.38 (−216.7%)	5.30 (−89.3%)	71 (+97.2%)
Subsidised BES with X_1 and X_2 limits	49.5	92.3	1.22	0.24	10.50 (+40.0%)	0.34 (−183.3%)	4.10 (−46.4%)	72 (+100.0%)

Where $C_{e,\text{without}}$ and C_e denote the electricity costs incurred without and with the PV-BES system, respectively. The $C_{m\&r}$ represents the maintenance and replacement costs associated with the PV-BES system.

The final metric, the self-consumption rate (SCR), is crucial for reflecting the system operator's benefit and can be calculated annually as (Quoilin et al., 2016)

$$SCR = \sum_{t=0}^{8759} \frac{(P_{dis}(t) + P_{pv,dir}(t)).\eta_{dis}}{P_{pv}(t)} \tag{26}$$

Eq. (26) implies that the Self-Consumption Ratio (SCR) represents the ratio of energy generated by the PV-BES system and consumed directly or indirectly within the microgrid to the annual energy produced by the PV system. Therefore, $P_{pv,dir}(t)$ denotes the PV generation utilised directly within the microgrid, excluding any energy exported to the grid or used for charging the BES.

5. Results

The optimisation results for the proposed EMS under the considered scenarios are summarised in Table 3. To evaluate the effectiveness of the proposed X_1 and X_2 price limits, the analysis includes results without these price limits for both the dynamic pricing and subsidised BES scenarios. Figs. 13(a)–11(d) illustrate the variation in the objective function relative to the size of the PV-BES. Figs. 11(e)–11(f) depict the changes in the objective function concerning variations in price limits of X_1 and X_2. The available roof space can accommodate up to 150 PV modules, resulting in a PV production capacity of 49.5 kWp across all scenarios. This makes further PV adoption economically viable. The results show that net metering offers a lower LCOE of 0.12 €/kWh and a shorter PBP of 2.8 years, with a relatively small BES size of 30.9 kWh. However, this scenario also yields a lower SCR of 36%. Conversely, the FiT with TOU scenario necessitates a larger BES size of 76.8 kWh and results in a higher LCOE of 0.41 €/kWh and a longer PBP of 3.6 years, yet achieves a considerably higher SCR of 62%.

Regarding the optimal BES size, previous studies have indicated that when only NPC optimisation is considered, net metering results in an optimal BES size of zero, as the grid effectively acts as a cost-free form of storage (Cerino Abdin and Noussan, 2018). However, minimisation of grid utilisation in Eq. (8) leads to non-zero BES values for the policy scenarios. The results indicate moderate BES sizes and SCR values for scenarios involving dynamic pricing and subsidised BES without X_1 and X_2 price limits. The dynamic pricing scenario without X_1 and X_2 price limits shows a BES size of 49.6 kWh, a LCOE of 0.36 €/kWh, and a PBP of 3.5 years, with an SCR of 57%. The subsidised BES scenario without X_1 and X_2 price limits improves slightly with a BES size of 61.3 kWh, a LCOE of 0.29 €/kWh, and a PBP of 3.4 years, achieving an SCR of 58%.

In scenarios incorporating X_1 and X_2 price limits, dynamic pricing and subsidised BES show substantial improvements in SCR, reaching 71% and 72%, respectively. These scenarios require the largest BES sizes of 87.5 kWh and 92.3 kWh, respectively, and demonstrate extended battery lifetimes of up to 10.5 years. The higher initial investment is reflected in higher LCOE values (0.38 €/kWh for dynamic pricing with X_1 and X_2 price limits and 0.34 €/kWh for subsidised BES with X_1 and X_2) price limits, along with longer PBPs of 5.3 and 4.1 years, respectively.

5.1. Daily power flow

Power flow analysis provides valuable insights into system performance across different scenarios. The power flow for each scenario is presented over two consecutive days in April, selected for their temperature and solar irradiation values closely matching the annual average[1]. The power flow patterns in the subsidising scenarios resemble those in the dynamic pricing scenario. Therefore, only the dynamic pricing scenarios are depicted, with and without the X_1 and X_2 price limits.

[1] The full-year power flow illustration is visually complex and difficult to interpret. Interested readers are encouraged to contact the authors for access to the complete power flow dataset. Furthermore, the yearly energy values are presented in Table 4 in the discussion section.

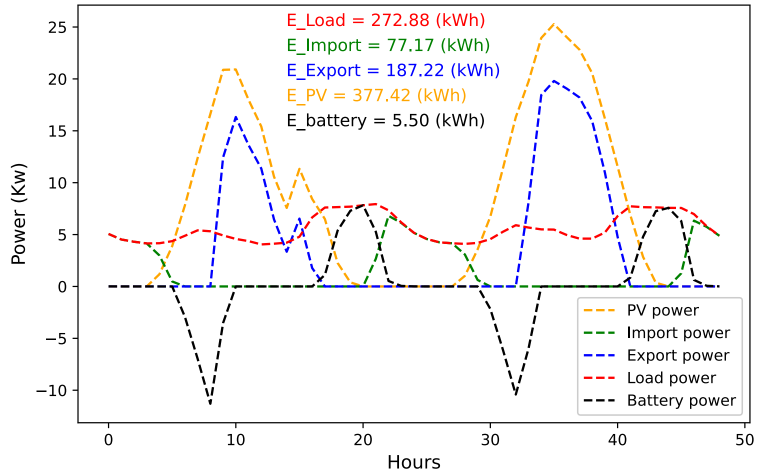


Fig. 7. Power flow for the Net metering scenario over two consecutive days in April 2021.

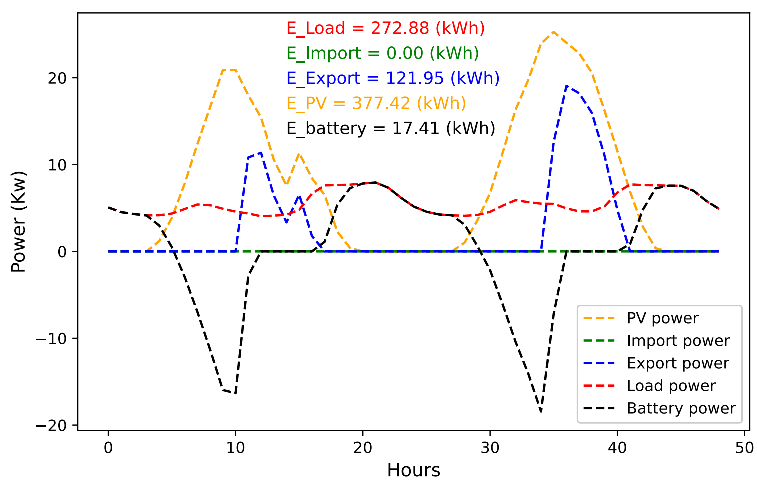


Fig. 8. Power flow for the FiT with TOU scenario over two consecutive days in April 2021.

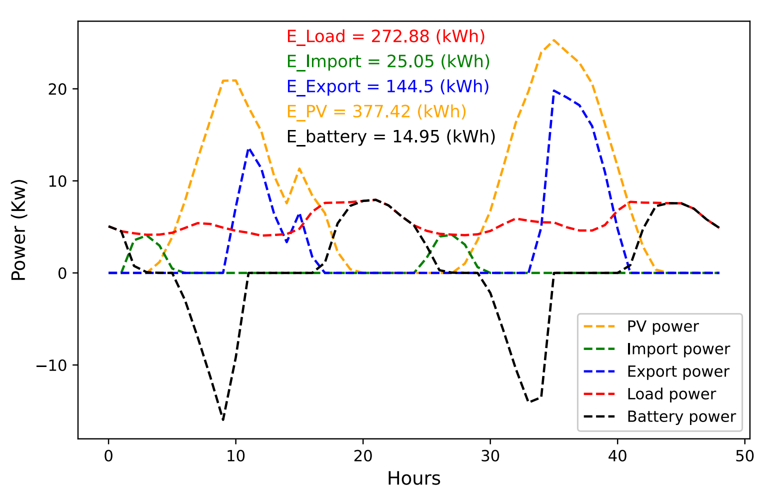


Fig. 9. Power flow for the Dynamic pricing scenario without X_1 and X_2 price limits over two consecutive days in April 2021.

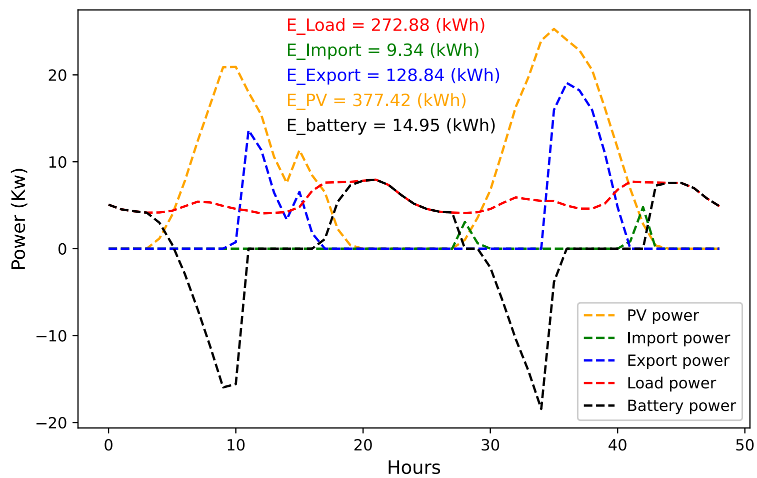


Fig. 10. Power flow for the Dynamic pricing scenario with X_1 and X_2 price limits over two consecutive days in April 2021.

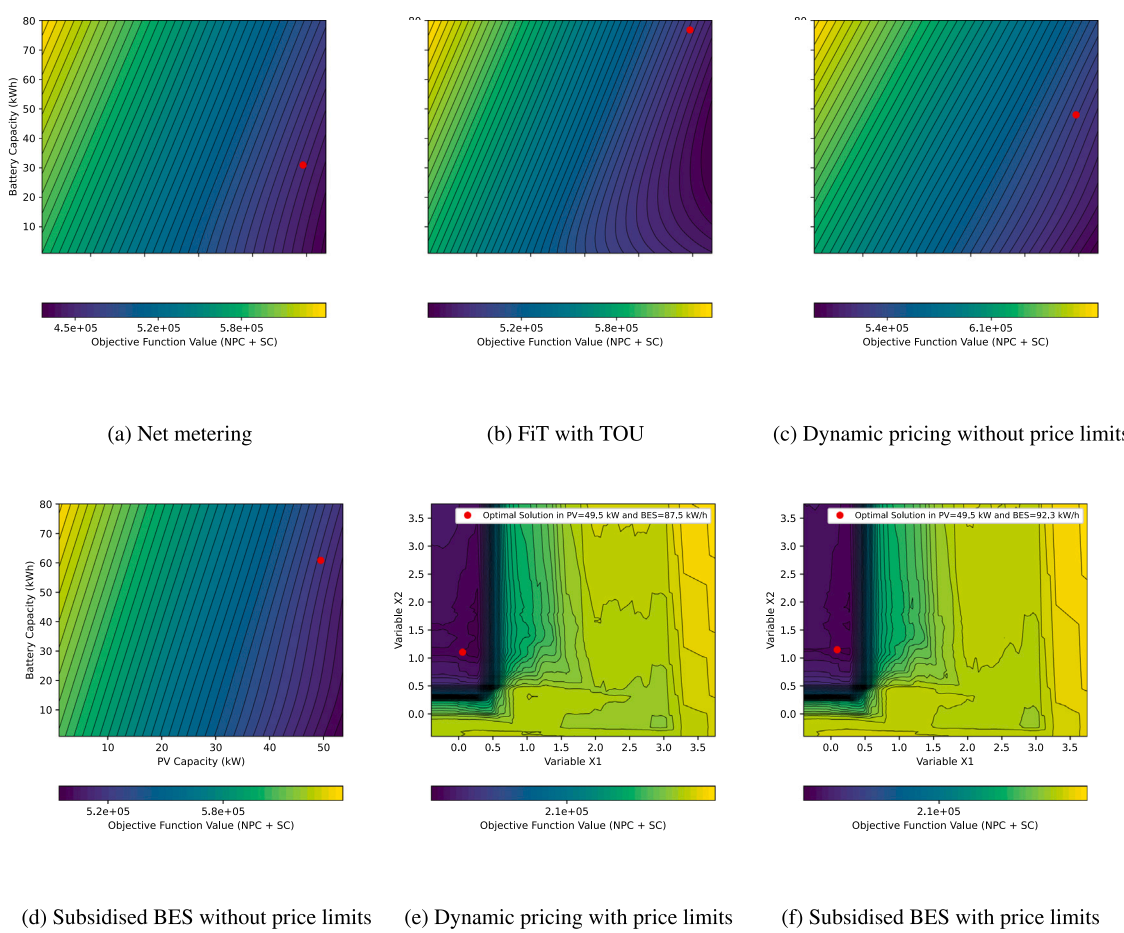


Fig. 11. Objective function values for each scenario. The red dots indicate the optimal solutions.

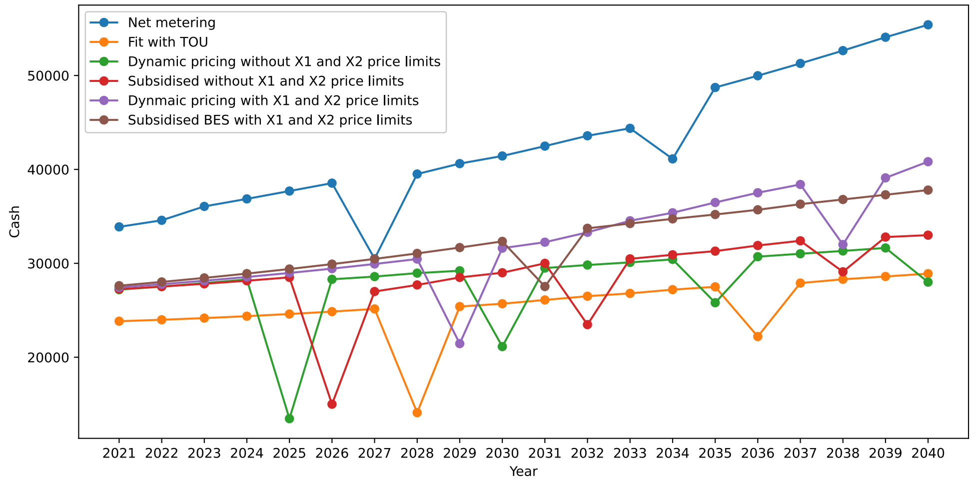


Fig. 12. Cash flow comparison among scenarios over the project lifetime.

In the net metering scenario (Fig. 7), the system exports a significant amount of generated energy (187.22 kWh) to the grid and imports 77.17 kWh, highlighting a low SCR despite high PV generation of 377.42 kWh. The BES's contribution is minimal, discharging only 5.50 kWh. Conversely, the system achieves zero import from the grid in the FiT with the TOU scenario (Fig. 8), and BES discharges 17.41 kWh to meet the load demand of 272.88 kWh. This scenario also shows reduced power exports (121.95 kWh), reflecting a higher SCR. Comparing the dynamic pricing scenarios without and with X_1 and X_2 price limits (Fig. 9 - Fig. 10), it is evident that the introduction of price limits reduces the exported energy from 144.5 kWh to 128.84 kWh. Notably, this reduction is achieved while maintaining the same discharging energy from the BES at 14.95 kWh.

5.2. Annual cash flow

The cash flow analysis of end-users in microgrid provides a detailed overview of the annual payments throughout the project's lifetime, taking into account the interest rate and replacement costs of system components (Sepúlveda-Mora and Hegedus, 2021). Fig. 12 presents a comparative cash flow analysis for the considered scenarios over a 20-year period. The total benefit for each scenario is determined by summing the annual benefits. Under the net metering scenario, the BES is expected to be replaced up to three times, resulting in an overall revenue of 853,354.6 €. In contrast, despite having lower replacement costs, the FiT and TOU scenario incurs higher energy costs for end-users. Consequently, this scenario yields the lowest total benefit, amounting to 506,187.87 €.

Under the dynamic pricing scenario without X_1 and X_2 price limits, the BES requires replacement every 5 years, resulting in substantial costs and consequently yielding a low total benefit of 558,899.25 €. Introducing a subsidy to the dynamic pricing scenario increases the total benefit to 571,814.86 €. When X_1 and X_2 price limits are incorporated into the dynamic pricing and subsidised BES scenarios, the total benefits rise to 643,552.43 € and 647,185.07 €, respectively.

5.3. Sensitivity analysis

The sensitivity analysis presented in Fig. 13 highlights the impact of BES price, demand changes, and electricity price change on the objective function value across the scenarios. The subsidised scenario is not illustrated due to its similar results to the dynamic pricing scenario. To discuss the sensitivity of scenarios with changing BES price and electricity demand, a point is specified with a red cross where the battery price is 1000 €/kWh, and the demand factor is 1.2. The FiT with TOU scenario (Fig. 13(b)) exhibits the highest objective function value at this point, approximately 4.54×10^5, indicating significant sensitivity to parameter changes and sharp steps in the contour lines. Net metering (Fig. 13(a)) shows a more horizontal contour pattern, suggesting greater sensitivity to battery price than to demand factor, with an objective function value of around 2.96×10^5. Dynamic pricing (Fig. 13(c)) is similarly more sensitive to battery price, with an objective function value of 4.51×10^5 at the specified point, considerably higher than the net metering scenario.

In addition, the sensitivity of scenarios concerning the impact of electricity price changes and battery price changes on the objective function is considered. Fig. 13(d) shows a relatively uniform spacing of the contour lines, indicating a consistent rate of increase in the objective function value concerning both parameters. Fig. 13(e) reveals that the objective function decreases as the FiT factor increases. Fig. 13(f) demonstrates that the objective function is less sensitive to price changes in dynamic pricing, suggesting more stability in this scenario.

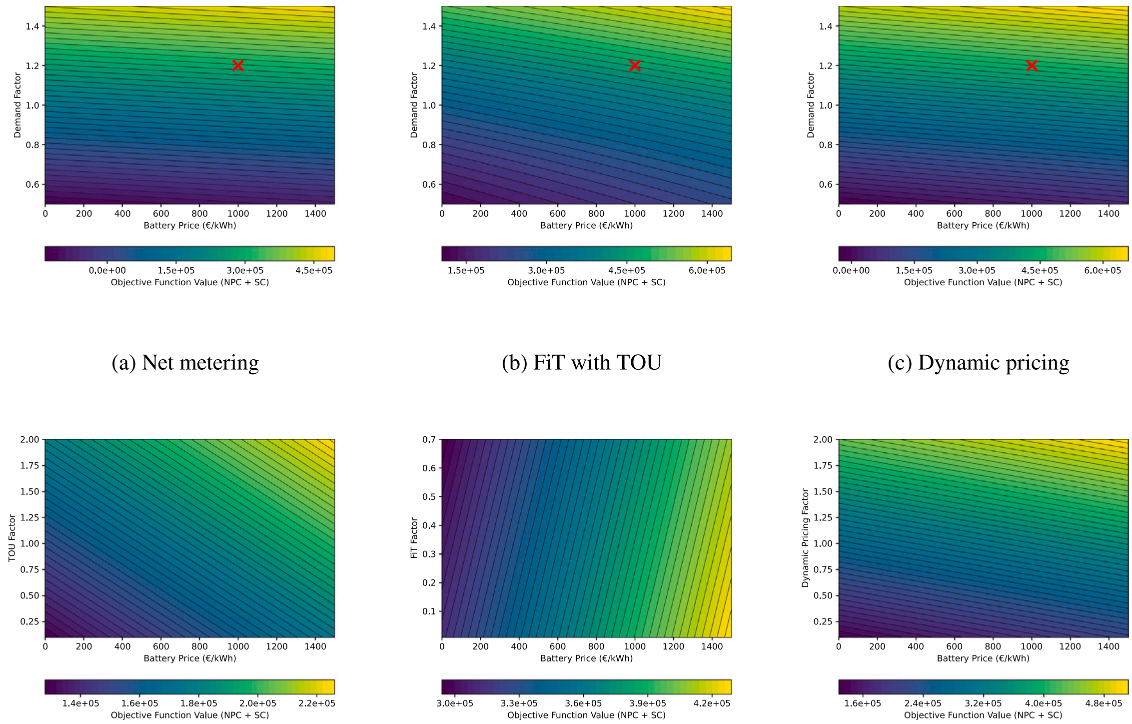
6. Discussion

Tables 4 and 5 summarise the quantitative and qualitative comparisons of the policy scenarios. The energy values represent annual totals, while the revenue is presented as an average over the duration of the project. The following points are discussed to evaluate the impact of each policy scenario on the techno-economic performance of PV-BES systems in the Netherlands.

In the net metering scenario, the results demonstrate a significant reliance on the grid for energy transactions, with the highest export values among all scenarios. This scenario benefits from a lower LCOE, a short PBP, and the maximum total revenue over the project's lifetime, making it financially attractive for end-users. However, the SCR is relatively low, leading to higher grid congestion and making it less attractive to DSOs. This result supports the current intention of the Dutch government to terminate the net metering scheme (Milchram et al., 2020).

A larger BES is required in the FiT with TOU scenario, resulting in a relatively higher LCOE for end-users. This scenario achieves a higher SCR than net metering despite the increased cost. Therefore, the higher costs can discourage the wider adoption of PV-BES systems (Günther et al., 2021).

Under the dynamic pricing scenario, although SCR is slightly reduced, the LCOE and PBP are less than in the FiT with TOU scenario. The total revenue in this scenario is more than in the FiT with TOU scenario, indicating a more balanced solution for end-users and system operators. In addition, dynamic pricing offers more stable financial outcomes despite market fluctuations, making it a more viable future policy. However, the optimisation assumes perfect foresight, whereas



(a) Net metering (b) FiT with TOU (c) Dynamic pricing

(d) Net metering (e) FiT with TOU (f) Dynamic pricing

Fig. 13. Sensitivity analysis for different scenarios. (a), (b) and (c) show the effect of BES price and demand change on the objective function value. (d), (e) and (f) show the effect of BES price and electricity price changes on the objective function value.

Table 4
Quantitative comparison of pricing policy scenarios, with P_l = 57999.98 kWh and P_{pv} = 52782.81 kWh fixed for all scenarios. Revenue values include percentage change relative to Net Metering as baseline.

Scenario	P_i (kWh)	P_e (kWh)	$P_{battery}$ (kWh)	Revenue (€/year) (with % change)	Sensitivity		
					BES Price	Electricity Price	Demand
Net Metering	30 500.69	26 029.86	746.33	42 667.73	High	Moderate	Low
FiT with TOU	22 525.27	18 870.33	1562.23	25309.39 (−40.7%)	High	High	High
Dynamic Pricing	26 671.69	22 591.24	1136.71	27944.96 (−34.5%)	High	Low	Low
Subsidised BES	24 494.04	20 636.03	1359.15	28590.74 (−33.0%)	–	–	–
Dynamic Pricing with X1 & X2 price limits	23 434.16	1969.62	1475.62	32177.62 (−24.6%)	–	–	–
Subsidised BES with X1 & X2 price limits	23 295.12	19 569.4	1491.45	32359.25 (−24.1%)	–	–	–

Table 5
Qualitative comparison of the assumed pricing policies.

Scenario	Advantages	Disadvantages
Net metering (Cerino Abdin and Noussan, 2018)	Financially attractive for end-users due to low LCOE and short payback period.	Leads to low self-consumption rate (SCR) and high grid congestion, which are not ideal for grid stability.
FiT with TOU (Talent and Du, 2018; Wang et al., 2024)	Encourages better self-consumption than net metering.	Requires higher BES capacity, increasing costs and LCOE, discouraging widespread adoption.
Dynamic pricing without X_1 and X_2 price limits (Zhou et al., 2018)	Balances costs and SCR better than FiT, offering moderate SCR and financial benefits.	Suffers from shorter BES lifetimes and higher replacement needs.
Subsidised BES without X_1 and X_2 price limits (D'Adamo et al., 2022)	Improves SCR slightly with subsidies reducing costs.	BES replacements are frequent, limiting long-term cost efficiency.
Dynamic pricing with X_1 and X_2 price limits (Manojkumar et al., 2022)	Significantly enhances SCR and BES lifetime.	Requires larger BES capacity, increasing initial investment and extending payback period.
Subsidised BES with X_1 and X_2 price limits	Optimal for SCR and BES lifetime; subsidies and price limit control variables reduce costs and replacement frequency.	

real-world price forecasts are uncertain, affecting its effectiveness. Furthermore, introducing a subsidy scheme for dynamic pricing significantly reduces both the PBP and the LCOE, making it a more attractive and feasible option for end-users.

Analysis results show that the net metering scenario is unfavourable when realising the energy transition due to the low SCR. The alternative solutions of the FiT with TOU and dynamic pricing can potentially promote energy transition, but both scenarios require additional support to reduce LCOE for end-users. However, subsidy schemes can hardly be realised in the Netherlands under the current budgetary constraints and regulatory framework, in which BES is not defined as a renewable energy resource (Mir Mohammadi Kooshknow and Davis, 2018). Therefore, any modifications to pricing policies should be supported by corresponding amendments to the regulatory framework.

Moreover, in general, changing a regulatory framework is a very complex and time-consuming process (Gallo et al., 2016). The alternative solution is to focus on changing business models. Business model frameworks can be seen as interrelated components (e.g., customers, value stream, and value proposition) working together to create and deliver value (Oliveira and Ferreira, 2011). For the BES case, the cost structure is a determining factor, and while the regulatory structure does not provide enough freedom to increase revenue, lowering the cost can mitigate this unfavourable regulatory condition. Therefore, incorporating the X_1 and X_2 price limits into the EMS results in postponing the replacement time of the BES and enhancing future economic benefits, as reflected in the cash flow analysis. This also leads to a larger BES capacity and an increased SCR. Although this new EMS design extends the PBP due to a larger BES, it is advantageous for microgrids and aggregated BES systems, where larger BES capacities are used. This benefit arises from the economies of scale, as the price per kWh decreases with higher BES capacities (Mauler et al., 2021).

6.1. Limitations

The study is based on several critical assumptions that could influence the interpretation of the results. First, the EMS is assumed to be rule-based, employing predefined rules and algorithms for system components (Ahmad et al., 2023). For future comparative analyses, more advanced EMSs, such as adaptive and learning-based techniques like reinforcement learning (Meng et al., 2024), can be considered. These methods can more effectively capture and respond to diverse pricing data.

Secondly, this study assumes perfect foresight in dynamic pricing scenarios, meaning future electricity prices are known in advance. While this is common in optimisation studies, real-world conditions involve uncertainties and forecasting errors, which may reduce the actual effectiveness of dynamic pricing strategies. Future research could explore integrating forecasting methods to account for real-time price variability and enhance the robustness of the approach.

Additionally, the study assumes that BES is located at the end-user's site, limiting its value to self-consumption and energy arbitrage. Future research can explore BES installations at the transmission and/or distribution levels, where it can provide additional services such as voltage and frequency regulation and investment deferral support. In addition, future studies could also assess various BES locations within relevant regulatory frameworks and business models. Furthermore, the present study examines the benefits DSOs gain from PV-BES systems and increase in SCR. However, more precise criteria, such as investment deferral potential, could provide deeper insights into PV-BES adoption. It is also essential to consider regulatory challenges, as current regulations in the Netherlands prohibit DSOs from owning BES systems, preventing them from directly benefiting from the services these systems provide.

7. Conclusion and policy implications

This study employs an integrated EMS-optimisation model and applies various evaluation criteria to explore the question: "How will different pricing policies impact the techno-economic potential of PV-BES in the Netherlands?" The findings suggest that while net metering is advantageous for end-users due to its lower costs, it leads to a low SCR. In contrast, the FiT with TOU pricing policy results in a higher LCOE and SCR, making it more favourable for DSOs.

Based on the study's findings, dynamic pricing combined with subsidies proves to be a highly effective strategy. Dynamic pricing motivates end-users to adjust their energy consumption in response to real-time electricity prices, thereby promoting more efficient energy use. However, the high initial costs associated with BES installations can be a significant barrier to adoption. To overcome this, introducing subsidies to offset these upfront costs would enhance the economic attractiveness of PV-BES systems for residential users. These subsidies can be offered as direct financial incentives or tax rebates (Li and Cao, 2022).

However, the provision of subsidies faces critical challenges. Current regulatory frameworks do not classify BES as a renewable energy resource, limiting the potential for subsidies and other supportive measures. Regulatory amendments could be pursued to recognise BES as part of the renewable energy ecosystem (Mir Mohammadi Kooshknow and Davis, 2018). Moreover, the current Dutch electricity market design does not adequately reward the benefits provided by BES. For instance, market mechanisms fail to compensate for the critical services BES offers, such as voltage and frequency regulation. Without appropriate market incentives, the viability of BES is restricted primarily to congestion management (Sijm et al., 2020b). As a result, the potential contribution of BES to broader economic and societal objectives remains uncertain to the Dutch government, leading to limited investment in BES (Sijm et al., 2020a).

The study highlights that larger BES installations significantly enhance self-consumption rates and overall system efficiency. Policymakers may consider implementing incentive programs tailored to encourage the deployment of larger BES capacities. Such incentives can include higher subsidy rates for larger systems. Moreover, establishing a framework for aggregated BES systems, where multiple households or communities can share a large BES, would optimise economies of scale and lower costs per kWh (Sturmberg et al., 2021). Additionally, installing larger BES units can overcome a key market barrier in the Netherlands, where minimum bid requirements for participating in the electricity market cannot be met by small-scale BES systems (Mir Mohammadi Kooshknow and Davis, 2018).

The study results also indicate that adopting advanced EMS with optimisation techniques for BES operation is crucial for maximising the benefits of PV-BES systems. Policies could encourage the use of smart EMS technologies that optimise BES charging and discharging cycles. By utilising predictive algorithms and real-time data, these EMSs can dynamically adjust energy flows, reduce discharge frequency and depth, and extend BES lifespan, thereby lowering replacement costs and enhancing return on investment for consumers.

CRediT authorship contribution statement

F. Norouzi: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Data curation, Conceptualization. **Aditya Shekhar:** Writing – review & editing, Validation, Supervision, Conceptualization. **T. Hoppe:** Writing – review & editing, Validation, Supervision, Conceptualization. **P. Bauer:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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