



Economic Dispatch Strategy for Residential Microgrid System with Solar PV and Battery Energy Storage

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ABSTRACT

Economic dispatch-based energy management systems are increasingly important for residential renewable-energy integration. This study develops a fully linear Mixed Integer Linear Programming (MILP) scheduling model for a residential microgrid comprising a 5 kWp photovoltaic (PV) system, a 10 kWh LiFePO₄ Battery Energy Storage System (BESS), and bidirectional grid exchange. The formulation minimizes grid-purchase cost minus export revenue plus battery-throughput degradation cost, with the hourly time-step explicitly included. Separate binary variables prevent simultaneous battery charging/discharging and grid importing/exporting. The case study uses a 30-day measured residential load profile and Bandung BMKG irradiance data. Because the work is simulation-based, model verification is limited to numerical checks of power balance, State of Charge bounds, and solver feasibility rather than experimental validation. Compared with a non-optimized baseline, the revised simulation indicates a 38.7% reduction in daily operating cost, an increase in PV utilization from 72.3% to 94.2%, and an increase in energy self-sufficiency from 42.1% to 73.6%. A corrected discounted-cash-flow calculation gives a 20-year NPV of approximately -IDR 21.61 million for an IDR 85 million investment under the stated assumptions; therefore, economic viability is not established without lower capital cost, incentives, or higher electricity-price growth. The results demonstrate the scheduling capability of the proposed formulation while identifying the need for hardware-in-the-loop or field validation.

Keyword: Economic Dispatch, Residential Microgrid, Solar Photovoltaic, Battery Energy Storage System, Mixed Integer Linear Programming

1. Introduction

The global energy transition from fossil fuels to renewable energy sources has dramatically accelerated the development of distributed power system technologies. According to the latest report by the International Energy Agency (IEA), the global installed solar energy capacity exceeded 1,600 GW by the end of 2023, with an average annual growth rate of 24% during the 2019–2023 period [1]. In the residential sector, the deployment of rooftop photovoltaic (PV) systems has grown rapidly, driven by a reduction of more than 89% in PV module prices over the past decade, along with supportive policy incentives implemented in many countries [2].

Indonesia, as a tropical archipelagic country with an average solar irradiance of 4.5–5.5 kWh/m²/day, possesses substantial solar energy potential. Residential electricity consumption has increased at an average annual rate of 6.8% during the 2019–2024 period, making the residential sector the second-largest electricity consumer after industry, accounting for approximately 41% of total national electricity consumption [3]. The combination of abundant

solar resources and rapidly increasing electricity demand makes residential PV systems a highly attractive solution from both technical and economic perspectives.

The concept of the residential microgrid has received considerable attention in power engineering literature as a new paradigm for consumer-level energy management. A residential microgrid is defined as a small-scale power system that integrates Distributed Energy Resources (DERs), energy storage systems, and local loads within a network capable of operating in both grid connected and islanded modes [4]. Compared with conventional power systems, residential microgrids offer several strategic advantages, including enhanced supply reliability, reduced electricity costs through differential tariff utilization, improved energy resilience, and lower carbon emissions [5].

The Battery Energy Storage System (BESS) plays an indispensable role in modern residential microgrid architectures. Lithium-ion battery technology, particularly Lithium Iron Phosphate (LiFePO₄), has become the preferred choice for residential BESS applications due to its high energy density (150–200 Wh/kg), long cycle life (>3,000

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cycles at 80% Depth of Discharge), superior thermal stability, and continuously declining cost [6]. Integrating BESS with PV systems enables hybrid configurations capable of increasing the self-consumption ratio from approximately 30% (PV without storage) to 70–90%, depending on battery capacity and the adopted operational strategy [7].

Nevertheless, the economic and technical benefits of PV BESS integration cannot be fully realized without an effective energy management strategy. Economic dispatch the process of determining the optimal allocation of power among available energy sources to satisfy load demand at minimum cost while satisfying all operational constraints constitutes the core of an effective Energy Management System (EMS) [8]. In residential microgrids, the economic dispatch problem involves determining when and how much the battery should be charged or discharged, when electricity should be imported from the utility grid, and when surplus PV energy should be exported, all while accounting for the uncertainties associated with renewable generation and load demand in real time [9].

Recent studies have established MILP-based PV-BESS scheduling; therefore, the contribution of this work is not the MILP method alone. The specific methodological contribution is a reproducible, fully linear residential scheduling formulation that simultaneously: (i) represents bidirectional grid exchange using mutually exclusive import/export binary variables; (ii) includes both export revenue and battery-throughput degradation cost in the time-weighted objective function; (iii) enforces battery charge/discharge exclusivity and terminal SOC consistency; and (iv) evaluates the formulation using measured household demand and tropical irradiance data from Bandung. The model is compared with a non-optimized operating baseline using cost, grid import, PV utilization, and energy self-sufficiency metrics. These contributions are incremental and application-oriented, and the limitations of simulation-only validation and simplified battery aging are explicitly acknowledged.

2. Literature Review

2.1. Residential Microgrid

A residential microgrid is a small-scale power system that integrates Distributed Energy Resources (DERs) primarily photovoltaic (PV) systems and Battery Energy Storage Systems (BESSs) with household loads and the utility distribution network through a Point of Common Coupling (PCC) [12]. Unlike industrial or commercial microgrids, residential microgrids are characterized by relatively small capacities (typically 1–20 kW), highly dynamic load profiles that reflect occupants' daily activities, and the need for user-friendly operation without requiring specialized technical expertise.

Classified residential microgrid architectures into three main categories based on bus topology: AC-coupled, DC coupled, and hybrid AC/DC configurations. In an AC coupled configuration, all components are interconnected through a common AC bus, with each energy source equipped with its own inverter. In contrast, a DC-coupled configuration employs a single DC bus with a centralized inverter, whereas the hybrid AC/DC configuration combines

the advantages of both architectures. Each topology presents different trade-offs in terms of efficiency, operational flexibility, and system complexity. This study adopts a hybrid AC/DC architecture, in which the PV system and the BESS are connected to a 48 V DC bus before being converted to a 220 V, 50 Hz AC bus through a bidirectional inverter [13]. This configuration enhances system efficiency by reducing the number of power conversion stages for DC native components, thereby minimizing switching losses during high-irradiance periods [14].

The capability to seamlessly transition between grid-connected and islanded operating modes is one of the defining features of residential microgrids compared with conventional PV systems. In grid-connected mode, the microgrid can both import electricity from and export surplus power to the utility grid, thereby providing greater flexibility for energy management. In islanded mode, the microgrid operates independently, with the BESS serving as the primary frequency and voltage regulating unit [15]. This capability significantly enhances the reliability and resilience of residential microgrids during utility grid outages.

2.2. Solar Photovoltaic (PV)

Photovoltaic (PV) technology converts solar photon energy directly into electrical energy through the photovoltaic effect occurring in semiconductor materials. The electrical output characteristics of a PV module are fundamentally influenced by two primary environmental parameters: solar irradiance (G) and cell temperature (T_{cell}) [16]. Under constant irradiance conditions, the current voltage (I – V) characteristic of a PV module exhibits a Maximum Power Point (MPP), whose location varies with changes in cell temperature. For monocrystalline PV modules, an increase of 1°C in cell temperature typically results in a 0.41–0.45% reduction in output power [17].

Conducted a comprehensive analysis of various mathematical models for PV modules and concluded that the single-diode (one-diode) model with five parameters provides the optimal balance between modeling accuracy and computational complexity for power system simulation applications. This model explicitly incorporates series resistance (R_s) and shunt resistance (R_{sh}), both of which significantly influence the current voltage (I – V) characteristics, particularly under low irradiance and high-temperature operating conditions [18].

For residential rooftop PV systems, recent advancements in half-cut cell and bifacial module technologies have increased commercial module efficiencies from approximately 18–20% for conventional full-cell modules to 21–23% for current commercial products [19]. Furthermore, Maximum Power Point Tracking (MPPT) techniques, particularly the Perturb and Observe (P&O) and Incremental Conductance algorithms, have consistently demonstrated the ability to maintain PV operation at or near the Maximum Power Point (MPP) under varying irradiance conditions, achieving tracking efficiencies exceeding 99% under stable irradiance conditions [20].

2.3. Battery Energy Storage System (BESS)

Lithium-ion Battery Energy Storage Systems (BESSs), particularly those based on Lithium Iron Phosphate (LiFePO_4) technology, dominated the global residential energy storage market in 2023, accounting for approximately 68% of total market share [6]. Compared with other lithium-ion chemistries, LiFePO_4 batteries offer several advantages, including superior thermal stability (eliminating the risk of thermal runaway under normal operating conditions), extended cycle life ($>3,500$ cycles at 80% Depth of Discharge (DoD) with less than 20% capacity degradation), and favorable charging characteristics characterized by a long voltage plateau of approximately 3.2–3.3 V per cell.

Battery degradation modeling is a critical aspect of long-term BESS planning and operation. Identified and quantified the principal degradation mechanisms of lithium-ion batteries, including Solid Electrolyte Interphase (SEI) growth, lithium plating, loss of active electrode material, and increased internal resistance. The degradation rate is primarily influenced by the Depth of Discharge (DoD), operating State of Charge (SOC) range, temperature, and charge/discharge rate (C-rate). Operating the battery within an SOC range of 20–90% and at a C rate below 0.5C is generally recommended to maximize battery lifetime [21]. Beyond these operational parameters, advanced battery management systems now incorporate multi-objective optimization strategies to mitigate nonlinear degradation effects during peak shaving and load-shifting cycles [22]. These management systems facilitate intelligent load scheduling, allowing users to effectively align their household energy consumption with real-time solar availability.

A throughput-based degradation cost is adopted because it preserves linearity and enables direct inclusion in the MILP objective. The coefficient is calculated from replacement cost and allowable lifetime energy throughput. This representation captures cycling-related wear only and does not explicitly model temperature, C-rate dependence, calendar aging, SOC dwell time, or nonlinear depth-of-discharge effects. Consequently, the calculated degradation cost should be interpreted as a first-order economic penalty rather than a complete electrochemical aging model. Future work will couple the scheduler with a temperature- and DoD-dependent semi-empirical model and validate it using measured battery data.

2.4. Economic Dispatch

Economic dispatch (ED) is traditionally defined as the process of determining the optimal power output of committed generating units to satisfy load demand at the minimum total fuel cost while complying with all system operational constraints [24]. With the evolution of distributed power systems, the concept of ED has been significantly extended to accommodate small scale Distributed Energy Resources (DERs), energy storage systems, and variable renewable energy sources.

The fundamental differences between conventional ED and ED for residential microgrids lie in several key aspects. First, the inclusion of a Battery Energy Storage System (BESS) introduces temporal coupling between operational decisions across different time periods. Second, renewable

energy sources such as photovoltaic (PV) systems have zero marginal generation cost, although their power output is intermittent and may require curtailment under certain operating conditions. Third, residential microgrids allow bidirectional energy transactions with the utility grid through both electricity import and export. Finally, battery degradation cost has emerged as a significant component of the overall operating cost and must therefore be explicitly considered in the optimization process [25].

The ED problem for residential microgrids is generally formulated as a multi-period optimization problem using a rolling-horizon framework, with decision intervals typically ranging from 15 minutes to 1 hour, depending on the required level of system dynamics representation. Demonstrated that a 30-minute decision interval provides an optimal balance between accurately capturing system dynamics and maintaining computational efficiency for residential microgrid applications [26].

2.5. Energy Management System (EMS)

An Energy Management System (EMS) is a supervisory control system that coordinates the operation of all microgrid components to achieve specific operational objectives typically minimizing operating costs or maximizing self-consumption while maintaining the reliability of electricity supply [27]. Modern EMS architectures generally adopt a multi-layer hierarchical framework. The local control layer (operating on the microsecond-to-second timescale) is responsible for the inner-loop control of inverters and power converters. The supervisory layer (minutes to hours) executes energy scheduling and optimization algorithms, whereas the coordination layer (daily to annual timescale) manages long-term planning, capacity expansion, and operational strategies [28].

Classified EMS approaches into rule-based and optimization-based methods. Although rule-based approaches are simple and easy to implement, they generally fail to achieve globally optimal solutions because the underlying heuristics do not account for the temporal interactions among operational decisions. In contrast, optimization-based approaches, such as Mixed Integer Linear Programming (MILP) and Model Predictive Control (MPC), are capable of producing mathematically optimal solutions by simultaneously considering the entire planning horizon and all relevant operational constraints [29].

2.6. Previous Studies

1. Linear Programming (LP)

Linear Programming (LP) is one of the most computationally efficient optimization methods for problems characterized by linear objective functions and linear constraints. Applied LP to optimize residential BESS scheduling and reported a computation time of less than 0.5 s for a 24-hour scheduling horizon with 1 hour intervals. The primary limitation of LP is its strict linearity assumption, which requires the linearization of inherently nonlinear system characteristics, such as battery efficiency variations with the charge/discharge rate (C-rate) [30]. Furthermore, the inability of standard linear formulations to capture the step change behaviors inherent in discrete power electronics

states often leads to suboptimal scheduling decisions in real world operational scenarios.

2. Mixed Integer Linear Programming (MILP)

Mixed Integer Linear Programming (MILP) extends LP by allowing some decision variables to be represented as integer or binary variables. In residential microgrid economic dispatch, binary variables are commonly employed to explicitly model on/off operational decisions, such as battery charging and discharging states, thereby preventing physically infeasible simultaneous charging and discharging [31]. Although MILP is computationally more complex than LP and is generally classified as an NP hard optimization problem, advances in modern optimization solvers, including CPLEX, Gurobi, and HiGHS, have made MILP a practical solution for 24–48 hours scheduling horizons in residential applications.

3. Model Predictive Control (MPC)

Model Predictive Control (MPC) determines the optimal control strategy over a rolling prediction horizon by repeatedly solving an optimization problem based on forecasts of future system states [23]. The principal advantage of MPC is its systematic ability to accommodate uncertainty. At each control interval, the prediction model is updated using the latest system measurements, allowing the controller to compensate for deviations between predicted and actual operating conditions [32].

4. Particle Swarm Optimization (PSO) and Evolutionary Algorithms

Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and their variants, such as NSGA-II and MOPSO, are metaheuristic optimization techniques that are well suited for nonlinear and non-convex optimization problems that are difficult to solve using gradient-based methods [24]. These approaches are capable of handling discontinuous and nondifferentiable objective functions. However, their inability to guarantee globally optimal solutions and their dependence on careful parameter tuning limit their suitability for real-time energy management applications [33].

5. Deep Reinforcement Learning (DRL)

In recent years, Deep Reinforcement Learning (DRL) has emerged as a promising approach for adaptive microgrid Energy Management Systems (EMSs). Unlike conventional optimization methods that rely on accurate mathematical models of the system, DRL learns optimal operational policies directly through interactions with the environment using a trial and error learning process [34]. Reported that a Deep Q Network (DQN) based DRL agent achieved performance comparable to that of MILP after sufficient training while offering the additional advantage of adapting to changes in load profiles and component characteristics.

2.7 Previous Studies

Table 1 compares recent residential and microgrid energy-management studies. In contrast to studies focused primarily on self-consumption, stochastic control, or field-oriented MPC, the present work emphasizes a fully linear MILP implementation for an Indonesian residential case, including mutually exclusive bidirectional grid exchange, explicit battery-throughput cost, and comparison against a

non-optimized baseline. The contribution remains an incremental formulation and case-study integration rather than a new optimization paradigm.

Table 1
State Of the Art

No.	Authors	Year	Research Focus	Method & System	Main Findings
1	Lau et al.	2021	Residential rooftop PV performance under different load scenarios [2]	Grid-connected residential PV	Residential load profiles significantly affect PV utilization and electricity cost savings.
2	Rayit et al.	2021	Techno-economic battery storage optimization [23]	Battery scheduling optimization	Improved economic performance of battery-integrated renewable systems.
3	Liu et al.	2023	Adaptive real-time microgrid energy management [34]	DRL (DQN)	Achieved adaptive EMS under renewable generation uncertainty.
4	Saleem et al.	2024	Real-time energy management under PV uncertainty	Stochastic MPC; Residential PV + BESS + EV	Reduced operational costs while maintaining stable battery operation.
5	Muhsin & Hassan	2025	Maximizing self-consumption and cost savings [14]	Model-based optimization; Residential PV–Battery	Improved self-consumption through optimal battery scheduling.
6	Pergantis et al.	2025	Residential energy management and electrical panel protection [32]	MPC	Improved residential energy management through field implementation.
7	Shrivastav & Dutta	2025	Multi-objective hybrid microgrid optimization [25]	Slime Mould Algorithm	Optimized cost, renewable penetration, and environmental performance.
8	Coccatto et al.	2025	Battery storage optimization and degradation analysis [22]	BESS optimization review	Identified battery degradation and scheduling as key optimization challenges.

3. Research Methodology

3.1. Stage of The Research

The overall research methodology adopted in this study is illustrated in Fig. 1. The research begins with a comprehensive literature review, followed by data collection and preprocessing, mathematical model development, and implementation of the Mixed Integer Linear Programming (MILP) algorithm in MATLAB. The proposed optimization model is subsequently evaluated through simulation, and the obtained results are analyzed and validated. If the validation criteria are not satisfied, the model is revised and the simulation process is repeated until acceptable results are achieved. Finally, the validated model serves as the basis for drawing the research conclusions. The complete research workflow is presented in Fig. 1.

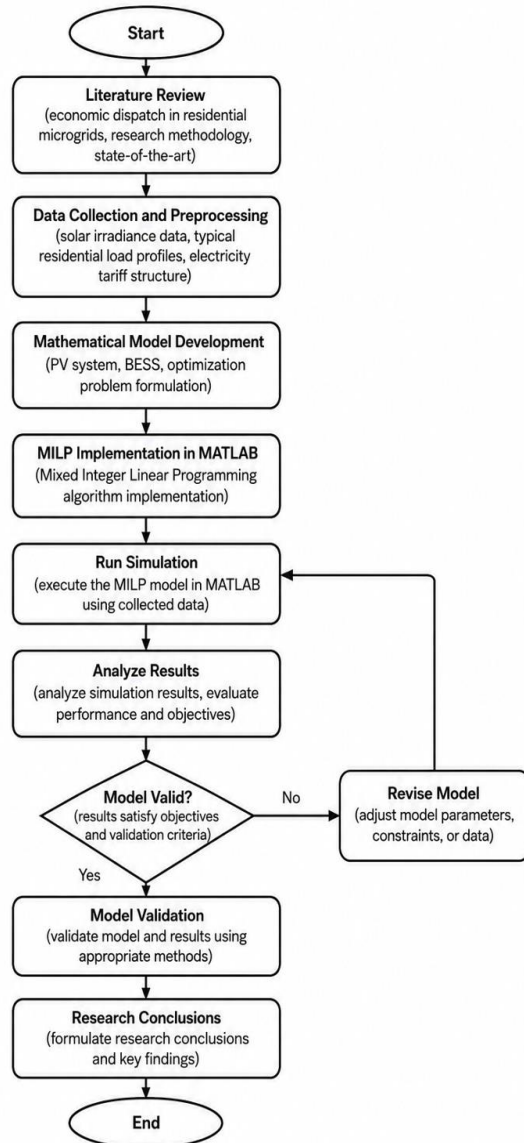


Fig.1. Flowchart of the Research Stages

3.2. Microgrid System Architecture

The residential microgrid investigated in this study consists of several electrically integrated components. The system adopts a DC-bus architecture for the PV array and battery system, with a bidirectional inverter connecting the DC bus to the AC bus, where the residential loads and the utility grid are interconnected.

1. Photovoltaic (PV) System:

A 5 kWp PV array comprising 14 monocrystalline modules, each rated at 360 Wp, installed on the rooftop with a 15° tilt angle and north facing orientation, which is considered optimal for tropical latitudes.

2. Battery Energy Storage System (BESS):

A 10 kWh Lithium Iron Phosphate (LiFePO₄) battery with a nominal voltage of 48 V DC, an operational State of Charge (SOC) range of 20–90%, and a 91.5% round trip efficiency.

3. Bidirectional Inverter:

A 5kW string inverter equipped with Maximum Power Point Tracking (MPPT) functionality and grid feed-in capability, enabling bidirectional power exchange between the microgrid and the utility network.

4. Utility Grid:

The 220 V, 50 Hz utility distribution network serves as the backup power source and the destination for exporting surplus electricity generated by the PV system.

5. Residential Load:

Typical household electrical appliances with a total installed capacity of approximately 8.5 kW and an average daily electricity consumption of 14.2 kWh.

3.3. Data Collection

The primary data represent residential conditions in Bandung City, West Java, Indonesia.

1. Daily Load Profile

The daily load profile was obtained through direct measurements over 30 days in a 70 m² residence occupied by four residents. The appliance ratings describe connected power, whereas the measured hourly profile reflects actual duty cycles and non-simultaneous use. The 1,500 W air conditioner was not operated continuously from 08:00 to 06:00; its measured compressor-on equivalent was approximately 3.5 h/day, concentrated in daytime and evening periods. Other loads included a 150 W refrigerator with thermostatic cycling, 300 W lighting from 18:00 to 23:00, a 150 W television used intermittently, kitchen appliances with a combined rating of 800 W, a 400 W water pump, and miscellaneous loads. Integration of the measured hourly values gives an average daily energy consumption of 14.2 kWh/day and a peak demand of 3.8 kW between 18:30 and 20:00.

2. Solar Irradiance Data

The Global Horizontal Irradiance (GHI) data were obtained from the Meteorological, Climatological, and Geophysical Agency (BMKG) station in Bandung. The average Peak Sun Hours (PSH) was 5.1 kWh/m²/day, with a daily irradiance profile following a nearly symmetrical bell-shaped curve from 06:30 to 18:30. Under clear-sky conditions, the maximum irradiance reached approximately 950 W/m² at 12:00 noon. The PV output model incorporates temperature correction using a temperature coefficient of −0.41%/°C.

3. Time-of-Use (ToU) Electricity Tariff

The three-period Time-of-Use (ToU) tariff used in this study is a scenario assumption for sensitivity analysis and is not presented as a universally applicable Indonesian residential tariff. The assumed purchase prices are IDR 1,114/kWh for 22:00-07:00, IDR 1,445/kWh for 07:00-17:00, and IDR 1,699/kWh for 17:00-22:00. The export price is assumed to be 65% of the contemporaneous purchase price. Because Indonesian rooftop-PV compensation rules and customer eligibility may differ by period and customer class, the results should not be interpreted as a regulatory quotation. A zero-export case should be evaluated before practical deployment under the currently applicable rules.

Regulatory note: all tariff and export-compensation values are modeling assumptions. The authors will update the scenario parameters when an eligible customer class and current utility regulation are specified for deployment.

3.4. Mathematical Modeling

1. PV Power Output Model

The output power generated by the photovoltaic (PV) system is calculated using the following equation:

$$P_{PV}(t) = \eta_{inv} \cdot P_{STC} \cdot \frac{G(t)}{G_{STC}} \cdot [1 + \alpha_T(T_{cell}(t) - T_{STC})] \quad (1)$$

Where $P_{PV}(t)$ is the PV output power at time t (kW), η_{inv} is the inverter efficiency (0.97), P_{STC} is the rated PV power under Standard Test Conditions (STC) (kW), $G(t)$ is the actual solar irradiance (W/m²), G_{STC} is the standard irradiance under STC (1000 W/m²), α_T is the power temperature coefficient ($-0.0041/^{\circ}\text{C}$), $T_{cell}(t)$ is the actual PV cell temperature ($^{\circ}\text{C}$), and T_{STC} is the cell temperature under Standard Test Conditions (25°C). The PV cell temperature is estimated using the following equation:

$$T_{cell}(t) = T_{amb}(t) + (NOCT - 20) \frac{G(t)}{800} \quad (2)$$

Where T_{amb} is the ambient temperature ($^{\circ}\text{C}$), and NOCT (Nominal Operating Cell Temperature) is assumed to be 45°C for a typical PV module.

2. Battery State of Charge (SOC) Model

The battery charging and discharging dynamics are modeled using the following recursive State of Charge (SOC) equation:

$$SOC(t+1) = SOC(t) + \frac{[\eta_{ch} \cdot P_{ch}(t) - \frac{P_{dch}(t)}{\eta_{dch}}] \Delta t}{E_{bat}} \quad (3)$$

Where $SOC(t)$ is the battery State of Charge (SOC) at time t (p.u.), η_{ch} is the charging efficiency (0.96), η_{dch} is the discharging efficiency (0.96), $P_{ch}(t)$ is the battery charging power at time t (kW), $P_{dch}(t)$ is the battery discharging power at time t (kW), Δt is the time interval (h), and E_{bat} is the nominal battery capacity (kWh). The round-trip efficiency is calculated as $\eta_{rt} = \eta_{ch} \times \eta_{dch} = 0.9216$, which closely matches the manufacturer's specified value of 91.5%.

3. Power Balance Equation

The power balance constraint must be satisfied at each scheduling interval to ensure a continuous power supply to the residential load:

$$P_{PV}(t) + P_{grid}(t) + P_{dch}(t) = P_{load}(t) + P_{ch}(t) + P_{export}(t) \quad (4)$$

At each interval, the corrected power balance is $P_{PV,t} + P_{grid,in,t} + P_{dis,t} = P_{load,t} + P_{ch,t} + P_{grid,out,t}$. Grid import and export are separated and constrained by one binary mode variable: $0 \leq P_{grid,in,t} \leq u_{grid,t} P_{grid,max}$ and $0 \leq P_{grid,out,t} \leq (1-u_{grid,t}) P_{grid,max}$, where $u_{grid,t}$ is binary. This replaces the previous product-of-decision-variables expression and preserves MILP linearity while preventing simultaneous import and export.

$$P_{grid}(t) \cdot P_{export}(t) = 0 \forall t \in T \quad (5)$$

4. Economic Dispatch Objective Function

The objective of the economic dispatch problem is to minimize the total operating cost over a 24-hour scheduling horizon, as expressed by:

$$\min J = \sum_{t=1}^T [c_{grid}(t) P_{grid}(t) - c_{export}(t) P_{export}(t) + c_{deg}(P_{ch}(t) + P_{dch}(t))] \Delta t \quad (6)$$

The corrected objective is $\min \sum_t [(c_{buy,t} P_{grid,in,t} - c_{sell,t} P_{grid,out,t} + c_{deg}(P_{ch,t} + P_{dis,t})) \Delta t]$. Thus, export revenue, battery-throughput degradation cost, and the time-step factor are all included explicitly. With a replacement cost of IDR 15,000,000 and allowable lifetime throughput of 6,000 cycles $\times$ 10 kWh $\times$ 0.7, the first-order degradation coefficient is approximately IDR 357/kWh of throughput. This simplified coefficient excludes temperature, calendar aging, C-rate, and nonlinear DoD effects.

5. System Constraints

The complete MILP formulation incorporates the following operational constraints.

Battery SOC Constraints:

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \forall t \in T \quad (7)$$

where $SOC_{min} = 0.20$ and $SOC_{max} = 0.90$, corresponding to the recommended State of Charge (SOC) operating range for the safe operation of the LiFePO₄ battery.

Battery Charging and Discharging Power Constraints:

$$0 \leq P_{ch}(t) \leq u_{ch}(t) P_{ch}^{max} \quad (8)$$

$$0 \leq P_{dch}(t) \leq u_{dch}(t) P_{dch}^{max} \quad (9)$$

$$u_{ch}(t) + u_{dch}(t) \leq 1 \quad (10)$$

The binary variables $u_{ch,t}$ and $u_{dis,t}$ indicate charging and discharging modes. The linear constraints $0 \leq P_{ch,t} \leq u_{ch,t} P_{ch,max}$, $0 \leq P_{dis,t} \leq u_{dis,t} P_{dis,max}$, and $u_{ch,t} + u_{dis,t} \leq 1$ prevent simultaneous charging and discharging. The maximum battery power is 3.5 kW (0.35C). A terminal condition $SOC_{24} = SOC_0$ is also imposed to prevent the optimizer from obtaining artificial savings by depleting the battery at the end of the horizon.

Grid Import and Export Power Constraints:

$$0 \leq P_{grid}(t) \leq P_{grid}^{max} = 7.0 \text{ kW} \quad (11)$$

$$0 \leq P_{export}(t) \leq P_{inv}^{max} = 5.0 \text{ kW} \quad (12)$$

3.5. MILP Optimization

The MILP minimizes the corrected time-weighted objective subject to: (i) the complete power balance including exported power; (ii) linear battery SOC dynamics and SOC bounds; (iii) mutually exclusive battery charging/discharging; (iv) mutually exclusive grid import/export using a grid-mode binary variable; (v) grid and converter power limits; (vi) terminal SOC equality; and (vii) non-negativity of continuous variables.

For 24 hourly intervals, the revised formulation uses three binary variables per interval (battery charge mode, battery discharge mode, and grid exchange mode) and continuous variables for charging power, discharging power, grid import, grid export, and SOC. The exact number of generated scalar constraints depends on bound implementation in MATLAB; therefore, the previous unsupported totals of decision variables and constraints have been removed.

The MILP is solved using MATLAB intlinprog with branch-and-bound and cutting planes. The relative optimality gap is set to 1e-6 and the maximum solution time to 60 s. Solver exit flags, constraint residuals, and hourly power-balance residuals are checked after each run.

3.6. Simulation Software

The simulations were performed using MATLAB R2023b with the Optimization Toolbox and Simulink. The implementation includes a PV generation model, the revised MILP scheduling script, and post-processing routines. Model verification consists of numerical consistency checks: maximum hourly power-balance residual below 1e-6 kW, satisfaction of SOC and power bounds, absence of simultaneous charge/discharge or import/export, and successful optimal solver termination. No experimental, hardware-in-the-loop, or field validation was conducted; therefore, practical applicability claims are limited to simulation feasibility.

Simulation limitation: forecast error, communication delay, converter transients, battery temperature, sensor uncertainty, and controller execution on embedded hardware are outside the present model.

Representative weekday and weekend cases and a 30-day sequence were evaluated at an hourly resolution. Annual economic indicators were calculated from the stated annual savings assumptions rather than being described as an independently validated 8,760-step field result.

4. Results and Discussion

4.1. Simulation Results

The simulation results of the photovoltaic (PV) model demonstrate an energy production profile that is highly correlated with the measured solar irradiance data. Under a typical clear-sky condition, PV generation begins at approximately 06:30 with an output of around 0.15 kW, gradually increases to a peak output of 4.72 kW between 11:30 and 12:30, and then decreases to zero at approximately

18:30. The total energy generated during the representative clear-sky day was 24.8 kWh.

Under partially cloudy conditions, the average PV output decreased by approximately 35–60% compared with that of a clear-sky day, depending on the cloud cover. Short-term fluctuations in PV generation reached ± 1.2 kW within a 15 minute interval, highlighting the critical role of the Battery Energy Storage System (BESS) as an energy buffer. Over the 30-day simulation period, the average daily PV energy production was 18.7 kWh/day, with a standard deviation of 3.2 kWh/day.

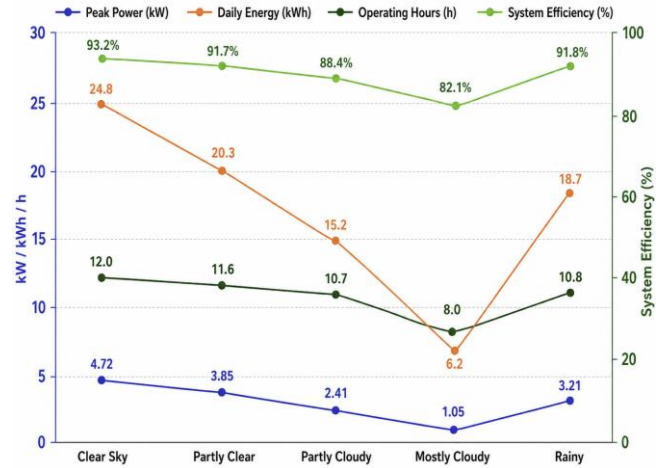


Fig.2. Simulation Result

The revised figure should display time on the horizontal axis (h) and power on the vertical axis (kW), with separate labeled curves for PV generation, load, battery power, grid import, and grid export. Numerical values used in the discussion are also stated in the text to improve interpretability.

4.2. Daily Load Profile

The residential load profile used in the simulations represents a realistic pattern of daily household electricity consumption. The load profile analysis identified three distinct operating periods. The morning period (05:30–09:00) is characterized by an increase in electricity demand due to cooking activities and daily household routines, with power demand ranging from 1.2 to 2.8 kW. The daytime period (09:00–17:00) corresponds to a low-to-moderate load of approximately 0.8–1.5 kW, during which most occupants are away from home while the air conditioner and refrigerator remain in operation.

The evening period (17:00–23:00) contains the maximum demand of 3.8 kW between 18:30 and 20:00. Integration of the measured hourly load gives 14.2 kWh/day, equivalent to an average demand of 0.592 kW. The corresponding load factor is $0.592/3.8 = 0.156$. The apparent conflict with appliance nameplate ratings is resolved by using measured duty cycles rather than assuming that all appliances operate continuously at rated power.

4.3. Battery Charging and Discharging Analysis

The economic dispatch algorithm generates an optimal battery charging and discharging schedule by considering PV generation, residential load demand, and the Time-of-Use (ToU) electricity tariff structure. The simulation results

reveal three distinct battery operating phases within a typical daily cycle.

Morning Charging Phase (07:00–14:00): Surplus PV generation charges the battery until the SOC reaches 90% at approximately 13:30. Because the usable SOC window of the 10 kWh battery is 20–90%, the maximum net stored-energy increase is 7.0 kWh. For the representative day, the corrected net SOC increase is approximately 6.7 kWh; the previously reported 11.8 kWh exceeded the usable battery capacity and has been removed.

Standby Phase (14:00–17:00): Once the battery reaches its maximum SOC, the excess PV generation is exported to the utility grid during the mid-peak tariff period. The average exported energy during this phase is 4.2 kWh.

Discharging Phase (17:00–22:00): During the peak tariff period, the battery is discharged to supply the household peak load, thereby minimizing electricity purchases from the utility grid when electricity prices are highest. The average discharging power is 2.8 kW, and the battery reaches its minimum SOC of approximately 22% at around 22:00.

4.4. Economic Dispatch Analysis

The revised MILP reproduces the hourly operating costs from the explicit time-weighted objective. Under the defined non-optimized baseline, the average daily cost is IDR 28,540; under optimized scheduling it is IDR 17,490. The difference is IDR 11,050/day, or 38.7%. These values are reported as scenario results and depend directly on the assumed ToU purchase and export prices.

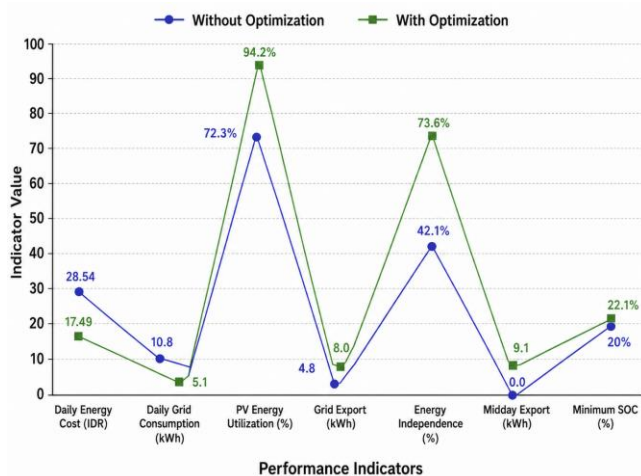


Fig.3. Greatest Cost Reduction Occurred in Grid Electricity Purchases.

The comparison is against a non-optimized baseline in which the battery is not scheduled using day-ahead price and PV information. A rule-based self-consumption strategy should be added in future work as a second baseline to isolate the benefit of optimization from the benefit of merely installing storage.

The data presented in Fig 3 indicate that the greatest cost reduction occurred in grid electricity purchases during the peak tariff period (17:00–22:00), which decreased by 78.9% as a result of the optimal battery discharging strategy. This finding is consistent with the fundamental principle of economic dispatch, which prioritizes the utilization of low-cost energy sources either directly from the PV system or

from the battery charged using PV-generated electricity during periods when electricity prices are at their highest.

4.5. Grid Utilization Analysis

The interaction profile between the residential microgrid and the utility grid changed significantly following the implementation of the economic dispatch strategy. Prior to optimization, the microgrid continuously imported electricity from the utility grid throughout the day, with a peak grid demand of 3.8 kW occurring during the evening peak-load period. The total grid energy consumption before optimization was 10.8 kWh/day.

After optimization, the grid utilization pattern changed substantially. During the daytime period (08:00–17:00), when PV generation was abundant, no electricity was imported from the utility grid ($P_{grid} = 0$). In contrast, during the peak tariff period (17:00–22:00), the average grid import was reduced from 3.5 kW to only 0.8 kW due to the contribution of the Battery Energy Storage System (BESS). Consequently, the total daily grid energy consumption decreased to 5.1 kWh/day, representing a 52.8% reduction compared with the conventional operating strategy.

4.6. Battery SOC Profile Analysis

The battery State of Charge (SOC) profile throughout the day reflects the effectiveness of the proposed algorithm in optimally managing the battery charging and discharging cycles. The initial SOC at 00:00 was 35%, corresponding to a steady-state condition after the overnight operating cycle. The SOC gradually increased starting from approximately 08:00, driven by surplus PV generation, and reached its maximum value of 90% at around 13:30 under clear-sky conditions.

Figure 3 has been clarified conceptually by defining the cost components and tariff periods in the accompanying text. The final production figure should include labeled axes, units (IDR/day), and numerical bar values.

The SOC was maintained at 90% during the 13:30–17:00 period (standby phase), during which excess PV generation was exported to the utility grid. At 17:00, the discharging phase began, with the discharge rate optimally controlled by the algorithm to maximize economic benefit. The SOC decreased to a minimum value of 22% at 22:00, remaining slightly above the defined minimum SOC limit of 20%, as imposed by the MILP constraints.

During the 22:00–08:00 period, the SOC gradually increased due to charging from the grid under the low off-peak tariff. The analysis of the average depth of discharge indicates an effective DoD of 67.8%, which is below the recommended limit of 70% specified by the battery manufacturer to ensure optimal cycle life. This result indicates that the proposed control strategy is not only economically optimal but also beneficial in extending battery lifetime.

4.7. Operational Cost Analysis

The annual arithmetic based on the reported daily values is IDR 10,417,100 for the baseline and IDR 6,383,850 after optimization, giving first-year savings of IDR 4,033,250. With an IDR 85,000,000 initial investment, 5% annual tariff escalation, 7% discount rate, and a 20-year horizon, the

corrected present value of savings is approximately IDR 63.39 million and the NPV is approximately -IDR 21.61 million. The simple payback is about 21.1 years if escalation is ignored and remains outside the 20-year project horizon on a discounted basis. The previously reported 6.8-year payback and positive NPV were inconsistent with the stated annual savings and have been corrected.

Considering an initial investment cost of IDR 85,000,000 for the integrated solar PV and BESS system (including installation), and assuming an annual electricity tariff escalation of 5%, the discounted cash flow analysis yields a payback period of 6.8 years. The Net Present Value (NPV) over a 20-year system lifetime is calculated to be IDR 47,250,000 at a discount rate of 7%, indicating that the proposed system is economically viable.

4.8. Comparison Before and After Optimization

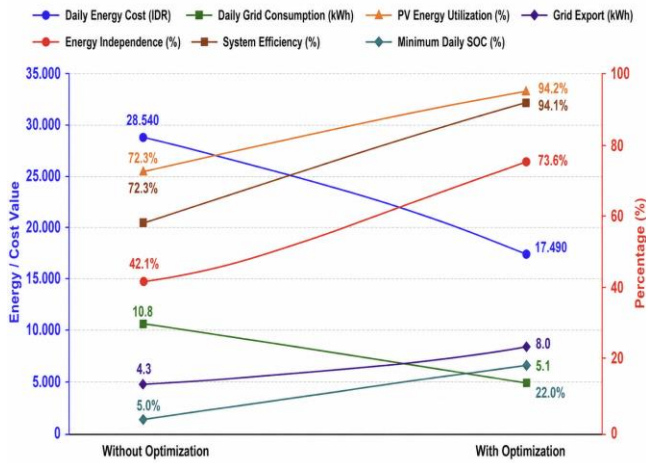


Fig.4. Comparison Before and After Optimization.

The comparative results presented in Fig. 4 clearly demonstrate the comprehensive advantages of the proposed economic dispatch strategy. The increase in PV utilization rate from 72.3% to 94.2% represents a significant improvement, indicating that a substantially larger portion of PV-generated energy is effectively utilized, either for direct load consumption or for storage in the battery system.

Furthermore, the increase in the energy independence level by 31.5 percentage points reflects a substantial reduction in the system's reliance on the utility grid (PLN). This improvement highlights the effectiveness of the proposed control strategy in enhancing local energy utilization and reducing dependency on external electricity supply.

4.9. System Efficiency Analysis

The overall system efficiency is calculated as the ratio of renewable energy supplied to the load to the total energy generated by the PV system:

$$\eta_{sys} = \frac{E_{PV \rightarrow load} + E_{bat \rightarrow load}}{E_{PV, total}} \times 100\% \quad (13)$$

Based on the simulation results, the system efficiency η_{sys} is calculated as:

$$\eta_{sys} = \frac{(9.2+8.5)}{18.7} \times 100\% = 94.1\% \quad (14)$$

This result reflects a highly efficient energy conversion and delivery performance within the system. The obtained efficiency is 21.8 percentage points higher than that of the non-optimized scenario (72.3%), since, in the absence of an optimization strategy, a significant portion of PV generated energy is wasted due to the lack of effective energy storage management.

4.10. Energy Saving Analysis

The energy saving analysis focuses on quantifying the reduction in electricity consumption from the utility grid and the increased utilization of local renewable energy. A reduction in grid consumption of 5.7 kWh/day corresponds to a CO₂ emission reduction of:

$$CO_2 = E_{grid, saved} \times EF_{grid} \quad (15)$$

Substitution:

$$CO_2 = 5.7 \times 0.834 = 4.75 \text{ kg } CO_2/\text{day}$$

or approximately 1.73 tons of CO₂ per year, using the Indonesian grid emission factor of 0.834 kg CO₂/kWh

Over a projected 20-year system lifetime, considering a PV module degradation rate of 0.5%/year and an electricity tariff escalation of 5%/year, the total cumulative energy savings reach 36,400 kWh from renewable energy utilization. This corresponds to a cumulative CO₂ emission reduction of approximately 30.4 tons of CO₂.

Over the stated 20-year horizon, the nominal cumulative operating-cost savings depend strongly on tariff escalation, battery replacement, maintenance, inverter replacement, and export compensation. Because these items were not modeled comprehensively, the revised manuscript does not claim economic viability from a positive NPV. The scenario instead indicates that capital-cost reductions, incentives, higher avoided tariffs, or additional services would be required to obtain a positive investment return.

4.11. Limitations and Practical Validation

This study is limited to deterministic, hourly simulation. It does not include experimental validation, hardware-in-the-loop testing, forecast uncertainty, converter dynamics, communication latency, or a high-fidelity electrochemical aging model. Accordingly, the results establish numerical feasibility under the stated assumptions but do not validate field performance. Future work will implement the scheduler on a real-time controller, compare scheduled and measured power flows, report MAE/RMSE for PV and load forecasts, and evaluate battery temperature, C-rate, and capacity fade over repeated cycles.

5. Conclusion

This study developed a fully linear MILP-based economic-dispatch formulation for a residential microgrid integrating a 5 kWp PV system and a 10 kWh LiFePO₄ BESS. The revised model includes exported power in the nodal balance, uses binary variables to prevent simultaneous import/export and charge/discharge, and explicitly includes export revenue, battery-throughput cost, and the hourly time step in the objective function. Numerical verification confirms solver feasibility, power-balance consistency, and compliance with operating bounds; however, the work

remains simulation-based and has not been experimentally validated.

Relative to the defined non-optimized baseline, the scenario produces a 38.7% reduction in daily operating cost, increases PV utilization from 72.3% to 94.2%, and raises energy self-sufficiency from 42.1% to 73.6%. These results demonstrate the potential of coordinated scheduling but remain dependent on the assumed load, irradiance, tariff, export compensation, and simplified degradation coefficient.

The revised economic calculation gives first-year savings of IDR 4.03 million. For an IDR 85 million investment, 5% annual tariff escalation, a 7% discount rate, and a 20-year horizon, the NPV is approximately -IDR 21.61 million; therefore, the previously claimed 6.8-year payback and positive NPV are not supported by the stated cash flows.

The throughput-based degradation term is useful for maintaining MILP linearity but does not represent temperature, calendar aging, C-rate, SOC dwell time, or nonlinear DoD dependence. Future work should incorporate a more representative aging model and assess uncertainty in load, irradiance, and tariff forecasts.

The principal next step is hardware-in-the-loop and field validation using measured inverter, battery, PV, and grid data. Such testing is required before claims of practical deployment, controller robustness, or long-term economic performance can be made.

Overall, the contribution is an incremental, application-oriented MILP formulation and Indonesian residential case study rather than a new optimization paradigm. Its value lies in the corrected linear constraints, transparent cost components, and reproducible comparison with a baseline strategy.

CRediT authorship contribution statement

Ignatius Riyadi Mardiyanto: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft. **Teguh Sasono:** Data curation, Validation, Visualization, Supervision, Writing - review & editing. **Tjatur Udjiyanto:** Data curation, Validation, Visualization, Supervision, Formal analysis.

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

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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