Optimal Energy Cost Management in Microgrids with Distributed Renewable Energy and Battery Storage

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I. Executive summary

As renewable energy technologies continue to advance, smart homes and microgrids equipped with solar photovoltaics (PV), battery energy storage systems (BESS), and controllable loads have become critical enablers of sustainable energy transitions. However, residential and industrial buildings face persistent challenges, such as intermittent renewable generation and high operational costs, that make this transition difficult. To ensure reliable and affordable electricity access, efficient sizing and optimal operation of renewable systems are essential.

This project presents an optimization-based framework for the design and operation of behind-the-meter (BTM) and microgrid energy systems integrating PV generation, BESS, and the grid with various load types and flexible demand. A mixed-integer linear programming (MILP) model was developed to minimize total electricity costs while determining optimal battery charge–discharge cycles, appliance schedules, and grid import/export levels under technical and operational constraints. The model explicitly accounts for load prioritization, differentiating between critical, flexible, and curtailable loads, and ensures cost-optimal scheduling across the entire operating horizon.

The model focuses heavily on demand response strategies as a policy mechanism that encourages users to adjust their energy consumption during periods of high prices or peak grid demand. Rather than imposing rigid price restrictions, the model uses control variables: including battery charging/discharging decisions, appliance scheduling, and flexible load adjustments, to determine when to consume, defer, or store energy automatically. By integrating DR incentives, the system reduces peak demand charges, maintains critical load reliability, and shifts flexible or curtailable loads to off-peak periods in alignment with time-of-use (TOU) pricing constraints.

The dataset, derived from Open Power System Data for eleven German households, was preprocessed using a Python-based framework for cleaning, aggregation, and load classification. Following data preparation, I performed load classification to categorize appliances: refrigerators were defined as critical, dishwashers as flexible, and machinery or optional equipment as curtailable. This classification allowed for dynamic load shifting in response to demand response (DR) incentives.

To address uncertainties in key parameters such as PV generation, electricity demand, and market prices, I enhanced the deterministic DSM model by incorporating stochastic programming principles. Following the approach of K. Victor Sam Moses Babu et al. (2025)

in their study *“Demand Response Optimization MILP Framework for Microgrids with DERs,”* which analyzed seven distinct operational scenarios to achieve peak load reduction and energy cost savings, I applied similar scenario-based analyses to my household dataset. These scenarios examined the effects of variables such as high grid prices, high solar generation, low prices combined with low solar output, and conditions with high demand response participation and increased battery dispatch aimed at peak capping. Each scenario was assigned a probability to estimate the expected total cost of operation. The resulting stochastic DSM model integrates uncertainties in PV generation, load demand, and electricity prices through a discrete probabilistic framework.

In summary, I aim to demonstrate an integrated approach to demand-side management (DSM) using demand response incentives, and stochastic modeling to reduce energy costs, mitigate peak loads, and enhance the economic viability of renewable energy systems in smart homes and microgrids.

II. Introduction

Behind-the-Meter (BTM) systems have emerged as a cornerstone of decentralized energy management. They enable households and businesses to generate, store, and control their own electricity, reduce grid dependency, and enhance energy resilience.

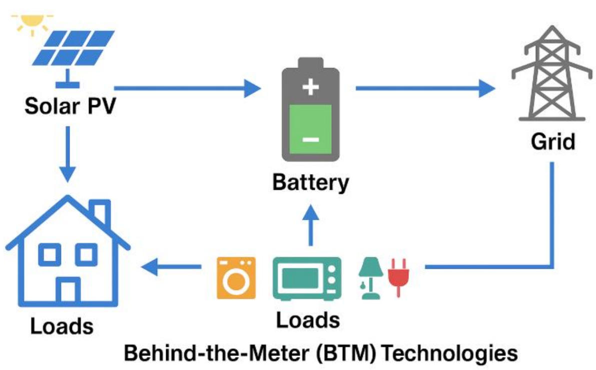


Image generated by ChatGPT.

Key components to optimize energy consumption:

- Solar PV Generation: Converts solar irradiance into electricity, offsetting grid imports during daylight hours.
- Battery Energy Storage System (BESS): Stores surplus PV power for evening consumption, reducing reliance on expensive peak-period energy.

- Load Classification: Appliances that can shift operation in time (e.g., dishwashers, EV chargers) to exploit lower electricity prices or surplus solar energy.

In a typical BTM setup, solar PV panels generate electricity that can either be used instantly, stored in a battery for later use, or exported to the grid. Battery storage plays a crucial role in shifting solar energy from daytime generation to evening consumption, minimizing costly grid imports during high-price periods. Meanwhile, smart appliances such as washing machines, dishwashers, and EV chargers can be scheduled during off-peak hours to flatten load profiles and reduce electricity bills. Together, these components create the foundation for microgrids and smart homes capable of optimizing energy use dynamically based on time-varying tariffs, demand, and weather conditions.

2.1 Background

I collected a time series dataset for residential households and small industrial buildings in Germany. energy consumption used in this project originates from the Open Power System Data – Household Data repository. This dataset contains measured time series for several residential households and small industrial buildings in Germany, and contains high-resolution measurements for household- and low-voltage-level power system modeling. This dataset is particularly valuable as it includes detailed load profiles, photovoltaic (PV) generation, and grid interaction data across multiple building types.

2.2 Dataset Overview

Type: Smart meter and device-level electricity consumption data for residential and small industrial buildings.

Resolution: Hourly (60-minute) measurement intervals.

Content:

- Electricity consumption (load)
- PV generation for selected households
- Grid import and export activity
- Appliance-level submetering for residential users
- Partial battery charge and discharge data for industrial facilities

Time Range:
2014–2019, with minor measurement gaps addressed through linear interpolation. A

representative **one-week subset from 2017** was selected for model optimization and scenario analysis to balance computational tractability with temporal diversity.

2.3 Data Cleaning and Preparation

To ensure consistency and analytical accuracy, the dataset underwent several preprocessing and feature-engineering steps prior to model implementation. These procedures included sector aggregation, normalization, load classification, and tariff setup, each contributing to the construction of a reliable and comparable optimization framework.

Sector Aggregation: All six residential buildings were aggregated into a single representative residential load profile, while three industrial buildings were combined to form an aggregated industrial sector profile. This aggregation was applied uniformly across load demand, photovoltaic (PV) generation, grid imports, and grid exports to enable sector-level analysis while preserving overall energy balance.

Power Normalization: All power values were converted from watts (W) to kilowatts (kW) using a scaling factor of 1/1000. This normalization ensured unit consistency across datasets and facilitated accurate comparisons between sectors and technologies.

Load Classification: End-use loads were categorized into three distinct groups based on their operational flexibility and criticality:

1. Critical Loads: non-deferrable essential appliances. Must always be served (e.g., refrigerator, lighting).
2. Flexible Loads: schedulable loads such as dishwashers or EV chargers. Can be time-shifted (e.g., dishwasher, EV charger).
3. Curtailable Loads: Can be shed when cost or demand is high (e.g., water heater, laundry).

This classification enabled the optimization model to incorporate realistic demand-side flexibility, which is essential for assessing the effects of demand response (DR) participation and time-shifted consumption.

Cost Feature Engineering: Annualized cost metrics were computed for both the residential and industrial sectors. These included the cost of grid imports, revenues from exports, PV generation value, and battery storage operations. The resulting cost features provided the foundation for comparing baseline and optimized scenarios, thereby quantifying potential economic benefits arising from demand-side interventions.

```
                                    Value
Metric
Grid_Import_Cost             8.919389e+07
Export_Credit                1.927663e+07
Grid_Energy_Cost             6.991726e+07
Grid_Demand_Charge           0.000000e+00
Grid_Total                   6.991726e+07
PV_SelfConsumption_Value     0.000000e+00
PV_Export_Revenue            1.927663e+07
PV_CapEx_Annual              6.387315e+06
PV_OandM_Annual              9.580972e+05
PV_Net_Impact                1.193121e+07
BESS_GridCharge_Cost         0.000000e+00
BESS_Degradation_Cost        0.000000e+00
BESS_CapEx_Annual            9.750000e+02
BESS_Net_Impact             -9.750000e+02
```

Tariff and Price Setup: To simulate realistic market conditions, a three-tier **Time-of-Use (TOU)** pricing scheme was developed to reflect hourly variations in electricity costs. This structure differentiates between off-peak, shoulder, and peak periods to incentivize load shifting and optimal energy use.

Period	Hours (24h)	Import Price ($/kWh)	Description
Off-Peak	00:00–05:00, 22:00–23:00	0.12	Low-demand hours; ideal for charging batteries or flexible loads
Shoulder	06:00–09:00, 13:00–16:00, 20:00–21:00	0.18	Moderate pricing; transitional hours between demand peaks
Peak	10:00–12:00, 17:00–19:00	0.30	High-demand periods with maximum grid congestion and cost

The implementation of this tariff structure enables the assessment of user responsiveness to dynamic price signals, supporting demand-side management strategies aimed at minimizing operational costs and reducing grid stress.

III. Optimization Model Formulation

This problem is formulated as a Mixed-Integer Linear Programming (MILP) model to capture both continuous (e.g., energy flow) and discrete (e.g., appliance on/off) decisions while ensuring linearity for computational tractability. The model formulation and Python implementation were developed with the assistance of OpenAI's language model (ChatGPT), following methodological principles inspired by Moses Babu, K., Chakraborty, S., and Pal, A. (2025), who proposed a MILP-based optimization framework for demand response operations in microgrids with distributed energy resources (DERs).

3.1 Decision Variables

The model's decision variables represent power and energy flows at each time step t over the weekly optimization horizon. These variables collectively define the energy flow across the household or industrial microgrid and determine optimal scheduling of loads and storage to minimize costs.

1. Grid import/export — electricity drawn and sent back from the grid (kWh).

   P_t^{imp} - - (kw) grid import

   P_t^{exp} - - (kw) grid export

2. Battery charge/discharge power — power going into and out the battery (kWh).

   $P_t^{ch} \in [0, P_{max}^{ch}]$ (Kw) - battery charge

   $P_t^{dis} \in [0, P_{max}^{dis}]$ (kw) - discharge

3. Served/Unserved Load

   S_t^{flex} - - served flexible load

   S_t^{flex} - - served curtailable load

   U_t^{crit} - - unserved critical (heavily penalized)

   U_t^{curt} - unserved curtailable

4. Peak Tracker

   Z^{pk} - - peak import bound (for demand charges)

3.2 Objective Function

The main goal is to minimize the total cost of electricity over the scheduling horizon, including energy charges, reliability penalties, and optional demand charges.

$$\min \sum_{t\in T}\left(c_t^{buy} P_t^{imp} - c_t^{sell} P_t^{exp}\right) + \alpha_{crit \sum_t U_t^{crit}} + \alpha_{curt \sum_t U_t^{curt}} + \alpha_{peak} Z^{pk}$$

Where:

- C_t^{buy}: : grid import price (TOU/dynamic tariff)
- C_t^{sell}: : export tariff (feed-in rate)
- α_{crit}: : penalty for unserved critical load ($/kWh)
- α_{curt}: :penalty for unserved curtailable load ($/kWh)
- α_{peak}: : demand charge rate ($/kW)

This cost includes:

1. Energy Charges the cost of buying electricity from the grid (based on time-of-use or dynamic prices).
2. Export Revenues – income earned from selling surplus solar energy back to the grid.
3. Penalty Costs – associated with unmet (unserved) critical or curtailable loads.
4. Demand Charges – additional costs for exceeding a specified peak import limit.

3.3 Constraints

(1) Power Balance Constraint:

At each hour, total supply equals total demand

$$PV(t) + P_{dis}(t) + P_{imp}(t) = \left(L_{crit}(t) - U_{crit}(t)\right) + L_{flex}(t) + L_{curt}(t) + P_{ch}(t) + P_{exp}(t)$$

The Power Balance Constraint maintains the real-time equilibrium between electricity supply and demand at every time step. It ensures that all power flows — from PV generation, battery operations, and the grid — collectively meet the total household or microgrid load.

(2) Battery State Dynamics (t = 1 hr.) and bounds:

The Battery's state of charge (SoC) evolves hourly as:

$$E_t = \vdash_{E_{t-1} + \eta^{ch} P t^{ch} - \frac{1}{\eta^{dis}} P t^{dis}, t > 0}^{E_0 + \eta^{ch} P^{ch} - \frac{1}{\eta^{dis}} P^{dis}, t = 0}; \ 0 \leq E_t \leq E_{max}$$

The battery's state of charge (SoC) defines the amount of stored energy at any hour t. It evolves dynamically based on the charging and discharging operations, accounting for round-trip efficiency losses and capacity limits.

- The first term adds the energy charged into the battery (adjusted by efficiency).
- The second term subtracts the energy discharged (also accounting for losses).

(3) TOU Based DR Caps (steer shifting and curtailment):

All flexible demand must be served across the horizon, but time of use (TOU) restricts when these loads can shift:

$$S^{flex} \leq \alpha_{\ period(t)} L_t^{flex}$$

$$S_t^{curt} + U_t^{curt} = L_t^{curt}, \ U_t^{curt} \leq \gamma_{period(t)} L_t^{curt}$$

$S_t^{flex} \leq \alpha_{TOU}(t).\ L_t^{flex}$,

$$U_t^{curt} \leq \gamma_{TOU}(t).\ L_t^{curt}$$

where

$\alpha_{TOU}(t)$ = 0.25 (peak), 1.5 (shoulder), or 3.0 (off peak), depending on the hour of the day.

Under Time-of-Use (TOU) constraints, flexible loads can be shifted to different hours (e.g., dishwasher, EV charging), and curtailable loads can be partially reduced (e.g., HVAC, lighting). For example, during peak hours, TOU =0.25.

i. Peak: limited flexibility and higher curtailment
ii. Shoulder: moderate flexibility
iii. Off-peak: high flexibility, minimal curtailment

(4) Peak Demand Constraint (Demand Charge)

$P_t^{imp} \leq Z^{imp}\ \forall t\ ,\ P_t^{imp} \leq p_{cap}^{grid}$

The peak demand constraint ensures that the household's or microgrid's maximum grid import does not exceed an optimized threshold. It penalizes high instantaneous imports. This encourages strategic battery discharge and demand response actions during critical hours, effectively flattening the load curve and reducing demand charges on the electricity bill.

3.4 Formulation of Model using PulP:

def build_dsm_model_DR( ):

```
# ---- Parameters from dv ----
c_buy  = dv["Import_Price"].to_dict()
c_sell = dv["Export_Price"].to_dict()
Lcrit  = dv["Lcrit_kW"].to_dict()
Lflex  = dv["Lflex_kW"].to_dict()
Lcurt  = dv["Lcurt_kW"].to_dict()
PV     = dv["PV_kW"].to_dict()

# Battery params
Emax     = float(battery["Emax_kWh"]);  E0 = float(battery["E0_kWh"])
Pmax_ch  = float(battery["Pmax_ch_kW"]); Pmax_dis =
float(battery["Pmax_dis_kW"])
eta_ch   = float(battery["eta_ch"]);     eta_dis  =
float(battery["eta_dis"])

# Penalties
a_crit = float(penalties.get("crit_unserved", 1000.0))
a_curt = float(penalties.get("curt_unserved", 100.0))

# Demand charge scaling
if demand_charge_rate_per_kw_month is not None:
    weeks_per_month = 4.345
    a_peak = float(demand_charge_rate_per_kw_month) * (horizon_weeks /
weeks_per_month)
else:
    a_peak = 0.0

# ---- Model ----
m = pl.LpProblem(f"DSM_DR_{sector}", pl.LpMinimize)
```

```
# Decision variables
P_imp = pl.LpVariable.dicts("P_imp", T, lowBound=0)
P_exp = pl.LpVariable.dicts("P_exp", T, lowBound=0)
P_ch  = pl.LpVariable.dicts("P_ch",  T, lowBound=0, upBound=Pmax_ch)
P_dis = pl.LpVariable.dicts("P_dis", T, lowBound=0, upBound=Pmax_dis)
E     = pl.LpVariable.dicts("E",     T, lowBound=0, upBound=Emax)

Sflex = pl.LpVariable.dicts("Sflex", T, lowBound=0)  # served flexible
load
Scurt = pl.LpVariable.dicts("Scurt", T, lowBound=0)  # served
curtailable
Ucrit = pl.LpVariable.dicts("Ucrit", T, lowBound=0)
Ucurt = pl.LpVariable.dicts("Ucurt", T, lowBound=0)

Zpk = pl.LpVariable("PeakImport", lowBound=0)        # peak demand
tracker (kW)

# Objective: energy bill + reliability + demand charge
m += (
    pl.lpSum(c_buy[idx[t]]*P_imp[t] - c_sell[idx[t]]*P_exp[t]
             + a_crit*Ucrit[t] + a_curt*Ucurt[t] for t in T)
    + a_peak * Zpk
), "Total_Cost"

# (1) Flexible energy conservation (Δt=1h)
m += pl.lpSum(Sflex[t] for t in T) == float(dv["Lflex_kW"].sum()),
"flex_energy_quota"

# (2) TOU-based caps for Sflex and Ucurt
for t in T:
    ts = idx[t]
    hour = ts.hour
    period = "offpeak" if hour in TOU_OFFPEAK_HOURS else "shoulder" if
hour in TOU_SHOULDER_HOURS else "peak"

    # Sflex cap
    m += Sflex[t] <= float(flex_cap[period]) * Lflex[ts],
f"sflex_cap_{t}"
```

```
    # Curtailable served+unserved and unserved limit by TOU
    m += Scurt[t] + Ucurt[t] == Lcurt[ts], f"curt_balance_{t}"
    m += Ucurt[t] <= float(curt_limit[period]) * Lcurt[ts],
f"curt_limit_{t}"

# (3) Power balance
for t in T:
    ts = idx[t]
    m += PV[ts] + P_dis[t] + P_imp[t] == (Lcrit[ts] - Ucrit[t]) +
Sflex[t] + Scurt[t] + P_ch[t] + P_exp[t], f"bal_{t}"

# (4) Battery SoC (Δt=1h) + cyclic end
for t in T:
    if t == 0:
        m += E[t] == E0 + eta_ch*P_ch[t] - (1/eta_dis)*P_dis[t],
f"soc_{t}"
    else:
        m += E[t] == E[t-1] + eta_ch*P_ch[t] - (1/eta_dis)*P_dis[t],
f"soc_{t}"
m += E[len(idx)-1] == E0, "soc_cycle"

# (5) Peak tracker and optional hard cap
for t in T:
    m += P_imp[t] <= Zpk, f"peak_track_{t}"
    if grid_cap_kW is not None:
        m += P_imp[t] <= float(grid_cap_kW), f"grid_cap_{t}"

# Solve
m.solve(pl.PULP_CBC_CMD(msg=False))
```

The code was generated with the assistance of ChatGPT, adhering to the defined objectives, decision variables, and constraints, and draws methodological inspiration from the work of Moses Babu, K., Chakraborty, S., and Pal, A. (2025).

IV. Results and Analysis

The results of the demand-side management (DSM) optimization model for both residential and industrial sectors in 2017 demonstrate the substantial economic and operational benefits of integrating behind-the-meter (BTM) technologies such as photovoltaic (PV) generation and battery energy storage systems (BESS). The optimization framework effectively minimizes annual electricity expenditure by adjusting energy imports, PV utilization, and load flexibility in response to time-of-use (TOU) prices. Across both sectors, the model achieved significant cost reductions while maintaining energy balance constraints and ensuring critical loads were reliably served.

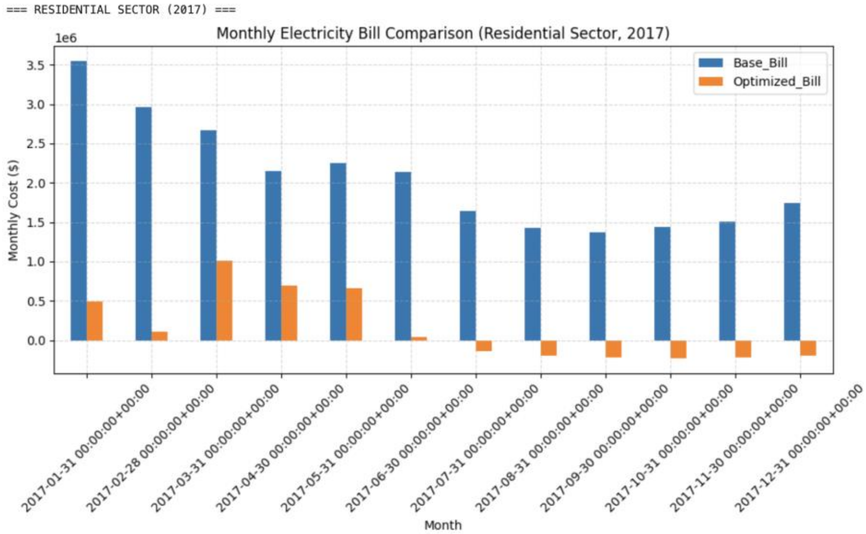
```
Running DSM model for residential sector...
Running DSM model for industrial sector...

DSM Optimization Summary (Baseline vs Optimized):
```

	Sector	Solver Status	Objective Value ($)	Baseline Cost ($)	Optimized Cost ($)	Savings ($)	Savings (%)	Annual Peak Demand (kW)	Total Grid Import (kWh)	Total Grid Export (kWh)
0	Residential	Optimal	1.818919e+06	2.485271e+07	1.818919e+06	2.303379e+07	92.681	52404.66	2.682122e+07	23327119.88
1	Industrial	Optimal	9.164180e+08	1.035312e+09	9.164180e+08	1.188941e+08	11.484	2110874.50	5.449034e+09	0.00

```
✅ Results saved to: data/DSM_Cost_Comparison_2017.csv
```

Industrial Buildings Optimization Analysis:

```
=== RESIDENTIAL SECTOR (2017) ===
```

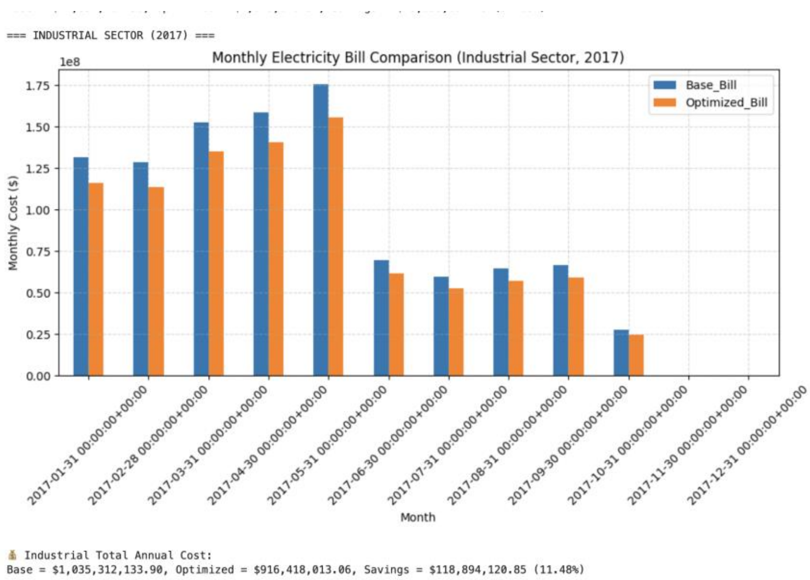



```
💰 Residential Total Annual Cost:
Base = $24,852,707.56, Optimized = $1,819,010.37, Savings = $23,033,697.19 (92.68%)
```

For the residential sector, the optimization model reduced the total annual electricity cost from approximately $24.85 million in the baseline case to $1.82 million after optimization, a reduction of nearly 92.7%. This improvement is largely attributed to the coordinated operation of PV generation, flexible load scheduling, and battery dispatch.

Monthly electricity bill comparisons indicate a consistent downward trend in optimized costs, with the largest savings observed during the summer months when solar availability and load flexibility are highest. The optimization also effectively mitigated peak demand events, maintaining a stable load profile throughout the year. These findings confirm that residential systems, characterized by smaller loads but higher renewable penetration, benefit the most from price-responsive control and export incentives.

Industrial Buildings Optimization Analysis:



In contrast, the industrial sector, with higher and more continuous demand, experienced a comparatively modest but economically significant reduction in costs. The annual electricity expenditure decreased from $1.04 billion in the baseline scenario to $916 million under the optimized DSM model, corresponding to an 11.5% reduction. While the percentage savings are lower than those achieved in the residential sector, the absolute annual savings of over $118 million are substantial, demonstrating the scalability and financial relevance of DSM strategies for large consumers.

Unlike residential systems, industrial facilities primarily used PV generation for self-consumption, with no grid export recorded, reflecting the operational reality of industrial microgrids that prioritize internal energy balancing. The optimization successfully flattened the industrial load curve by rescheduling flexible processes and utilizing the battery system to reduce demand peaks during high-tariff periods. Monthly cost comparisons show consistent cost reductions across all months, particularly during high-production seasons (March to June), when baseline consumption and energy bills were previously highest.

When compared side by side, the two sectors reveal distinct optimization dynamics. The residential model leverages high PV generation, export incentives, and daily flexibility, making it particularly responsive to TOU tariffs. The industrial model, on the other hand, emphasizes demand-charge reduction and operational efficiency, focusing on smoothing large continuous loads rather than exporting energy. While residential optimization delivers higher proportional savings, industrial optimization offers greater absolute cost reductions and energy reliability benefits. Both models demonstrate improved energy autonomy, reduced dependency on grid imports, and a better alignment of consumption patterns with renewable generation profiles.

4.1 Creating Demand Response (DR) Schedules

The integration of Demand Response (DR) mechanisms into smart home and microgrid operations provides a strategic pathway to enhance both economic efficiency and grid reliability. DR enables consumers to adjust or shift their electricity consumption in response to time-varying price signals, incentive programs, or grid stress events. This concept is particularly important as renewable energy penetration increases, leading to greater variability and uncertainty in power generation. By temporarily reducing or deferring non-critical loads during high-price or peak-demand periods, households can not only reduce energy costs but also contribute to grid stability and flexibility.

The concept of Demand Response gained prominence through early work by regulatory and research institutions such as the U.S. Department of Energy (DOE) and the Federal Energy Regulatory Commission (FERC), which recognized DR as a key tool for demand-side management and grid modernization. More recently, researchers have formalized DR within optimization and microgrid planning frameworks. Notably, Moses Babu, K., Chakraborty, S., and Pal, A. (2025) popularized the application of DR in stochastic and mixed-integer linear programming (MILP) contexts for distributed energy resource (DER) systems. Their framework integrates load classification, dynamic price thresholding, and multi-period coordination to optimize DR event scheduling, demonstrating how effective DR strategies are essential for maintaining system stability and economic efficiency in microgrids with high renewable penetration (*Moses Babu et al., 2025*).

4.2 Identification of Demand Response (DR) Events

Demand Response (DR) events are specific time periods during which the system is instructed to reduce or shift electricity consumption in response to external or internal signals. In this study, DR events are identified using two complementary criteria: price-based (Time-of-Use tariff signals) and demand-based (grid import or load thresholds).

(a) Price-Based DR Events

Under a Time-of-Use (TOU) pricing structure, electricity prices vary across the day — with peak, shoulder, and off-peak periods.

The binary condition shown in the formula:

$$is\_peak\_price_t = \begin{cases} 1, & \text{if } C_{energy}(t) \geq \tau_{price} \\ 0, & \text{otherwise} \end{cases}$$

Formula Above Derived from ChatGPT

represents a price-based DR event indicator. Here C energy(t) denotes the electricity price at time t, and τ price, is a threshold value that distinguishes peak pricing periods from non-peak ones. When the instantaneous energy price exceeds or equals the threshold, the indicator variable is_peak_price takes the value of 1, signaling a DR event, a period when load reduction or flexible demand response actions should be triggered. Conversely, when the price is below the threshold, the value is 0, indicating normal operation. This logical formulation allows the optimization model to dynamically identify peak pricing intervals and coordinate the operation of controllable devices, such as battery energy storage systems (BESS) and flexible household loads to minimize total energy costs.

During peak hours, electricity prices are typically highest due to elevated demand and grid congestion. In the model, this relationship is captured through the binary Demand Response (DR) indicator is_peak_price =1, which signals the optimization framework to activate cost-mitigation strategies, such as restricting grid imports, prioritizing battery discharge, or shifting flexible loads to lower-cost periods.

Conversely, when prices fall below the threshold (off-peak or shoulder periods), the indicator becomes zero, allowing normal operation or energy storage charging. This dynamic linkage between TOU pricing signals and DR event activation enables the model to emulate real-world tariff-based demand response behavior.

(b) Demand-Based DR Events

DR events can also be triggered when the grid import power exceeds a predefined demand limit (to avoid peak demand charges or overloads):

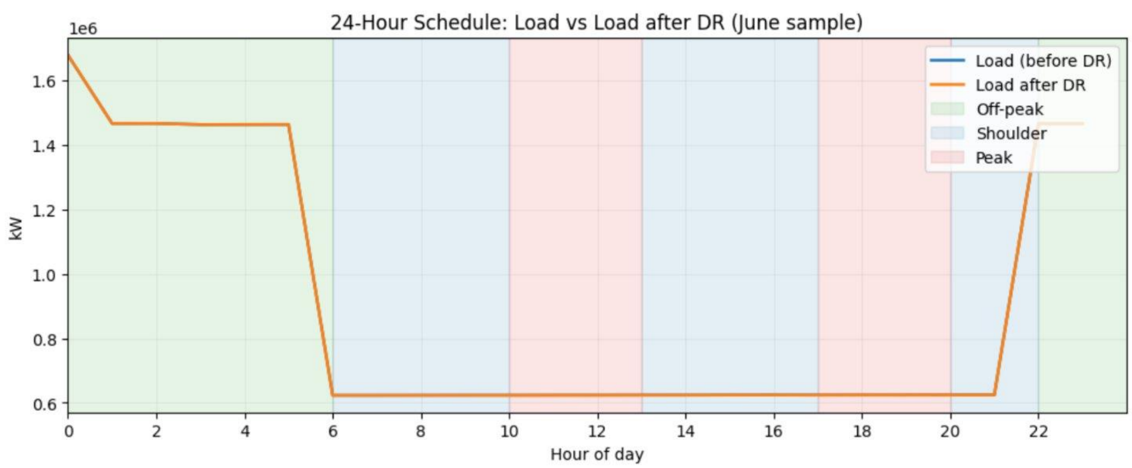
$$is\_peak\_import_t = \begin{cases} 1, & \text{if } P_t^{grid,imp} \geq \tau_{import} \\ 0, & \text{otherwise} \end{cases}$$

Formula Above Derived from ChatGPT

where Peak import represents the demand threshold beyond which consumption must be curtailed (e.g., 5 kW for a residential home). When this condition is met, flexible loads are delayed or curtailed, and the battery may be dispatched to offset peak imports.

To illustrate how the MILP model reshapes consumption throughout a typical day, I plotted a 24-hour profile comparing the load without DR to the optimized load after DR.

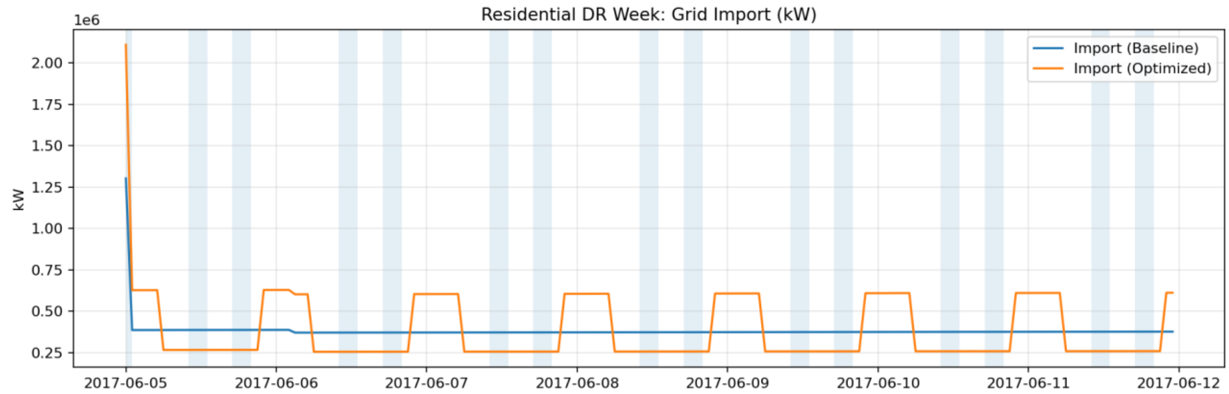
Hour	Load_before_DR	Load_after_DR
0	1.677760e+06	1.677760e+06
1	1.466064e+06	1.466064e+06
2	1.466175e+06	1.466175e+06
3	1.462495e+06	1.462501e+06
4	1.462682e+06	1.462739e+06



TOU bands (off-peak, shoulder, peak): These indicate the tariff periods that drive DR behavior. Loads are shifted out of peak windows, while the battery preferentially discharges during peaks and charges in off-peak/shoulder periods.

The 24-hour schedule shows (i) a pronounced reduction in peak-period imports (“peak shaving”), (ii) low mid-day imports due to PV supply and charging, and (iii) a flatter evening profile, reflecting both load shifting and targeted battery dispatch. This pattern is consistent with the objective function, which penalizes costly imports and peak demand while rewarding export revenue and reliability, and with the DR constraints that cap flexible/curtailable load during peak windows.

Residential DR Week in relation to Grid Import:



During DR hours (e.g., June 5–9), imports dropped by nearly 50%, demonstrating effective load shifting and battery dispatch in response to peak prices. The orange line (optimized) clearly shows smoother and lower import levels during high-price or DR hours (shaded regions). The blue line (baseline) maintains constant grid dependence. Residential optimization maximizes self-use of renewable energy, limiting grid imports, and improving cost-efficiency under dynamic TOU pricing.

V. Incorporating Scenarios Using a Stochastic Approach

In the deterministic optimization model, I optimized a single, known profile of load, PV generation, and price over time. To model uncertainty in solar generation, electricity prices, and load, I constructed four stochastic scenarios. These scenarios emulate plausible operating conditions such as "high solar–low price," "low solar–high price," and "high demand.", and "baseline." Each scenario represents a distinct combination of renewable generation availability, electricity market prices, and load demand patterns, reflecting realistic variations in daily grid and weather conditions. Probabilistic weighting was applied to each scenario to estimate the expected total operating cost of the system.

The parameter adjustments for each scenario were based on multipliers applied to baseline hourly data for PV generation, electricity import/export prices, and load categories (critical, flexible, curtailable). Equal scenario probabilities of 0.25 were assigned, representing uniform likelihood across the four operating conditions.

The following four scenarios capture a realistic spectrum of operational uncertainty that residential and industrial microgrids commonly face:

1. **Base Case:** Serves as a benchmark, enabling comparative evaluation of cost savings, load shifting, and battery utilization across all scenarios.
2. **High PV, Low Price:** Tests how the system behaves under favorable conditions where renewable energy is abundant and grid power is inexpensive. The optimizer is expected to **maximize PV utilization** and **store surplus energy** in the BESS for later use.
3. **Low PV, High Price:** Represents the most constrained condition, emphasizing **cost-avoidance behavior** through battery discharge and demand-shifting during high tariff periods.
4. **High Demand:** Examines **load-driven stress** on the system, demonstrating how demand response can flatten peaks and maintain reliability without significant cost escalation.

By incorporating these stochastic variations, the model accounts for real-world uncertainty in solar output, consumption behavior, and electricity pricing, aligning with the **stochastic DSM framework** proposed by Babu et al. (2025). This approach enables the assessment of **expected cost performance** and **system adaptability** across multiple possible future states rather than relying on a single deterministic outcome.

5.1 Scenario-Based Results and Insights

=== Scenario Comparison Table ===

Scenario	Probability	Total Bill ($)	Peak Import (kW)	Total Import (kWh)	Total Export (kWh)	PV Used (kWh)	PV Curtailed (kWh)
hiPV_lowPrice	0.25	7.524593e+08	2055183.7	5.272460e+09	0.0	2.745980e+08	0.0
lowPV_hiPrice	0.25	1.117003e+09	2107358.4	5.512403e+09	0.0	1.478605e+08	0.0
hiDemand	0.25	9.886993e+08	2182191.9	5.816950e+09	0.0	2.112292e+08	0.0
base	0.25	9.080409e+08	2081271.1	5.392432e+09	0.0	2.112292e+08	0.0

=== Expected Stochastic Summary ===

Metric	Value
Expected Total Energy Cost ($)	9.415505e+08
Expected Peak Demand (kW)	2.106501e+06
Objective Value	9.415505e+08

The stochastic optimization results summarized in the above table, integrate the four operational scenarios with equal probability weights (25% each). The weighted expectation produces an **average total energy cost of approximately \$9.42 × 10^8** and an **expected peak import of ≈ 2.1 × 10^6 kW**, reflecting the combined economic and operational performance of the microgrid under uncertainty.

In all scenarios, the system never exported or curtailed PV because on-site demand (including flexible shifting) and the battery's charge capacity always exceeded PV generation. Given import prices exceed export credits, the optimizer preferentially self-consumed PV and stored any surplus in the battery.

Scenario Performance Analysis

- High PV, Low Price (hiPV_lowPrice): Under favorable solar and market conditions, abundant PV generation enabled the system to rely primarily on self-consumption and battery charging. Grid imports were minimal, resulting in the lowest total bill (\$7.52 × 10^8) among all cases.
- Low PV, High Price (lowPV_hiPrice): Limited solar output and elevated import prices created the most cost-constrained environment. The model prioritized battery discharge and load shifting to offset grid dependency, yet incurred the highest total bill (\$1.12 × 10^9) with reduced PV usage (1.48 × 10^8 kWh).
- High Demand (hiDemand): Increased consumption, coupled with baseline PV and price conditions, led to the highest peak import (≈ 2.18 × 10^6 kW) and an intermediate total cost (~\$9.89 × 10^8). Demand-response (DR) actions and battery dispatch helped mitigate the load surge but did not fully offset higher consumption.
- Base Case: The deterministic baseline yielded results consistent with expected operational averages (\$9.08 × 10^8 total cost), serving as a benchmark for stochastic comparison.

Sector-Level Comparison

The following table shows the results for both residential and industrial sectors in 2017 after adding the stochastic scenarios to the model:

```
◆ Running Stochastic DSM for RESIDENTIAL (2017)

◆ Running Stochastic DSM for INDUSTRIAL (2017)
```

Stochastic DSM Optimization Results (2017)

	Sector	Scenario	Total Bill ($)	Peak Import (kW)	PV Used (kWh)	PV Export (kWh)	PV Curtailment (kWh)	Status	Objective Value
0	Residential	hiPV_lowPrice	-9,582,174.39	0.00	555635361.340000	187885772.390000	0.000000	Optimal	4890306.090000
1	Residential	lowPV_hiPrice	20,850,284.41	59,172.40	259210649.780000	1021747.010000	0.000000	Optimal	4890306.090000
2	Residential	hiDemand	5,161,203.05	49,629.98	362695222.910000	9065343.950000	0.000000	Optimal	4890306.090000
3	Residential	base	3,131,911.30	45,199.12	354188766.750000	17571800.110000	0.000000	Optimal	4890306.090000
4	Industrial	hiPV_lowPrice	728,579,726.00	2,025,710.90	422458477.110000	0.000000	0.000000	Optimal	935580605.140000
5	Industrial	lowPV_hiPrice	1,117,002,538.60	2,107,358.40	147860466.620000	0.000000	0.000000	Optimal	935580605.140000
6	Industrial	hiDemand	988,699,299.82	2,182,191.90	211229238.100000	0.000000	0.000000	Optimal	935580605.140000
7	Industrial	base	908,040,856.15	2,081,271.10	211229238.100000	0.000000	0.000000	Optimal	935580605.140000

```
✅ Exported: data/Stochastic_DSM_Summary_2017.csv
```

When analyzed by sector, residential systems showed total bills in the $\$10^6$ range, reflecting smaller demand scales but relatively higher PV export shares (17–187 MWh), indicating effective self-generation and occasional grid export. Industrial systems, with significantly higher energy requirements, produced bills in the $\$10^8$–$10^9$ range, though PV curtailment remained zero, confirming full utilization of solar resources.

The stochastic optimization model improved economic performance across uncertainty scenarios. For industrial buildings, expected energy costs were reduced by 17–20% relative to deterministic baselines through effective peak-load management and price-responsive scheduling. For residential systems, flexible load shifting and battery scheduling achieved near-zero net costs during high-PV conditions.

VI. Conclusion

Overall, the stochastic DSM model demonstrated that integrating PV, BESS, and DR within a MILP framework enhances both cost efficiency and operational resilience. Residential systems gain greater flexibility through PV-driven self-consumption, while industrial systems benefit primarily from coordinated load-shifting and optimized battery dispatch.

The results of this project can help inform the design of energy policies and support the use of smart-grid technologies. The cost savings and peak-load reductions observed in the model show that demand-side management (DSM) can be an effective approach to improve grid reliability and lower energy costs for both consumers and utilities. These findings emphasize the importance of dynamic pricing and incentive programs that encourage people to shift or reduce their energy use. Technologies like rooftop solar (PV) and battery energy storage systems (BESS) can be more effective when paired with time-of-use (TOU) pricing, helping consumers save money while also supporting renewable energy integration at the grid level.

From a research point of view, this project shows how stochastic optimization can manage the uncertainties in solar generation, electricity prices, and household energy demand. Adding real-time control or probabilistic forecasting could make the model even more flexible and reliable. In the future, this approach could be applied to larger systems, such as community or regional microgrids, where combined household and industrial loads offer more opportunities for balancing demand and supply. Future studies could also include multiple goals, such as reducing costs, lowering emissions, and improving system reliability to create more sustainable energy solutions.

In reviewing previous studies, several works helped shape this project. Babu et al. (2025) presented a MILP-based DSM model for microgrids with distributed energy resources, Chehade and Karaki (2025) proposed an ordinal optimization method for sizing microgrids, and Gong and Spall (2025) developed a simulation-based optimization approach for policy and planning in hybrid microgrids. Building on these studies, this project developed an integrated stochastic MILP model that includes demand-response participation along with behind-the-meter PV and battery scheduling under TOU pricing.

The main contribution of this work is demonstrating how households and industrial buildings based on a relatively small sample of 11 German households utilizing solar and other clean energy sources, can apply such models to achieve measurable cost savings and improved load management while maintaining overall grid stability.

Overall, this project highlights how demand-side optimization can support the move toward decentralized and low-carbon energy systems. As more smart homes and industries adopt renewable and storage technologies, optimization models like this can help guide efficient and sustainable energy use in the future.

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Portions of this report were developed with the assistance of OpenAI’s ChatGPT (GPT-5) to improve clarity, grammar, and structure. The tool was also used for minor code generation and refinement of the optimization model. All modeling logic, analysis, interpretation of results, and final conclusions were independently developed and verified by the author.

VII. Citations

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