IJESG
e-ISSN 2636-7904
International Journal of Energy and Smart Grid
Vol 8, Number 1, 2023
Doi: 10.55088/ijesg.1335769

Research Article

POWER BILL OPTIMIZATION FOR GRID-TIE SOLAR PV-BATTERY HOUSE

Kiswendsida E. Ouedraogo**[1], Pinar Oguz Ekim[2], Erhan Demirok[3]

[1]Izmir Economics University Orcid[1]:https://orcid.org/0000-0002-1615-1693
[2]Izmir Economics University Orcid[2]: https://orcid.org/0000-0003-1860-4526
[3]Dokuz Eylul University Orcid[3]: https://orcid.org/0000-0002-0266-0366
[*] Corresponding author; ouedraogo.elias@gmail.com

Abstract: *This study focuses on the optimization of power bills for a house equipped with a grid-tie solar PV-battery system. Rather than adhering to conventional load scheduling practices or minimizing grid power usage at each time interval, a novel approach is adopted wherein the optimization is performed for the entire 24-hour period simultaneously. By directly incorporating time-of-use rates into the cost function, an absolute optimal solution is attained. The findings indicate that compared to single time step optimization, the proposed method results in a reduction of the power bill ranging from 6% to 10%, depending on load-generation variations. Furthermore, if the utility or government enforces the summer tariff consistently throughout the year, the savings escalate to a range of 15% to 22%. Introducing a more intelligent tariff structure can thus serve as an effective means to expedite the transition towards renewable energy by incentivizing individual investments in solar PV, battery systems, and smart home energy management.*

Keywords: *smart house; renewable energy integration; solar PV; energy storage; Home battery*

Received: 1August 2023 *Accepted: 17 December 2023*

1. Introduction

Problem overview: Electricity grids worldwide face technical, socio-economic, and environmental challenges, including aging infrastructure [1]. In Europe, for instance, 36% of power capacity is set to shut down by 2030 [2]. This aging system lacks smart grid features, resulting in increased power outages, particularly in impoverished nations [3]. The growing penetration of intermittent solar and wind energy, which rose by 15% in 2019, further adds uncertainty to generation [4], endangering grid stability. Without decarbonization efforts, CO2 emissions and associated climate change issues will worsen.

Current solution: Smart grids and energy storage serve as tools to facilitate the energy transition [5]. While there is no universally agreed-upon definition of a "smart grid," research papers often consider any grid system enabling load control, automated power recording, tariff acquisition, and bill optimization as smart [3]. Presently, in standard smart grid control system, excess green energy is prioritized over grid power and stored in batteries, minimizing grid consumption.

Proposed direction: From a customer perspective, incorporating time-of-use rates (ToU) into optimization equations and solving the problem for multiple time steps simultaneously (e.g., 24 steps instead of 1 step) may reduce the overall energy bill, possibly at the expense of grid power. Essentially, storing excess green energy and utilizing grid energy during cheaper tariff periods can contribute to bill reduction. The proliferation of electric cars with their substantial batteries makes load-generation-tariff-based bill optimization more appealing to households compared to traditional grid power minimization.
Study Scope: This paper addresses the optimization of the overall energy bill for a smart grid-connected solar PV-battery house, considering unpredictable load-generation variations.

2. Literature Review

Since the 1973 oil crisis, optimizing energy consumption has been a concern for power industry stakeholders, including consumers, utilities, and governments [6]. Consumers aim to reduce bills and lower CO2 emissions, while utilities seek to avoid investing in low-capacity factor power plants and transmission systems to meet peak demand. For instance, a study optimizing a microgrid with solar PV, wind turbines, and batteries found that utility operation costs can be reduced by up to 28% through demand response programs [7]. Governments prioritize enhancing energy supply chain performance and reliability to strengthen the economy and social welfare.

The residential sector accounts for around 25% of global electricity consumption [8]. Energy bill optimization has been addressed through energy efficiency measures, smart demand control, time-of-use (ToU) tariff design, solar PV, and battery solutions [9]. Retrofitting old air conditioners with variable-speed AC units and replacing old lamps with efficient LED lamps can achieve up to 40% savings [10-12]. Research on smart houses focuses on load scheduling algorithm development, demand response optimization, and integration of renewable energy (RE) and electric energy storage (EES) systems. Load scheduling separates the house load into deferrable (e.g., washing machine, air conditioner) and non-deferrable loads (e.g., lights, TV), optimizing peak-to-average ratio (PAR) and energy bills [13-15]. Model predictive control (MPC) combined with ToU rates and feed-in tariffs can reduce costs by 13% for PV-battery houses' AC consumption [16]. Linear programming, genetic algorithms, quadratic programming, and neural networks have been used for cost function optimization [17,18]. For instance, studies optimizing thermostatically controlled AC consumption in PV-battery houses achieved cost reductions of 20% to 30% [19,20]. While load scheduling achieves lower PAR and energy bills, its implementation poses convenience issues due to deferrable load timings. However, IoT-based solutions can automate scheduling by adjusting AC power based on weather forecasts or ToU rates [21]. Financial incentive-based demand response schemes have improved power factor by 17% for 300 houses [22]. Punishment-based optimization temporarily disconnects customers from the grid if they fail to comply with load reduction orders to prevent blackouts [23].

EES is increasingly adopted by residential houses and utilities for grid frequency stabilization. Although battery costs are high, their size is minimized in studies. However, controlling a group of residential users' EES as a single battery yields the benefits of large-scale EES, reducing power shortage by 23% for a group of users [24]. The concept extends to vehicle-to-grid (V2G) systems where electric car batteries integrate with the grid. Optimizing solar PV and V2G systems using linear programming resulted in payback periods ranging from 4 to 8 years based on battery charge profiles [25]. This study optimizes the energy bill of a smart grid-connected solar PV-battery house without imposing load scheduling on users. Furthermore, instead of standard time step optimization, simultaneous 24-hour consumption is considered for optimization.

3. System Modeling

The study examines four smart house system cases, as shown in Figure 1, incorporating PV panels, battery, and loads [26,27]. Feed-in tariff restrictions prevent residential users from feeding solar power into the grid, given the opposition and scalability challenges of subsidies [26,27]. Sun radiation data for a typical meteorological year (TMY) in California is obtained from PVGIS and soda pro, while system efficiency is adjusted to match the annual generation from the prediction of global solar atlas [26-28]. A PV cost of \$1.5/Watt from TESLA is assumed [29]. The load consists of household appliances, HVAC, and lighting, utilizing a California residential base load profile [30]. Load scheduling is not considered for optimization. The battery capacity and state of charge serve as

simulation variables, with charge-discharge limits set at 0.5C for commercially available cells. A base battery capacity of 30 kWh (100% of daily mean energy production) is used, subject to revision for convergence [30,31]. The battery system cost is set at $150/kWh, considering projected cell costs of $100/kWh by 2025 [31]. ToU rates vary by country, with California's actual tariff applied [32]. The grid energy is assumed to be unlimited, while the house's subscribed power is limited to 150% of peak load for realistic modeling. The simulation scenarios are as follows:
Case 1: Minimize hourly grid power withdrawal [33]. Multiply the obtained grid power profile by ToU rates to calculate the energy bill.
Case 2: Express the cost function as the hourly energy bill. Simultaneously minimize the sum of 24-hour bill functions to obtain the daily energy bill, as hourly optimization may yield local minima.
Case 3: Use the battery charge-discharge profile from case 2 as a reference. Introduce an uncertain load to analyze its impact, adding a normally distributed random load between ±50% of peak demand.
Case 4: Conduct a sensitivity analysis to assess the effect of PV generation variations on case 2. Utilize data for a specific year, such as 2015, instead of adding random solar radiation values to the TMY PV output.

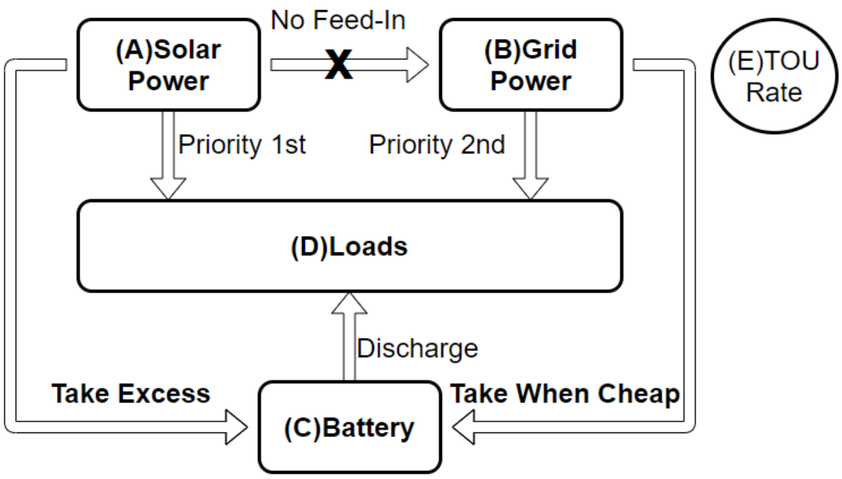

Figure 1. System Illustration

4. Mathematical Modeling

The simulation utilizes key inputs, including solar power (A), load power (D), and Time-of-Use (ToU) rates (E). These inputs generate outputs: the battery charge-discharge profile (C) and grid power (B). Post-simulation processing yields various key performance indicators (KPIs) such as the bill, Peak-to-Average Ratio (PAR), simple payback period (SPB), grid power standard deviation, and more. The system settings can be found in Table 1.

Table 1. System Settings

No	Items	Value	Unit
1	PV rated AC power	4.77	kW
2	PV location lat.	34.271	deg
3	PV location long.	-118.517	deg
4	PV energy output	1813	kWh/kWp/Yr
5	PV daily energy output	23.7	kWh/day
6	PV cost	1.5	$/W
7	Battery base capacity	30	kWh
8	Battery limits	0.5	C
9	Battery cost	150	$/kWh
10	Peak load	4.77	kW
11	Minimum load	0.76	kW
12	Mean load	1.9	kW
13	Grid power limit	7.2	kW

In terms of data, a preliminary simulation using 8760 hours of data revealed extended computation times exceeding 10 minutes on a laptop featuring an Intel Core i3 4005U 1.7GHz processor and 4GB RAM running MATLAB 2018. To expedite the simulation process, the annual solar and load data points were reduced by calculating a representative Typical Day (TD) dataset, akin to the Typical Meteorological Year (TMY) approach. The TMY approach considers the most representative monthly data spanning a period of at least 10 years. To obtain Typical Day (TD) data, the average value of a specific hour is calculated for each month. For example, the average PV output at 10 am in January represents the TD data for that hour in January. This approach significantly reduces the data from 8760 hours to 288 hours (24 hours multiplied by 12 months), resulting in a 96% reduction. Consequently, the entire year is now represented by only 12 data points. A random load is generated using the formula provided in equation (1). As for the PV output, the Typical Meteorological Year (TMY) output serves as the base, and data from the year 2015 is utilized for sensitivity analysis.

$$P_{loadTDrand} = P_{loadTDbase}(1 - 0.5 + rand\ [0,1]) \quad (1)$$

$P_{loadTDrand}$ $[kW]$: Random generated load power
$P_{loadTDbase}$ $[kW]$: Base load power

The actual Time-of-Use (ToU) rates, specific to California residential users with photovoltaic (PV) panels and energy storage systems (EES), are used. These rates are applied during both summer (June to October) and winter (November to May) seasons to ensure practicality and real-world relevance. Additionally, a semi-synthetic ToU rate, which extends the summer tariff into the winter period, is employed as a test tariff to assess the potential improvement of the proposed optimization method and its efficiency.

CVX Optimization is a MATLAB toolbox utilized for convex function optimization. In the first case (Case 1), at each hourly time step k, the objective function being minimized is the grid power as defined in eq (2), where the only unknown variable is the battery power. The linearity of Pgrid allows for it to be assumed as a convex function.

$$Pgrid1(k) = -PVout(k) + Pload(k) + Pbatt(k) \quad (2)$$

k $[-]$: Hour time index
$Pgrid1$ $[kW]$: Power consumption from the grid
$PVout$ $[kW]$: Solar PV system power output
$Pload$ $[kW]$: House power consumption
$Pbatt$ $[kW]$: Battery charge/discharge power

To incorporate losses caused by non-unity battery round trip efficiency, the term Pbatt (k) in eq (2) is adjusted by dividing it by the efficiency of the battery "Efficiencybatt" when the battery is in the charging mode. The calculation of the hourly bill for Case 1 is determined using eq (3). The total yearly bill is then calculated by integrating the typical daily bills over 12 months.

$$Bill1(k) = Pgrid1(k) * dh * ToUR(k) \quad (3)$$

$Bill1$ [\$]: Bill amount in USD
dh $[h]$: Time step in hour
$ToUR$ $[\$ / kWh]$: Electricity time of use rate in USD/kWh

The optimization problem is subject to several constraints, including the maximum (max), minimum (min) limits on grid power, the battery power as well as the energy state of charge as specified in eq (4)-(6).

$$Pgridmin \leq Pgrid1(k) \leq Pgridmax \quad (4)$$

$$Pbattmin \leq Pbatt1(k) \leq Pbattmax \quad (5)$$

$$SoCmin * Qbatt \leq Ebatt(k+1)) \leq SoCmax * Qbatt \quad (6)$$

SoC $[\%]$: Battery state of charge
$Qbatt[kWh]$: Battery capacity
$Ebatt$ $[kWh]$: Battery energy at time k

The bill and grid energy are calculated by integrating the function Bill1(k) and Pgrid1(k) respectively. The Peak-to-Average Ratio (PAR) is defined according to equation (7).

$$PAR = max\,(Pgrid1)/mean(Pgrid1) \quad (7)$$

In order to determine the simple payback period (SPB), it is crucial to have knowledge of the bill before and after making the investment in the PV-Battery system. The bill when solely relying on the grid as the power source is considered as the baseline for comparison as in eq (8).

$$Bill0 = \int_{n=1}^{n=12} \int_{k=1}^{k=24} Pload(n+k) * dh * ToUR(n+k) \quad (8)$$

$n[-]$: Month index

The simple payback period (SPB) is calculated according to eq (9), where CAPEX represents the capital expenditure required for constructing the Renewable Energy System (RES) and Energy Storage System (EES). A comprehensive analysis would typically include additional factors such as operational expenditure (OPEX), cost of capital, inflation rate, materials depreciation, and other relevant considerations. However, for the purpose of showcasing the value trend of the proposed method, these factors have been omitted in this study to maintain simplicity.

$$SPB = (CAPEX_{PV} + CAPEX_{batt})/(Bill0 - Bill1) \tag{9}$$

In the second proposed case (Case 2), a different approach is taken where instead of optimizing the grid power and subsequently calculating the bill, the cost function is directly formulated as shown in eq (10). This means that the bill for a specific day, denoted as 'n', is determined by minimizing the sum of the bills for all 24 hours. In eq (10), each optimization involves 24 unknown variables: Pbatt1, Pbatt2, ..., Pbatt24, representing the battery power at each hour. Since this is a linear combination of linear functions, the cost function (Bill2) remains linear as well, allowing it to be assumed as convex for optimization purposes.

$$Bill2 = \int_{n=1}^{n=12} \int_{k=1}^{k=24} \big(PVout(n+k) + Pload(n+k) + Pbatt(n+k)\big) * dh * ToUR(n+k) \tag{10}$$

The optimization constraints for the cost function (Bill2) are similar to those of the grid power (Pgrid1). There are 24 constraints for the hourly limits of grid power and 24 constraints for the limits of battery charge and discharge power. However, since the hourly battery power profile is not available as in Case 1, it is not possible to directly calculate the battery energy level and ensure it stays within the desired state of charge. To address this issue, an additional constraint is introduced in eq (11) where the sum of the 24-hour battery power is set to nearly zero. This constraint ensures that the net energy transfer of the battery over the course of the day is zero.

At the end of the simulation, the cumulative battery power is computed to examine the range of charge and discharge levels. If this range falls within the battery's state of charge (SoC) requirements, the optimization results are considered valid. Otherwise, lower charge or discharge rates are set for a new optimization attempt. The bill, grid energy, and Peak-to-Average Ratio (PAR) are calculated using the established methodology as mentioned previously.

$$-0.01 \leq Pbatt1 + Pbatt2 + \ldots\ldots + Pbatt24 \leq 0.01 \tag{11}$$

In both Case 1 and Case 2, a base load (PloadTDB) and a base PV generation (PVoutTDTMY) are utilized. In Case 3, the load is replaced by a randomly variable load (PloadTDRand), and in Case 4, the PV generation is replaced by PVoutTD2015. The optimized battery charge/discharge profile obtained in Case 2 serves as a model for charge/discharge in Case 3 and Case 4. This means that whenever the calculated state of charge and power of the battery for the next time step fall within the specified limits, the current battery power is used as the command for charge/discharge. If the limits are exceeded, the battery power is set to zero for that time step.

Case 3 and Case 4 examine how an offline optimized battery power profile can still be effective under varying load and generation conditions. In practice, historical load and PV generation data can be employed to calculate the optimal battery power profile. The key performance indicators (KPIs) of the system are calculated using the same methodology as in Case 1.

5. Simulation Results

The absolute key performance indicators (KPIs) for Case 1 are summarized in table 2, considering both the official Time-of-Use (ToU) rates and the synthetic rates. The synthetic ToU rates result in a 16% increase in the base bill. However, it is worth noting that the simple payback period (SPB) decreased by 16% as well. These seemingly contradictory figures can be explained by the fact that the synthetic ToU rates yield a base bill0 that is 17% higher than that of the real ToU rates. In reality, the savings achieved with the synthetic ToU rates are nearly 20% higher compared to the savings with the real ToU rates. The grid energy, grid mean power, and Peak-to-Average Ratio (PAR) remain consistent regardless of the ToU rates. This outcome confirms that Case 1 optimizes only for grid power and not the overall bill.

Table 2. Reference Case Absolute Results

KPI	Real ToUR	Synthetic ToUR
$Bill_0$ (No Investment) [$]	5048	5938
$Bill_1$ [$]	2202.9	2533.0
GridEnergy1 [kWh]	7185.0	7185.0
PAR_1 [-]	5.0	5.0
$GridPmean_1$ [kW]	0.8	0.8
SPB_1 [Month]	49.1	41.0

In Figures 2-3, the grid power profiles of Case 1 and the compared cases under real Time-of-Use (ToU) rates are analyzed. It can be observed that, relative to Case 1, the peak hours of Case 2 are shifted forward. Upon closer examination, a zoomed view reveals that the peak hours in Case 2 occur between midnight and 6 am, unlike Case 1 where they are between 10 pm and 2 am. Additionally, in the summer season, the peak hours in Case 2 last longer compared to the winter season. The extended duration of peak hours during the night indicates that the optimization method used in Case 2 prioritizes storing energy during low tariff periods for later utilization. This is further supported by the fact that the grid power in Case 2 drops to nearly zero between 8 am and 10 pm. Furthermore, in Figure 3, it can be observed that the grid power profiles of Case 3 and Case 4 closely resemble that of Case 2. This suggests that load or generation variations have minimal influence on the optimized battery power profile.

IJESG
e-ISSN 2636-7904
International Journal of Energy and Smart Grid
Vol 8, Number 1, 2023
Doi: 10.55088/ijesg.1335769

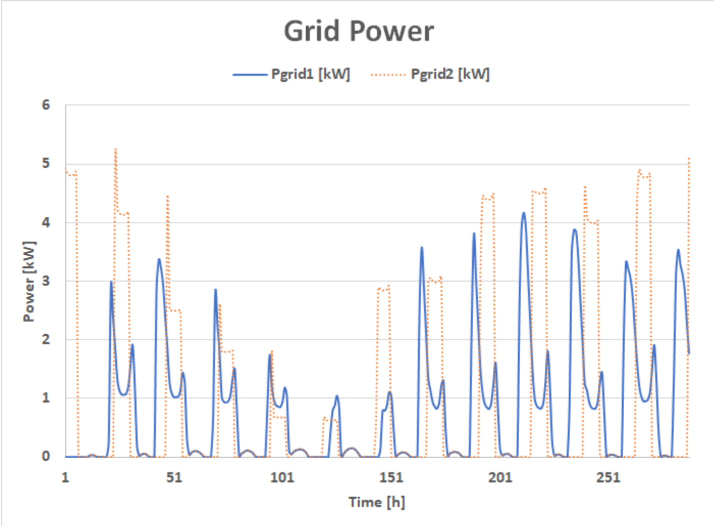

Figure 2. Grid Power Case 1-2

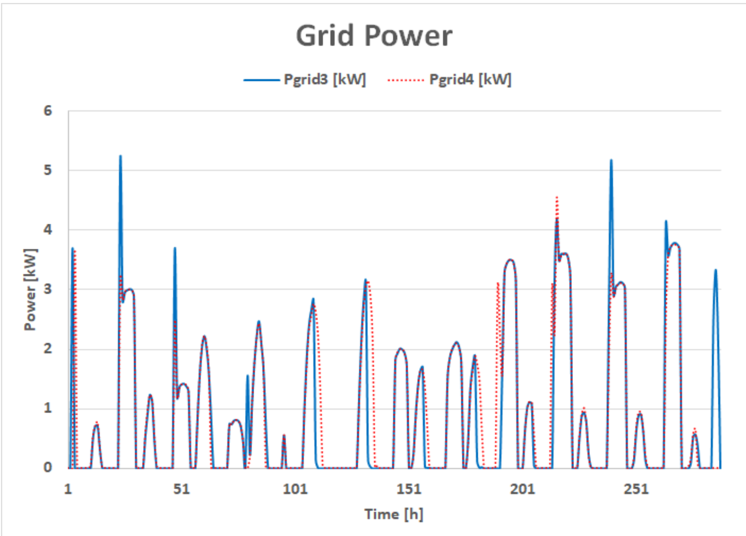

Figure 3. Grid Power Case 3-4

The bill profiles shown in Figure 4 illustrate that Case 2 has a lower bill during nighttime compared to Case 1. This outcome can only be achieved if the power tariff is low during that period, which is indeed the case. Despite the power profile of Case 2 being higher during the same time period, the optimized strategy allows for cost savings due to the lower tariff at night. Similarly, the bill profiles of Case 3 and Case 4 in Figure 5 closely resemble that of Case 2, indicating that the billing patterns align with the optimized power profiles.

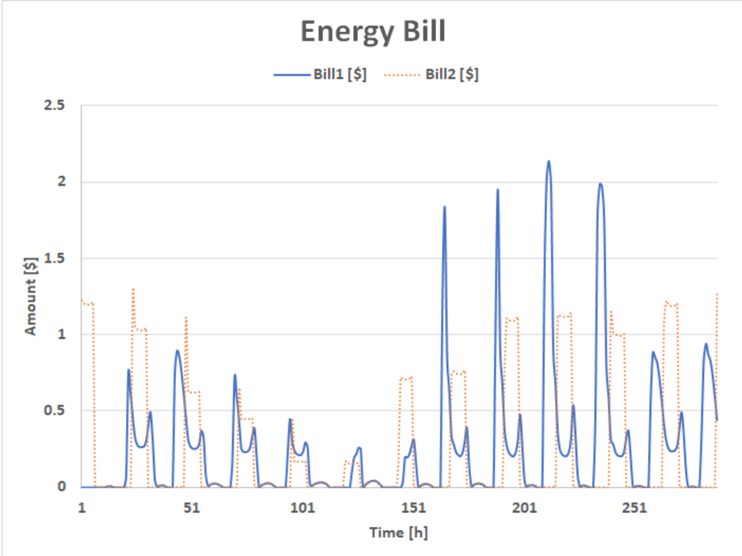

Figure 4. Energy Bill 1-2

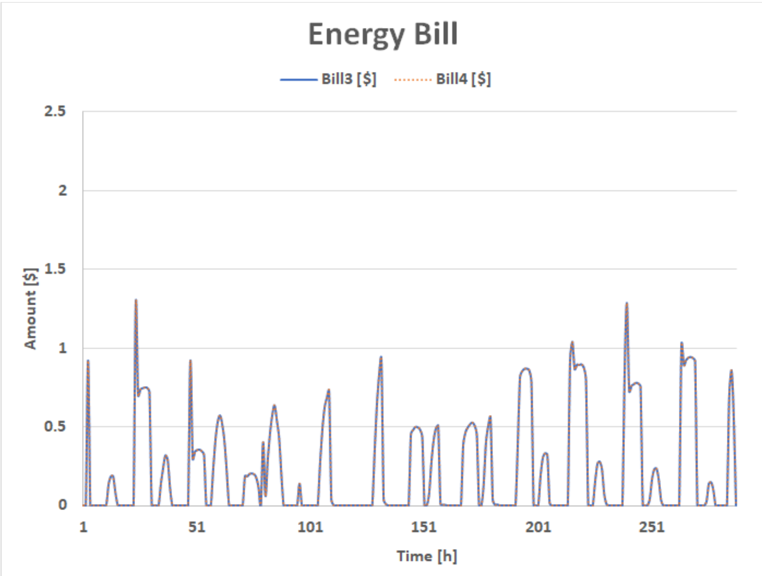

Figure 5. Energy Bill 3-4

The hourly grid power and bill profiles presented earlier are not easily understandable when comparing different optimization methods to Case 1. However, a more effective comparison can be made using the Key Performance Indicators (KPIs) shown in Figure 6. Analyzing the bill reductions, Case 2 and Case 4 exhibit approximately a 6% reduction, while Case 3 shows a higher reduction of 10%. This indicates that variations in the load have a greater impact on the system compared to variations in generation. The Simple Payback Periods (SPBs) are directly proportional to the bills, meaning they follow a similar trend. All the compared cases consume 6%-14% more grid energy than Case 1.

Regarding the Peak-to-Average Ratios (PARs), it is noteworthy that PAR 3 is exceptionally high at 16.6%. This occurs when the load changes, and the optimized battery peak charge power coincides

IJESG
e-ISSN 2636-7904
International Journal of Energy and Smart Grid
Vol 8, Number 1, 2023
Doi: 10.55088/ijesg.1335769

with the new peak load, resulting in a high overall peak power from the grid. The slight reduction in PAR 4 can be explained if the peak PV power aligns with the peak load power or if the battery's peak discharge matches the peak load. In both cases, less power is required from the grid, resulting in a lower PAR value.

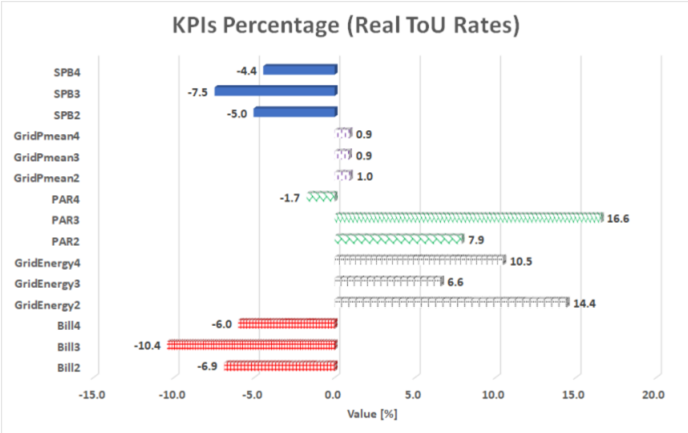

Figure 6. Real ToU Rates KPIs

The KPIs results for the synthetic Time-of-Use (ToU) rates are presented in Figure 7. The profiles of the KPIs are similar to those of the real ToU rates, but the magnitude of the bills differs significantly. In all three cases studied, the bill reduction with synthetic ToU rates is more than double (15%-22%). This highlights the crucial importance of the ToU rates for the effectiveness of the optimization process. In countries where the ToU rates are flat, storing energy for later use would not provide any benefit. From a customer perspective, the overall results of 24-hour simultaneous bill minimization are positive. However, from a utilities standpoint, the increased Peak-to-Average Ratio (PAR) and the higher consumption of grid energy may not be welcomed. Nevertheless, it is worth noting that the peak grid power occurs during off-peak times, which can still be considered a positive outcome by utilities since it increases the plant capacity factor.

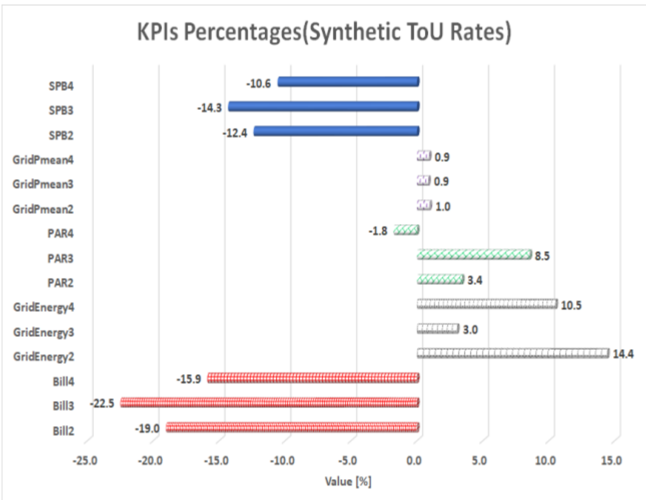

Figure 7. Synthetic ToU Rates KPIs

6. Conclusion

This study focuses on minimizing a household's energy bill by optimizing the 24-hour bill profile instead of individual time step power usage. The method efficiently utilizes Time-of-Use (ToU) rates to store energy during low tariff periods for use during peak tariff periods. By avoiding the need for load scheduling methods, bill reductions of 6% to 10% are achieved, depending on load or PV output variations. If the summer ToU rates are extended to the winter, savings can potentially reach 15%-22%, highlighting the potential of ToU rates to promote PV-battery system investments.

In comparison, load scheduling methods only provide 6%-10% savings according to a cited study, and they come with customer constraints. The proposed method achieves greater savings without imposing any constraints on customers. Although the Peak-to-Average Ratio (PAR) ratios increase up to 16%, a closer examination of the grid power profile reveals that the peak occurs during a low tariff off-peak period, which does not add extra stress to the grid. This indicates a better utilization of generation capacity, leading to improved return on investment for power plants.

From the customer's perspective, the Simple Payback (SPB) period is reduced by 4% to 14%, resulting in a time gain of up to 14 months. The next step in the study is to implement this optimization strategy in hardware using affordable electronics, making the solution accessible to a larger number of households.

References

[1] D. Burillo, M. Chester, and B. Ruddell, “Electric Grid Vulnerabilities to Rising Air Temperatures in Arizona,” *Procedia Engineering*, vol. 145, pp. 1346–1353, 2016 doi:10.1016/j.proeng.2016.04.173.

[2] J. Farfan and C. Breyer, “Aging of European power plant infrastructure as an opportunity to evolve towards sustainability,” *International Journal of Hydrogen Energy*, vol. 42, no. 28, pp. 18081–18091, Jul. 2017, doi: 10.1016/j.ijhydene.2016.12.138.

[3] O. Majeed Butt, M. Zulqarnain, and T. Majeed Butt, “Recent advancement in smart grid technology: Future prospects in the electrical power network,” *Ain Shams Engineering Journal*. Vol. 12(1), pp.687-695, Jul. 07, 2020, doi: 10.1016/j.asej.2020.05.004.

[4] “Global Electricity Review 2020 - Ember.” https://ember-climate.org/project/global-power-2020/ (accessed Sep. 25, 2020).

[5] P. Carvalho, “Smart metering deployment in Brazil,” *Energy Procedia*, vol. 83, pp. 360–369, Dec. 2015, doi: 10.1016/j.egypro.2015.12.211.

[6] S. Alpanda and A. Peralta-Alva, “Oil crisis, energy-saving technological change and the stock market crash of 1973-74,” *Review of Economic Dynamics*, vol. 13, no. 4, pp. 824–842, Oct. 2010, doi: 10.1016/j.red.2010.04.003.

[7] S. Rajamand, “Effect of demand response program of loads in cost optimization of microgrid considering uncertain parameters in PV/WT, market price and load demand,” *Energy*, vol. 194, p. 116917, Mar. 2020, doi: 10.1016/j.energy.2020.116917.

[8] "Electricity Information 2019 – Analysis - IEA." https://www.iea.org/reports/electricity-information-overview (accessed Sep. 25, 2020).

[9] C. Camarasa, C. Nägeli, Y. Ostermeyer, M. Klippel, and S. Botzler, "Diffusion of energy efficiency technologies in European residential buildings: A bibliometric analysis," *Energy and Buildings*, vol. 202. Elsevier Ltd, p. 109339, Nov. 01, 2019, doi: 10.1016/j.enbuild.2019.109339.

[10] E. lo Cascio, Z. Ma, D. Borelli, and C. Schenone, "Residential Building Retrofit through Numerical Simulation: A Case Study," *Energy Procedia*, vol. 111, pp. 91–100, Mar. 2017, doi: 10.1016/j.egypro.2017.03.011.

[11] A. Synnefa et al., "Transformation through Renovation: An Energy Efficient Retrofit of an Apartment Building in Athens," *Procedia Engineering*, vol. 180, pp. 1003–1014, Jan. 2017, doi: 10.1016/j.proeng.2017.04.260.

[12] S. N. J. Al-Saadi, J. Al-Hajri, and M. A. Sayari, "Energy-Efficient Retrofitting Strategies for Residential Buildings in hot climate of Oman," *Energy Procedia*vol. 142, pp. 2009–2014, Dec. 2017, doi: 10.1016/j.egypro.2017.12.403.

[13] S. M. Hosseini, R. Carli, and M. Dotoli, "Model Predictive Control for Real-Time Residential Energy Scheduling under Uncertainties," in Proceedings - 2018 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2018, pp. 1386–1391, Jan. 2019, doi:10.1109/SMC.2018.00242.

[14] R. Halvgaard, L. Vandenberghe, N. K. Poulsen, H. Madsen, and J. B. Jørgensen, "Distributed Model Predictive Control for Smart Energy Systems," *IEEE Transactions on Smart Grid*, vol. 7, no. 3, pp. 1675–1682, May 2016, doi: 10.1109/TSG.2016.2526077.

[15] D. Dongol, T. Feldmann, and E. Bollin, "A model predictive control based peak shaving application for a grid connected household with photovoltaic and battery storage," in SMARTGREENS 2018 - Proceedings of the 7th International Conference on Smart Cities and Green ICT Systems, vol. 2018-March, pp. 54–63, 2018 doi: 10.5220/0006685300540063.

[16] S. Seal, B. Boulet, and V. R. Dehkordi, "Centralized model predictive control strategy for thermal comfort and residential energy management," *Energy*, vol. 212, p. 118456, Dec. 2020, doi: 10.1016/j.energy.2020.118456.

[17] R. Halvgaard, L. Vandenberghe, N. K. Poulsen, H. Madsen, and J. B. Jørgensen, "Distributed Model Predictive Control for Smart Energy Systems," *IEEE Transactions on Smart Grid*, vol. 7, no. 3, pp. 1675–1682, May 2016, doi: 10.1109/TSG.2016.2526077.

[18] H. M. Ruzbahani, A. Rahimnejad, and H. Karimipour, "Smart Households Demand Response Management with Micro Grid," 2019 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, USA, 2019, pp. 1-5, doi:10.1109/ISGT.2019.8791595.

[19] M. J. M. al Essa, "Home energy management of thermostatically controlled loads and photovoltaic-battery systems," *Energy*, vol. 176, pp. 742–752, Jun. 2019, doi: 10.1016/j.energy.2019.04.041.

[20] M. Shakeri et al., "An intelligent system architecture in home energy management systems (HEMS) for efficient demand response in smart grid," *Energy and Buildings*, vol. 138, pp. 154–164, Mar. 2017, doi: 10.1016/j.enbuild.2016.12.026.

[21] A. Parsa, T. A. Najafabadi, and F. R. Salmasi, “Implementation of smart optimal and automatic control of electrical home appliances (IoT),” in IEEE Proceedings 2017 Smart Grid Conference, SGC 2017, Mar. 2018, pp. 1–6, doi: 10.1109/SGC.2017.8308861.

[22] H. M. Ruzbahani, A. Rahimnejad and H. Karimipour, "Smart Households Demand Response Management with Micro Grid," 2019 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, USA, 2019, pp. 1-5, doi: 10.1109/ISGT.2019.8791595.

[23] K. Ma, G. Hu, and C. J. Spanos, “A cooperative demand response scheme using punishment mechanism and application to industrial refrigerated warehouses,” *IEEE Transactions on Industrial Informatics*, vol. 11, no. 6, pp. 1520–1531, Dec. 2015, doi: 10.1109/TII.2015.2431219.

[24] A. Mahmood, A. R. Butt, U. Mussadiq, R. Nawaz, R. Zafar, and S. Razzaq, “Energy sharing and management for prosumers in smart grid with integration of storage system,” in ICSG 2017 - 5th International Istanbul Smart Grids and Cities Congress and Fair, Istanbul, Turkey, Jun. 2017, pp. 153–156, doi: 10.1109/SGCF.2017.7947623.

[25] H. Turker and I. Colak, “Multiobjective optimization of Grid- Photovoltaic- Electric Vehicle Hybrid system in Smart Building with Vehicle-to-Grid (V2G) concept,” in 7th International IEEE Conference on Renewable Energy Research and Applications, ICRERA 2018, pp. 1477–1482, doi: 10.1109/ICRERA.2018.8567002.

[26] “HOME - www.soda-pro.com.” http://www.soda-pro.com/ (accessed Sep. 25, 2020).

[27] “Photovoltaic Geographical Information System (PVGIS) | EU Science Hub.” https://ec.europa.eu/jrc/en/pvgis (accessed Sep. 25, 2020).

[28] “Global Solar Atlas.” . [Online]. Available: https://globalsolaratlas.info/map?c=11.523088,8.4375,3 (accessed Sep. 25, 2020).

[29] “Solar Panels | Tesla.” . [Online]. Available: https://www.tesla.com/solarpanels (accessed Sep. 25, 2020).

[30] “Commercial and Residential Hourly Load Profiles for all TMY3 Locations in the United States - Datasets - OpenEI DOE Open Data.” . [Online]. Available: https://openei.org/doe-opendata/dataset/commercial-and-residential-hourly-load-profiles-for-all-tmy3-locations-in-the-united-states (accessed Sep. 25, 2020).

[31] “Electricity storage and renewables: Costs and markets to 2030,” /publications/2017/Oct/Electricity-storage-and-renewables-costs-and-markets, Accessed: Sep. 25, 2020. [Online]. Available: /publications/2017/Oct/Electricity-storage-and-renewables-costs-and-markets.

[32] “Time of Use, TOU, Pricing Plans, TOU Pricing Plans | San Diego Gas & Electric.” . [Online]. Available: https://www.sdge.com/whenmatters (accessed Sep. 25, 2020).

[33] X. Wu, X. Hu, Y. Teng, S. Qian, and R. Cheng, “Optimal integration of a hybrid solar-battery power source into smart home nanogrid with plug-in electric vehicle,” *Journal of Power Sources*, vol. 363, pp. 277–283, Sep. 2017, doi: 10.1016/j.jpowsour.2017.07.086.