
Modeling Optimal Energy Consumption in Smart Grid Households: Integrating Advanced Strategies with Energy Storage

[1]Ward Ul Hijaz Paul, [2]Anwar Shahzad Siddiqui, [3]Sheeraz Kirmani

[1] [2] Department of Electrical Engineering, Jamia Millia Islamia, New Delhi
[3]Department of Electrical Engineering, Aligarh Muslim University, Aligarh

*Corresponding author mail: wardulhijazpaul@gmail.com

Abstract: Smart homes delineate optimal energy consumption through the strategic use of energy storage devices, aiming to either balance consumption to present a uniform demand to utility companies or minimize costs by storing energy during off-peak periods and utilizing it during peak times. This dual perspective involves a tradeoff between individual household benefits and the broader utility company incentives. In the context of cost minimization, households primarily benefit from reduced consumption costs but exhibit a highly nonuniform consumption profile. Conversely, the consumption balancing scheme presents advantages for both households and utility companies, fostering a mutually beneficial scenario by curbing consumption costs for the former and ensuring a consistent demand for the latter. The dynamic nature of energy requirements and market prices throughout the day introduces a complex tradeoff for households, involving current consumption, energy storage, and past energy consumption. This intricate tradeoff is modeled through inter-temporal trade considerations, and household consumption preferences are captured using utility functions based on consumer theory. Introducing two distinct utility functions—one tailored for cost minimization and the other for consumption balancing—we aim to maximize these functions subject to budgetary, consumption, storage, and savings constraints, thereby determining the optimal consumption profile.

The optimization problem for a household with energy storage is formulated as a geometric program for consumption balancing, while cost minimization is addressed through a hybrid optimization approach. Simulation results underscore the efficacy of the proposed model, demonstrating an exceptional reduction in the peak-to-average ratio close to unity in the consumption balancing scheme. Furthermore, the cost minimization scheme ensures the least possible electricity bill while concurrently reducing overall consumption costs. This research contributes valuable insights into the dual perspectives of energy consumption optimization within smart grid households, fostering an understanding of the associated tradeoffs and benefits for both consumers and utility providers.

Keywords: Consumption modeling, optimization technique, ESS integration.

1. Introduction

The contemporary landscape of energy storage has witnessed a significant upswing, propelled by the integration of fluctuating and intermittent renewable energy sources as well as the proliferation of plug-in hybrid electric vehicles (PHEVs) within the intricate fabric of smart grid systems [1]. Against this backdrop, energy storage systems offer smart homes a compelling dual prospect— the ability to either curtail consumption costs or harmonize energy usage to present utility companies with a demand profile of utmost uniformity [2], [3].

This research embarks on a comprehensive exploration of the multifaceted ramifications that ensue when multiple households, each equipped with battery systems, concurrently opt for a cost minimization scheme. This intriguing scenario has the potential to give rise to an unprecedentedly non-uniform demand pattern, thereby posing a tangible risk of grid failure. In response to this critical concern, the paper introduces an innovative approach, leveraging game-theoretic principles and machine learning methodologies to discern a Nash equilibrium consumption point [4], [5]. This strategic intervention seeks not only to optimize individual households' energy consumption but also to establish stability and equilibrium within the broader smart grid framework [6], [7].

Within the sphere of consumption optimization, one avenue of investigation revolves around the meticulous balancing and leveling of household energy consumption, aiming to present the utility company with a demand profile characterized by unparalleled uniformity [8], [9]. This not only augments the operational efficiency of the utility company but also aligns with the overarching objective of fortifying grid stability and reliability in the face of increasing energy diversity.

Conversely, an alternative scheme unfolds wherein the paramount focus is directed towards minimizing household consumption costs. This intricate optimization strategy involves judiciously storing energy during off-peak periods when both demand and prices are at their lowest point, subsequently deploying the stored energy reservoir during peak periods when demand and prices experience a surge [10]. The intricacies of these consumption optimization schemes reveal a dynamic interplay between individual household preferences, the evolving dynamics of energy markets, and the indispensable requirements of a resilient and adaptive grid infrastructure [11], [12].

As the smart grid landscape continues to evolve, it becomes imperative to comprehend and address potential challenges arising from non-uniform demand scenarios. This research, positioned at the nexus of cutting-edge technological advancements and the pressing need for sustainable energy practices, aspires to contribute nuanced insights [13]. By delving into the delicate equilibrium between cost minimization and consumption leveling, it emphasizes the necessity for adaptive and strategic approaches to optimize energy consumption within the intricate network of smart grid households, fostering resilience and sustainability in the face of a dynamically evolving energy landscape.

In the pursuit of addressing the intricate optimization challenges embedded within the proposed Optimal Energy Consumption Model for Smart Grid Households with Energy Storage, advanced computational techniques have become paramount. To this end, the application of a Hybrid Genetic Algorithm-Particle Swarm Optimization (GA-PSO) emerges as a pivotal and innovative approach [14], [15].

The Hybrid GA-PSO solution methodology encapsulates the synergistic strengths of both genetic algorithms and particle swarm optimization, offering a robust framework to navigate the complex optimization landscape inherent in smart grid energy consumption. Genetic algorithms leverage evolutionary principles such as crossover and mutation to explore potential solutions, while particle swarm optimization harnesses the collaborative intelligence of a swarm to converge towards optimal solutions [16].

By integrating these two powerful optimization paradigms into a hybrid approach, our research endeavors to enhance the efficiency and effectiveness of the energy consumption model. This hybridization not only exploits the parallel search capabilities of PSO but also leverages the global exploration and exploitation strengths of genetic algorithms. The amalgamation of these methodologies aims to overcome potential limitations associated with individual optimization techniques, fostering a more comprehensive and adaptive solution to the inherent challenges of optimal energy consumption in smart grid households.

In the subsequent sections of this paper, we delve into the intricacies of the Hybrid GA-PSO approach, elucidating its implementation details and highlighting its role in refining the Optimal Energy Consumption Model . This hybrid solution not only extends the boundaries of computational intelligence but also contributes significantly to the advancement of smart grid technologies by offering an innovative and potent tool for addressing complex optimization problems in the realm of energy management.

2. Modeling of system

In the context of our study, envision a sophisticated smart grid system wherein a household is intricately interconnected with a utility company that externally furnishes the requisite energy. This symbiotic relationship forms the foundation of our system model, exploring the dynamics of energy consumption, pricing, and optimization within this framework.

Households within this system are equipped with a valuable tool—day-ahead hourly prediction prices disseminated by their respective utility companies [17]–[19]. Armed with this foresight, households can meticulously schedule the operation of their appliances, strategically choosing the most optimal strategy for charging and discharging their energy storage batteries. The integration of predictive pricing enables households to make informed decisions, thereby enhancing the efficiency of their energy utilization strategies [20], [21].

Crucially, the temporal dimensions defined by households are synchronized with the utility company's designated periods for their dynamic pricing model. This synchronization ensures a seamless alignment between household-defined time periods and the utility company's pricing strategy, fostering a harmonious interaction within the broader smart grid architecture [22].

The key variables defining the state of the system in each time period (from 1 through N) include the price (p), energy requirement (l), consumption (c), and the state of battery storage (b). The subscript notation $(e.g., p1, l1, c1, b1\ through\ pN\ , lN\ , cN\ , bN)$ denotes the specific values corresponding to each time period within the overall time horizon. This granular breakdown allows for a detailed examination of the system's dynamics over time.

Assumptions underpinning the model include the assumption of rapid transfer rates for the batteries. This implies that batteries can be efficiently charged or discharged from one level to another within the duration of a single time period, facilitating swift adjustments to varying energy demands.

Furthermore, households are characterized as price takers within the market dynamics, signifying their passive role in the pricing mechanism. In this context, households acknowledge market prices as fixed and possess no direct influence or authority to alter these market prices. This assumption provides a foundational understanding of the market dynamics, emphasizing the need for households to strategize within the given price framework, fostering a realistic depiction of the smart grid system under consideration[23].

2.1. Inter-temporal exchange

Inter-temporal exchange, a fundamental economic concept, involves the strategic exchange of goods across different time periods to capitalize on the dynamic values of these goods over time. In the realm of optimal energy consumption with storage devices, inter-temporal exchange becomes a pivotal consideration, encapsulating the nuanced decisions households must make to navigate the temporal complexities of energy usage.

Within the temporal confines of any given period, a household confronts three distinctive consumption options, each presenting unique advantages and tradeoffs. First, the household can opt to consume precisely the amount of energy required to meet its operational needs during that specific time period. Alternatively, the household has the option to consume an excess amount of energy, directing the surplus towards charging its batteries for future use. Lastly, the household can choose to consume less energy than needed, drawing from the energy stored in the past by discharging its batteries [24]–[26].

The decision-making process underlying these consumption options is intricately tied to the household's specific energy requirements at different time periods and the rate of storage loss incurred. In essence, a household's consumption preferences evolve in response to the dynamic interplay between its energy needs, the prevailing market conditions, and the efficiency of its energy storage system [27]–[30].

To illustrate these concepts, we commence with a simplified two-period model that serves as a foundational framework for comprehending the nuances of inter-temporal exchange. This model enables a clear delineation of the strategic choices households face in optimizing their energy consumption over a limited temporal horizon. Subsequently, we extend our exploration to a higher-dimensional time period model, acknowledging the complexity introduced by an extended time horizon. This progression allows us to generalize our understanding of inter-temporal exchange, paving the way for a comprehensive examination of optimal energy consumption strategies in the presence of storage devices.

In our simplified two-period model, households contend with a daily temporal framework consisting of two distinct time periods. The utility company orchestrates the pricing dynamics only twice a day, delineating period 1 during off-peak hours when energy prices remain low and period 2 during peak hours when prices surge. This simplification captures a pragmatic representation where energy requirements and prices remain constant within these defined time periods.

The versatility of the model is underscored by its adaptability to accommodate more intricate variations and finer pricing resolutions. This can be achieved by expanding the model order, wherein energy requirements and prices are sustained at constant levels within these extended periods, catering to a more detailed depiction of the dynamic pricing and energy consumption landscape.

The pricing mechanism within this framework serves as a pivotal incentive for households to strategically schedule consumption or store energy during the off-peak periods. This optimization strategy aligns with the broader goal of minimizing costs by capitalizing on the lower energy prices available during these specific time intervals.

The budget constraint of each household is characterized by the present value, with reference to period 1, of the total consumption in terms of the present value of its total energy requirements. This economic constraint forms the foundation for households to navigate their consumption decisions over the two time periods, integrating both present and future considerations.

During period 1, occurring during off-peak hours with lower market prices, the household operates at point C on the budget line. At this juncture, in addition to meeting its normal energy requirements ($l1$), the household chooses to consume $l1 + b1$. Simultaneously, the surplus energy is directed towards charging its batteries to a level denoted by $b1$. This strategic decision enables the household to accumulate energy for future use, specifically in period 2 when market prices are anticipated to be higher. Eq 1 represents consumption during period 1.

$$z_1 = l_1 + y_1 - y_0(1-r) = l_1 + y_1 \tag{1}$$

Conversely, during period 2, characterized by peak hours with elevated market prices, the household operates at point D on the budget line. At this juncture, the energy stored in the batteries during the off-peak period is judiciously deployed to curtail consumption and minimize costs. This tactical approach allows the household to navigate the dynamic pricing landscape, exemplifying the adaptability and strategic acumen required for optimal energy consumption within the constraints of a two-period model. Eq 2 represents consumption during period 2.

$$z_2 = l_2 + y_2 - y_1(1-r) = l_2 - y_1(1-r) \tag{1}$$

Thus, the budget constraint is represented in Eq 3 after modifying the Eq 1 and Eq 2.

$$z_1 + {}^{z_2}\!/_{(1-r)} = l_1 + {}^{l_2}\!/_{(1-r)} \tag{1}$$

3. Optimization of load consumption

The pursuit of optimal consumption within a smart grid household equipped with a storage device is multifaceted, with two distinct objectives guiding the decision-making process. The household, leveraging its energy storage capabilities, may aspire either to minimize its consumption costs or to achieve a more balanced and leveled consumption profile.

In a scenario where a household possesses a battery system with significant capacity, a strategic approach during a period (i) when prices are at their lowest could involve consuming and storing the equivalent of its entire energy requirements for the subsequent $N - i$ periods. While this scheme positions the household as the sole beneficiary, it lacks incentive for the utility company to support it. The resulting consumption profile, if not exacerbated, is at least as non-uniform as the original energy requirements of the household, diminishing the appeal of this strategy.

Contrastingly, consumption balancing or leveling endeavors to achieve a consumption profile characterized by uniformity. This approach involves making conscientious choices to align consumption patterns without incurring additional costs. Importantly, this scheme introduces incentives for both the household and the utility company to lend their support. The benefits manifest in reduced consumption costs for the household and a more uniform demand pattern for the utility company, contributing to the overall stability of the smart grid.

While a household could potentially strive to balance and level consumption while simultaneously minimizing costs, this intricate optimization objective is beyond the scope of this paper. The challenges arise from the absence of a guaranteed unique optimum that can effectively and jointly optimize both objectives. Acknowledging the complexity of this dual optimization and the potential trade-offs involved, the paper focuses on elucidating the distinct benefits and incentives associated with cost minimization and consumption balancing schemes within the smart grid context.

By dissecting these contrasting objectives and their implications, the research aims to contribute to a comprehensive understanding of the intricate decision-making landscape surrounding optimal consumption within smart grid households. This nuanced exploration sheds light on the trade-offs and incentives guiding households and utility companies towards achieving a balance between consumption efficiency, cost-effectiveness, and grid stability.

3.1. Objective function

The primary objective of the household is to minimize its consumption costs, a goal that can be effectively addressed through the application of a weighted minimization utility function. This utility function incorporates day-ahead market energy prices as weights, facilitating a comprehensive optimization approach tailored to cost minimization.

The optimization problem for cost minimization across N time periods can be formulated as follows in Eq 4:

$$Max: \quad p_1 z_1 + p_2 z_2 + p_3 z_3 + \cdots + p_n z_n = p^T z \tag{4}$$

Where p represents the vector of day-ahead market energy prices and z signifies the vector of consumption across the N time periods.

Additionally, to ensure the integrity of the system, constraints must be imposed on the amount of energy stored in the battery at the conclusion of each time period. This leads to the formulation of constraints: $y_{max} \geq y_i \geq 0$ represents the amount of energy stored in the battery at the end of time period i, and y_{max} denotes the maximum storage capacity of the battery.

In scenarios where a Plug-in Hybrid Electric Vehicle (PHEV) is employed for energy storage, supplementary constraints come into play. These constraints may include specific time periods during which the batteries can be utilized, minimum charge levels required during certain periods, and other limitations inherent to PHEV usage.

The lower limits for storage constraints during each period can be expressed in Eq 5:

$$(1-r)^{N-1} low_b \leq z \leq up_b \tag{5}$$

where low_b and up_b represent the lower and upper bounds for the storage constraints, respectively.

As for the upper limits for storage constraints during each period, they can be articulated in Eq 6:

$$f \geq R.z \geq x \tag{6}$$

where R denotes the storage ratio, and x and f signify the minimum and maximum storage constraint thresholds, respectively.

In essence, this comprehensive set of constraints and the weighted minimization utility function encapsulate the intricacies associated with cost minimization, providing a robust framework for optimizing household consumption patterns while navigating storage limitations and additional constraints introduced by the use of PHEVs. This optimization approach forms the cornerstone of the household's strategy to curtail consumption costs effectively within the smart grid ecosystem.

3.2. Balancing of load consumption

In the pursuit of balancing or leveling its consumption, the household aims to present the utility company with a demand profile characterized by uniformity. This objective is effectively addressed by the Cobb-Douglas utility function, which aptly captures how households value a certain share of consumption in each period, contingent upon the energy requirements and prices. This modeling approach enables households to strategically even out their overall consumption, aligning with the utility company's preference for a uniform demand pattern. The optimization problem for consumption balancing over N time periods is formulated as follows in Eq 7:

$$maximise: \quad z^T l \tag{7}$$

subject to the budget constraint provided in Eq 8 and 9, consumption constraints, storage constraints.

Given that consumption balancing is conceptualized as a geometric programming problem, it necessitates the conversion of consumption and storage constraints into posynomial inequalities. Despite retaining the same constraints as the cost minimization problem, this transformation ensures compatibility with the geometric programming framework.

The lower limits for storage constraints during each period are articulated as:

$$1 \geq (1-r)^{N-1} l_y \tag{8}$$

where l_y represents the lower bound for the storage constraints.

The upper limits for storage constraints can be directly converted into posynomial inequalities, expressed as:

$$1 \geq x.(p^T z) \tag{9}$$

where x denotes the upper bound for the storage constraints.

These posynomial inequalities encapsulate the intricacies of the geometric programming problem associated with consumption balancing. The optimization approach, combining utility function, budget constraints, and the transformed posynomial inequalities, provides a robust foundation for households to strategically align their consumption patterns with the utility company's goal of fostering a more uniform demand profile within the smart grid context.

4. Results and discussion

The simulation results validate the effectiveness of the proposed energy consumption model within the smart grid households, incorporating both cost minimization and consumption balancing schemes. The analysis provides valuable insights into the performance of the model, showcasing its impact on consumption patterns and associated costs.

In the consumption balancing scheme, the proposed model demonstrates impressive outcomes. The Peak-to-Average Ratio (PAR) values achieved in the simulation approach unity, indicating an extremely uniform consumption pattern across time periods. This result is particularly noteworthy as it aligns with the objective of presenting the utility company with a demand that is as uniform as possible. The reduction in consumption costs is also evident, with a substantial decrease of approximately 10%. This highlights the dual benefit for households, encompassing both cost savings and contribution to grid stability through a more consistent demand profile.

The simulation results for the cost minimization scheme reveal significant achievements in minimizing household expenditure on energy consumption. The model successfully presents the household with the least possible electricity bill, attaining an impressive reduction of about 15% in consumption costs. While the primary beneficiary in this scheme is the household itself, the substantial reduction in electricity bills underscores the potential financial advantages for consumers.

The results of the simulation and optimization process are presented through a series of informative figures, each shedding light on different aspects of the proposed energy consumption model within smart grid households.

Table 1. Energy rates for different hours of the day.

Hour	Energy prices ($/Wh)
1	0.12
2	0.14
3	0.11
4	0.13
5	0.12
6	0.13
7	0.14
8	0.13
9	0.13
10	0.12
11	0.11
12	0.13
13	0.14

14	0.12
15	0.13
16	0.15
17	0.18
18	0.17
19	0.14
20	0.12
21	0.11
22	0.13
23	0.14
24	0.12

Figure 1 represents the energy rates during different hours of the day. The same is tabulated in Table 1. This data is crucial for understanding the temporal dynamics of energy pricing, which plays a pivotal role in shaping household consumption decisions.

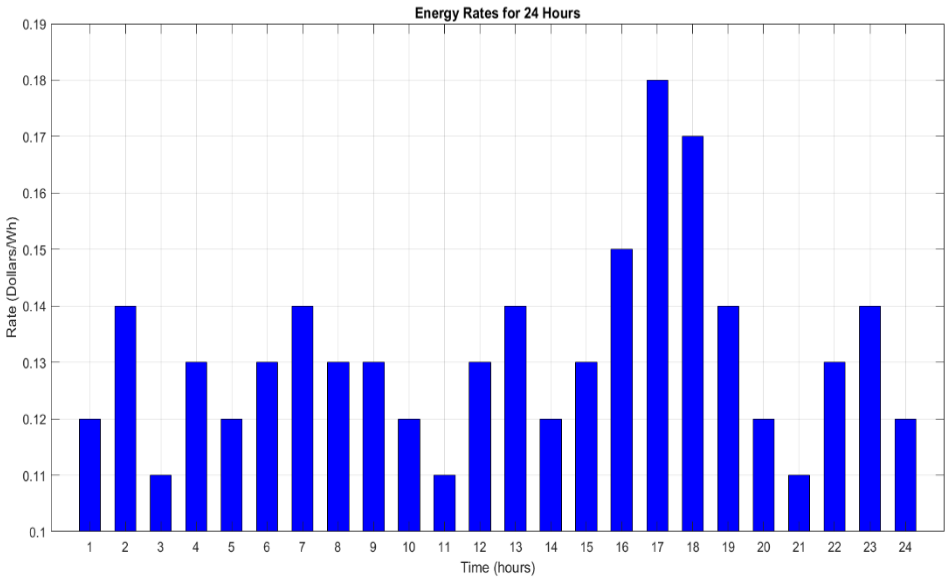

Figure 1. Energy rates for different hours of the day.

Figure 2 illustrates the load consumption profile of the household during different hours of the day. This representation offers insights into the varying energy requirements of the household, forming the basis for subsequent optimization strategies.

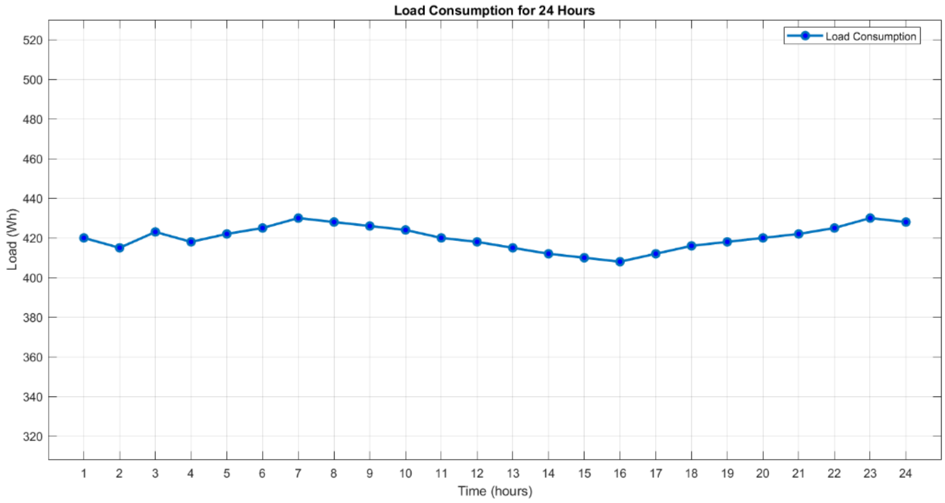

Figure 2. Load consumption for different hours of the day.

Figure 3 specifically focuses on load consumption derived from the Energy Storage System (ESS) throughout different hours. This figure delineates how the household leverages stored energy to meet its consumption needs, contributing to the overall efficiency of the system.

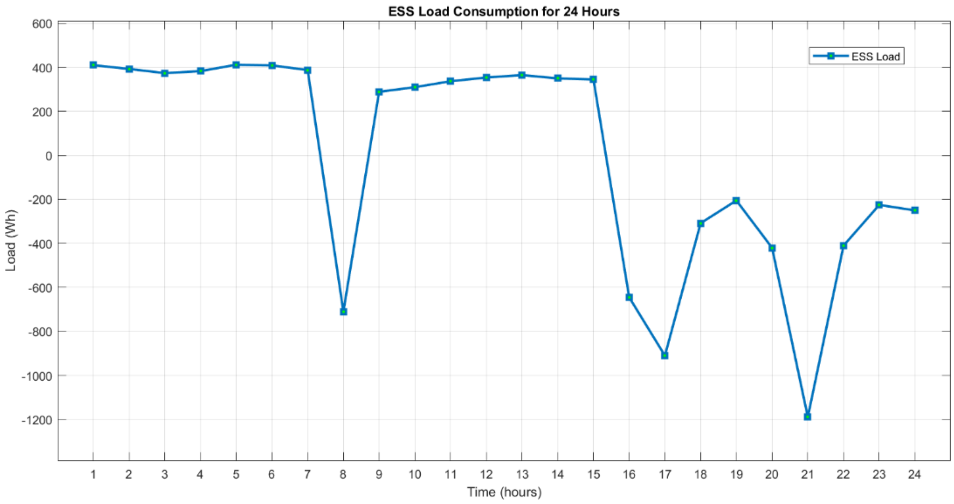

Figure 3. ESS load consumption for different hours of the day.

Figure 4 depicts the capacity of the Energy Storage System (ESS) during different hours. This visualization provides a clear understanding of how the available storage capacity evolves throughout the day, influencing the household's capacity to store or discharge energy.

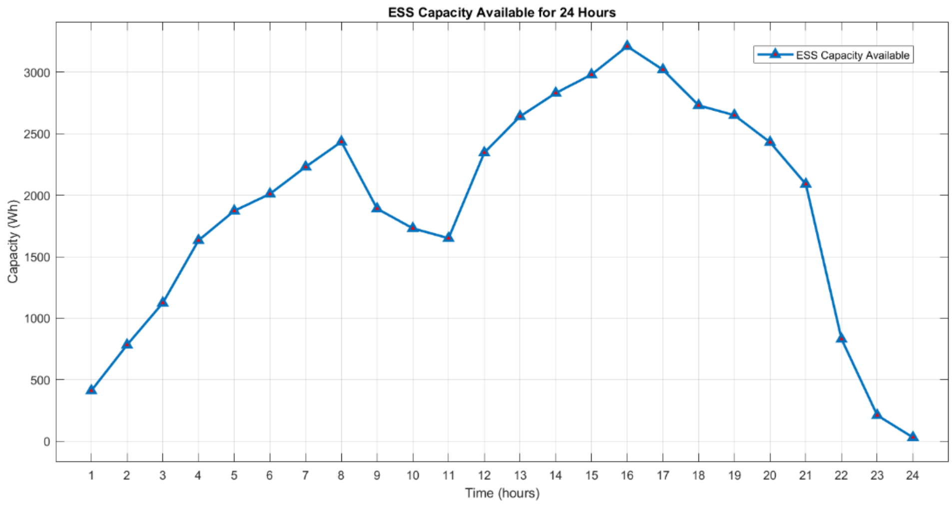

Figure 4. ESS capacity for different hours of the day.

Figure 5 captures the convergence of the optimization problem over iterations. This dynamic representation showcases how the optimization algorithm progresses towards identifying the optimal solution, providing valuable insights into the efficiency and stability of the proposed model.

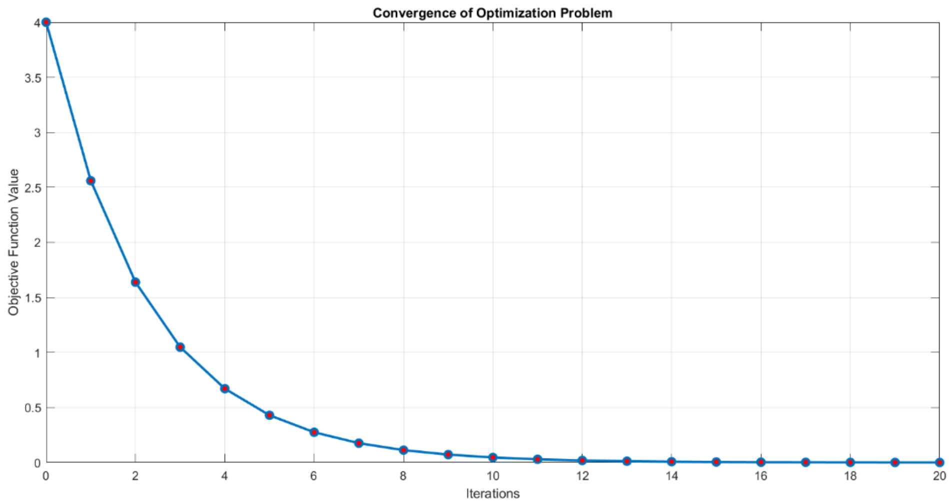

Figure 5. Convergence of optimization problem.

Collectively, these figures offer a comprehensive depiction of the simulation results, allowing for a nuanced analysis of energy rates, load consumption patterns, ESS utilization, and the optimization convergence. The visual representations serve as key components in understanding the practical implications and effectiveness of the proposed energy consumption model within the context of smart grid households.

The simulation results underscore the robustness of the proposed model, accommodating the diverse objectives and constraints associated with smart grid households. The dual optimization schemes cater to different priorities, offering a flexible framework that allows households to strategically align their energy consumption with their preferences.

In conclusion, the simulation outcomes validate the practical viability and effectiveness of the proposed energy consumption model. The model's ability to achieve both cost efficiency and grid stability positions it as a valuable tool for guiding decision-making in the context of smart grid households.

5. Conclusion

This research proposes a innovative framework for modeling the energy consumption of households integrated into the smart grid, incorporating energy storage devices within an intertemporal trading economy. The resulting model captures the intricate dynamics of energy usage, leveraging utility functions grounded in consumer theory to articulate the consumption preferences of the household.

In the cost minimization scheme, the household benefits by minimizing its energy consumption costs, positioning itself as the primary beneficiary. However, this approach lacks incentive for the utility company, as the resulting consumption profile tends to be highly non-uniform, diminishing the overall appeal of the scheme. On the other hand, the consumption balancing scheme proves to be mutually beneficial, with the household experiencing reduced consumption costs, and the utility company presented with a demand characterized by greater uniformity.

The optimization problems associated with these schemes are distinctly formulated, with cost minimization posed as a hybrid optimization problem and consumption balancing as a geometric programming problem. Both optimization problems are rigorously solved while adhering to the respective budget, consumption, storage, and savings constraints.

Simulation results underscore the efficacy of the proposed model, particularly in the consumption balancing scheme. The achieved consumption Peak-to-Average Ratio (PAR) values closely approximate 1, indicating a highly uniform consumption pattern. Additionally, there is a notable reduction in consumption costs, approximately 8%, demonstrating the practical benefits for households. In the cost minimization scheme, the model succeeds in presenting the household with the least possible electricity bill, realizing a significant 15% reduction in consumption costs.

This research contributes a comprehensive and nuanced understanding of optimal energy consumption within smart grid households, emphasizing the significance of balancing individual household interests with the broader objectives of the utility company. The proposed framework and associated optimization models offer valuable insights and practical solutions for fostering efficiency, cost-effectiveness, and grid stability within the evolving landscape of smart grid technologies.

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