IJRRS
International Journal of Reliability, Risk Saftey: Theory and Application
Online ISSN: 2676-3346

Vol. 6/ Issue 2/ 2023/ pp. 1-13
DOI: 10.30699/IJRRS.6.2.1
Received: 15 May 2023, Accepted: 22 August 2023

Original Research Article

Charge Management of Energy Storage Devices Considering Battery Wear in IoT-based Distribution Networks

Moaied Mohseni*[1]

1. Khuzestan regional electric company, Ahvaz, Iran

*** moaiadmohsenii@gmail.com**

Abstract

This research paper comprehensively analyzes the advantages of integrating energy storage resources into an energy management system, highlighting how it can significantly improve profitability and overall energy quality. One of the key benefits is the ability to regulate charging and discharging cycles, which helps prolong the service life of storage devices. In addition, the study delves into the influence of consumer behavior and the Internet of Things (IoT) on energy storage charge management, identifying important insights for enhancing efficiency. The optimization process for this investigation utilizes the YALMIP and MOSEK toolboxes, ensuring rigorous and accurate results. The experimentation is conducted on an IEEE standard 33-bus network, offering a robust foundation for real-world applications. The research outcomes demonstrate remarkable enhancements in both technical and economic parameters, including energy storage resources. By harnessing the potential of energy storage, businesses and industries can achieve greater cost savings and operational efficiencies. Furthermore, the paper considers the longevity of storage resources, comprehensively comparing results. This factor is crucial in determining such systems' long-term benefits and sustainability. In conclusion, the study underscores the immense advantages that IoT technology brings to energy management and its positive impact on consumers. By leveraging IoT capabilities and integrating energy storage resources intelligently, optimal consumption management can be achieved, leading to a more sustainable and efficient energy ecosystem.

Keywords: Internet of things; energy management; electrical energy storage; consumer behavior; distributed generation.

Nomenclature

Symbol	Description
c_t^{DG}	production price of dg
$c_{t,wholesale}^{DG}$	major sell rate of dg production
c_t^{TOU}	Retail rate with term of use
$c_t^{TOU,wholesale}$	major sell rate market with term of use
$c_{min}^{TOU,wholesale}$	Lowest major sell rate market with term of use
$c_{max}^{TOU,wholesale}$	utmost major sell rate market with term of use
c_{min}^{TOU}	Lowest Retail sell rate market with term of use
c_{max}^{TOU}	utmost Retail sell rate market with term of use
d_{KL}	kullback leibler distance
$f_{customer}$	fitness function of consumer
$f_{discomfort}$	Inconvenience expenditure
$f_{Payment}$	Electricity payment expenditure
M	A biggish finite digit
$MUT^{\mathcal{L}}$	Minimum loading time
$N(\varepsilon_1^i)$	Number of consumers with the ε_1^i coefficient
L_t^{Total}	total load considering normal consumer behavior
PD_t^{total}	The whole power demand of the net
PD_n^t	Node load of n

Symbol	Description
$\mathcal{P}_n^{base}$	The node basis electricity of n
$\mathcal{P}_{Total}^{base}$	The general basis power of the net
$\mathcal{P}_t^{DG}$	retail electricity procure from dg
$\mathcal{P}_{t,wholesale}^{DG}$	major sell electricity procure from dg
$\underline{\mathcal{P}}_t^{DG}$, $\overline{\mathcal{P}}_t^{DG}$	Lowest / utmost range of dg
$\mathcal{P}_t^{Grid}$	electricity procure of the net
$\mathcal{P}_{i,t}^{Grid}$	electricity procure of the net by consumer i
$\underline{\mathcal{P}}_t^{Grid}$, $\overline{\mathcal{P}}_t^{Grid}$	Lowest / utmost range of the net power
$\mathcal{P}_t^{UpGrid}$	electricity procure of the upstream net
$\mathcal{P}_t^{\mathcal{L}}$	Electric power of Load
$\breve{\mathcal{P}}_t^{\mathcal{L}}$	Ideal Electric power of Load
$\hat{\mathcal{P}}_t^{\mathcal{L}}$	Nominal Electric power of Load
$\mathcal{P}_t^{S}$	electric storage charging
$\underline{\mathcal{P}}_t^{S}$, $\overline{\mathcal{P}}_t^{S}$	Lowest / utmost electric storage charging
$\Pr(\varepsilon_1^i)$	Possibility relevant to the ε_1^i
$\Pr(\chi)$	Possibility relevant to the χ
$Pr^{new}(\chi)$	New Possibility relevant to the χ
t, Δt	time distance and its duration
t_{ini}, t_{final}	Initial and final time
$\mathcal{T}$	collection of time splits

Symbol	Description
$t^{\pounds}_{operation}$	Operating time for each load
$t^{\pounds}_{des}$	eligible time to start the time flexible load
$\gamma^{\pounds}_{t}$	inconvenience rate of the load
$\delta^{\pounds}_{t}$	assumed Parameter indicates the importance of time flex load postponement
$\varepsilon_1, \varepsilon_2$	Coefficients Weighting of the consumer expenditure
ε^{i}_{1}	Weight Coefficient of the i^{th} consumer expenditure
$\xi^{\pounds}_{t}$	changing load situation
$\tau^{\pounds}_{t}$	binary for turn on/turn off situation of the load
σ^{2}_{TOU}	Rate amount with term of use
$\sigma^{2}_{TOU,desired}$	eligible rate amount with term of use
Ω^{Bus},Ω^{DG}, Ω^{Line}	collection of DGs, lines ,nodes
Ω^{TFL},Ω^{PFL},Ω^{NFL}	collection of time flex, power flex and non-flex loads
Ω^{Load},$\Omega^{customers}$	collection of loads and consumers
$\Omega^{storage}$	collection of batteries
$U^{ch}_{i,h}$	Storage charge status
$\mathrm{U}^{\mathrm{dch}}_{\mathrm{i,h}}$	Storage discharge status

Symbol	Description
$SOC_{i,h}$	The amount of energy available during each time interval in each storage
$XC^{ch}_{i,h}$	Counter The number of times the storage is in charging mode
$XM^{ch}_{i,h}$	Indicates a binary variable that the storage has started charging at a specified
T	Time Scheduling time for storage
$XC^{dch}_{i,h}$	Counter The number of times the storage is in discharge mode
$XM^{dch}_{i,h}$	Indicates a binary variable that the storage has started discharging at a specified time
$XN^{ch}_{i,h}$	A binary variable that indicates when the storage has started to stop charging
$XN^{dch}_{i,h}$	A binary variable that indicates when the storage has started to stop discharging
Γ^{ch}_{i}	Indicates the minimum number of hours that the storage unit is continuously in charging mode
Γ^{dch}_{i}	Indicates the minimum number of hours the storage is continuously in discharge mode

1. Introduction

Today, the use of renewable energy sources in power networks to generate electricity is on the rise, driven by new trends in energy supply and growing global environmental concerns arising from fossil fuel products [1]. The rate of utilizing energy sources based on solar power is increasing, reducing installation costs [2]. Energy storage management is crucial to enhance energy storage systems' safety, reliability, and performance. This paper introduces a cloud storage management system for energy storage, aiming to improve the computing power and data storage capability of cloud computing. Through the Internet of Things (IoT), all storage data is seamlessly measured and transmitted to the cloud [3]. Solar power generation sources can be installed on rooftops in low-pressure distribution networks, with capacities of less than 10 kW, benefiting consumers worldwide. The reasons for this widespread adoption include varying sunlight intensity in different areas, cost savings, and incentives and subsidies offered in this field. Utilizing solar power-based production resources offers various advantages, such as reducing network dependence on global electricity supply, improving voltage profiles, and minimizing losses in the network [4]. However, integrating these renewables into distribution networks has not been without challenges. As the volume of these resources increases in distribution networks and during periods of increased load consumption, it can cause reverse load distribution in the network [5]. Reversed load playback on the network can lead to several issues, including increased harmonics, elevated node voltage levels, performance errors in network protection systems, heightened network losses, and reduced reliability. To mitigate the negative effects of a significant presence of production-based resources, two main solutions are employed in modern distribution networks, focusing on solar power. The first approach involves using traditional methods to handle momentary changes in the load. The second method employs advanced technologies, such as controlling reactive power using solar power-based production resources, implementing Flexible AC tools at the distribution network level, and utilizing energy storage technology at the local level. Emphasizing storage technology can significantly reduce the adverse impacts of solar sources in the network. Numerous papers have been published on planning and managing batteries and determining their optimal size [6, 7]. In [8], the authors describe the optimal battery size in power distribution networks equipped with solar power sources to control network voltage. In [9], a static synchronous compensator for controlling increased network voltage has been examined, but an economic evaluation is lacking. A critical review of various energy storage technologies, including their types, categories, and comparisons, is presented in [10]. The authors in [11] evaluated the economic aspects of using storage devices in the power grid to optimize electricity purchase and reduce network losses during peak times, but restrictions on exploitation were not considered. In [12], a real-time control method was used to smooth the load profile in the distribution network, and storage capabilities were incorporated, though economic issues were not addressed. [13] examines the size and location of storage devices in the network, highlighting their importance in managing network losses, voltage control, and load management. [14] explores the simultaneous use of traditional methods, such as voltage regulators, alongside storage sources to control network voltage. Furthermore, [15] addresses the network decongestion problem and prevention of voltage increase from storage sources for optimal network operation. [16] tackles the voltage issue in the network with storage devices in line with economic objectives, utilizing reverse load reduction and volume reduction. The authors control the number of voltage fluctuations resulting from sudden power output changes in solar production sources from storage. However, it is essential to note that charging and discharging optimization were not provided. In [17], storage expansion at the distribution network level was based solely on the cost of investment and land usage without discussing the benefits. The presence of these new technologies has not been extensively studied. In [18], the authors focus on optimal programming for storage devices in distribution networks to reduce network losses, but environmental considerations are not considered. Similarly, [19] aims to decrease network costs and losses using storage resources at the distribution network level.

A new approach to battery pack modeling is introduced in [20], where several previously published models are combined into a comprehensive framework. This paper elaborates on the sub-model connection, basic principles, required configurations, and new parameters.

The introduction of IoT (Internet of Things) technology has revolutionized traditional energy management systems, transforming them into responsive embedded systems that reflect consumer preferences in their energy supply process [21]. While the concept of IoT is relatively simple, its practical implementation necessitates various infrastructures, such as communication systems, tools, sensors, actuators, and control and protection systems [22-23]. Two-way customer communication with the smart grid operator brings numerous technical and economic benefits to all system stakeholders, including consumers, distribution system operators, and central control units, such as government agencies [24]. IoT's potential in smart grids offers connectivity across all sectors, leading to high potential and various advantages in multiple fields. Notable research on the use of IoT in smart grids is reviewed in [25], exploring its potential in the US grid [26] and smart cities [27] and investigating several advantages of IoT-based systems in research [28]. Technical benefits, such as load profile flattening, peak shaving, minimizing drop, and optimizing voltage deviation, can be achieved with IoT technology, which necessitates proper modeling of IoT-based energy management systems. Efficiently integrating distributed (renewable) energy sources and energy storage to meet consumer energy needs while minimizing power generation and transmission costs is a primary concern in modern energy management systems [29]. The paper [30] presents the evolutionary steps and generations that have shaped the development of IoT, along with the motivations for its creation. The popularity of IoT has made it a brand for consumer-oriented technology solutions, but this paper aims to provide an overview of its development. Regarding the smart grid, one of the most crucial aspects is its increased vulnerability to cyber threats. [31] presents a bibliographic review of research papers focusing on the security aspects of IoT. Furthermore, [32] describes the role of advanced sensing systems in the future electrical network using IoT technology to monitor energy flow between nodes in an electrical network effectively. In the context of smart cities, [33] emphasizes the importance of advanced IoT-based measurement systems for two-way energy flow. Leveraging emerging IoT technologies [34] highlights implementing applications in smart grids, incorporating advanced sensing systems and smart converters to enhance electricity network performance and municipal services. This paper proposes a bi-level power management strategy for an active distribution network (ADN) in the presence of a virtual power plant (VPP). The VPP comprises a renewable energy source (RES) parking lot, an energy storage system (ESS), and an electric vehicle (EV) coordinated with the VPP operator (VPPO). The coordination framework between the VPPO and the distribution system operator is also addressed [35].

While most existing research focuses on determining the optimal size and location of storage resources in distribution networks, this paper highlights the importance of effectively managing these resources. The study evaluates whether energy storage resources in distribution networks can be optimally utilized to their fullest potential, considering their lifespan and potential value for investment. The longevity of storage resources is crucial in the operation of new distribution networks since frequent charging and discharging cycles can significantly reduce their lifespan and lead to additional costs.

To address these challenges, the paper quantitatively evaluates IoT-based energy management systems in distribution systems. The proposed framework facilitates IoT-based system control and considers the customer's perspective and the electrical energy storage. The accurate modeling of storage devices throughout the day and night ensures proper control of their charge and discharge rates to prevent premature lifespan reduction. Various analyses are conducted to demonstrate the impact of time-of-use (TOU) pricing and customer satisfaction on economic parameters (e.g., total cost and customer discomfort cost) and technical parameters (e.g., peak load, average load, and load factor).

The primary focus of this paper is to evaluate the presence of energy storage resources from both economic and technical perspectives while considering the behavior of IoT-based consumers in distribution networks with a significant volume of solar power generation resources. The study demonstrates that incorporating IoT technology into the smart grid yields more benefits than without this structure.

One notable aspect of this research is analyzing the charging management of energy storage devices, considering consumer behavior in IoT-based distribution networks, which has not been extensively explored in previous studies. Therefore, this paper aims to provide an efficient consumer behavior analysis while considering the IoT-based structure, offering valuable insights for optimizing energy management in distribution networks.

Overall, this paper introduces a comprehensive IoT-based approach for home energy management focusing on TOU, load profile extraction, storage charge management, and considering the effects on storage device lifespan. Using IoT technology and statistical analysis enhances energy efficiency, reduces costs for consumers, and ensures the system's longevity of energy storage resources.

The innovation of this paper can be summarized as follows:

1. Application of IoT for Home Energy Management based on Time-of-Use (TOU): The paper introduces IoT technology for managing home energy consumption by taking advantage of time-of-use pricing. IoT enables real-time communication and control, allowing consumers to optimize their energy usage during different periods based on varying electricity prices.
2. Total Load Profile Extraction Following Normal Distribution Function: The paper proposes a method to extract the total load profile of consumers, which follows a normal distribution function. This approach provides a statistical representation of energy consumption patterns, enabling a better understanding and analysis of energy usage behavior.
3. Implementation of IoT-based Storage Charge Management: The study incorporates IoT technology to manage energy storage systems' charging and discharging cycles effectively. By utilizing IoT connectivity, the charging and discharging rates can be optimized to improve the efficiency of energy storage utilization.
4. Evaluation of Distribution Function Convergence using Kulback-Leibler (KL) Distance: To assess the performance of the proposed energy management strategy, the paper employs the Kulback-Leibler (KL) distance to measure the difference between the actual total distribution function of consumers and the normal distribution function. This analysis helps determine the accuracy and effectiveness of the proposed load profile extraction method.
5. Consideration of Storage Wear and Lifespan Management: To address the issue of storage wear caused by intermittent charging and discharging, the paper considers the impact on the service life of energy storage systems. By optimizing charging and discharging cycles through IoT-based management, the aim is to avoid premature degradation of storage devices and extend their lifespan.

Sections 2 and 3 of the paper are dedicated to problem modeling and formulation. In Section 4, we present the simulation of our proposed approach. Finally, Section 5 provides the conclusion of our study.

2. Model Description

The mathematical model for problem optimization is comprehensively described in this section. The control system type utilized here combines decentralized and centralized control. The home energy management department operates locally based on specific interests and receives information from the central server. After conducting the necessary analyses, the results are sent back to the central server. Decisions regarding changes in electricity prices are made at the central server based on the information received, considering the central server's interests. These decisions are then communicated to the home energy management units, and the iterative process continues until the best decision is reached. Implementing the Internet of Things (IoT) plays a crucial role in facilitating communication and management across various distribution system components. The utilization of IoT brings numerous benefits to consumers and the electricity market alike. Decisions are formulated based on constraints, benefits, and information received from the IoT Central Unit, and the updated information is sent back to the Central Unit for each unit. Data analysis occurs at the center, gathering relevant information to make the final optimization decision. Figure (1) visually represents the structure of the Internet of Things in this context, illustrating the interconnectedness of consumers and the electricity market with the central server through communication channels.

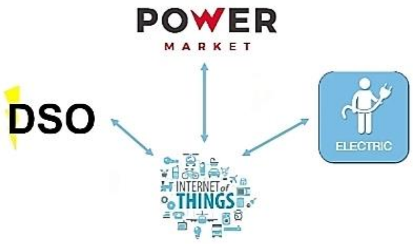

Figure 1. Schematic of Proposed IoT-Based Infrastructure

Electricity consumers receive time-based tariff prices from the central server and provide their load profile (power purchased from the grid) for big data analysis. The electricity procured from the upstream network is transmitted to the central server. The objective is to achieve optimal time consumption and wholesale tariff. To achieve this, the amount of power purchased from wholesale and consumer markets is sent to the electricity market. The resulting prices from the electricity market are then sent back to the central server, and this iterative process continues until the best price is reached. In this iterative approach, consumers and the electricity market interact with the central server, exchanging data and information to determine the most favorable electricity prices and consumption patterns. The use of big data analysis and the iterative nature of the process contribute to optimizing the overall energy consumption and tariff decisions. This approach enables consumers to make informed decisions based on the prevailing electricity prices, contributing to efficient energy utilization and cost management.

2.1 MILP Model of Customer Behavior

The home energy management system gathers information about the electrical equipment in the home and the number of common desires. It optimizes the electricity consumption based on the electricity price received from the central server. The loads in a home can be categorized into three types: non-flexible loads (NFL), time-flexible loads (TFL), and power-flexible loads (PFL).

1. None flexible loads (NFL) are fixed and operated at specific times with a predetermined power level.
2. Time-flexible loads (TFL) are loads that can have their operating times shifted, allowing consumers to adjust the schedule according to their preferences.
3. Power flexible loads (PFL) have fixed operating times but can be adjusted to increase or decrease their power consumption based on specific conditions.

Each home in the system is equipped with renewable resources and energy storage. The cost of using renewable resources is factored into the overall cost, and consumers can choose the proportion of their energy supply from renewable sources and municipal electricity, depending on the cost of using renewable products or the electricity price.

The main goal of the energy management system in this study is to minimize the total cost incurred by the consumer and the level of dissatisfaction. The energy management system aims to find an optimal solution that minimizes both the cost of electricity consumption and the level of dissatisfaction experienced by the consumer. This optimization process considers the different types of loads, electricity prices, renewable resources, and storage options available to achieve an efficient and cost-effective energy consumption strategy for the home. Therefore, the objective function of the energy management system can be defined as follows:

$$f_{Customer} = \varepsilon_1 f_{Payment} + \varepsilon_2 f_{discomfort} \tag{1}$$

Where $\varepsilon_1, \varepsilon_2$ are constant coefficients selected as:

$$\begin{aligned} &\varepsilon_1 + \varepsilon_2 = 1, \\ &\varepsilon_1, \varepsilon_2 \geq 0 \end{aligned} \tag{2}$$

The selection of coefficients in the energy management system is entirely based on the consumer's preferences. Each consumer has complete control over their choices, and the analysis and studies of home energy management are conducted accordingly. This consumer-centric approach allows individuals to customize their energy consumption strategy based on their interests and priorities. The vector of home energy management decision variables can be represented as follows:

$$\begin{aligned} &X \equiv \left[P_t^{L}, \tau^{L}, \ldots, P_t^{S}, E_t^{S} \ldots, P_t^{DG} \right], \\ &L \in \Omega^{load}, DG \in \Omega^{DG}, S \in \Omega^{strg}, t \in T \end{aligned} \tag{3}$$

The program includes the power consumption of each load, their latency, the energy storage capacity, the power output of distributed generation sources, and the energy level of the storage. Real numbers represent all variables in this program. Additionally, $f_{\text{discomfort}}$ and f_{payment} are used to calculate the cost of payment and total consumer discomfort, respectively, and they can be computed as follows:

$$f_{Payment} = \sum_{t \in T} \left(\underbrace{c_t^{TOU} P_t^{Grid}}_{FromGrid} + \underbrace{c_t^{DG} P_t^{DG}}_{FromDG} \right) \tag{4}$$

$$f_{discomfort} = \sum_{t \in T} \sum_{L \in \Omega^{PFL}} \gamma_t^{L} \left(\breve{P}_t^{L} - P_t^{L} \right) + \sum_{t \in T} \sum_{L \in \Omega^{TFL}} \gamma_t^{L} \delta_t^{L} \tau_t^{L} \tag{5}$$

Where$\delta_t^{\mathcal{L}}$ as a hypothetical vector that shows the effect of time delay on TFL loads and is expressed as follows:

$$\delta_t^{L} = \begin{cases} 0 & t \leq t_{des}^{L} \\ t - t_{des}^{L} & t > t_{des}^{L} \end{cases} \tag{6}$$

Also, $\tau_t^{\mathcal{L}}$ is a fixed fine for Any load and $\breve{\mathcal{P}}_t^{\mathcal{L}}$ is the shape of the desired load for each power flexible load. It can be determined conforming consumers as follows:

$$\breve{P}_t^{L} = \begin{cases} \hat{P}_t^{L} & t \in t_{operation}^{L} \\ 0 & t \notin t_{operation}^{L} \end{cases} \tag{7}$$

Equation (7) states that ideal Plug-and-Forget Load (PFL) devices must operate at their rated power during the allowable period distance and be OFF at all other times. Assuming relationships (1) to (7), the priorities of the consumer objective function can be linear. The electricity consumption of PFL loads is treated as a continuous variable, while the execution time of Time-of-Use Flexible Load (TFL) devices is considered a binary variable. To effectively manage home energy, it is essential to adhere to the boundary conditions of the problem. To achieve a feasible solution, the following passable method is proposed, and various boundary constraints must be met:

$$\sum_{L \in \Omega^{Load}} P_t^{L} + \sum_{S \in \Omega^{Storage}} P_t^{S} = \sum_{DG \in \Omega^{DG}} P_t^{DG} + P_t^{Grid} \tag{8}$$

$$\sum_{L \in \Omega^{Load}} P_t^{L} = \sum_{L \in \Omega^{PFL}} P_t^{L} + \sum_{L \in \Omega^{TFL}} P_t^{L} + \sum_{L \in \Omega^{NFL}} P_t^{L} \tag{9}$$

$$0 \leq P_t^{L} \leq \breve{P}_t^{L}, \qquad \forall L \in \Omega^{FPL}, t \in T \tag{10}$$

$$P_t^{L} \equiv \tau_t^{L} \hat{P}_t^{L}, \qquad \forall L \in \Omega^{FTL}, t \in T \tag{11}$$

$$P_t^{L} \equiv \breve{P}_t^{L}, \qquad \forall L \in \Omega^{NFL}, t \in T \tag{12}$$

$$\underline{P}_t^{DG} \leq P_t^{DG} \leq \overline{P}_t^{DG}, \qquad \forall DG \in \Omega^{DG}, t \in T \tag{13}$$

$$\underline{P}_t^{Grid} \leq P_t^{Grid} \leq \overline{P}_t^{Grid}, \qquad \forall t \in T \tag{14}$$

$$\tau_t^{L} \in \{0,1\}, \qquad \forall L \in \Omega^{FTL}, t \in T \tag{15}$$

$$\xi_t^{L} \equiv \tau_t^{L} - \tau_{t-1}^{L}, \qquad \forall L \in \Omega^{FTL}, t \in T \tag{16}$$

$$\tau_{t_i}^{L} \geq \xi_t^{L} ; \forall L \in \Omega^{FTL}, t_i \in [t, t+MUT^{L}-1] \quad (17)$$

Equation (8) illustrates the total power from distributed generation and electricity obtained from the net, which should equal the power consumption of the loads and the charging power of the energy storage. Equation (9) shows that the sum of the three types of loads (PFL, TFL, NFL) equals the overall network load. Flexible power loads have fixed on and off times that cannot be changed, with only their rated power being adjustable within this range (from zero, representing off, to their ideal level).

According to Equation (10), other loads are flexible regarding their on and off times, but their power value remains fixed. They can shift their entire ideal consumption curve in the time domain. Relationship (11) emphasizes that the known data is a given problem and is determined by consumers based on each home appliance's ideal power consumption waveform. This information will be expressed in the simulation section.

Inflexible loads, as described in Equation (12), remain unchanged. The power level harvested from each distributed generation should fall within the range of the minimum (often zero) to the maximum available renewable power, as stated in Equations (13,14). Equations (15-17) define constraints for binary variables.

Upon receiving Time-of-Use (TOU) price data from the center, consumers can plan their load according to their preferences. Customers can choose the weight of ε1 to indicate their priorities between reducing electricity bills and minimizing inconvenience costs. Energy storage also allows storing energy during low-cost periods and discharging it during higher-priced periods.

NFL loads must not exceed their predefined standards. Still, time-flex loads can adjust their operating time, and power-flex loads can regulate their electrical power output to optimize cost and minimize discomfort. After planning, each consumer's total net hourly consumption information is sent to the center for data analysis and utilization [32].

2.2 Modeling of energy storage resources

The reason for introducing these additional constraints is to optimize the operation and management of energy storage resources within distribution networks. Energy storage plays a vital role in balancing the intermittent nature of renewable energy sources, such as solar and wind power, by storing excess energy during periods of low demand and supplying it during peak demand hours. To achieve this optimal utilization, the control strategy for energy storage systems needs to be more sophisticated and adaptive. By imposing constraints that account for intermittent charging and discharging, the energy storage resources can be better integrated into the overall network operation. These constraints may consider factors like battery aging, efficiency losses during charging and discharging, and dynamic energy demand and supply variations.

Moreover, by controlling the energy storage more effectively, the overall stability and reliability of the distribution network can be improved, leading to enhanced energy efficiency and reduced operational costs. Furthermore, these additional constraints enable the energy storage resources to provide various grid services, such as peak shaving, frequency regulation, and voltage support, which are crucial for maintaining a robust and resilient distribution network. By optimizing the operation of energy storage systems, the network operators can ensure a more balanced and sustainable energy supply, even with the increasing integration of renewable energy sources.

$$U_{i,h}^{ch} P_{ESS}^{min} \leq P_{i,h}^{ch} \leq U_{i,h}^{ch} P_{ESS}^{max} \quad (18)$$

$$U_{i,h}^{dch} P_{ESS}^{min} \leq P_{i,h}^{dch} \leq U_{i,h}^{dch} P_{ESS}^{max} \quad (19)$$

$$U_{i,h}^{ch} + U_{i,h}^{dch} \leq 1 \quad (20)$$

$$SOC_{i,h} = SOC_{i,h-1} + (\eta_i^{ch} P_{i,h}^{ch} - P_{i,h}^{dch} / \eta_i^{dch}) \Delta t \quad (21)$$

$$SOC_i^{min} \leq SOC_{i,h} \leq SOC_i^{max} \quad (22)$$

$$0 \leq XC_{i,h}^{ch} \leq TU_{i,h}^{ch} \quad (23)$$

$$0 \leq XC_{i,h}^{dch} \leq TU_{i,h}^{dch} \quad (24)$$

$$(T+1)U_{i,h}^{ch} - T \leq XC_{i,h+1}^{ch} - XC_{i,h}^{ch} \leq 1 \quad (25)$$

$$(T+1)U_{i,h}^{dch} - T \leq XC_{i,h+1}^{dch} - XC_{i,h}^{dch} \leq 1 \quad (26)$$

$$XC_{i,h}^{ch} \geq \Gamma_i^{ch} XC_{i,h}^{ch} \quad (27)$$

$$XC_{i,h}^{dch} \geq \Gamma_i^{dch} XC_{i,h}^{dch} \quad (28)$$

$$U_{i,h}^{ch} - U_{i,h-1}^{ch} = XM_{i,h}^{ch} - XN_{i,h}^{ch} \quad (29)$$

$$U_{i,h}^{dch} - U_{i,h-1}^{dch} = XM_{i,h}^{dch} - XN_{i,h}^{dch} \quad (30)$$

$$XM_{i,h}^{ch} + XN_{i,h}^{ch} \leq 1 \quad (31)$$

$$XM_{i,h}^{dch} + XN_{i,h}^{dch} \leq 1 \quad (32)$$

$$XM_{i,h}^{dch} + XM_{i,h}^{ch} \leq 1 \quad (33)$$

$$XN_{i,h}^{dch} + XN_{i,h}^{ch} \leq 1 \quad (34)$$

The useful life of these resources is reduced by increasing the frequency of intermittent charging and discharging cycles of batteries in the network. This causes the batteries to wear out sooner than expected, and failure to address this issue can result in additional costs to the network. Therefore, it is necessary to restructure distribution networks and pay attention to energy consumption management to address this issue. In addition to discussing the importance of battery longevity, it is also necessary to consider more complete specifications and restrictions of storage resources. The following relationships show how to model these resources and optimize energy savings accurately. In the above relations, $U_{i,h}^{ch}$, $U_{i,h}^{dch}$ they show the binary variables and the charge and discharge mode of the storage, respectively. If the size of these variables is equal to 1, it means that the storage is in charge or discharge mode. The amount of energy available during each time interval in each storage is expressed $SOC_{i,h}$using a variable. T refers to the planning time, which in this paper equals 24 hours. And, $XC_{i,h}^{ch}$, $XC_{i,h}^{dch}$ counters are the number of times the storage is in charge or discharge mode. $XM_{i,h}^{ch}$, $XM_{i,h}^{dch}$ Binary variables indicate that the storage device has started charging or discharging at a specified time. Also, $XN_{i,h}^{ch}$, $XN_{i,h}^{dch}$ binary variables will equal 1 when the storage device starts charging or discharging. The parameters Γ_i^{ch} , Γ_i^{dch}also indicate the minimum number of hours the storage must be continuously charged or discharged. Equations (18) and (19) define the acceptable range for the power received or delivered by the storage per hour, representing the limits within which the charging and discharging operations must be conducted. Equation (20) ensures that charging and discharging of the storage cannot occur simultaneously during a specific hour, preventing conflicting operations. Equations (21) and (22) provide information about the amount of energy available in the storage and the allowable amount that can be stored, respectively. These equations help in managing the energy level of the storage effectively. To address managing the frequency of recharging and discharging the storage devices and prevent premature battery wear or failure, the paper introduces additional constraints (23) to (34). These constraints utilize binary variables to control the charging and discharging cycles of the storage in a more optimized manner. Equations (23) and (24) specify that the number of charge and discharge counters should be positive and less than the normal operating time, ensuring a valid count of charging and discharging cycles. Constraints (25) and (26) state that if the storage is in charge or discharge mode, one unit should be added to the corresponding charge or discharge counter. This ensures accurate counting of charging and discharging cycles. Equations (27) and (28) for charge and discharge modes, respectively, emphasize that the minimum time the storage must remain in a specific mode cannot be less than a preset value (for charge mode) and (for discharge mode). These constraints help in controlling the duration of charging and discharging operations. Equations (29) and (30) for charge and discharge modes, respectively, indicate that the binary variables (for charge mode) and (for discharge mode) will be activated when the storage status changes from one mode to another. This ensures that the storage device transitions smoothly between charge and discharge operations. Equations (31) and (32) emphasize that the storage device cannot simultaneously be in charge and discharge modes in any of its working situations, preventing conflicting operations. Relationships (33) and (34) further emphasize the asymmetry between the two different storage modes, ensuring that the storage operates effectively and consistently within its intended mode. By incorporating these relationships and constraints, the paper achieves a more comprehensive and sophisticated control over storage devices' charging and discharging cycles. This approach optimizes energy storage management in distribution networks, leading to improved battery longevity, reduced operational costs, and enhanced overall network efficiency.

3. Impact of price tariff (TOU) on consumer behavior

The first step of the study involves evaluating the influence of pricing tariffs on various parameters of a smart home. The pricing of electricity is based on the consumption time tariff, and the hours of the day are categorized into three parts: low load, medium load, and high load, as presented in Table 1. The research aims to optimize the Time-of-Use (TOU) pricing to align with the central server's goals. For this purpose, the price of electricity generated by distributed generation sources is assumed to be uniform and represented as a single unit. The price of electricity in each hour will be expressed as a proportion of this unit price [36].

Table 1. Network electricity consumption hours [36]

Peak load	**Mid load**	**No load**	
19pm-22pm(4hr)	7am-19pm(12hr)	11pm-7am(8 hr)	**Time**
0-3pu	0-3pu	0-3pu	**price**

The study considers various scenarios to investigate the impact of price fluctuations on the issue. In these scenarios, the average consumption time tariff is set to be equal to a per unit (PU) value, creating a competitive environment between renewable products and the electricity distribution network. If the average price of the electricity tariff is higher than that of renewable generation, consumers will be more inclined towards renewable production. On the other hand, if the average price of the tariff is lower than that of distributed generation, consumers will prefer to rely on the supply network for all their consumption. To strike a balance, it is assumed that the average tariff equals the price of distributed production, i.e., per unit (PU). The study introduces a parameter called the standard deviation of price to model price fluctuations. This parameter represents the variability or volatility of electricity prices. Consumer reaction to price changes, particularly Time-of-Use (TOU) pricing, is significant. Naturally, altering the price variance (TOU) can influence consumer behavior. Therefore, a model is formulated to determine the consumption hour tariff based on the standard deviation and the average tariff. This model aims to find the tariff associated with each hour of the day and night. The times of no-load, medium load and peak load are clearly defined, and the mean and standard deviation of the price are considered as specific input parameters of the problem, with allowable limits based on Table (1). The price of electricity is treated as an unknown and is related to the periods of no-load, medium-load, and peak load. By examining different scenarios and using this model, the study aims to understand how price fluctuations impact consumer behavior and their choices between renewable generation and the electricity distribution network. This analysis can provide valuable insights into optimizing the pricing structure to encourage greater utilization of renewable energy and achieve a more balanced and sustainable energy consumption pattern.

3.1 Data solving for load collecting

Upon gathering the load data of each consumer, data processing is conducted at the center to calculate the total load profile in the distribution network. To simplify the computations further, the load profile of the entire distribution system is obtained by aggregating each consumer's information, as indicated in equation (35). Next, the accumulated load on all buses is distributed based on the load of the nominal basis of each bus, following equations (36) and (37). The specific timing of when these calculations are performed would depend on the energy management system's scheduling and operational procedures. The load data from each consumer would be collected periodically or in real-time, depending on the system's capabilities. The data processing and load profiling would then occur based on the frequency of data updates and the specific requirements of the distribution network's operation. This process could be performed at regular intervals, such as every hour, or when significant changes in the load profiles or system conditions necessitate reevaluation. Ultimately, the goal is to maintain an up-to-date and accurate representation of the distribution network's load profile to optimize energy management and grid stability.

$$PD_t^{Total} = \sum_{i \in \Omega^{customers}} \mathrm{P}_{i,t}^{Grid}\left(\varepsilon_1, c_t^{TOU}\right) \tag{35}$$

$$PD_n^t = \frac{\mathrm{P}_n^{base}}{\mathrm{P}_{Total}^{base}} PD_t^{Total} \tag{36}$$

$$\mathrm{P}_{Total}^{base} = \sum_{n \in \Omega^{bus}} \mathrm{P}_n^{base} \tag{37}$$

Where $\mathcal{P}_{i,t}^{Grid}$ Refers to the purchased electricity of the consumer i from the net. In this paper, to show the relationship between the effect of two parameters and without considering the total losses, several valuable curves have been extracted, and a probability distribution function has been considered, selecting all consumers with the parameter. Therefore, the relationship (35) is:

$$L_t^{Total} = \sum_{\varepsilon_1^i} N\left(\varepsilon_1^i\right) \Pr\left(\varepsilon_1^i\right) \mathrm{P}_t^{Grid}\left(\varepsilon_1^i, c_t^{TOU}\right) \tag{38}$$

Considering the law of probability for each density function as follows:

$$\sum_{\varepsilon_1^i} \Pr\left(\varepsilon_1^i\right) = 1 \tag{39}$$

This paper's objective is to obtain the load profile of the entire distribution system for each price using the standard normal probability density function and assess the effects of variations in the distribution function. The parameter (KL) represents the convergence level, which indicates the interval the probability distribution function covers. The (KL) parameter helps determine the distribution curve's spread or width, allowing for a clearer understanding of the range of probabilities associated with different load levels. This analysis enables a comprehensive evaluation of the impact of price changes on the distribution system's load profile, providing valuable insights for optimizing energy management strategies and enhancing the overall efficiency and reliability of the distribution network.

$$d_{KL} = \sum_{\chi}\left(\Pr(\chi)\log\frac{\Pr(\chi)}{\Pr^{new}(\chi)}\right) \tag{40}$$

Indeed, the utilization of the standard normal distribution function allows for the demonstration of various effects for each parameter. Different variations in the distribution curve can be observed by altering the parameters. The study's results reveal that when there is a significant deviation from the standard normal distribution function, the load profile curve exhibits more frequent maximum and minimum peaks.

This finding indicates that changes in the distribution function's parameters can influence the load patterns significantly. A higher level of deviation from the standard normal distribution may lead to more pronounced fluctuations in the load profile, resulting in increased occurrences of peak and off-peak loads. These fluctuations could affect the distribution network's stability and energy management strategies.

3.2 Market Preferences

Decisions in the electricity market are commonly adjusted based on Time-of-Use (TOU) prices to optimize the total supply profile. The load profile of the distribution system is determined by calculating the difference between the cost of purchasing electrical energy from the upstream network and the revenue generated from selling electricity to consumers. This relationship can be expressed as follows:

$$\max benefit = \sum_{t\in\tau}(C_{t,wholesale}^{TOU} \quad P_t^{UPGRID} - C_t^{TOU} PD_t^{TOTAL}) \tag{41}$$

The distribution system profile quantifies the net financial outcome for the electricity distribution system. When the revenue from selling electricity to consumers exceeds the cost of procuring electrical energy from the upstream network, it results in a positive distribution system profile, indicating a profit for the distribution system. Conversely, if the cost of procuring electrical energy is higher than the revenue from electricity sales, the distribution system profile would be negative, representing a financial loss for the distribution system.

To foster competition between distributed generation units, several important boundary constraints should be taken into consideration:

1. Average Price Equality: The average price of Time-of-Use (TOU) tariffs should equal the average price of distributed generation units. This constraint is formulated based on relations (42) and (43) to ensure a level playing field for distributed generation and encourage competition between different generation sources.
2. Price Limits: The prices of TOU tariffs should fall within their prescribed range to maintain fairness and prevent pricing that could negatively impact consumers or providers. This constraint is defined in relations (44) and (45) to enforce appropriate pricing boundaries.
3. Price Variance Control: The price variance of TOU tariffs can be selectively adjusted to observe the impact of price changes on consumer behavior. Relations (46) and (47) provide the framework to analyze how price fluctuations affect consumer decisions and demand patterns.
4. By incorporating these boundary constraints, the electricity market can be structured to facilitate competition among distributed generation units and ensure that pricing remains fair and within acceptable limits. These constraints are vital in optimizing energy distribution, promoting renewable energy integration, and enhancing overall efficiency and sustainability in the electricity market.

$$\sum_{t\in T} c_t^{TOU} = \sum_{t\in T} c_t^{DG} \quad (42)$$

$$\sum_{t\in T} c_{t,wholesale}^{TOU} = \sum_{t\in T} c_{t,wholesale}^{DG} \quad (43)$$

$$c_{\min}^{TOU} \le c_t^{TOU} \le c_{\max}^{TOU} \quad (44)$$

$$c_{\min}^{TOU,wholesale} \le c_t^{TOU,wholesale} \le c_{\max}^{TOU,wholesale} \quad (45)$$

$$\operatorname{var}\left(\sum_{t\in T} c_t^{TOU}\right) = \sigma_{TOU,desired}^2 \quad (46)$$

$$\operatorname{var}\left(\sum_{t\in T} c_t^{TOU}\right) = \sigma_{TOU,wholesale,desired}^2 \quad (47)$$

4. Simulation Results

This section delves into various aspects of distribution network reconfiguration in the Internet of Things (IoT). It begins by exploring the energy management system of a home, followed by an analysis of the role of network consumers in shaping the load profile for each home and their electricity consumption patterns. The distribution of network consumption is assumed to follow a normal distribution function, enabling the calculation of the overall network load profile. The study investigates how electricity pricing influences grid load profiles and electricity costs. In conclusion, the network load profiles are visualized at different pricing points. The analysis proceeds with the assumption that the load profile distribution in the network buses follows a uniform function, allowing for determining the load on each network bus.

Table .2. Information of all types of customer load [36]

Type	Name	Time (h)	kW	γ_t^L ($/kWh)
Time Flex	Wash-machine	2hr working duration	0.7	1
Power Flex	Light	11-17	0-0.8	0.8
	Air conditioner	Full time	0-1.4	1.4
Non Flex	Kettle	8-9,17-18, 20-21	0.3	0
	Toaster	8-9	0.2	0
	Refrigerator	Full time	0.2	0

Table 3. Technical and economic data of the distribution network [36]

Mid load	Peak load	discomfort	cost	ε_1
1.7164	3.0317	0.0174	45.1201	0
1.7481	3.7532	0.0873	44.1113	0.1
1.5929	2.4608	0.4483	42.0398	0.2
1.5098	2.4699	1.3417	39.3618	0.3
1.2913	2.5572	3.3390	35.7096	0.4
1.0849	1.9115	7.3074	30.8990	0.5
0.8631	1.6400	15.3327	24.3335	0.6
0.4125	1.5844	34.3327	14.2211	0.7
0.2308	1.7644	47.4616	9.1808	0.8
0.2125	1.0729	47.4851	9.1333	0.9
0.1943	1.4466	47.214	9.2647	1

This paper investigates the optimization of an energy management system (EMS) based on the Internet of Things (IoT) for a standard 33-bus network (IEEE) with 2,000 consumers. Each consumer has a 1 kW/3 kWh battery and a 2 kW rooftop photovoltaic system. The research is conducted over 24-hour intervals, and the consumers are differentiated based on their benefit factors, leading to varying energy consumption behaviors. Table (3) provides essential technological and economic data concerning the distribution network, where 1.5 kW/3 kWh batteries are employed for efficient energy storage, minimizing wastage during charge and discharge cycles. The cost structure includes 0.001 per unit per hour for time-flexible loads and 1 per unit per kilowatt-hour for power-flexible loads. The results obtained from the IoT-based EMS optimization are visually represented in Figure 2. The analysis reveals a scenario where customers prioritize minimizing discomfort rather than focusing solely on cost considerations. Consequently, PowerFlex loads operate at their maximum rating, while time-flexible loads are scheduled precisely as desired, without any delays. The study offers valuable insights into the impact of consumer preferences on load profiles. It highlights the significance of optimizing the EMS for enhancing energy efficiency and consumer satisfaction in the distribution network.

Table 4. The results of several pricing strategies used for market decision-making

Item	Value	Item	Value
DG unit location	Bus 6, 7, 13, 18, 28, 33	$c_{t,min}^{TOU}$	0 pu
DG unit capacity	500,1200,1350,1350,1200,500kW	$c_{t,max}^{TOU}$	3 pu
DG power factor	1,0.8, 0.9, 0.9, 0.8, 1	No Load interval	0-7
Voltage Limits	0.95-1.05 pu	Mid interval	7-19
$c_{t,wholesale}^{DG}$,c_t^{DG}	1 pu	Peak interval	19-24

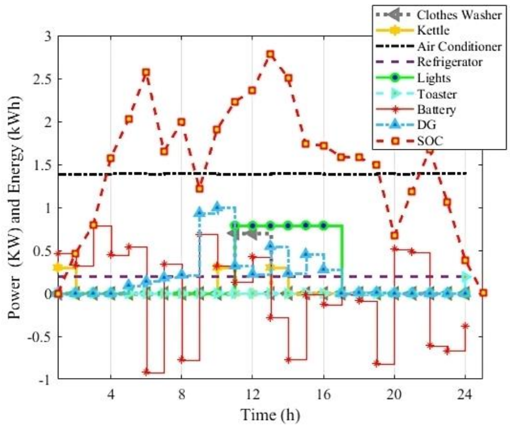

Figure 2 . Energy management system results for $\sigma^2 = 1$ and $\varepsilon = 0$

Table (4) shows that as consumer weight ε_1 increases, the cost of payment decreases while discomfort, peak load, and average load decrease.

4.1 The effect of the presence and absence of energy storage devices on the technical parameters

Table (5) displays voltage measurements recorded on the buses connected to Distributed Generation (DG) sources during peak hours at 14 and 15 hours. The data highlights that in the absence of storage resources, the network voltage experiences an increase due to the substantial presence of DG resources, leading to distribution network issues. However, with the integration of storage sources, a notable reduction in the voltage level is observed, effectively maintaining the mains voltage within acceptable limits. This underscores the positive impact of storage resources on mitigating network voltage fluctuations. To ensure a reliable energy supply and prevent intermittent charging and discharging, a minimum working mode duration of 2 hours is applied for each energy storage source. This strategic approach optimizes charging and discharging cycles, enhancing energy efficiency. Considering that DG production is directly influenced by solar power availability, which varies throughout the day, Figure (3) depicts the output power of each DG source as a percentage of its maximum capacity, aligned with the solar power patterns during day and night. Additionally, the figure illustrates the corresponding electricity prices over 24 hours, facilitating a comprehensive understanding of the dynamic relationship between DG output, solar power, and electricity prices. This analysis is essential for devising effective energy management strategies that align with fluctuating solar energy availability and pricing dynamics.

Table 5. The result of changing consumers' interests on their behavior

bus	14pm		15pm	
	Without storage	With storage	Without storage	With storage
6	1.099	0.978	1.088	0.973
7	1.097	0,989	1.095	0.980
28	1.095	0.977	1.093	0.974
13	1.094	0.983	1.093	0.978
18	1.091	0.990	1.088	0.975

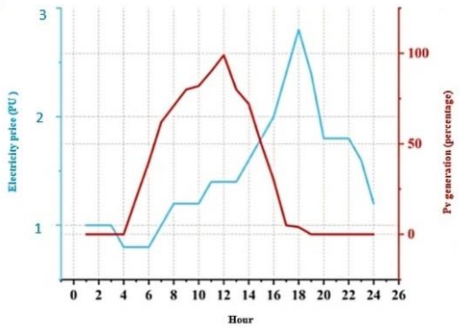

Figure 3. DG production profiles within 24 hours and electricity prices

Table 6 offers a comprehensive cost analysis of energy management under three scenarios: (1) without the presence of storage resources, (2) with the presence of storage resources but without considering longevity, and (3) with the presence of storage resources and considering longevity as a crucial factor. The results highlight that including storage resources has substantially reduced operating costs, which holds significant economic value. Despite considering the importance of storage life, the cost of energy management has slightly increased compared to the case without longevity consideration. However, it is essential to note that even with this consideration, the cost of energy management remains significantly lower compared to operating without these resources. The cost reduction can be primarily attributed to the positive impact of storage resources on optimizing power purchase and sale management with the upstream network. Figure 4 illustrates the power flow between the distribution network and the upstream network for a clearer visualization of power exchange dynamics with the network. This graphical representation effectively portrays how integrating storage resources contributes to more efficient and cost-effective energy management, showcasing the advantageous impact on the overall network operation.

Table 6. Voltage magnitude in DG buses with and without energy

Without storage	With the presence of storage and without regard to the importance of longevity	With the presence of storage and considering the importance to longevity
4057.818	3474.373	3687.405
Percentage reduction	14.37%	9.12%

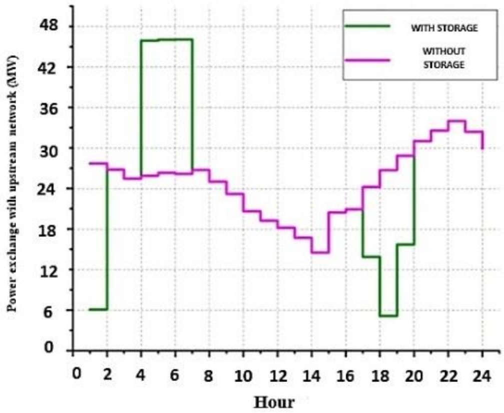

Figure 4. Power exchange rate with the upstream network during 24 hours

According to Figure (4), the presence of energy storage sources has positively impacted the network's power purchasing and selling mechanisms. During hours when the electricity prices were low, the amount of power purchased from the upstream network increased, while during hours of high electricity prices, the amount of power purchased decreased. Power injection and discharge of storage devices met the shortage during high-priced hours. This enhanced flexibility in buying and selling contributed to the reduction in operating costs, making the presence of energy storage resources economically beneficial for the network. Figure (5) provides a detailed insight into the behavior of storage devices connected to bus 23 in two scenarios. In the first scenario, where storage depletion and resource management constraints were considered, the storage device operated strategically to optimize its charging and discharging cycles. During low-priced hours, the storage entered the charge mode, increasing its energy level to the maximum of 1.5 priorities. In contrast, during high-priced hours, the storage was in discharge mode, injecting power into the grid and decreasing its energy level. In the second scenario, where storage wear was not considered, the device operated with more frequent charge cycles, resulting in a higher energy level than in the first scenario. However, this scenario may lead to faster wear and tear of the storage source due to increased charge-discharge cycles. The comparison between the two scenarios shows that considering the wear and tear of storage sources resulted in a more controlled and strategic operation, reducing the number of charge cycles to preserve the storage's longevity and optimize its energy usage. Overall, the presence of energy storage resources not only improved the technical aspects of the network, such as voltage control but also contributed to reduced operating costs, making it economically advantageous for the network to incorporate these resources. The careful management of storage wear and energy levels plays a significant role in ensuring the optimal performance and longevity of storage sources, thereby enhancing the overall efficiency and profitability of the distribution network.

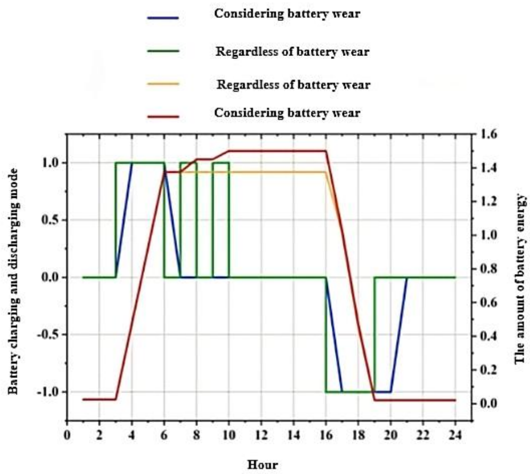

Figure 5. Energy level and charging and discharging modes of energy storage sources connected to bus 23 in two different scenarios

5. Conclusion

This paper presents an in-depth energy storage device charging management analysis, considering consumer behavior in IoT-based distribution networks. Utilizing two-way communication between the IoT center and other system components enables efficient achievement of network objectives. The IoT's capabilities include controlling consumer benefits by managing revenue and constructing energy costs based on suitable retail and wholesale prices (Time-of-Use, TOU) from the upstream grid. In this dynamic system, consumers have various choices, ensuring comprehensive consideration of diverse demands. Data analysis, with the standard normal distribution modeling the consumer consent coefficient, aids in computing the cumulative load, empowering the electricity market to optimize pricing methods for maximum benefits.

A primary focus of this research is to explore the potential negative effects of integrating energy storage sources into distribution networks, particularly on the longevity of storage resources when combined with distributed solar generation sources. The paper emphasizes the importance given to the issue of storage resource longevity, leading to the introduction of optimization techniques that minimize intermittent charge and discharge rates, safeguarding the resources' service life. Despite potential increases in the cost of grid energy management due to the implemented constraints, the paper highlights their significance in preserving the storage resources' lifespan.

The results demonstrate the essential role of energy storage resources in distribution networks, especially when integrated with distributed solar generation. These resources effectively contribute to voltage control and enable cost reductions during periods of high electricity prices, particularly during overnight hours. The paper provides valuable insights into the operation and optimization of energy storage equipment, emphasizing its positive impact on network performance and overall cost-effectiveness. The findings support the inclusion of energy storage in IoT-based distribution networks as a strategic and beneficial approach for both technical and economic reasons.

6. References

[1] M. M. Haque and P. Wolfs, "A review of high PV penetrations in LV distribution networks: Present status, impacts and mitigation measures," *Renewable and Sustainable Energy Reviews*, vol. 62, pp. 1195-1208, 2016/09/01/ 2016, doi: https://doi.org/10.1016/j.rser.2016.04.025.

[2] N. D. Laws, B. P. Epps, S. O. Peterson, M. S. Laser, and G. K. Wanjiru, "On the utility death spiral and the impact of utility rate structures on the adoption of residential solar photovoltaics and energy storage," *Applied Energy*, vol. 185, pp. 627-641, 2017/01/01/ 2017, doi: https://doi.org/10.1016/j.apenergy.2016.10.123.

[3] W. Li, M. Rentemeister, J. Badeda, D. Jöst, D. Schulte, and D. U. Sauer, "Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation," *Journal of Energy Storage*, vol. 30, p. 101557, 2020/08/01/ 2020, doi: https://doi.org/10.1016/j.est.2020.101557.

[4] K. W. Kow, Y. W. Wong, Rajparthiban K. Rajkumar, and R. K. Rajkumar, "A review on performance of artificial intelligence and conventional method in mitigating PV grid-tied related power quality events," *Renewable and Sustainable Energy Reviews*, vol. 56, pp. 334-346, 2016/04/01/ 2016, doi: https://doi.org/10.1016/j.rser.2015.11.064.

[5] M. Karimi, H. Mokhlis, K. Naidu, S. Uddin, and A. H. A. Bakar, "Photovoltaic penetration issues and impacts in distribution network – A review," *Renewable and Sustainable Energy Reviews*, vol. 53, pp. 594-605, 2016/01/01/ 2016, doi: https://doi.org/10.1016/j.rser.2015.08.042.

[6] R. A. Shalwala, "PV integration into distribution networks in Saudi Arabia," University of Leicester, 2012.

[7] P. Zhang, W. Li, S. Li, Y. Wang, and W. Xiao, "Reliability assessment of photovoltaic power systems: Review of current status and future perspectives," *Applied Energy*, vol. 104, pp. 822-833, 2013/04/01/ 2013, doi: https://doi.org/10.1016/j.apenergy.2012.12.010.

[8] M. N. Kabir, Y. Mishra, G. Ledwich, Z. Xu, and R. C. Bansal, "Improving voltage profile of residential distribution systems using rooftop PVs and Battery Energy Storage systems," *Applied Energy*, vol. 134, pp. 290-300, 2014/12/01/ 2014, doi: https://doi.org/10.1016/j.apenergy.2014.08.042.

[9] F. H. M. Rafi, M. J. Hossain, and J. Lu, "Hierarchical controls selection based on PV penetrations for voltage rise mitigation in a LV distribution network," *International Journal of Electrical Power & Energy Systems*, vol. 81, pp. 123-139, 2016/10/01/ 2016, doi: https://doi.org/10.1016/j.ijepes.2016.02.013.

[10] S. Koohi-Fayegh and M. A. Rosen, "A review of energy storage types, applications and recent developments," *Journal of Energy Storage*, vol. 27, p. 101047, 2020/02/01/ 2020, doi: https://doi.org/10.1016/j.est.2019.101047.

[11] J. Sardi, N. Mithulananthan, M. Gallagher, and D. Q. Hung, "Multiple community energy storage planning in distribution networks using a cost-benefit analysis," *Applied Energy*, vol. 190, pp. 453-463, 2017/03/15/ 2017, doi: https://doi.org/10.1016/j.apenergy.2016.12.144.

[12] E. Reihani and R. Ghorbani, "Load commitment of distribution grid with high penetration of photovoltaics (PV) using hybrid series-parallel prediction algorithm and storage," *Electric Power Systems Research*, vol. 131, pp. 224-230, 2016/02/01/ 2016, doi: https://doi.org/10.1016/j.epsr.2015.09.004.

[13] J. Sardi, N. Mithulananthan, and D. Q. Hung, "Strategic allocation of community energy storage in a residential system with rooftop PV units," *Applied Energy*, vol. 206, pp. 159-171, 2017/11/15/ 2017, doi: https://doi.org/10.1016/j.apenergy.2017.08.186.

[14] X. Liu, A. Aichhorn, L. Liu, and H. Li, "Coordinated Control of Distributed Energy Storage System With Tap Changer Transformers for Voltage Rise Mitigation Under High Photovoltaic Penetration," *IEEE Transactions on Smart Grid*, vol. 3, no. 2, pp. 897-906, 2012, doi: https://doi.org/10.1109/TSG.2011.2177501

[15] P. F. Lyons *et al.*, "Design and analysis of electrical energy storage demonstration projects on UK distribution networks," *Applied Energy*, vol. 137, pp. 677-691, 2015/01/01/ 2015, doi: https://doi.org/10.1016/j.apenergy.2014.09.027.

[16] K. Mahani, F. Farzan, and M. A. Jafari, "Network-aware approach for energy storage planning and control in the network with high penetration of renewables," *Applied Energy*, vol. 195, pp. 974-990, 2017/06/01/ 2017, doi: https://doi.org/10.1016/j.apenergy.2017.03.118.

[17] O. Babacan, W. Torre, and J. Kleissl, "Siting and sizing of distributed energy storage to mitigate voltage impact by solar PV in distribution systems," *Solar Energy*, vol. 146, pp. 199-208, 2017/04/01/ 2017, doi: https://doi.org/10.1016/j.solener.2017.02.047.

[18] L. Bai, T. Jiang, F. Li, H. Chen, and X. Li, "Distributed energy storage planning in soft open point based active distribution networks incorporating network reconfiguration and DG reactive power capability," *Applied Energy*, vol. 210, pp. 1082-1091, 2018/01/15/ 2018, doi: https://doi.org/10.1016/j.apenergy.2017.07.004.

[19] J. Xiao, Z. Zhang, L. Bai, and H. Liang, "Determination of the optimal installation site and capacity of battery energy storage system in distribution network integrated with distributed generation," *IET Generation, Transmission & Distribution*, vol. 10, no. 3, pp. 601-607, 2016, doi: https://doi.org/10.1049/iet-gtd.2015.0130.

[20] M. Dubarry, G. Baure, C. Pastor-Fernández, T. F. Yu, W. D. Widanage, and J. Marco, "Battery energy storage system modeling: A combined comprehensive approach," *Journal of Energy Storage,* vol. 21, pp. 172-185, 2019/02/01/ 2019, doi: https://doi.org/10.1016/j.est.2018.11.012.

[21] G. Bedi, G. K. Venayagamoorthy, R. Singh, R. R. Brooks, and K. C. Wang, "Review of Internet of Things (IoT) in Electric Power and Energy Systems," *IEEE Internet of Things Journal*, vol. 5, no. 2, pp. 847-870, 2018, doi: https://doi.org/10.1109/JIOT.2018.2802704

[22] B. N. Silva, M. Khan, and K. Han, "Internet of Things: A Comprehensive Review of Enabling Technologies, Architecture, and Challenges," *IETE Technical Review,* vol. 35, no. 2, pp. 205-220, 2018/03/04 2018, doi: https://doi.org/10.1080/02564602.2016.1276416

[23] M. Aazam, S. Zeadally, and K. A. Harras, "Deploying Fog Computing in Industrial Internet of Things and Industry 4.0," *IEEE Transactions on Industrial Informatics,* vol. 14, no. 10, pp. 4674-4682, 2018, doi: https://doi.org/10.1109/TII.2018.2855198

[24] S. S. Reka and T. Dragicevic, "Future effectual role of energy delivery: A comprehensive review of Internet of Things and smart grid," *Renewable and Sustainable Energy Reviews,* vol. 91, pp. 90-108, 2018/08/01/ 2018, doi: https://doi.org/10.1016/j.rser.2018.03.089.

[25] B. L. Risteska Stojkoska and K. V. Trivodaliev, "A review of Internet of Things for smart home: Challenges and solutions," *Journal of Cleaner Production,* vol. 140, pp. 1454-1464, 2017/01/01/ 2017, doi: https://doi.org/10.1016/j.jclepro.2016.10.006.

[26] S. E. Collier, "The Emerging Enernet: Convergence of the Smart Grid with the Internet of Things," *IEEE Industry Applications Magazine,* vol. 23, no. 2, pp. 12-16, 2017, doi: https://doi.org/10.1109/MIAS.2016.2600737

[27] S. Talari, M. Shafie-khah, P. Siano, V. Loia, A. Tommasetti, and J. P. S. Catalão, "A Review of Smart Cities Based on the Internet of Things Concept," *Energies,* vol. 10, no. 4, p. 421, 2017. [Online]. Available: https://www.mdpi.com/1996-1073/10/4/421.

[28] Q. Yang, "13 - Internet of things application in smart grid: A brief overview of challenges, opportunities, and future trends," in *Smart Power Distribution Systems*, Q. Yang, T. Yang, and W. Li Eds.: Academic Press, 2019, pp. 267-283. Doi: https://doi.org/10.1016/B978-0-12-812154-2.00013-4

[29] G. Xu, W. Yu, D. Griffith, N. Golmie, and P. Moulema, "Toward Integrating Distributed Energy Resources and Storage Devices in Smart Grid," *IEEE Internet of Things Journal*, vol. 4, no. 1, pp. 192-204, 2017, doi: https://doi.org/10.1109/jiot.2016.2640563

[30] L. Atzori, A. Iera, and G. Morabito, "Understanding the Internet of Things: definition, potentials, and societal role of a fast evolving paradigm," *Ad Hoc Networks,* vol. 56, pp. 122-140, 2017/03/01/ 2017, doi: https://doi.org/10.1016/j.adhoc.2016.12.004.

[31] J. Sakhnini, H. Karimipour, A. Dehghantanha, R. M. Parizi, and G. Srivastava, "Security aspects of Internet of Things aided smart grids: A bibliometric survey," *Internet of Things,* vol. 14, p. 100111, 2021/06/01/ 2021, doi: https://doi.org/10.1016/j.iot.2019.100111.

[32] R. Morello, C. De Capua, G. Fulco, and S. C. Mukhopadhyay, "A smart power meter to monitor energy flow in smart grids: The role of advanced sensing and IoT in the electric grid of the future," *IEEE Sensors Journal,* vol. 17, no. 23, pp. 7828-7837, 2017, doi: https://doi.org/10.1109/JSEN.2017.2760014

[33] R. Morello, S. C. Mukhopadhyay, Z. Liu, D. Slomovitz, and S. R. Samantaray, "Advances on Sensing Technologies for Smart Cities and Power Grids: A Review," *IEEE Sensors Journal*, vol. 17, no. 23, pp. 7596-7610, 2017, doi: https://doi.org/10.1109/JSEN.2017.2735539

[34] D. Minoli, K. Sohraby, and B. Occhiogrosso, "IoT Considerations, Requirements, and Architectures for Smart Buildings—Energy Optimization and Next-Generation Building Management Systems," *IEEE Internet of Things Journal*, vol. 4, no. 1, pp. 269-283, 2017, doi: https://doi.org/10.1109/JIOT.2017.2647881.

[35] A. Rohani, M. Abasi, A. Beigzadeh, M. Joorabian, and G. B. Gharehpetian, "Bi-level power management strategy in harmonic-polluted active distribution network including virtual power plants," *IET Renewable Power Generation,* vol. 15, no. 2, pp. 462-476, 2021, doi: https://doi.org/10.1049/rpg2.12044.

[36] S. Lei, Y. Hou, F. Qiu, and J. Yan, "Identification of Critical Switches for Integrating Renewable Distributed Generation by Dynamic Network Reconfiguration," *IEEE Transactions on Sustainable Energy,* vol. 9, no. 1, pp. 420-432, 2018, doi: https://doi.org/10.1109/TSTE.2017.2738014.