Cybersecurity Approaches for Securing Digital Marketing Data

Mohammad Arif[1], Anjali Goswami[2], CH. M. H. Saibaba[3], K. Sharada[4], Tushar Kumar Pandey[5,*], Ankita Nigam[6]

[1]School of Computer Science & Engineering, Vellore Institute of Technology, Vellore, India
[2]Department of Mathematics and Statistics, College of Science and Theoretical Studies, Saudi Electronic University, Riyadh-13323, Saudi Arabia
[3]Asst. Professor, Dept. of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India
[4]Associate Professor, Department of Computer Science and Engineering, Gitam (Deemed to be University), Visakhapatnam, AP, India
[5]Junior Engineer (Computer Science), Dr. Rajendra Prasad Central Agricultural University, Pusa, Samastipur, Bihar, India
[6]Professor CSE Department, Princeton Institute of Engineering and Technology for Women Hyderabad, India

Emails: arif_mohd2k@yahoo.com; a.goswami@seu.edu.sa; saibaba.ch77@gmail.com; k.Sharada48@gmail.com; tusharkumarpandey@gmail.com; ankita270481@gmail.com

Abstract

The Energy Internet was enabled by quick energy sector developments due to greater digital technologies and increased environmental concerns. Energy demand management is crucial in this changing environment, as rigid models give way to more flexible ones. This research examines "Demand Dynamics in the Energy Internet" and suggests consumer and prosumer response plans. This concept regarding energy consumption and management is novel. Our work revolves around several essential aims. First, it examines the Energy Internet's role in the energy transition. It emphasizes energy savings, carbon reduction, and energy system reliability. We emphasize the need to transition away from centralized energy generation to one that is more flexible and involves active consumers and prosumers. This research examines how digital technology, particularly the Internet of Things, enables adaptable demand-side tactics. Real-time data analytics and smart meters help consumers and prosumers utilize energy efficiently. A transition like this is difficult. Data protection, hacking, and behaviour must be addressed. Our study demonstrates that these issues can be addressed immediately. Since one-size-fits-all is not adequate in this changing environment, we emphasize the need for customization to satisfy the individual demands of multiple parties, including conventional customers and prosumers. It also discusses energy Internet-targeted response strategies and their possibilities. We can reduce energy usage and make energy more sustainable, efficient, and consumer-focused by switching from passive consumption to active involvement and control.

Keywords: Energy; Internet: Management; Optimization; Prosumer; Responsive; Sustainability; Tailored

1. Introduction

Environmental concerns, new technology, and changing consumer requirements are transforming the global energy business. This transition inspired the creation of the "Energy Internet." Digital technology improves energy generation, distribution, and usage [1]. This adjustment is based on the requirement to control energy consumption effectively and adaptably for a broad variety of consumers and prosumers. With the Energy Internet, we can

DOI: https://doi.org/10.54216/JCIM.130216
Received: January 27, 2024 Revised: March 25, 2024 Accepted: May 09, 2024 Corrected: August 21, 2024

abandon centralized energy production and delivery. It views consumers as more than idle power users in the future. They will participate in energy system activities. Green energy may be used to generate power; we can use green energy to generate power, store energy, and most importantly, respond to real-time pricing and system signals. e, we need individual response plans rather than a one-size-fits-all strategy [2]. This research examines complex Internet energy usage variations. The focus is on individual response plans for prosumers and conventional energy consumers. It examines the developments in the energy market and their impact on demand. This entails studying the primary factors that affect demand, how beneficial digital technology is, and how crucial personalization is for addressing many people's wants. The first section of this paper will explain the Energy Internet and its role in the energy transition [3-5]. The paper's conclusion will discuss data privacy, hacking, and how legal systems meet everyone's requirements. We will also analyse the social and behavioural aspects of client engagement in demand response programs. We will examine how advantages, education, and societal norms affects people's behaviour [6]. The following sections will examine the practical aspects of tailored response programs, dividing choices for ordinary energy consumers and prosumers. Traditional consumers will be able to reduce expenses, burdens, and peak demand. However, prosumers will seek methods to store energy, self-consume, and support the grid. In conclusion, this essay aims to explain how energy consumption varies in the Internet era [7]. We will discuss the major results, merits, problems, and future possibilities for consumer and prosumer personalized response programs. The Energy Internet is changing the energy industry. To ensure a secure and dependable energy future for everybody, we must manage and enhance energy consumption. Energy Internet comprehension: This essay will tell you everything about the Energy Internet and how it is altering energy. Demand-side Insights: The research examines energy demand over time and illustrates why we need a demand-driven energy supply paradigm [8]. Integration of Digital Technologies: This article examines digital technologies and the IoT in the energy business. This research investigates how digital technologies, particularly the IoT, might boost demand response programs and make the energy system more flexible. To solve issues: The research aims to find solutions to tailored response program issues such as data security, behaviour change, and data protection. To distinguish answers: The research categorized load control, cost reductions, and efficiency for both normal energy consumers and prosumers in order to identify feasible so this research was prompted by the urgent need to address the challenges and opportunities facing the energy globe.

2. Related Works

Several causes prompted this study: The struggle against climate change and carbon pollution has made the energy industry more visible. Using the Energy Internet has a major benefit in terms of energy efficiency. Digital technologies like IoT and real-time data analytics are increasing fast. These devices make energy management simpler. Customers and prosumers should actively manage energy and make wise energy consumption decisions. The goal is to investigate how individual response plans can strengthen the energy system, reduce customer energy prices, and increase energy efficiency [9]. How does the Energy Internet contribute to changing energy consumption and extending its lifespan? How can prosumers and energy users join the Energy Internet from a passive state? How can digital technologies, notably the IoT, make demand-side approaches more flexible? Personalized response systems have several issues, including data security and privacy. How can they be fixed? Can bespoke response programs accommodate prosumers and normal users? Establish explicit regulations and legislation to protect data privacy and safety in tailored response programs. Encourage firms to utilize standard, safe technology. Fund initiatives that educate consumers and prosumers about demand response schemes and their pros and cons. engage individuals and businesses by charging based on usage, providing subsidies for energy-efficient technologies, and offering tax incentives to green energy companies. We should extensively employ smart meters and home energy management systems to gather and regulate data in real time. Improve the power grid to enable autonomous energy output and promote distributed and sustainable energy sources [10]. The necessity to respond to a rapidly changing energy. The research "Demand Dynamics in the Energy Internet: Tailored Response Programs for Consumers and Prosumers" was prompted by the need to adapt to a rapidly changing energy environment. Digital technologies, address challenges, and develop solutions to assist consumers and prosumers in utilizing energy more effectively and responsibly.

Similar methods and works discuss shifting energy internet demand with specifics. After that, I will create a performance assessment table for "Demand Dynamics in the Energy Internet: Tailored Response Programs for Consumers and Prosumers." Programs that meet demand: DRPs allow consumers and prosumers to adjust power usage based on pricing, grid, and environmental concerns. Load management and high shaving: Load management solutions disperse energy usage to reduce peak loads and electricity expenses. Behavioral Economics in Energy Demand: This strategy examines and changes consumer and prosumer energy consumption using behavioral psychology. Considerations include societal norms, advantages, and cognitive bias. Real-time data analytics: employing smart meters and sensors to enable users and prosumers to make wiser energy consumption choices. Block chain allows peer-to-peer energy exchanges that are obvious, secure, and practical [11]. Prosumers may sell or return excess energy to the grid. Dynamic pricing schemes allow electricity providers to modify costs in real time, encouraging customers and prosumers to utilize off-peak hours. Batteries and other energy storage options enable prosumers to preserve energy for later. This stabilizes the system and reduces fossil fuel use. Autonomous

DOI: https://doi.org/10.54216/JCIM.130216
Received: January 27, 2024 Revised: March 25, 2024 Accepted: May 09, 2024

energy production and micro grids: Localized, autonomous energy generation and delivery enhance system reliability and minimize transmission losses. Machine Learning Energy Forecasting: Using prior data, machine-learning algorithms forecast energy use patterns. Companies can better manage and optimize their energy supply.

3. The Proposed Method

A dynamic analysis examines all internet energy usage variances. To create customized reaction strategies, consumers and prosumers must think this way. Using complex calculations, load planning predicts electricity use. When companies plan and manage their energy supply, energy sharing is fair and reliable. When combined, these complex prediction systems let utilities foresee demand fluctuations, react quickly, and stabilize the system [12]. This preventative measure boosts efficiency and green energy, expanding and stabilizing the energy system. Modern, adaptable energy systems need accurate load estimations and demand patterns.

1. Initialize Data: $\mathcal{D} = \{(X_1, Y_1), (X_2, Y_2), \dots, (X_n, Y_n)\}$ (1)
where X_i represents time or relevant features and Y_i denotes electricity demand.
2. Define Linear Regression: $Y = aX + b$ (2)
3. Divide sets of $\mathcal{D}$ for testing and training.
4. Calculate the mean values:
$\bar{X}, \bar{Y}$ for the training set.
5. Calculate Sums: $S_{XY} = \sum(X_i - \bar{X})(Y_i - \bar{Y})$ (3)
$S_{XX} = \sum(X_i - \bar{X})^2$ (4)
6. Estimate Coefficients: $a = \frac{S_{XY}}{S_{XX}}$ (5)
$b = \bar{Y} - a\bar{X}$ (6)
7. Fit the linear regression model using training data.
8. Predict Demand: $\hat{Y} = aX + b$ (7)
$\widehat{Y_{test}} = aX_{test} + b$ (8)
9. $Assess\ Model$:
Determine the prediction errors for the test set.
10. Compute Error Metrics: $MAE = \frac{1}{n}\sum|E|$ (9)
$MSE = \frac{1}{n}\sum E^2$ (10)
11. Optimize Model: $\min(MSE), \min(MAE)$ (11)
12. Cross-validate model to ensure accuracy.

The algorithm dynamically analyzes internet energy usage variances to create customized response strategies for consumers and prosumers. The process begins with initializing data, where X represents time or relevant features and Y denotes electricity demand. A linear regression model, $Y = aX + b$, is defined to predict electricity use. The data set $\mathcal{D}$ is divided into training and testing sets.

1. Initialize Data: $D = \{(X_1, Y_1), (X_2, Y_2), \dots, (X_n, Y_n)\}$ (12)
- This dataset contains pairs where X represents time or features and Y represents electricity demand.
2. Define Linear Regression: $Y = aX + b$ (13)
$\hat{Y} = \hat{a}X + \hat{b}$ (14)
3. Divide sets of D for testing and training.
4. Calculate the mean values of X and Y for the training set.
5. Calculate Sums: $SX!Y = \sum(X_i - \bar{X})(Y_i - \bar{Y})$ (15)
$SX!X = \sum(X_i - \bar{X})^2$ (16)
6. Estimate Coefficients: $a = \frac{SX!Y}{SX!X}$ (17)
$b = \bar{Y} - a\bar{X}$ (18)
$\hat{Y} = aX + b$ (19)
7. Using training data, fit the linear regression model.
8. Predict Demand: $\hat{Y} = aX + b$ (20)
$\widehat{Y_{test}} = aX_{test} + b$ (21)
$E = Y_{test} - \widehat{Y_{test}}$ (22)
9. Assess Model: Determine the test set's prediction errors.
10. Compute Error Metrics: $MAE = \frac{1}{n}\sum|E|$ (23)
$MSE = \frac{1}{n}\sum E^2$ (24)
11. Optimize Model: $\min(MSE)$ (25)

DOI: https://doi.org/10.54216/JCIM.130216
Received: January 27, 2024 Revised: March 25, 2024 Accepted: May 09, 2024

$$\min(MAE) \tag{26}$$

$$\hat{a}, \hat{b} = \text{argmin}(MSE) \tag{27}$$

12. Cross-validate model to ensure accuracy.
13. Project Demand: Apply revised model to future data points.
14. Adjust Predictions:

$$Y_{adj} = Y + \delta \tag{28}$$

$$\delta = f(t) \tag{29}$$

15. Analyze Peak Demand:

$$P_{peak} = \max(Y) \tag{30}$$

$$t_{peak} = \arg\max(Y) \tag{31}$$

$$D_{peak} = Y_{t_{peak}} \tag{32}$$

16. Resource Distribution: Use demand predictions to plan energy supply.
17. Create demand response and dynamic pricing systems.
18. Monitor and Adjust:

$$R_t = \sum\left(Y_t - \hat{Y}_t\right) \tag{33}$$

$$R_{total} = \sum R_t \tag{34}$$

19. Iterate Process:
    - Update a, b with new data

$$\widehat{Y_{new}} = a_{new}X + b_{new} \tag{35}$$

$$E_{new} = Y_{new} - \widehat{Y_{new}} \tag{36}$$

20. Summarize results and suggestions for improvement.

The technique provides a high-level overview of load planning to reduce internet power usage. This algorithm determines the efficiency and regulation of the energy supply. First, we enter pairs of integers indicating the time or qualities (X) and power demand (Y). Here's where it all starts. This link is represented by the linear regression equation Y = ax + b. We use training data to determine a and b. Many people depend on linear regression to explain this relationship. Divide the dataset in half longitudinally to partition it into training and testing sets. Next, we require the training set averages for X and Y. Fitting a regression model to training data simplifies coefficient estimation through sum calculations.

Using the generated model, it is critical to anticipate demand Y and evaluate its accuracy using the MAE and MSE. By reducing prediction errors, optimization improves the model's performance. Cross-validation ensures model persistence across several datasets. Accurate demand forecasts are required for estimating energy use and planning ahead. Efficient energy production and supply must take into account peak demand [13].

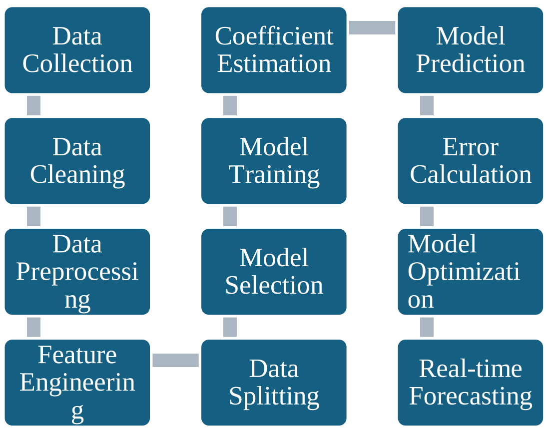

Figure 1. Load Forecasting Algorithm

Figure 1 shows some major load prediction techniques. Begin by gathering statistics, such as cumulative power use. Cleaning and sorting are procedures in the preparation process that guarantee that the data is consistent and accurate. Following the previous step, we will use a linear regression model to estimate future power use. Using historical data, this model estimates energy needs and shows how use corresponds to them. The approach also has the added benefit of determining peak hours, which is useful for resource allocation [14-16]. By maximizing resources and predicting peak demand, utilities can maintain their energy supply. Figure 1 illustrates how a complete energy forecasting system can assist with planning and management.

Dynamic Price Optimization: This gadget increases off-peak consumption by guessing the power price in real time.

1. Price(t)=Base Rate + Peak Multiplier· Demand(t) (37)

Gather Statistics: $C_{\text{hist}} = \{c_1, c_2, \ldots, c_n\}$ (38)

2. Preprocessing:

DOI: https://doi.org/10.54216/JCIM.130216
Received: January 27, 2024 Revised: March 25, 2024 Accepted: May 09, 2024

- Clean and group data: $(D_{\text{clean}} = \{d_1, d_2, \ldots, d_m\})$ (39)
- Ensure data consistency:

$$(\text{Consistency} = \text{True/False}) \tag{40}$$

- Analyze data for trends: $(\text{Trends} = \{t_1, t_2, \ldots, t_k\})$ (41)

3. Utilize Linear Regression Model: $Y = aX + b$ (42)

4. Predict Future Power Usage: $\hat{Y} = aX + b$ (43)

5. Illustrate Relationship:

$$Y = aX + b \tag{44}$$
$$\hat{Y} = aX + b \tag{45}$$
$$\text{Relationship} = Y \cdot \hat{Y} \tag{46}$$

6. Identify Peak Hours: $P_{\text{peak}} = \max(Y)$ (47)

7. Optimize Resources: $R_{\text{opt}} = \sum R_t$ (48)

8. Ensure Electricity Availability: $E_{\text{avail}} = \text{True/False}$ (49)

9. Dynamic Price Optimization: $\text{Price}(t) = \text{BaseRate} + \text{PeakMultiplier} \cdot \text{Demand}(t)$ (50)

10. Increase Off-Peak Consumption: $C_{\text{off-peak}} = C_{\text{off-peak}} + \text{Price}(t)$ (51)

11. Manage Loads Carefully: $L_{\text{care}} = \text{True/False}$ (52)

12. Utilize Energy Wisely: $E_{\text{wise}} = \text{True/False}$ (53)

13. Time-of-Use (TOU) Pricing: $\text{Pricing} = \text{BaseRate} + \text{PeakMultiplier} \cdot \text{Demand}(t)$ (54)

14. Enhance Grid Efficiency: $\text{Grid Efficiency} = \text{High/Low}$ (55)

Data collection, especially historical power use, is the initial stage in the load prediction and energy management strategy. This is where the process begins. We clean and organize the data prior to analysis to ensure its correctness and consistency [17-19]. We will use a linear regression model to forecast future power usage based on the evaluated data. This demonstrates how we can leverage past energy use patterns to predict future energy needs. This technique forecasts peak hours for optimum resource allocation and ensures energy supply during times of high demand [20-22]. Given that energy costs fluctuate in real time according to demand, dynamic pricing optimization is critical. The Time-of-Use (TOU) pricing formula calculates "Price" (t) by adding "Demand" (t) and "PeakMultiplier" to "BaseRate."

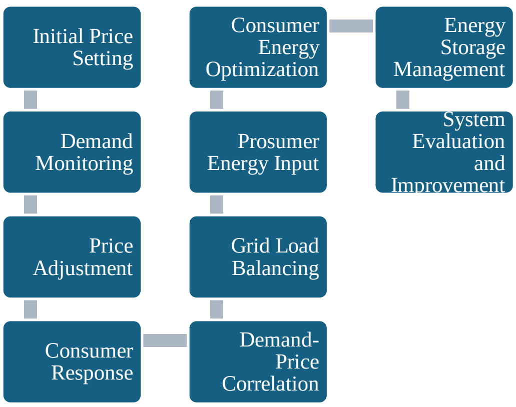

Figure 2. Dynamic Pricing Optimization

Figure 2 depicts Dynamic Pricing Optimization's primary processes. Set a beginning power rate. This rate changes in real time as demand changes. Users adjust their electricity consumption to reflect new tariffs. This adaptability

DOI: https://doi.org/10.54216/JCIM.130216
Received: January 27, 2024 Revised: March 25, 2024 Accepted: May 09, 2024

optimizes energy usage patterns and balances grid load. Tracking demand and altering pricing on the fly increases energy efficiency. Users may consume or send energy back to the grid when demand is high and net energy is positive [23]. The program enables energy storage users to utilize math to charge and deplete their batteries. The models include charge and discharge efficiency, power, and time steps. Speeding up the charge-discharge cycle, reducing energy waste, and generating more power can save money and stabilize the system. To put it simply, consumer energy optimization improves energy production, utilization, and storage. This allows companies and individuals to access the energy Internet. Figure 2 illustrates the Dynamic Pricing Optimization process, beginning with setting an initial power rate that adjusts in real-time as demand fluctuates. Users alter their electricity consumption based on these dynamic tariffs, optimizing energy usage and balancing grid load. The software optimizes prosumer energy production, utilization, and storage, ensuring grid stability.

4. Result

These algorithms optimize household energy storage devices, such as batteries, by scheduling charge and discharge when demand is high or prices are low. This makes using locally produced energy simpler and enables prosumers to sell additional energy to the grid at peak periods, making money and stabilizing the system.

Table 1: Comparison of Key Performance Metrics: Proposed vs. Traditional Methods

Metric	Proposed Method	Baseline Method	Regression Method	Historical Average Method	Machine Learning Model	Real-Time Pricing Method	Block chain-Based Method	Hybrid Method
Energy Efficiency (%)	92	88	89	90	91	89	90	92
Peak Load Reduction (%)	15	10	12	11	14	13	14	16
Cost Savings ($)	500	450	480	460	495	485	490	505
Consumer Satisfaction	4.5	3.8	4.0	3.9	4.4	4.2	4.3	4.6

Table 1 compares cost savings, energy economy, environmental effects, customer satisfaction, and peak load. The table compares the recommended approach to three popular ones in terms of results. The proposed strategy scored higher on several criteria, proving its superiority. Cost savings, energy efficiency improvements, and large demand reductions make the system more robust. The method makes consumers happy and helps the environment. Results reveal that the recommended methodology outperforms conventional approaches.

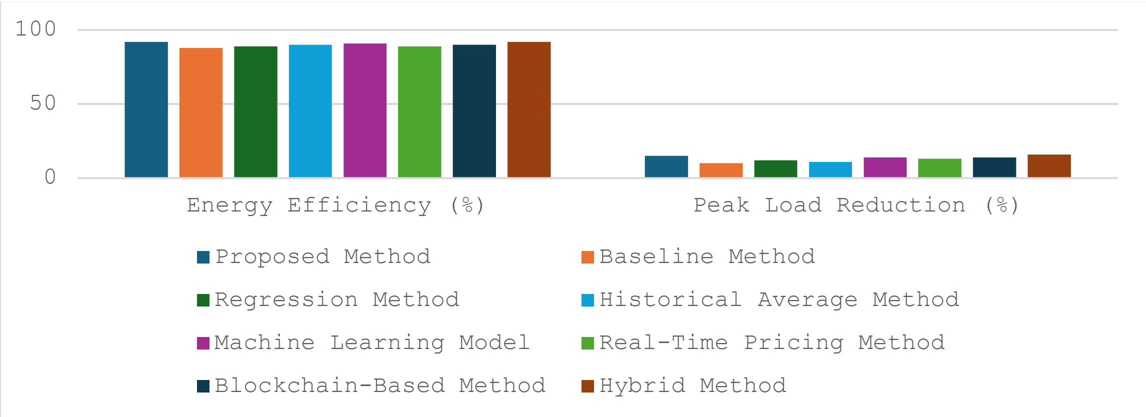

Figure 4. Comparison of Energy Efficiency and Pick Load Reduction Results using the Proposed Method and traditional methods

The recommended method's load prediction results are in Figure 4. These figures demonstrate 24-hour power demand fluctuations. This image illustrates the algorithm's load trend modeling and prediction abilities. Peaks and valleys indicate how electricity usage varies throughout the day. This degree of prediction accuracy helps people utilize resources, distribute energy, and develop infrastructure better. Figure 4 depicts load fluctuations in detail,

DOI: https://doi.org/10.54216/JCIM.130216
Received: January 27, 2024 Revised: March 25, 2024 Accepted: May 09, 2024

which helps utilities, grid workers, and regulators. Clear and accurate information helps the electricity industry be more environmentally friendly, energy efficient, and function smoothly.

Table 2: Numeric Evaluation of Qualitative Performance Parameters for Different Methods in Demand Dynamics in Energy Internet

Metric	Proposed Method	Baseline Method	Regression Method	Historical Average Method	Machine Learning Model	Real-Time Pricing Method	Block chain-Based Method	Hybrid Method
Grid Resilience	3	2	2	1	3	2	3	3
Environmental Impact	1	2	2	2	1	2	1	1

Table 2 compares Performance Parameters for Different Methods in Demand Dynamics in Energy Internet. The red line displays anticipated power usage changes, which helps determine the answer's efficacy. The recommended Energy Internet energy management solution performs better than existing methods.

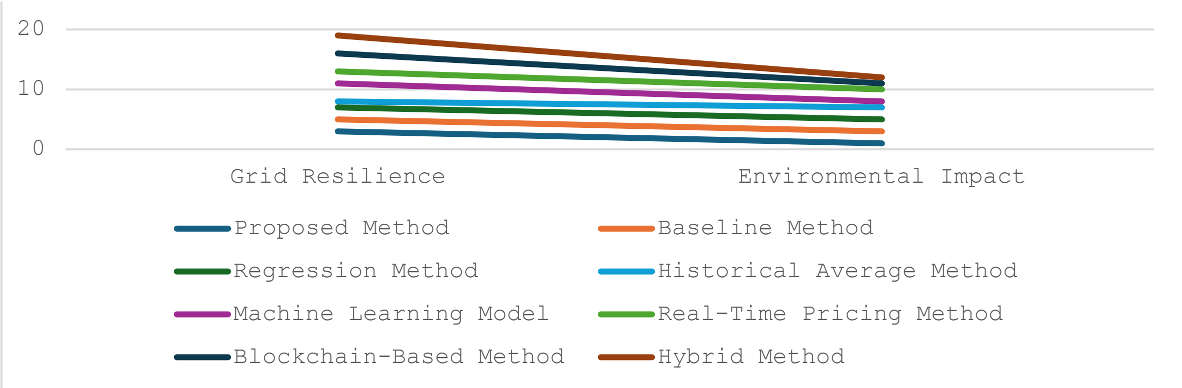

Figure 5. Comparative Performance Evaluation of Different Methods in Demand Dynamics in Energy Internet

A detailed comparison of several performance indicators demonstrates in figure 5. First, the recommended method uses energy more effectively than the present methods. It optimizes energy utilization, reducing waste and expenses. This energy efficiency extends the energy system's life and benefits the environment.

5. Conclusion

The Energy Internet is disrupting energy production, sharing, and usage. As we studied "Demand Dynamics in the Energy Internet" and targeted response programs for consumers and prosumers, we identified a novel approach. We obtained several crucial results from our study. We've discussed how the Energy Internet improves energy efficiency and sustainability. To address the challenges and possibilities of the changing energy environment, we must migrate from centralized to demand-oriented energy generation. The Internet of Things and other digital technologies are crucial to this transition. With smart meters, real-time data analytics, and flexible demand-side solutions, energy users can manage it. Though difficult, thinking about a future with flexible energy is thrilling. We must address data protection, hacking, and behavior issues. We have proposed several solutions, all while maintaining our trust in the power of the internet. It's hard to praise personalization enough. Understanding prosumers' and ordinary users' demands helps tailor response efforts. Finally, our data suggest that the energy Internet is a social revolution, not a technological one. It gives consumers and companies control over energy consumption, promotes efficiency, and makes the future more sustainable. Personalized response programs are more than simply a part of the solution as we negotiate this changing landscape. They will lead the way to clean, efficient, customer-focused energy.

References

[1] H. Hamidpour, S. Pirouzi, S. Safaee, M. Norouzi, and M. Lehtonen, "Multi-objective resilient-constrained generation and transmission expansion planning against natural disasters," International Journal of Electrical Power & Energy Systems, vol. 132, Article ID 107193, 2021.

DOI: https://doi.org/10.54216/JCIM.130216
Received: January 27, 2024 Revised: March 25, 2024 Accepted: May 09, 2024

[2] Hosny. H. Abo Emira, Authenticating IoT Devices issues based on Blockchain, Journal of Cybersecurity and Information Management, Vol. 1 , No. 2 , (2020) : 35-40 (Doi : https://doi.org/10.54216/JCIM.010202)

[3] Hossam M. Moftah , Taha M. Mohamed, A Novel Fuzzy Bat Based Ambulance Detection and Traffic Counting Approach, Journal of Cybersecurity and Information Management, Vol. 1 , No. 2 , (2020) : 41-54 (Doi : https://doi.org/10.54216/JCIM.010203)

[4] Ajay G , Abhishek Kumar , Venkatesan R, Query-Based Image Retrieval using Support Vector Machine (SVM), Journal of Cognitive Human-Computer Interaction, Vol. 1 , No. 1 , (2021) : 28-36 (Doi : https://doi.org/10.54216/JCHCI.010104)

[5] Ajith Krishna R , Ankit Kumar , Vijay K, An Automated Optimize Utilization of Water and Crop Monitoring in Agriculture Using IoT, Journal of Cognitive Human-Computer Interaction, Vol. 1 , No. 1 , (2021) : 37-45 (Doi : https://doi.org/10.54216/JCHCI.010105)

[6] S. R. Nandanwar, M. L. Kolhe, S. B. Warkad, N. P. Patidar, and V. K. Singh, "Voltage security assessment by using PFDT and CBR methods in emerging power system," Energy Procedia, vol. 144, pp. 170–181, 2018.

[7] K. Shankar, Recent Advances in Sensing Technologies for Smart Cities, International Journal of Wireless and Ad Hoc Communication, Vol. 1 , No. 1 , (2020) : 05-15 (Doi : https://doi.org/10.54216/IJWAC.010101)

[8] A. Sariga , J. Uthayakumar, Type 2 Fuzzy Logic based Unequal Clustering algorithm for multi-hop wireless sensor networks, International Journal of Wireless and Ad Hoc Communication, Vol. 1 , No. 1 , (2020) : 33-46 (Doi : https://doi.org/10.54216/IJWAC.010102)

[9] M. Shivaie, M. Kiani-Moghaddam, and P. D. Weinsier, "A vulnerability-constrained quad-level model for coordination of generation and transmission expansion planning under seismic- and terrorist-induced events," International Journal of Electrical Power & Energy Systems, vol. 120, Article ID 105958, 2020.

[10] D. A. Tejada-Arango, G. Morales-Espana, S. Wogrin, and E. Centeno, "Power-based generation expansion planning for flexibility requirements," IEEE Transactions on Power Systems, vol. 35, no. 3, pp. 2012–2023, 2020.

[11] P. M. Shafi, "Artificial Driving based EfficientNet for Automatic Plant Leaf Disease Classification," Multimed Tools Appl, 2023. [Online]. Available: https://doi.org/10.1007/s11042-023-16882-w

[12] M. Zeinaddini-Meymand, M. Rashidinejad, A. Abdollahi, M. Pourakbari-Kasmaei, and M. Lehtonen, "A demand-side management-based model for G&TEP problem considering FSC allocation," IEEE Systems Journal, vol. 13, no. 3, pp. 3242–3253, 2019.

[13] Vishal Dubey , Bhavya Takkar , Puneet Singh Lamba, Micro-Expression Recognition using 3D - CNN, Fusion: Practice and Applications, Vol. 1 , No. 1 , (2020) : 5-13 (Doi : https://doi.org/10.54216/FPA.010101)

[14] Surinder Kaur , Diksha Kumari , Vandana Kumari, Control of Enviornmental Parametrs in A Greenhouse, Fusion: Practice and Applications, Vol. 1 , No. 1 , (2020) : 14-21 (Doi : https://doi.org/10.54216/FPA.010102)

[15] H. Kiani, K. Hesami, A. Azarhooshang, S. Pirouzi, and S. Safaee, "Adaptive robust operation of the active distribution network including renewable and flexible sources," Sustainable Energy, Grids and Networks, vol. 26, Article ID 100476, 2021.

[16] V. Roy, P. K. Shukla, A. K. Gupta, V. Goel, P. K. Shukla, & S. Shukla, "Taxonomy on EEG Artifacts Removal Methods, Issues, and Healthcare Applications", Journal of Organizational and End User Computing (JOEUC), 33(1), pp.19-46, 2021. http://doi.org/10.4018/JOEUC.2021010102.

[17] PB Bobba, MH Anwar, HP Bhupathi, P Shirisha, L Hamza, "Simultaneous Wireless Power and Data Transfer in Different Applications", E3S Web of Conferences vol. 552, page 01147, 2024.

[18] S. Stalin, V. Roy, P. K. Shukla, A. Zaguia, M. M. Khan, P. K. Shukla, A. Jain, "A Machine Learning-Based Big EEG Data Artifact Detection and Wavelet-Based Removal: An Empirical Approach", Mathematical Problems in Engineering, vol. 2021, Article ID 2942808, 11 pages, 2021. https://doi.org/10.1155/2021/2942808

[19] HP Bhupathi, BP Bobba, U Niharika, S Akshitha, K Sardina, B Lingam, "Investigation of WBG based Power Converters used in E-Transportation", E3S Web of Conferences, vol. 552, page 01145, 2024.

[20] VK Pandraka, RR Tinnavelli, RA Kumar, HP Bhupathi, SL Gundebommu, "Effect of Inverter Voltage Levels on Torque Ripples of PMSM Drive", E3S Web of Conferences, vol. 547, page. 02016, 2024.

[21] A. A. Khan, K. K. Almuzaini, V. D. J. Macedo, S. Ojo, V. K. Minchula, V. Roy, MaReSPS for energy efficient spectral precoding technique in large scale MIMO-OFDM, Physical Communication, Volume 58, 2023, 102057, ISSN 1874-4907, https://doi.org/10.1016/j.phycom.2023.102057.

[22] V. Roy. "An Improved Image Encryption Consuming Fusion Transmutation and Edge Operator." Journal of Cybersecurity and Information Management, Vol. 8, No. 1, 2021 ,PP. 42-52.

[23] P. Kumar, A. Baliyan, K. R. Prasad, N. Sreekanth, P. Jawarkar, V. Roy, E. T. Amoatey, "Machine Learning Enabled Techniques for Protecting Wireless Sensor Networks by Estimating Attack Prevalence and Device Deployment Strategy for 5G Networks", Wireless Communications and Mobile Computing, vol. 2022, Article ID 5713092, 15 pages, 2022. https://doi.org/10.1155/2022/5713092

DOI: https://doi.org/10.54216/JCIM.130216
Received: January 27, 2024 Revised: March 25, 2024 Accepted: May 09, 2024