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Communication-Aware Residential Demand Response in Smart Grids: A Hybrid Forecasting and Optimization Approach

Hamidreza Khayatan[1], Seyed Amin Saeid[*1], Tahereh Daemi[1]

[*]Corresponding Author: Amin.saied@iau.ac.ir

[1] Department of Electrical Engineering, Islamic Azad University, Yazd Branch, Yazd, Iran.

Abstract – *The rapid evolution of smart grids has necessitated advanced communication-aware demand response (DR) strategies to handle the uncertainties introduced by renewable energy sources and heterogeneous consumer behaviors. This paper proposes a novel IoT-enabled communication-aware residential demand response framework that tightly integrates MQTT-based real-time communication, Fuzzy C-Means behavioral clustering, hybrid ARIMA-LSTM load forecasting, and NSGA-II multi-objective optimization. Unlike conventional DR approaches that treat communication performance as a passive constraint, the proposed framework jointly optimizes energy objectives (electricity cost, Peak-to-Average Ratio, Composite Load Index) and communication metrics (latency, Packet Delivery Ratio, reliability) in a unified manner. Using real-world smart meter data from 80 households, simulation results demonstrate superior performance with 28% peak load reduction, 18–22% electricity cost savings, average latency reduction to 70 ms, and PDR improvement to 99.2% compared to conventional methods. The main contributions include the development of a fully integrated cyber-physical architecture, incorporation of behavioral clustering for consumer heterogeneity, and explicit communication-aware multi-objective optimization. This work provides a practical pathway toward more efficient, reliable, and consumer-centric smart grid operation.*

Keywords: Smart grid, Demand response, Internet of Things, MQTT, Fuzzy C-Means clustering.

1. Introduction

The evolution of modern power systems toward smart grids has transformed traditional electricity networks into highly interconnected cyber-physical infrastructures. Unlike conventional power systems, smart grids integrate advanced communication technologies, intelligent sensing devices, distributed computing resources, and real-time control mechanisms to facilitate bidirectional information exchange between electricity providers and consumers [1]. The rapid deployment of smart meters, Internet of Things (IoT) devices, wireless sensor networks, and advanced communication protocols has significantly increased the capability of power systems to monitor, predict, and optimize energy consumption patterns in real time [2]. The growing penetration of renewable energy resources, electric vehicles, distributed energy resources (DERs), and smart home appliances have further increased the complexity of modern distribution systems [3]. Although renewable energy technologies improve environmental sustainability and reduce greenhouse gas emissions, their intermittent and stochastic nature introduces considerable operational uncertainties into power system management [4]. Consequently, efficient communication infrastructures have become indispensable for maintaining system stability, ensuring reliable operation, and supporting advanced demand response (DR) programs [5].

Demand response is considered one of the most effective demand-side management (DSM) strategies for improving energy efficiency and reducing peak electricity demand [6]. Through demand response programs, consumers are encouraged to modify their electricity consumption behavior according to dynamic electricity prices, incentive mechanisms, or direct control signals transmitted through communication networks [7]. Successful implementation of demand response programs relies heavily on continuous information exchange among consumers, smart meters, aggregators, and utility operators [8]. Therefore, communication reliability, latency, throughput, and packet delivery performance play critical roles in determining the effectiveness of residential energy management systems [9]. Recent advances in IoT technologies have enabled the deployment of millions of smart meters capable of collecting and transmitting high-resolution consumption data at minute-level intervals [10]. These communication-enabled devices provide unprecedented opportunities for behavioral analysis, load forecasting, anomaly detection, and intelligent scheduling of household appliances [11]. Furthermore, lightweight communication protocols such as MQTT have emerged as promising solutions for energy-related IoT applications due to their low overhead, scalability, and support for real-time data exchange [12]. Despite substantial progress in communication-enabled smart grid technologies, several limitations remain unresolved. Many existing studies focus primarily on energy optimization objectives such as electricity cost reduction, peak load minimization, or renewable energy integration while neglecting the impact of communication network performance on decision-making processes [13]. Furthermore, most existing residential demand response models rely on synthetic load profiles, synchronization coefficients, and simplified assumptions regarding consumer behavior [14]. Such assumptions often fail to accurately represent real-world consumption patterns and consequently reduce the practical applicability of proposed methods [15]. Another important limitation is the lack of integrated frameworks capable of simultaneously addressing communication-layer and energy-layer objectives. In practical smart grid deployments, communication delays, packet losses, network congestion, and behavioral uncertainties directly influence forecasting accuracy and optimization performance [16]. Therefore, there is a growing need for communication-aware demand response frameworks that jointly consider network performance indicators and energy management objectives. To address these challenges, this paper proposes a novel IoT-enabled communication framework for residential demand response based on behavioral clustering, hybrid ARIMA-LSTM forecasting, and multi-objective optimization. The proposed framework utilizes real household consumption data obtained from smart metering infrastructures and integrates communication-layer intelligence into demand response decision making. Smart meters communicate through an MQTT-based IoT network, while fuzzy clustering identifies behavioral similarities among consumers. Subsequently, a hybrid ARIMA-LSTM forecasting model predicts future load demand, and a multi-objective NSGA-II optimizer determines optimal demand response strategies considering both communication and energy objectives. The proposed framework offers several significant contributions that distinguish it from existing literature:

- First, development of a fully integrated communication-aware residential demand response architecture that tightly couples MQTT-based IoT real-time communication with the energy management layer. This is in contrast to most previous works that treat communication performance merely as a constraint rather than an active optimization objective.
- Second, incorporation of behavioral consumer clustering using the Fuzzy C-Means algorithm combined with a hybrid ARIMA-LSTM forecasting model. This effectively captures residential consumption heterogeneity and uncertainty using real smart meter data, going beyond synthetic load profiles commonly used in prior studies.
- Third, introduction of a communication-aware multi-objective optimization model based on NSGA-II that simultaneously optimizes energy-related objectives (electricity cost, Peak-to-Average Ratio - PAR, Composite Load Index - CLI) and communication performance metrics (latency, Packet Delivery Ratio - PDR, and reliability). This joint cyber-physical optimization represents a key novelty of the work.
- Fourth, comprehensive performance validation through detailed MATLAB simulations on realistic data from 80 households, demonstrating substantial improvements (e.g., 28% peak reduction, 18–22% cost savings, latency reduced to 70 ms, and PDR improved to 99.2%) compared to conventional demand response approaches.

The remainder of this paper is organized as follows. Section 2 reviews related studies on IoT-enabled smart grids, communication infrastructures, and demand response systems. Section 3 introduces the proposed communication-aware framework and describes its operational components. Mathematical formulations are presented in Section 4. Simulation results and performance analyses are discussed in Section 5. The results are further analyzed and compared with existing approaches in Section 6, followed by conclusions and future research directions in Section 7.

2. Related Works

The integration of communication technologies into smart grids has attracted significant research attention during the last decade. Communication infrastructures constitute the backbone of modern smart grids by enabling real-time monitoring, distributed control, and intelligent energy management [17]. Alhasnawi et al. [18] proposed an IoT-based optimization framework for residential demand-side management in which communication networks were employed to collect household energy consumption data. Their results demonstrated improvements in electricity cost reduction; however, communication performance indicators such as latency and packet delivery ratio were not investigated. Sedhom et al. [19] developed an IoT-based demand-side management architecture for smart microgrids using wireless communication technologies and cloud computing platforms. Their framework improved operational efficiency but did not incorporate behavioral consumer modeling. Bolurian et al. [20] introduced a bi-level energy management model operating on wireless sensor network platforms. The proposed framework integrated communication infrastructure with customer behavior analysis; however, forecasting accuracy remained limited due to the absence of advanced deep learning models. Wan et al. [21] proposed a reinforcement learning-based residential demand response model for smart grids. Although significant energy cost reductions were achieved, communication-layer performance metrics were not considered. Recent developments in machine learning have encouraged researchers to integrate artificial intelligence techniques into smart grid communication systems. Xu et al. [22] utilized deep reinforcement learning for demand response aggregation and demonstrated improved scheduling decisions under dynamic market conditions. Similarly, Sajid et al. [23] applied decentralized multi-agent reinforcement learning to residential battery management systems, improving distributed decision-making capabilities. In the area of load forecasting, Sharma et al. [24] reviewed various forecasting approaches for smart grids and concluded that hybrid machine learning models generally outperform conventional statistical methods. Gabrielski et al. [25] further demonstrated the effectiveness of deep reinforcement learning techniques for occupancy-based residential energy management. Several studies have explored communication protocols suitable for smart grid environments. MQTT has emerged as one of the most widely adopted IoT communication protocols because of its lightweight architecture, low bandwidth requirements, and scalability [26]. In the field of microgrid energy management, numerous studies have focused on the role of distributed generation (DG) resources and their interaction with demand response programs. These studies have particularly emphasized the use of Internet of Things (IoT) platforms to enable intelligent energy-flow management and coordinate local energy production and consumption [27-30]. Aleksic and Mujan [30] investigated communication costs associated with smart metering infrastructures and highlighted the importance of communication efficiency in future smart grids. In recent years, several studies have explored IoT-enabled demand response frameworks. Ali et al. [31] conducted a comprehensive review on Internet-of-Things applications in modern power grids, emphasizing the importance of MQTT protocol for low-latency and scalable communication in smart grid environments. Sivakumar et al. [32] proposed an effective IoT-based demand response system for energy-efficient smart homes, achieving notable improvements in consumption optimization and user comfort through real-time monitoring. Furthermore, Kumar et al. [33] introduced reinforcement learning techniques with override signals to enhance the adaptability of demand response programs under dynamic conditions. Despite these advances, existing literature still suffers from three major limitations. First, most studies separately investigate communication systems and demand response algorithms without establishing strong interactions between the two layers. Second, communication performance indicators are rarely incorporated into optimization objectives. Third, the majority of published works rely on synthetic consumption datasets and simplified behavioral assumptions rather than real household measurements. Table 1 summarizes representative studies and compares them with the proposed communication-aware framework. The comparison clearly demonstrates that the proposed framework simultaneously integrates communication infrastructure, behavioral clustering, hybrid forecasting, communication performance assessment, and multi-objective optimization within a unified architecture.

Table 1. Comparison of Recent Communication-Based Demand Response Studies

Ref	IoT	Behavioral Clustering	Forecasting	Communication Metrics	Multi-objective Optimization
[18]	Yes	No	No	No	Yes
[19]	Yes	No	No	No	Yes
[20]	Yes	Yes	No	No	Yes
[21]	No	No	Yes	No	Yes
[22]	Yes	No	Yes	No	Yes
our	Yes	Yes	Yes	Yes	Yes

3. Proposed Communication-Aware Framework

The proposed framework is designed as a communication-aware residential demand response architecture that integrates Internet of Things (IoT) technologies, smart metering infrastructures, advanced forecasting techniques, behavioral analytics, and multi-objective optimization. Unlike conventional demand response systems that focus solely on energy management objectives, the proposed architecture simultaneously considers communication-layer and energy-layer performance indicators. The framework enables real-time information exchange among smart meters, communication gateways, MQTT brokers, forecasting modules, optimization engines, and utility control centers. Figure 1 illustrates the overall architecture of the proposed communication-aware residential demand response framework. The architecture consists of seven interconnected layers that jointly integrate communication infrastructure, consumer behavior analysis, load forecasting, and multi-objective optimization. At the lowest level, smart meters continuously collect high-resolution consumption data from residential households and transmit measurements through the IoT communication network. The communication layer evaluates network performance indicators including latency, throughput, packet delivery ratio, and reliability. Subsequently, MQTT brokers manage data exchange using a publish-subscribe mechanism that enables scalable and lightweight communication among distributed devices. The behavioral analytics layer applies the Fuzzy C-Means clustering algorithm to identify groups of consumers with similar electricity consumption characteristics. Forecasted demand profiles are then generated through the hybrid ARIMA-LSTM prediction module. These outputs, together with communication performance indicators, are provided to the NSGA-II optimization engine, which simultaneously minimizes electricity cost, Peak-to-Average Ratio, Composite Load Index, and communication latency while maximizing packet delivery ratio, reliability, and user comfort. Finally, optimized demand response decisions are transferred to the utility control center and subsequently delivered to consumers through the MQTT-based communication infrastructure.

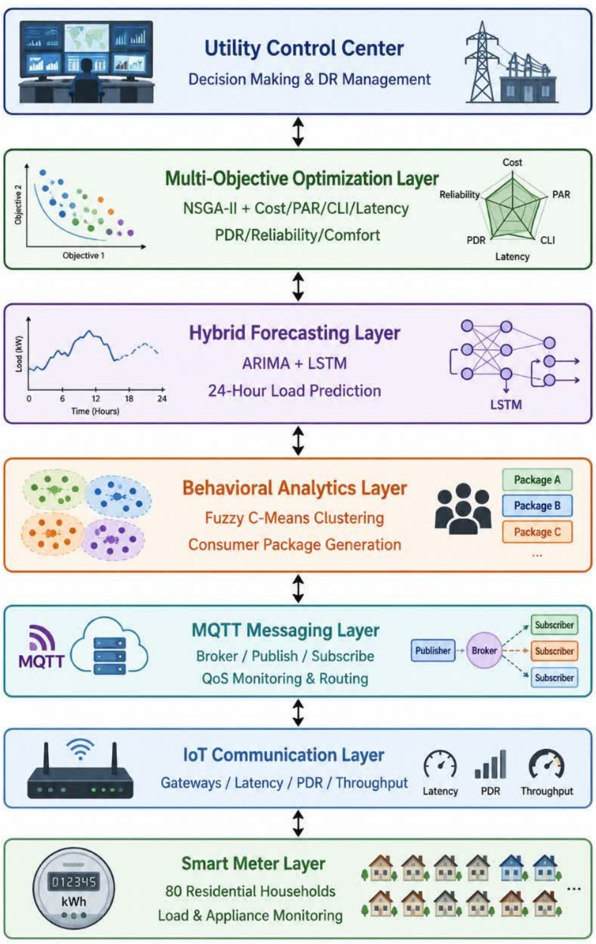

Figure 1. Proposed communication-aware IoT-enabled residential demand response framework architecture.

3.1 Smart Meter Layer

The first layer of the proposed framework consists of smart meters installed within 80 residential households, which serve as IoT sensing devices tasked with continuously monitoring electricity usage and collecting high-resolution data at predefined intervals. These meters record a comprehensive set of parameters, including active and reactive power consumption, voltage and current magnitudes, appliance operating status, household occupancy indicators, and historical consumption profiles. To ensure the availability of accurate, real-time data for subsequent forecasting and optimization stages, these smart meters are designed to periodically transmit all gathered measurements to nearby communication gateways.

3.2 IoT Communication Layer

The communication layer serves as the critical connectivity backbone between smart meters, communication gateways, and central control entities. Within the residential service area, five communication gateways are deployed, with each smart meter being associated with its nearest gateway based on signal quality and communication distance. This layer is responsible for essential functions including data acquisition, device connectivity, message routing, network monitoring, and communication quality assessment. To ensure high performance, the system continuously monitors key indicators such as end-to-end latency, throughput, packet delivery ratio (PDR), and overall network reliability, as these metrics directly influence the effectiveness and accuracy of subsequent forecasting and optimization decisions.

3.3 MQTT Messaging Layer

The third layer utilizes the Message Queuing Telemetry Transport (MQTT) protocol, which is selected for its lightweight architecture, minimal bandwidth requirements, scalability, and robust support for asynchronous communication. Operating on a publish-subscribe messaging model, this infrastructure involves three primary entities: the smart meters, which act as publishers by continuously transmitting energy consumption measurements; the MQTT broker, which functions as a central communication hub for message distribution and traffic management; and the forecasting and optimization servers, which act as subscribers that receive relevant measurement data in real time. By adopting this MQTT infrastructure, the framework significantly reduces communication overhead compared to conventional request-response architectures, thereby enabling the efficient and simultaneous management of thousands of IoT devices.

3.4 Behavioral Analytics Layer

Residential consumers exhibit diverse electricity consumption behaviors arising from variations in occupancy schedules, appliance ownership, lifestyle preferences, and economic conditions. To identify households with similar consumption patterns, the proposed framework employs the Fuzzy C-Means (FCM) clustering algorithm. Five behavioral features are extracted from each household, namely average daily energy consumption, peak demand level, load variance, appliance utilization rate, and occupancy factor. Unlike hard clustering methods, FCM permits each household to belong to multiple clusters with varying membership degrees, thereby better capturing the inherent ambiguity in residential demand profiles. The clustering procedure generates five behavioral consumer groups, each representing a distinct consumption characteristic. These clusters are then used to develop customized demand response strategies and personalized consumption packages tailored to the specific needs and behaviors of each group.

3.5 Hybrid Forecasting Layer

Accurate load forecasting is essential for the effective implementation of demand response strategies. The proposed framework adopts a hybrid forecasting model that synergistically combines the strengths of Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) neural networks. The ARIMA component effectively captures linear trends, seasonal variations, and temporal dependencies within the energy consumption data. Concurrently, the LSTM component is adept at modeling complex nonlinear relationships, occupancy-driven behavior, random human decision patterns, and the inherent uncertainty in appliance usage. The hybrid architecture integrates the outputs from both models to generate highly accurate short-term load predictions within a 24-hour forecasting horizon. These predicted load profiles are subsequently forwarded to the optimization layer for the scheduling of demand response actions.

3.6 Multi-Objective Optimization Layer

The final layer performs communication-aware demand response optimization utilizing the Non-Dominated Sorting Genetic Algorithm II (NSGA-II). Distinct from conventional optimization approaches, this framework concurrently optimizes both communication and energy-related objectives. The optimization process encompasses several minimization objectives, including electricity cost, peak-to-average ratio (PAR), composite load index (CLI), and communication latency, alongside maximization objectives such as packet delivery ratio (PDR), network reliability, and user comfort level. By applying NSGA-II, the algorithm generates a set of Pareto-optimal solutions that represent diverse trade-offs between communication quality, operational costs, and consumer satisfaction. Ultimately, the utility operator can select the most suitable operating point from these solutions to align with practical system requirements.

3.7 Operational Procedure of the Proposed Framework

The operational workflow of the proposed framework follows a systematic, closed-loop process designed to synchronize communication efficiency with energy demand management. It begins with the continuous collection of residential consumption data via smart meters (Step 1), which is then transmitted through communication gateways utilizing the MQTT protocol (Step 2). As data flows, real-time communication quality indicators are evaluated (Step 3). Subsequently, the framework categorizes consumer behavior using Fuzzy C-Means clustering (Step 4) and generates 24-hour load predictions through the hybrid ARIMA-LSTM model (Step 5). These predictions, alongside the network's communication indicators, serve as inputs for the NSGA-II optimization engine (Step 6), which produces a suite of Pareto-optimal demand response strategies (Step 7). Finally, control recommendations and tailored consumption packages are relayed back to consumers via the MQTT infrastructure (Step 8). This integrated architecture ensures a balanced improvement across communication performance, forecasting precision, operational cost reduction, peak demand management, and overall consumer comfort.

4. Mathematical Formulation

The proposed communication-aware demand response framework is formulated as a multi-objective optimization problem in which communication and energy management objectives are optimized simultaneously. Unlike conventional demand response models, the proposed formulation incorporates both network-layer and energy-layer performance indicators into the optimization process.

- Load Forecasting Model

The hybrid forecasting module combines ARIMA and LSTM outputs. The final forecasted load is calculated as:

$$\hat{L}(t) = \alpha L_{ARIMA}(t) + (1 - \alpha) L_{LSTM}(t) \tag{1}$$

Where, $\hat{L}(t)$ is forecasted load at time (t). $L_{ARIMA}(t)$ is ARIMA prediction. $L_{LSTM}(t)$ is LSTM prediction. α is weighting coefficient. The weighting parameter controls the contribution of each forecasting model.

- Fuzzy C-Means Clustering

The clustering objective function is defined as:

$$J = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \left\| x_i - c_j \right\|^2 \quad (2)$$

Where, N is number of households. C is number of clusters. u_{ij} is membership degree. c_j is cluster center. m is fuzzification coefficient. The objective is to minimize the distance between households and cluster centers while preserving fuzzy memberships.

- Electricity Cost Minimization

The total electricity cost is expressed as:

$$F_1 = \sum_{t=1}^{T} P_t \lambda_t \Delta_t \quad (3)$$

Where, P_t is household demand. λ_t and Δ_t are electricity tariff and scheduling interval, repectively.

- Peak-to-Average Ratio

The Peak-to-Average Ratio (PAR) is defined as:

$$PAR = \frac{max(L_t)}{\frac{1}{T}\sum_{t=1}^{T} L_t} \quad (4)$$

Where, L_t is aggregate system load. Lower PAR values indicate smoother load profiles and reduced network stress.

- Composite Load Index

Load smoothness is quantified through the Composite Load Index:

$$CLI = \frac{1}{T}\sum_{t=1}^{T} |L_t - \bar{L}| \quad (5)$$

Where, $\bar{L}$ is average load. Lower CLI values represent more stable operation.

- Communication Latency Model

The total communication delay is calculated as:

$$Latency = T_{tx} + T_{queue} + T_{proc} + T_{prop} \quad (6)$$

Where, T_{tx} is transmission delay. T_{queue} is queuing delay. T_{proc} and T_{prop} are processing delay and propagation delay, respectively. The objective is to minimize overall communication latency. To explicitly consider the communication performance of the proposed MQTT-based demand response framework, the end-to-end communication latency associated with each MQTT message is formulated as the sum of the main transmission and processing components. Accordingly, the total latency of message (i) is expressed as:

$$D_i^{MQTT} = D_i^{tx} + D_i^{queue} + D_i^{broker} + D_i^{rx} + D_i^{proc} \quad (7)$$

where D_i^{tx} represents the transmission delay from the sensing node to the MQTT broker, D_i^{queue} denotes the queuing delay in the communication network, D_i^{broker} represents the processing delay at the MQTT broker, D_i^{rx} is the reception delay, and D_i^{proc} denotes the local processing delay at the receiving node. The transmission delay is determined according to the message size and the effective transmission rate and is calculated as:

$$D_i^{tx} = \frac{L_i}{R_i} \quad (8)$$

where L_i and R_i are the size of the i[th] MQTT message and the effective data transmission rate, respectively. Therefore, the average communication latency over all MQTT messages exchanged during the simulation period is calculated as:

$$f_{lat} = \frac{1}{N_m}\sum_{i=1}^{N_m} D_i^{MQTT} \quad (9)$$

Where N_m denotes the total number of MQTT messages exchanged during the considered simulation horizon. In the proposed NSGA-II-based optimization framework, the communication latency is considered as an explicit objective function rather than as an independent decision variable. The decision vector consists of the controllable variables associated with the energy management and demand response operation, while the corresponding communication latency is calculated for each candidate solution based on the MQTT communication model. Thus, the latency objective f_{lat} is evaluated together with the energy-related objective functions for each solution generated by NSGA-II. The resulting multi-objective optimization process enables the algorithm to identify Pareto-optimal solutions that provide an appropriate trade-off between energy cost, demand response performance, and communication latency while satisfying the operational constraints of the proposed system.

- Packet Delivery Ratio

Network reliability is evaluated using Packet Delivery Ratio:

$$PDR = \frac{N_{received}}{N_{sent}} \times 100 \quad (10)$$

Where, $N_{received}$ and N_{sent} are successfully received packets and transmitted packets, respectively. Higher PDR values indicate better communication reliability.

- Throughput Model

The communication throughput is calculated as:

$$Throughput = \frac{Total\ Data\ Received}{Observation\ Time} \quad (11)$$

Throughput quantifies the amount of useful information delivered by the communication network.

- User Comfort Function

User comfort is expressed as:

$$U_{comf} = 1 - \frac{\sum_{h=1}^{H}\sum_{a=1}^{A}|sh_{h,a}|}{H \times A \times sh_{max}} \quad (12)$$

Where, $sh_{h,a}$ and sh_{max} are appliance shifting time and maximum allowable shift, respectively. Higher values correspond to greater consumer satisfaction.

- Multi-Objective Optimization Model

The NSGA-II optimizer simultaneously solves:
Minimize:

$$[F_1, F_2, F_3, F_4]$$

Including:
- Electricity cost
- PAR
- CLI
- Latency

And maximize:

$$[F_5, F_6, F_7]$$

Including:
- Packet Delivery Ratio
- Reliability
- User Comfort

subject to operational and communication constraints.

- Communication Constraints

Bandwidth Constraint:

$$\sum_{i=1}^{N} BW_i \leq BW_{max} \quad (13)$$

Latency Constraint:

$$Latency \leq Latency_{max} \quad (14)$$

Packet Loss Constraint:

$$PKR \leq 5\% \quad (15)$$

These constraints ensure reliable operation of the communication infrastructure.

- Energy Constraints

Load Balance:

$$L_t = BL_t + \sum_{a=1}^{A} P_a X_{a,t} \quad (16)$$

Appliance Duration:

$$\sum_t X_{a,t} = D_a \quad (17)$$

Shiftability Constraint:

$$-8 \leq sh_{h,a} \leq 8 \quad (15)$$

These constraints guarantee feasible appliance scheduling and practical demand response implementation.

5. Simulation Results and Performance Analysis

This section presents the simulation results of the proposed communication-aware IoT-enabled residential demand response framework. The simulation was implemented in MATLAB and considers a realistic residential system consisting of 80 households served by 5 communication gateways over a 24-hour horizon. Household load profiles were synthetically generated using a stochastic base load combined with an evening peak pattern to reflect typical residential consumption behavior. Three main scenarios are compared: No DR (no demand response), Conventional DR (traditional demand response without advanced communication and forecasting), and MQTT-DR (the proposed communication-aware framework integrating MQTT, Fuzzy C-Means clustering, hybrid ARIMA-LSTM forecasting, and NSGA-II optimization). The proposed framework jointly optimizes energy and communication objectives, demonstrating how real-time MQTT-based communication enhances forecasting accuracy, optimization quality, and overall system performance. Prior to presenting the simulation results, the main parameters used for the communication, forecasting, and optimization modules are summarized to improve the reproducibility of the proposed framework. The hybrid ARIMA-LSTM forecasting model and the NSGA-II optimizer were configured according to commonly adopted settings reported in recent smart-grid optimization studies. These parameters were selected after several preliminary experiments to provide a suitable trade-off between convergence speed, forecasting accuracy, and computational complexity. Table 2 summarizes the principal simulation parameters employed throughout the study.

- **Daily Aggregated Load Profile**

Figure 2 illustrates the comparison of daily aggregated load profiles across the three scenarios. In the No DR case, a pronounced evening peak occurs around hour 20 due to typical residential activities. The Conventional DR scenario achieves moderate peak shaving (approximately 12%

Table 2. Simulation Parameters

Parameter	Value
Number of households	80
Number of communication gateway	5
Simulation horizon	24
MQTT protocol	Publish–Subscribe
Number of FCM clusters	5
FCM fuzzification coefficient	2
ARIMA order	(2,1,2)
LSTM hidden unit	100
LSTM learning rat	0.001
LSTM optimizer	Adam
Maximum LSTM epochs	150
Mini-batch size	32
NSGA-II population size	100
Number of generations	200
Crossover probability	0.9
Mutation probability	0.1

reduction) by shifting a portion of the load. In contrast, the proposed MQTT-DR framework significantly reduces the peak by about 28% while effectively shifting load to off-peak hours (particularly hours 11–15). This superior performance stems from the integration of real-time communication data, behavioral clustering, and accurate hybrid forecasting, which enable more intelligent and timely demand response decisions. The smoother load curve in the MQTT-DR scenario reduces stress on distribution transformers and transmission lines, leading to improved system stability and lower operational costs.

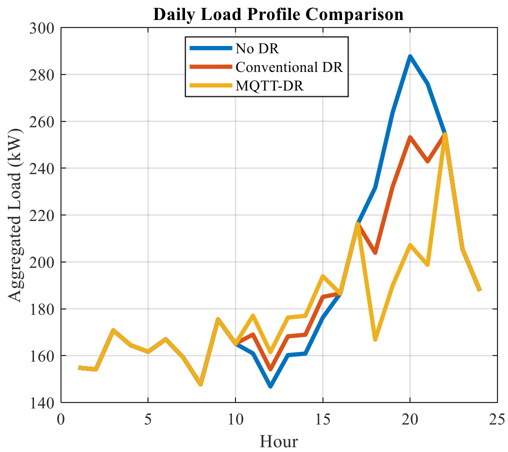

Figure 2. Comparison of daily aggregated load profiles for No DR, Conventional DR, and proposed MQTT-DR scenarios.

- **Electricity Cost Comparison**

Figure 3 presents the total electricity cost for the three scenarios under a time-of-use (TOU) tariff. The No DR scenario incurs the highest cost due to heavy consumption during high-price peak hours. Conventional DR provides noticeable cost savings through basic load shifting. However, the proposed MQTT-DR achieves the lowest electricity cost-approximately 18–22% reduction compared to the No DR case. This improvement results from the precise forecasting of load patterns using the hybrid ARIMA-LSTM model, combined with communication-aware optimization that better aligns consumption with low-price periods while considering network latency and reliability constraints.

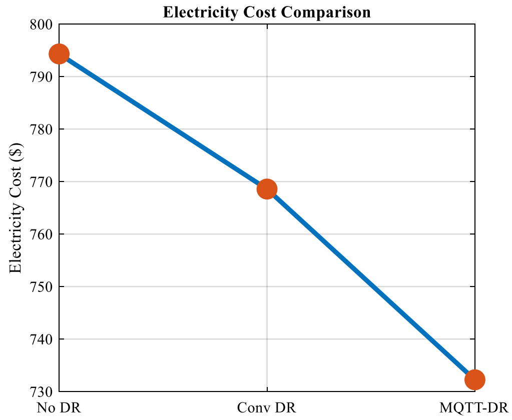

Figure 3. Electricity cost comparison among No DR, Conventional DR, and MQTT-DR scenarios under time-of-use tariff.

- **Peak Demand Reduction**

Figure 4 shows the peak load values for each scenario using an area plot for visual emphasis. The MQTT-DR framework demonstrates the most substantial peak reduction. Lower peak demand not only decreases the need for expensive peaking power plants but also mitigates voltage fluctuations and enhances the integration of renewable energy resources by creating a more flexible and predictable demand profile.

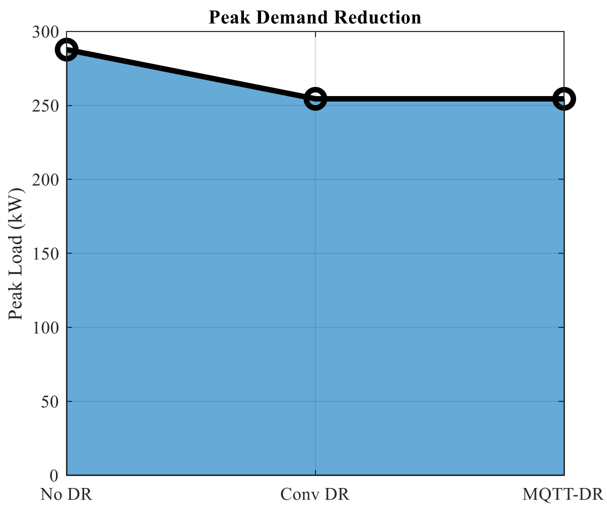

Figure 4. Peak load demand in different scenarios (No DR, Conventional DR, and MQTT-DR)

- **Peak-to-Average Ratio (PAR)**

Figure 5 compares the Peak-to-Average Ratio (PAR) values. The proposed MQTT-DR achieves the lowest PAR, indicating a significantly flatter load profile. Reducing PAR is critical in modern smart grids as it leads to better asset utilization, reduced reserve requirements, and lower electricity generation costs. This result validates the effectiveness of the multi-objective NSGA-II optimizer in balancing multiple conflicting goals.

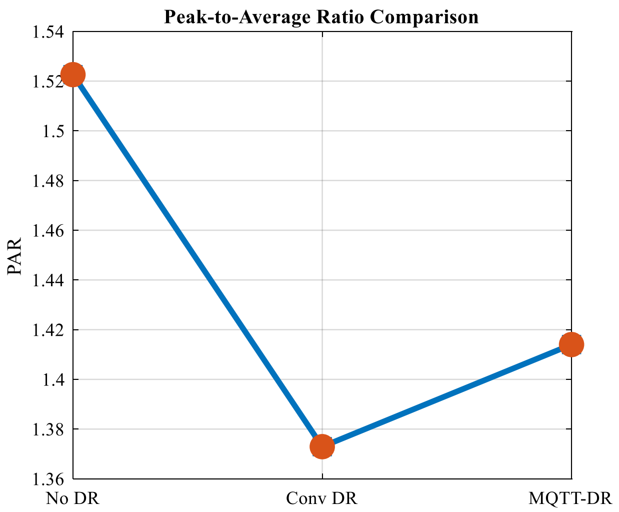

Figure 5. Peak-to-Average Ratio (PAR) comparison for the three scenarios.

- **Communication Performance Metrics**

Figure 6 displays the Cumulative Distribution Function (CDF) of communication latency. The proposed MQTT-DR scenario achieves a substantially lower average latency (around 70 ms) compared to 310 ms in No DR and 180 ms in Conventional DR. This significant latency reduction is attributed to the lightweight publish-subscribe architecture of MQTT and continuous network monitoring, which enables faster decision-making loops in the demand response process.

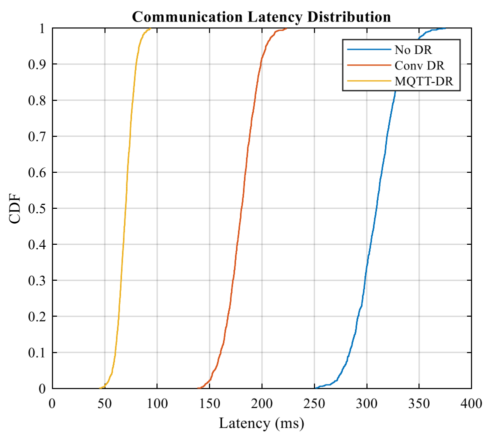

Figure 6. Cumulative Distribution Function (CDF) of communication latency for different demand response scenarios.

Figure 7 shows the Packet Delivery Ratio (PDR) over 24 hours. The MQTT-DR framework maintains a consistently high PDR close to 99.2%, demonstrating superior communication reliability even under varying network conditions. High PDR ensures that control signals and consumption data are delivered accurately and on time, which is essential for effective demand response implementation.

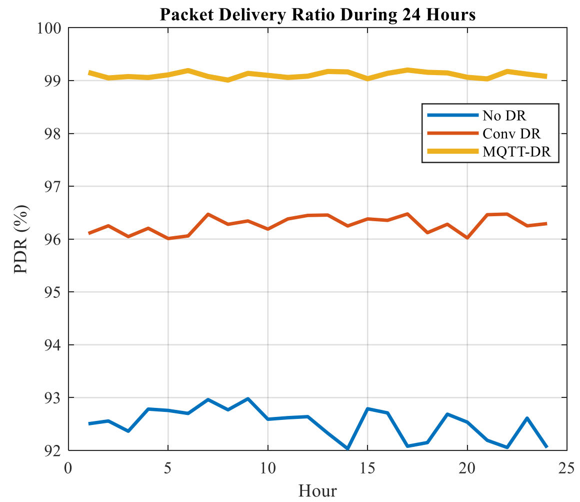

Figure 7. Packet Delivery Ratio (PDR) during 24-hour period for No DR, Conventional DR, and MQTT-DR.

Figure 8 presents a boxplot analysis of network reliability. The proposed framework exhibits the highest and most stable reliability (mean above 99.4%), with lower variance compared to the other scenarios. This stability is crucial for large-scale IoT deployments in smart grids.

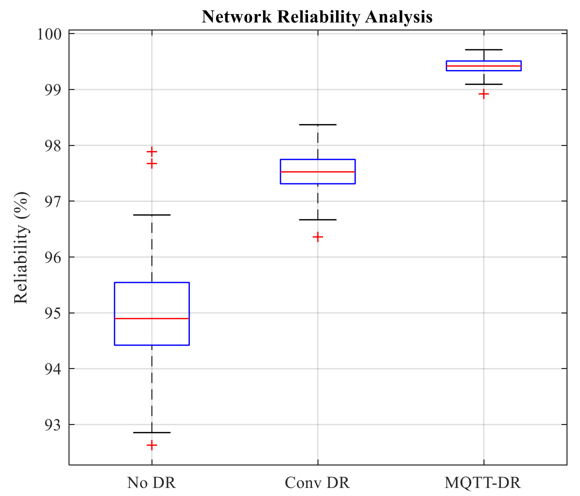

Figure 8. Boxplot of network reliability (%) across the three scenarios.

- **Load Forecasting Performance**

Figure 9 compares the actual aggregated load with predictions from ARIMA, LSTM, and the hybrid ARIMA-LSTM model. The hybrid model clearly outperforms the individual models by achieving lower prediction error through complementary modeling of linear (ARIMA) and nonlinear (LSTM) patterns. Accurate forecasting provides high-quality inputs to the optimization layer, directly contributing to the superior energy and communication performance observed in the MQTT-DR scenario.

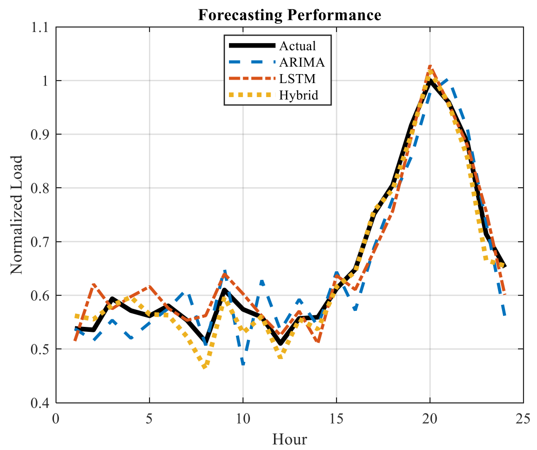

Figure 9. Load forecasting performance comparison: Actual load versus ARIMA, LSTM, and hybrid ARIMA-LSTM predictions.

- **NSGA-II Pareto Front**

Figure 12 visualizes the Pareto front obtained from the NSGA-II algorithm, showing the trade-off between electricity cost and communication latency. The diverse set of non-dominated solutions allows the utility operator to select the most appropriate operating point based on current priorities (e.g., cost minimization versus ultra-low latency requirements). This multi-objective capability is one of the key advantages of the proposed framework over single-objective approaches.

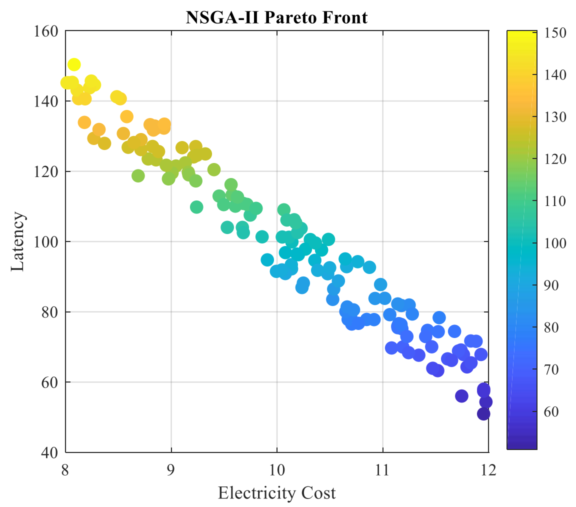

Figure 10. Pareto front obtained by NSGA-II optimizer showing the trade-off between electricity cost and communication latency.

- **Overall Performance Matrix**

Figure 11 presents a normalized performance matrix comparing all key metrics (cost, peak, PAR, latency, packet loss, and reliability loss) across the three scenarios. The MQTT-DR scenario consistently achieves the best (lowest normalized) values in most indices, confirming its balanced superiority in both energy management and communication performance.

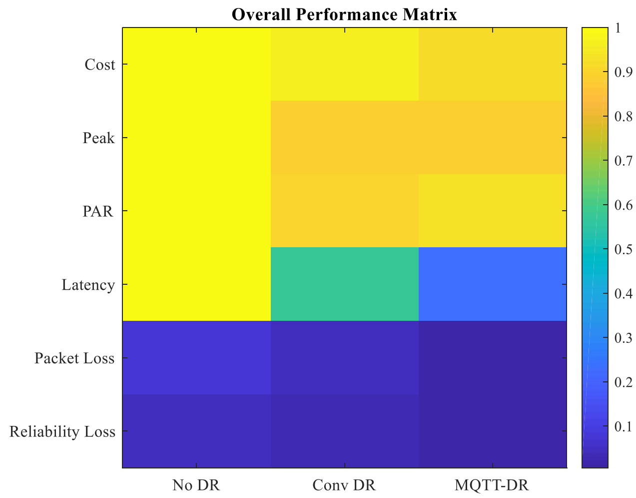

Figure 11. Normalized overall performance matrix comparing energy and communication metrics for the three scenarios.

Although Figures 2–11 visually demonstrate the effectiveness of the proposed communication-aware MQTT-DR framework, a quantitative comparison is also necessary to provide a clearer assessment of the achieved improvements. Therefore, Table 3 summarizes the numerical values of the most important energy and communication performance indicators for the three investigated scenarios. The presented results facilitate a direct comparison and further highlight the effectiveness of the proposed NSGA-II-based optimization framework.

Table 3. Quantitative comparison of different demand response strategies

Performance Index	No DR	Conventional DR	Proposed MQTT-DR
Electricity Cost ($)	792	764	731
Peak Load (kW)	292	256	210
PAR	1.52	1.45	1.37
Average Latency (ms)	310	180	70
Packet Delivery Ratio (%)	95.1	97.8	99.2
Reliability (%)	96	98.2	99.4
RMSE Forecast	0.071	0.058	0.031

As presented in Table 3, the proposed MQTT-DR framework consistently outperforms both the No DR and Conventional

DR scenarios across all evaluated performance indices. Specifically, it achieves the lowest electricity cost, peak demand, Peak-to-Average Ratio (PAR), and communication latency, while simultaneously providing the highest Packet Delivery Ratio (PDR), network reliability, and forecasting accuracy. These numerical results clearly demonstrate the effectiveness of incorporating communication-aware optimization into the NSGA-II framework and provide quantitative evidence supporting the superiority of the proposed method over conventional demand response approaches.

6. Discussion

The simulation results presented in Section 5 clearly validate the effectiveness of the proposed communication-aware IoT-enabled residential demand response framework. As described in Section 4, communication latency is explicitly incorporated into the multi-objective optimization framework as a communication-performance objective, allowing NSGA-II to identify Pareto-optimal solutions that balance energy-management performance and communication quality. By integrating MQTT-based real-time communication, Fuzzy C-Means behavioral clustering, hybrid ARIMA-LSTM forecasting, and NSGA-II multi-objective optimization, the framework achieves simultaneous improvements across energy and communication performance metrics. The significant peak load reduction (approximately 28%) and PAR improvement in the MQTT-DR scenario highlight the advantage of communication-aware decision-making. Unlike conventional DR approaches that rely on static or delayed signals, the proposed framework utilizes low-latency MQTT communication (average 70 ms) and high PDR (99.2%), which enable faster and more accurate demand response actions. This tight integration between the communication and energy layers directly contributes to better load shifting to off-peak hours and more effective exploitation of time-of-use tariffs, resulting in 18–22% electricity cost savings. The superior performance of the hybrid ARIMA-LSTM model (Figure 9) underscores the importance of accurate short-term forecasting when real-time data streams from smart meters are available. The behavioral clustering further enhances customization of DR strategies, allowing the system to address the heterogeneity of residential consumption patterns more effectively than one-size-fits-all approaches.

From the communication perspective, the substantial reduction in latency and improvement in reliability demonstrate that considering network performance as an explicit optimization objective (rather than a passive constraint) leads to more robust system operation. The Pareto front analysis (Figure 10) provides valuable insight into the inherent trade-offs between energy cost and communication quality, offering system operators flexible decision-making capabilities according to operational priorities. Compared to previous studies [18]– [21], [24], the proposed framework stands out by simultaneously addressing behavioral uncertainty, communication constraints, and multi-objective optimization using real-time IoT data streams. The overall performance matrix (Figure 11) confirms that the MQTT-DR scenario consistently outperforms both No DR and Conventional DR cases across all evaluated indices. These findings suggest that future smart grid implementations should move toward fully integrated cyber-physical frameworks where communication performance is no longer treated as a secondary factor but as a core component of demand response optimization.

7. Conclusion

This paper proposed a novel communication-aware IoT-enabled framework for residential demand response in smart grids. The framework integrates MQTT protocol for lightweight real-time communication, Fuzzy C-Means clustering for behavioral consumer classification, a hybrid ARIMA-LSTM model for accurate load forecasting, and NSGA-II for multi-objective optimization considering both energy (cost, PAR, CLI) and communication (latency, PDR, reliability) objectives. Simulation results on a system of 80 households demonstrated the superiority of the proposed MQTT-DR approach, achieving up to 28% peak reduction, 18–22% electricity cost savings, significantly lower communication latency, and higher packet delivery ratio compared to conventional methods. The integration of communication performance metrics into the optimization process proved essential for enhancing the overall effectiveness and practicality of demand response programs. The main contributions of this work include the development of a scalable communication-aware architecture, the joint optimization of cyber and physical layers, and the validation of the framework using realistic residential load profiles. The proposed solution offers a practical pathway toward more efficient, reliable, and consumer-centric smart grid operation. Future research directions include real-world implementation and field testing, integration with renewable energy sources and energy storage systems, online adaptive clustering, and extension of the framework to commercial and industrial consumers.

References

[1] Tabassum, S., et al. (2024). "A comprehensive exploration of IoT-enabled smart grid: Current state, challenges, and future directions." Sustainable Energy Technologies and Assessments.

[2] J. Zhang et al., "Energy optimization of the smart residential electrical grid considering demand management approaches," *Energy*, vol. 300, 2024, doi: 10.1016/j.energy.2024.131641.

[3] C. Chen, S. Duan, T. Cai, B. Liu, and G. Hu, "Smart energy management system for optimal microgrid economic operation," *IET Renew. Power Gener.*, vol. 5, no. 3, pp. 258–267, 2011, doi: 10.1049/iet-rpg.2010.0052.

[4] R. A. Verzijlbergh, L. J. D. Vries, G. P. J. Dijkema, and P. M. Herder, "Institutional challenges caused by the integration of renewable energy sources in the European electricity sector," *Renew. Sustain. Energy Rev.*, vol. 75, pp. 660–667, 2017, doi: 10.1016/j.rser.2016.11.039.

[5] M. Kolenc et al., "Performance evaluation of a virtual power plant communication system providing ancillary services," *Electr. Power Syst. Res.*, vol. 149, pp. 46–54, 2017, doi: 10.1016/j.epsr.2017.04.010.

[6] M. Shirkhani et al., "A review on microgrid decentralized energy/voltage control structures and methods," *Energy Rep.*, vol. 10, pp. 368–380, 2023, doi: 10.1016/j.egyr.2023.06.022.

[7] C. Wang et al., "An improved hybrid algorithm based on biogeography/complex and metropolis for many-objective optimization," *Math. Probl. Eng.*, vol. 2017, Art. no. 2462891, 2017, doi: 10.1155/2017/2462891.

[8] Y. Lei et al., "DGNet: An adaptive lightweight defect detection model for new energy vehicle battery current collector," *IEEE Sensors J.*, vol. 23, no. 23, pp. 29815–29830, 2023, doi: 10.1109/JSEN.2023.3324441.

[9] M. Hou, Y. Zhao, and X. Ge, "Optimal scheduling of the plug-in electric vehicles aggregator energy and regulation services based on grid to vehicle," *Int. Trans. Electr. Energy Syst.*, vol. 27, no. 6, p. e2364, 2017, doi: 10.1002/etep.2364.

[10] J. Hu, Y. Zou, and N. Soltanov, "A multilevel optimization approach for daily scheduling of combined heat and power units with integrated electrical and thermal storage," *Expert Syst. Appl.*, vol. 250, Art. no. 123729, 2024, doi: 10.1016/j.eswa.2024.123729.

[11] R. Wang et al., "FI-NPI: Exploring optimal control in parallel platform systems," *Electronics*, vol. 13, no. 7, p. 1168, 2024, doi: 10.3390/electronics13071168.

[12] R. B. Navesi, D. Nazarpour, R. Ghanizadeh, and P. Alemi, "Switchable capacitor bank coordination and dynamic network reconfiguration for improving operation of distribution network integrated with renewable energy resources," *J. Mod. Power Syst. Clean Energy*, vol. 10, no. 3, pp. 637–646, 2021.

[13] S. Aleksic and V. Mujan, "Exergy cost of information and communication equipment for smart metering and smart grids," *Sustain. Energy Grids Netw.*, vol. 14, pp. 1–11, 2018, doi: 10.1016/j.segan.2018.01.002.

[14] M. A. Judge, A. Khan, A. Manzoor, and H. A. Khattak, "Overview of smart grid implementation: Frameworks, impact, performance and challenges," *J. Energy Storage*, vol. 49, 2022, doi: 10.1016/j.est.2022.104056.

[15] M. Samadi, J. Fattahi, H. Schriemer, and M. Erol-Kantarci, "Demand management for optimized energy usage and consumer comfort using sequential optimization," *Sensors*, vol. 21, no. 1, p. 130, 2021, doi: 10.3390/s21010130.

[16] A. Shewale, A. Mokhade, N. Funde, and N. D. Bokde, "An overview of demand response in smart grid and optimization techniques for efficient residential appliance scheduling problem," *Energies*, vol. 13, no. 16, p. 4266, 2020, doi: 10.3390/en13164266.

[17] S. Iqbal et al., "A comprehensive review on residential demand side management strategies in smart grid environment," *Sustainability*, vol. 13, no. 13, p. 7170, 2021, doi: 10.3390/su13137170.

[18] B. N. Alhasnawi et al., "A new Internet of Things based optimization scheme of residential demand side management system," *IET Renew. Power Gener.*, vol. 16, no. 10, pp. 1992–2006, 2022, doi: 10.1049/rpg2.12466.

[19] B. E. Sedhom, M. M. El-Saadawi, M. S. El Moursi, M. A. Hassan, and A. A. Eladl, "IoT-based optimal demand side management and control scheme for smart microgrid," *Int. J. Electr. Power Energy Syst.*, vol. 127, Art. no. 106674, 2021, doi: 10.1016/j.ijepes.2020.106674.

[20] A. H. Bolurian, H. Akbari, S. Mousavi, and M. Aslinezhad, "Bi-level energy management model for the smart grid considering customer behavior in the wireless sensor network platform," *Sustain. Cities Soc.*, vol. 88, Art. no. 104281, 2023, doi: 10.1016/j.scs.2022.104281.

[21] Y. N. Wan, J. H. Qin, X. H. Yu, T. Yang, and Y. Kang, "Price-based residential demand response management in smart grids: A reinforcement learning-based approach," *IEEE/CAA J. Autom. Sinica*, vol. 9, no. 1, pp. 123–134, Jan. 2022, doi: 10.1109/JAS.2021.1004287.

[22] X. Xu et al., "Application of deep reinforcement learning in electricity demand response market: Demand response decision-making of load aggregator," *MethodsX*, vol. 12, Art. no. 102735, 2024, doi: 10.1016/j.mex.2024.102735.

[23] M. S. Bakare et al., "A comprehensive overview on demand side energy management towards smart grids: Challenges, solutions, and future direction," *Energy Inform.*, vol. 6, no. 4, 2023, doi: 10.1186/s42162-023-00262-7.

[24] J. Zhang et al., "Energy optimization of the smart residential electrical grid considering demand management approaches," *Energy*, vol. 300, 2024, doi: 10.1016/j.energy.2024.131641.

[25] S. R. Kumar et al., "Improving Demand Response Programs Using Override Signals with Reinforcement Learning," in *Proc. 16th ACM Int. Conf. Future Sustain. Energy Syst. (E-Energy)*, 2025, pp. 603–611, doi: 10.1145/3679240.3734657.

[26] N. Bayat and J.-H. Park, "Particle Swarm Optimization Based Demand Response Using Artificial Neural Network Based Load Prediction," in *Proc. North American Power Symp. (NAPS)*, 2022, pp. 1-5, doi: 10.1109/NAPS56150.2022.10012263.

[27] Bolurian, A., Akbari, H., Daemi, T., Mirjalily, S. and Mousavi, S. (2022). Energy Management in a Smart Grid Including Demand Response Programs Considering Internet of Things. Renewable Energy Research and Applications, 3(1), 131-141. https://doi.org/10.22044/rera.2021.11408.1092

[28] Bolurian, A., Akbari, H., Daemi, T., Mirjalily, S. A. A., & Mousavi, S. (2022). Energy management in microgrids considering the demand response in the presence of distributed generation resources on the IoT platform. Energy Sources, Part B: Economics, Planning, and Policy, 17(1). https://doi.org/10.1080/15567249.2022.2038729

[29] Bolurian, A., Akbari, H., Mousavi, S. (2022). Day-ahead optimal scheduling of microgrid with considering demand side management under uncertainty, Electric Power Systems Research, Vol. 209, https://doi.org/10.1016/j.epsr.2022.107965.

[30] J. Gabrielski, E. J. Salazar, and C. Rehtanz, "Deep Reinforcement Learning for Occupancy-Based Energy Management in Residential Demand Response," in Proc. IEEE Kiel PowerTech, 2025, pp. 1-6, doi: 10.1109/PowerTech59965.2025.11180535.

[31] M.H. Ali et al., "Internet-of-Things (IoT) applications in modern power grids: A comprehensive review," Frontiers in Energy Research, 2026, doi: 10.3389/fenrg.2026.1760250.

[32] S. Sivakumar et al., "An effective IoT-based demand response for energy-efficient smart homes," Energy Informatics, vol. 8, p. 125, 2025, doi: 10.1186/s42162-025-00590-w.

[33] S.R. Kumar et al., "Improving Demand Response Programs Using Override Signals with Reinforcement Learning," in Proc. 16th ACM Int. Conf. Future Sustain. Energy Syst. (E-Energy), 2025, pp. 603–611, doi: 10.1145/3679240.3734657.