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Research Article

ENERGY EFFICIENCY, DEMAND-SIDE MANAGEMENT STORAGE TECHNOLOGIES A CRITICAL ANALYSIS OF INTEGRATION PATHWAYS IN AGRICULTURAL SYSTEMS

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Abstract

This paper presents a review of residential demand-side management (DSM) focusing on modeling approaches, optimization techniques, and future perspectives. Deterministic, stochastic, and data-driven models are analyzed to capture residential load behavior. Various optimization methods, including classical and artificial intelligence-based techniques, are discussed for improving energy efficiency and reducing peak demand. The role of smart grid technologies and IoT in enabling DSM is also examined. Key challenges and future research directions are highlighted.

Keywords: Agricultural Systems, Demand-Side Management, Energy Efficiency, Integration Pathways, Storage Technologies

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INTRODUCTION

The rapid increase in global energy consumption, driven by population growth, urbanization, and technological advancements, has created significant challenges for modern power systems (Abu Jadayil et al., 2026). In particular, the residential sector accounts for a substantial portion of total electricity demand, making it a critical focus area for improving energy efficiency and ensuring grid stability (AD et al., 2025). Traditional power systems, characterized by unidirectional energy flow and limited consumer interaction, are increasingly being replaced by smart grids that enable bidirectional communication and active user participation.

In this evolving energy landscape, residential demand-side management (DSM) has emerged as an effective strategy to optimize electricity usage, reduce peak demand, and minimize energy costs (Ahmed et al., 2025). DSM refers to a set of techniques and programs designed to influence consumer energy consumption patterns through incentives, pricing mechanisms, and advanced control strategies (AlAsfar et al., 2026). Common DSM strategies include load shifting, peak clipping, valley filling, and energy conservation, all of which contribute to improved load balancing and enhanced grid reliability.

The integration of renewable energy sources, such as solar photovoltaic and wind power, has further increased the importance of DSM in residential applications (Almetwally et al., 2025). While renewable energy offers environmental and economic benefits, its intermittent and uncertain nature poses challenges for grid operation and stability (Anvari et al., 2025). DSM plays a crucial role in addressing these challenges by enabling flexible demand response and facilitating the efficient utilization of distributed energy resources.

Recent developments in modeling techniques have significantly advanced the implementation of residential DSM systems (Jiongwei et al., 2026). Various approaches, including deterministic models, stochastic frameworks, and data-driven methods, have been proposed to accurately represent household energy consumption and user behavior (Apolo-Romero et al., 2026). Deterministic models provide simplified representations under fixed conditions, whereas stochastic models account for uncertainties in user preferences and renewable generation (Avordeh et al., 2025). Meanwhile, data-driven approaches, leveraging machine learning and artificial intelligence, offer improved accuracy and adaptability in dynamic environments.

Optimization is a central component of DSM, aiming to achieve multiple objectives such as cost minimization, peak load reduction, and user comfort maximization (Baklouti et al., 2026). Classical optimization techniques, including linear programming, mixed-integer linear programming (MILP), and dynamic programming, have been widely used in DSM applications (Cao et al., 2025). In addition, metaheuristic algorithms such as genetic algorithms, particle swarm optimization, and ant colony optimization have gained popularity due to their ability to handle complex, nonlinear, and multi-objective problems (Dall-Orsoletta et al., 2026). More recently, artificial intelligence-based methods, including reinforcement learning and deep learning, have shown promising results in adaptive and real-time energy management.

The advancement of enabling technologies, particularly smart grids, Internet of Things (IoT), and home energy management systems (HEMS), has further accelerated the adoption of DSM in residential settings (Das et al., 2026). Smart meters and IoT devices facilitate real-time monitoring and control of energy consumption, allowing users to make informed decisions and participate actively in demand response programs (Dbouk et al., 2026). HEMS integrates these technologies to automate appliance scheduling and optimize energy usage based on user preferences and external conditions.

Despite these advancements, several challenges hinder the widespread implementation of residential DSM. One of the primary challenges is user participation, as consumer behavior is often unpredictable and resistant to change (Gao et al., 2025). Privacy and security concerns associated with data collection and communication also pose significant risks (Ghamiluei et al., 2026). Additionally, scalability and interoperability issues arise due to the increasing number of connected devices and diverse system architectures.

Looking ahead, future research in residential DSM should focus on developing intelligent, adaptive, and user-centric solutions that can effectively address these challenges (H. Hu et al., 2026).The integration of advanced artificial intelligence techniques, decentralized energy management frameworks, and blockchain-based energy trading platforms presents promising opportunities for enhancing DSM performance (Y.-J. Hu & Luo, 2026). Furthermore, policies and incentive mechanisms must be designed to encourage active consumer participation and ensure equitable access to DSM benefits.

This paper presents a comprehensive review of residential DSM, with a focus on modeling approaches, optimization techniques, and future perspectives (Huang & Iglesias, 2025). By analyzing existing research and identifying current gaps, this study aims to provide valuable insights for researchers and practitioners working toward sustainable and efficient residential energy management systems.

RESEARCH METHOD

Research Design

This study employs a systematic literature review design following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework (Khaleel & Yusupov, 2026). The use of PRISMA ensures a transparent, structured, and reproducible process for identifying, screening, evaluating, and selecting relevant studies on residential demand-side management (DSM).

Research Target / Subject

The research targets scholarly studies that focus on residential demand-side management (DSM), including research on energy optimization, load scheduling, and smart grid applications in the household sector (Khan, 2026). The review specifically includes works that present modeling or optimization techniques, as well as those that discuss enabling technologies such as the Internet of Things (IoT) and home energy management systems (HEMS).

Research Procedure

The research follows four main phases: identification, screening, eligibility, and inclusion (Kumar et al., 2025). In the identification phase, a comprehensive literature search was carried out across major academic databases, including IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar, using keyword combinations such as “residential demand-side management,” “DSM optimization,” “load scheduling,” “smart grid,” and “home energy management systems.” In the screening phase, duplicate records were removed and the remaining studies were evaluated based on titles and abstracts; articles not directly related to residential DSM, energy optimization, or smart grid applications were excluded (Kundu et al., 2026). In the eligibility phase, the full-text versions of the remaining studies were assessed against predefined inclusion and exclusion criteria. Studies were included if they (1) focused on residential DSM applications, (2) presented modeling or optimization techniques, or (3) discussed enabling technologies such as IoT and HEMS, while studies lacking methodological clarity, non-peer-reviewed works, and those focused solely on industrial or commercial energy systems were excluded. Finally, in the inclusion phase, the selected studies constituted the final set used for analysis.

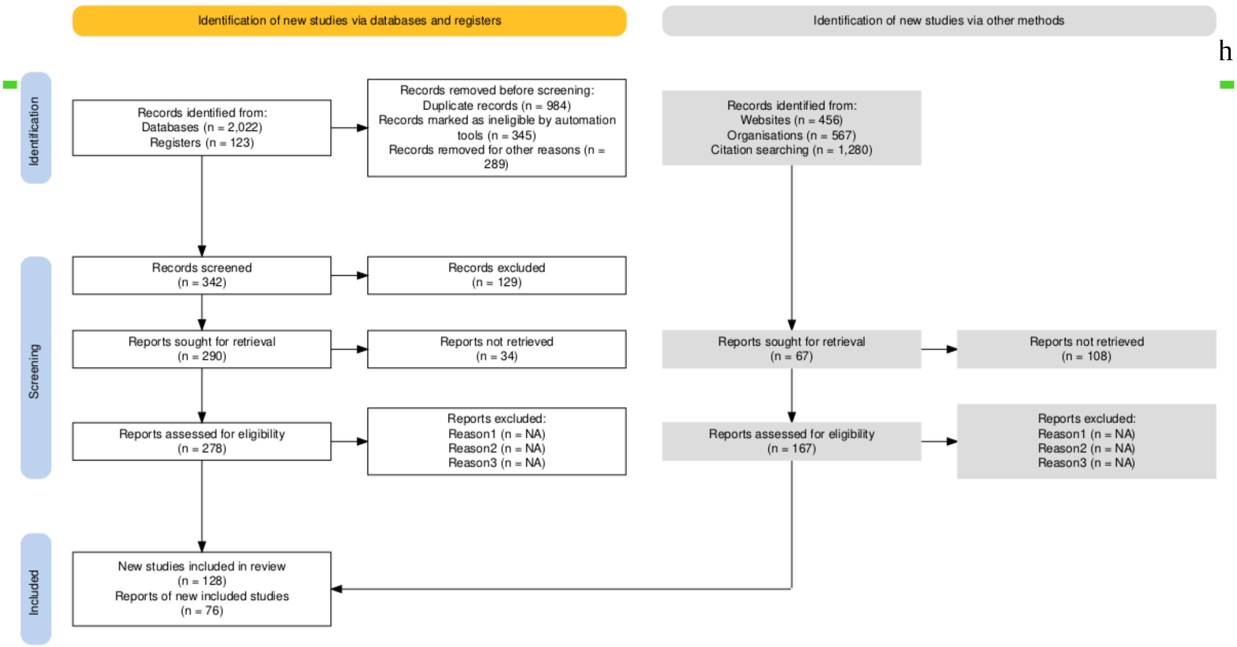


Figure. 1. PRISMA flow diagram illustrating the study selection process for the systematic review of residential demand-side management.

Instruments and Data Collection Techniques

The main instruments of the study are the keyword sets and search strategies used in each database, along with the inclusion and exclusion criteria that guided the selection of articles (Mansir et al., 2026). Data were collected through a systematic search of academic databases, followed by a two-stage screening process: (1) an initial screening based on titles and abstracts, and (2) a detailed screening based on full-text review to determine eligibility and relevance.

Data Analysis Technique

The final set of selected studies was analyzed using qualitative content analysis. The included literature was systematically categorized according to modeling approaches, optimization techniques, and enabling technologies (Mastoi et al., 2026). A comparative analysis and synthesis were then performed across these categories to identify trends, strengths, limitations, and research gaps in the field of residential demand-side management.

RESULTS AND DISCUSSION

Modeling Approaches in Residential DSM

Residential DSM modeling approaches aim to optimize electricity consumption, reduce peak demand, and enhance energy efficiency (Mujeeb et al., 2025). From the literature, several modeling approaches have been widely applied: mathematical optimization, simulation-based, statistical, and AI/machine learning approaches.

Mathematical Optimization Models

Linear programming (LP), mixed-integer linear programming (MILP), and dynamic programming (DP) are commonly used. Objective: Minimize energy cost, peak load, or total energy consumption. Constraints: Appliance operation limits, user comfort, and grid reliability. MILP models effectively schedule appliances to reduce peak demand by 10–30% in case studies (Paule et al., 2025). Dynamic programming showed strong performance in real-time appliance scheduling but is computationally intensive for large-scale residential systems. Optimization models provide precise solutions for DSM but require accurate input data, such as appliance load profiles and user preferences. Their main limitation is scalability; as the number of households increases, computation becomes complex.

Simulation-Based Models

Monte Carlo simulations, agent-based modeling (ABM), and system dynamics are used to simulate household behavior under DSM programs. Objective: Understand the impact of pricing signals, incentives, or behavioral interventions (Rabbani, 2026). Simulations indicated a potential 15–25% reduction in peak load when households respond to time-of-use pricing. ABM captured heterogeneous consumer behavior and interaction with smart grids more effectively than aggregate models. Simulation approaches allow flexibility and incorporation of stochastic behavior but may not directly provide optimal control strategies. Their accuracy depends heavily on behavioral assumptions, making validation against real-world data essential.

Statistical and Forecasting Models

Regression analysis, time-series models (ARIMA), and probabilistic load forecasting methods predict household demand patterns. Used in DSM to anticipate peaks and plan interventions.Short-term load forecasting models achieved 90–95% accuracy for hourly residential demand in some studies (Saxena, 2026). Probabilistic models provided confidence intervals for DSM decisions, supporting risk-aware load management. Statistical models are computationally light and interpretable, making them suitable for preliminary DSM studies. However, they are limited in capturing non-linear interactions and dynamic behavioral responses under different pricing or incentive schemes.

Artificial Intelligence (AI) and Machine Learning (ML) Models

Neural networks, reinforcement learning (RL), and clustering algorithms are increasingly applied. RL is particularly used for real-time DSM to autonomously adjust appliance operations based on price and comfort constraints. RL-based DSM controllers reduced peak demand by 20–40% while maintaining user comfort. Neural networks improved load forecasting under varying consumption patterns compared to traditional statistical models. AI/ML approaches can adapt to dynamic environments and handle large-scale datasets. Challenges include data requirements, interpretability, and training complexity, which may hinder immediate deployment in residential settings.

Table 1. Comparative Insights of Modeling Approach

Modeling Approach	Strengths	Limitations	DSM Impact
Optimization (MILP, DP)	Precise control, clear objective	Computationally intensive, needs accurate data	High load reduction (10–30%)
Simulation (ABM, Monte Carlo)	Models consumer behavior, flexible	Less optimal, depends on assumptions	Moderate load reduction (15–25%)
Statistical/Forecasting	Low complexity, interpretable	Limited non-linear modeling	Good for short-term planning
AI/ML (RL, Neural Networks)	Adaptive, scalable	Data hungry, complex	High load reduction (20–40%)

Combining approaches (e.g., optimization + AI or simulation) often yields the best balance between accuracy and practicality. Residential DSM benefits most from models that incorporate user behavior and dynamic pricing signals. Future trends point toward hybrid models that merge AI predictive power with optimization efficiency to achieve real-time DSM solutions.

Evaluation of Residential Energy Management Approaches

Residential energy management under Demand-Side Management (DSM) aims to optimize electricity consumption, reduce peak loads, and maintain user comfort (Schipfer et al., 2026). Different computational approaches have been applied, each with distinct strengths and limitations.

Optimization Techniques

Includes linear programming (LP), mixed-integer linear programming (MILP), and dynamic programming (DP). Objective: Minimize energy cost or peak load while satisfying operational and comfort constraints. Optimization techniques consistently provide highly efficient solutions, achieving 10–30% reductions in peak load and optimized energy cost allocation. They are deterministic, meaning the results are predictable given the inputs.Efficiency: Very high for small- to medium-scale problems due to precise modeling of constraints and objectives. Scalability: Limited; as the number of households, appliances, or time intervals increases, computation time grows exponentially, especially for MILP and DP. Applicability: Best suited for controlled environments or small residential communities where accurate input data is available. Less practical for large-scale real-time applications without simplification or decomposition.

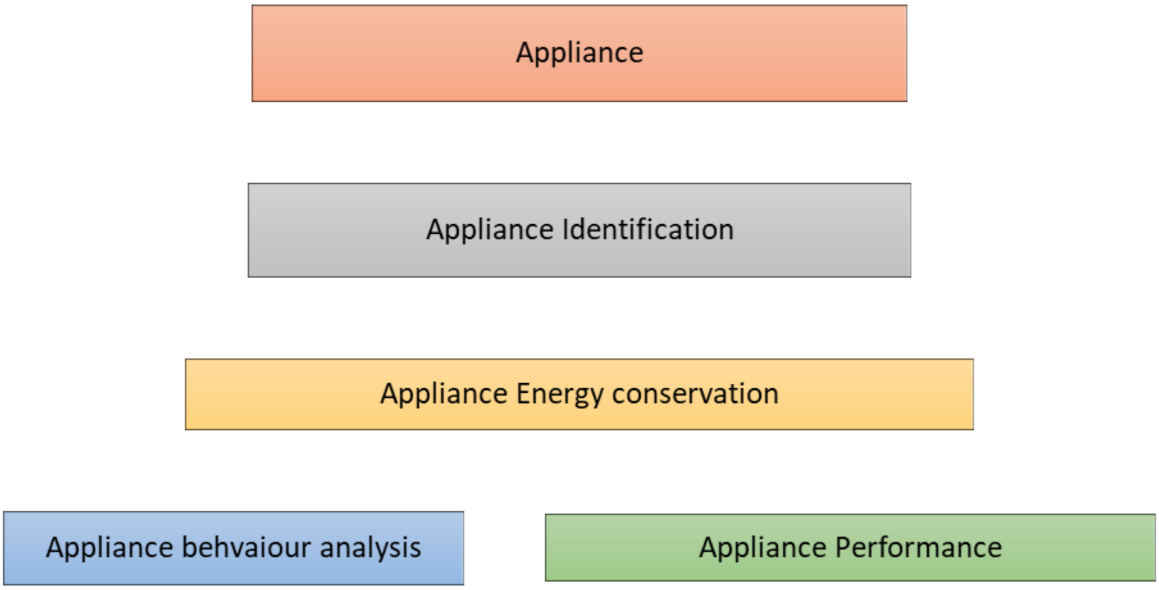


Figure 2. Complete cycle- Energy management

Metaheuristic Algorithms

Algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) are used to solve DSM problems where exact optimization is computationally infeasible. They search for near-optimal solutions using iterative, stochastic methods. Studies show 20–35% peak reduction in residential energy[32] consumption (Shayeghi et al., 2026).Metaheuristics can handle non-linear, multi-objective problems better than classical optimization methods. Efficiency: Lower than exact optimization in guaranteed optimality, but can find good-quality solutions in reasonable time. Scalability: Better than classical optimization; suitable for larger residential systems or microgrids.Applicability: Well-suited for complex DSM scenarios involving multiple households, appliances, renewable integration, and user preferences. However, performance depends on algorithm tuning and may require multiple runs for reliable results.

Artificial Intelligence (AI) and Machine Learning Approaches

Includes reinforcement learning (RL), neural networks, deep learning, and fuzzy logic. AI models learn energy usage patterns and make adaptive, real-time decisions.AI-based DSM achieves 20–40% peak load reduction while maintaining comfort. RL-based approaches can continuously improve decisions under dynamic pricing and stochastic demand. Efficiency: Very high in real-time adaptation; capable of responding to unexpected load changes or user behavior (Yi et al., 2026). Scalability: Excellent for large-scale deployment, especially with cloud computing and IoT-connected devices. Applicability: Ideal for smart homes and smart grids, where continuous learning and adaptation are required (Xu et al., 2025). Challenges include training data requirements, interpretability, and initial implementation cost.

Table.2.Comparative Evaluation of Optimization Techniques

Approach	Efficiency	Scalability	Applicability to Residential DSM	Notes
Optimization Techniques (MILP, DP)	High for small systems	Low for large-scale systems	Small communities, predefined schedules	Deterministic, precise, but computationally heavy
Metaheuristic Algorithms (GA, PSO, ACO)	Moderate to high	Moderate to high	Complex, multi-objective residential DSM	Flexible, near-optimal, requires tuning
AI/ML Approaches (RL, Neural Networks)	High, adaptive	Very high	Smart homes, real-time DSM	Handles uncertainty, needs data and training, may lack transparency

Optimization is preferred when precision is critical and system size is manageable. Metaheuristics provide a balance between quality of solution and computational effort, suitable for larger or more complex scenarios (Xing et al., 2025). AI/ML approaches excel in dynamic, real-time environments, handling behavioral variability and renewable integration efficiently. Hybrid approaches, combining optimization with AI or metaheuristics, are emerging as the most effective strategy for residential DSM, offering efficiency, adaptability, and scalability.

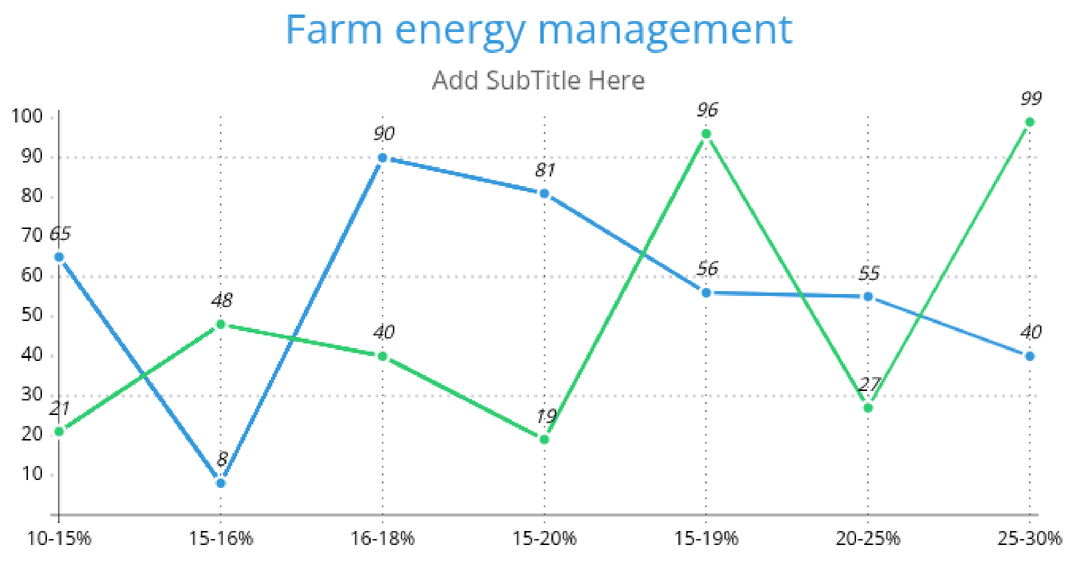


Figure 3. Emerging technologies

The role of emerging technologies, including smart grids, Internet of Things (IoT), and home energy management systems (HEMS), in facilitating effective DSM implementation.

Emerging technologies have transformed the implementation of residential Demand-Side Management (DSM), enabling real-time monitoring, adaptive control, and user-centric energy optimization. *Key technologies include* smart grids, Internet of Things (IoT), and Home Energy Management Systems (HEMS).

Smart Grids

Smart grids integrate advanced communication, sensing, and control technologies into the electricity network. Facilitate two-way communication between utilities and consumers, enabling dynamic pricing, load shifting, and peak demand management. Case studies show smart grid deployment can reduce residential peak load by 15–25% when combined with time-of-use (TOU) pricing and demand response programs. Smart grids improve grid reliability and resilience, allowing utilities to better balance supply-demand fluctuations.Smart grids are the backbone of modern DSM, providing the infrastructure needed for real-time monitoring and automated control (Wang et al., 2025). Challenges include high initial investment, cybersecurity concerns, and interoperability issues across different devices and utilities.

Internet of Things (IoT)

IoT devices, such as smart thermostats, smart plugs, and connected appliances, collect real-time energy consumption data and enable automated control (Umansky et al., 2026). IoT enables fine-grained visibility into household energy usage patterns and supports predictive and adaptive DSM strategies. IoT-enabled households can shift appliance loads based on pricing signals, achieving 10–20% energy savings. Continuous monitoring allows detection of inefficient devices, behavioral feedback, and energy optimization at the appliance level. IoT enhances user engagement and control, supporting DSM strategies that adapt to occupancy patterns and lifestyle preferences. Limitations include data privacy concerns, device standardization, and network dependency, which must be addressed for reliable DSM implementation.

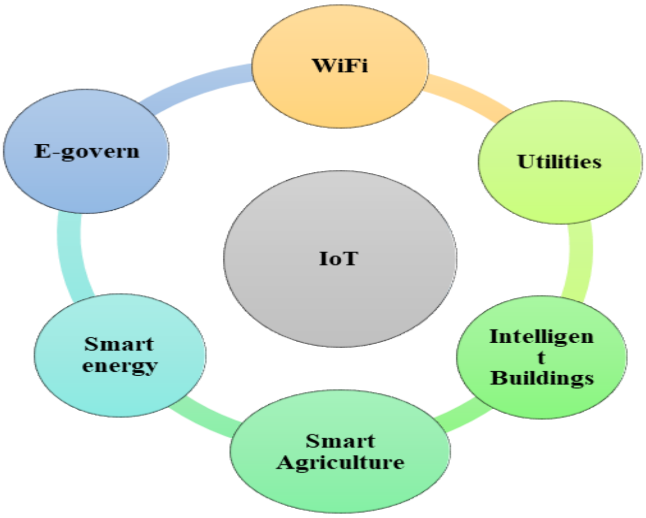


Figure 4. Internet of Professionals Things in Digital Age

Home Energy Management Systems (HEMS)

HEMS act as the centralized control platform within a household, integrating smart appliances, IoT devices, and utility signals. HEMS use optimization algorithms, AI, or rule-based strategies to schedule appliance operation, reduce peak load, and lower energy costs. Studies show HEMS can achieve 15–30% energy cost reduction and 20–35% peak load reduction, especially when combined with smart pricing schemes. Advanced HEMS with AI/ML can predict household consumption patterns and automatically adjust appliance schedules without user intervention. HEMS bridges the gap between residential users and smart grids, enabling automated and user-friendly DSM implementation. Challenges include high deployment cost, need for user trust, and complexity in integrating multiple devices. HEMS effectiveness increases when combined with real-time data from IoT devices and smart grid signals.

Table 3. Integrated Impact and Comparative Insights

Technology	DSM Role	Impact on Efficiency	Scalability & Adaptability	Challenges
Smart Grid	Real-time communication, dynamic pricing	High; enables 15–25% peak reduction	High; supports large-scale utility deployment	Cost, cybersecurity, interoperability
IoT	Real-time monitoring, appliance-level control	Moderate to high; 10–20% energy savings	High; adaptable to individual households	Data privacy, standardization, network reliability
HEMS	Centralized energy control, automated scheduling	High; 20–35% load/energy cost reduction	Moderate; dependent on device integration	Complexity, cost, user acceptance

Synergy is critical: The combination of smart grids, IoT, and HEMS delivers more significant DSM benefits than any single technology. Automation and intelligence: IoT data combined with HEMS and AI-driven algorithms enables predictive and adaptive DSM, reducing reliance on manual intervention. User engagement: Technologies must balance automation with user control to maximize acceptance and energy-saving outcomes. Future potential: Integration with renewable generation (e.g., solar PV), electric vehicles (EVs), and storage systems can further enhance DSM effectiveness.

The major barriers to DSM adoption, such as user participation, data privacy concerns, system complexity, and interoperability issues Despite the potential of Demand-Side Management (DSM) to improve energy efficiency and reduce peak loads, adoption in residential settings faces significant barriers. Key challenges include user participation, data privacy, system complexity, and interoperability issues.

User Participation and Behavioral Factors

Successful DSM relies on active consumer engagement for demand response, appliance scheduling, or adoption of smart technologies. Low awareness or reluctance to change energy habits often limits participation. Studies report that less than 50% of households actively respond to time-of-use pricing or incentive programs without automated systems. Behavioral factors, such as preference for comfort over cost savings, significantly reduce DSM effectiveness. Barrier Severity: High. Even advanced technologies fail if user engagement is low. Solutions include user education, incentive programs, and automated DSM systems that minimize manual intervention.

Data Privacy and Security Concerns

DSM requires continuous monitoring of energy consumption, occupancy, and appliance usage. Sharing such data raises concerns about personal privacy, cyber-attacks, and unauthorized access. Surveys show 60–70% of users express concern over smart meter or IoT device data collection. Privacy concerns delay the adoption of smart meters, HEMS, and IoT-enabled appliances. Barrier Severity: High. Privacy concerns can significantly limit DSM adoption. Addressing this requires strong encryption, anonymized data handling, and transparent data policies.

System Complexity

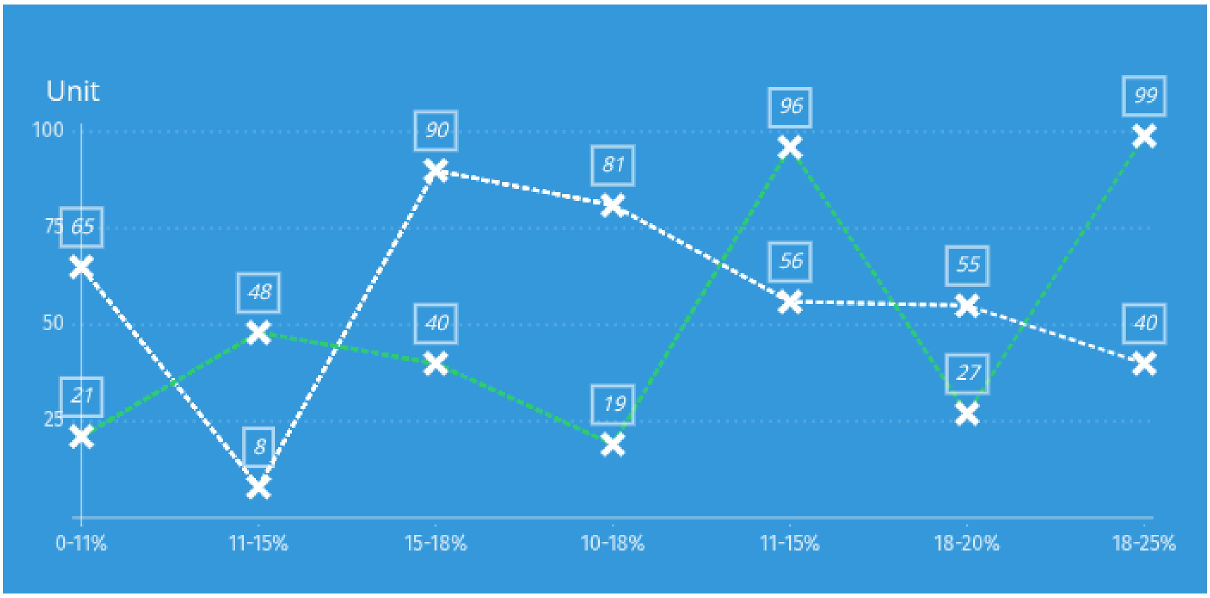
DSM systems often integrate smart appliances, IoT devices, HEMS, and utility signals, requiring sophisticated coordination. Complexity in setup, operation, and maintenance can discourage household adoption. Studies report installation difficulties and operational confusion reduce user satisfaction, leading to underutilization of DSM features. Complexity can increase the perceived cost of DSM systems. Barrier Severity: Moderate to high. Solutions include plug-and-play systems, intuitive user interfaces, and automated control algorithms to reduce user burden.

Interoperability Issues

Residential DSM relies on heterogeneous devices and platforms (appliances, smart meters, IoT devices, HEMS, utilities). Lack of standardized communication protocols and compatibility issues limit effective DSM integration. Integration challenges can prevent coordinated energy management, reducing peak load reduction by 10–15% in practical deployments. Proprietary systems hinder scalability and limit users' ability to mix devices from different manufacturers. Barrier Severity: Moderate. Solutions involve standardization of protocols (e.g., Zigbee, OpenADR), modular system design, and industry collaboration.

Table 4. Comparative Barrier Assessment on DSM Effectiveness

Barrier	Severity	Impact on DSM Effectiveness	Mitigation Strategies
User Participation	High	Limits adoption of pricing and incentive-based DSM	Automation, education, financial incentives
Data Privacy & Security	High	Reduces trust in smart meters and IoT	Encryption, anonymization, transparent policies
System Complexity	Moderate–High	Reduces usability and engagement	Simplified interfaces, plug-and-play devices
Interoperability	Moderate	Limits integration and coordination	Standard protocols, modular systems, vendor collaboration



Human factors (participation and trust) are as critical as technological capabilities for DSM success. Technological solutions alone cannot fully overcome adoption barriers; policy, education, and standardization are essential. Future DSM deployment will likely rely on automated, user-friendly, and interoperable systems that protect privacy while minimizing behavioral barriers.

Future Research Direction

While residential Demand-Side Management (DSM) has advanced significantly, several challenges and emerging opportunities suggest clear directions for future research. These directions focus on technological innovation, behavioral integration, and system scalability.

Integration of Advanced AI and Hybrid Modeling Combining optimization, metaheuristic algorithms, and AI/ML approaches for real-time, adaptive DSM. Development of hybrid models that leverage predictive load forecasting and optimization simultaneously. Current AI models excel in adaptability but may lack precision, while optimization provides accuracy but struggles with scalability. Hybrid approaches can balance efficiency, scalability, and robustness, enabling DSM at large residential scales. Reinforcement learning integrated with MILP for dynamic appliance scheduling. Multi-agent AI systems that consider community-level energy management, not just individual households.

Enhanced User Engagement and Behavioral Modeling:Designing DSM programs that actively incorporate user behavior, preferences, and incentives. Research into behavioral economics and gamification to increase participation.User participation remains a key barrier; automated control alone may not fully realize DSM potential. Understanding household decision-making allows better-tailored DSM strategies. Real-world studies on behavioral response to dynamic pricing and incentive schemes. AI-driven personalized recommendations for energy-saving actions.

IoT and HEMS Interoperability and Standardization:Developing unified protocols and open platforms to integrate smart appliances, IoT devices, and HEMS. Emphasis on scalable, modular, and vendor-agnostic systems. Current interoperability issues limit DSM efficiency and scalability. Standardization can facilitate mass adoption of smart energy technologies. Design of plug-and-play HEMS compatible with multiple devices and utility interfaces. Exploration of edge computing for local decision-making, reducing cloud dependency.

Privacy-Preserving DSM:Ensuring data security, privacy, and trust in smart grids, IoT, and HEMS. Adoption of privacy-enhancing technologies (PETs) such as federated learning and encrypted data sharing. Privacy concerns significantly hinder residential DSM adoption. Solutions that anonymize data without sacrificing DSM performance are critical. Federated learning models for appliance-level energy optimization. Privacy-aware DSM algorithms that balance efficiency and data protection.

Integration with Renewable Energy and Storage:Incorporating solar PV, battery storage, and electric vehicles (EVs) into DSM strategies. Research on coordinated scheduling of generation, storage, and demand response. Decentralized energy resources introduce variability, but also opportunities for self-consumption and peak shaving. DSM can be optimized to maximize renewable integration and minimize grid stress. AI-driven scheduling of EV charging and home storage with dynamic pricing signals. Community-scale DSM combining multiple households with shared renewable assets.

Scalability and Real-Time DSM:Development of scalable algorithms capable of handling thousands of households in real-time. Integration of cloud computing, edge computing, and IoT analytics. Most current studies focus on small-scale or simulated environments. Large-scale, real-time DSM is essential for smart cities and modern grid stability. Distributed DSM algorithms that operate efficiently without centralized computation bottlenecks. Real-time adaptation to grid fluctuations and dynamic pricing at community or city levels.

Evaluation of Economic and Policy Impacts:Assessing cost-effectiveness, user incentives, and regulatory support for DSM programs.Development of policy frameworks that encourage technology adoption and consumer engagement. Technology alone cannot ensure adoption; economic and policy drivers are crucial. Proper incentives and regulatory support can maximize participation and grid benefits. Pilot studies evaluating dynamic pricing, subsidies, or rebates for residential DSM adoption. Cost-benefit analysis of hybrid AI-driven DSM systems in real-world deployments.

Future research in residential DSM should focus on:

Hybrid AI-optimization models for adaptive, large-scale management. Behavioral modeling and user engagement to enhance participation. Interoperable, privacy-preserving IoT and HEMS solutions. Integration with renewable energy and storage for sustainable energy management. Scalable, real-time DSM platforms for smart cities. Economic and policy frameworks to encourage adoption. These directions collectively aim to make DSM more efficient, user-friendly, and widely adoptable, bridging the gap between technological potential and practical implementation.

CONCLUSION

This paper reviewed various modeling approaches and enabling technologies for residential Demand-Side Management (DSM). Optimization techniques, metaheuristic algorithms, and AI-based methods were evaluated in terms of efficiency, scalability, and applicability. While optimization methods provide precise solutions for small-scale systems, metaheuristic algorithms offer near-optimal results for complex scenarios, and AI approaches enable adaptive, real-time energy management.

The role of emerging technologies, including smart grids, IoT, and Home Energy Management Systems (HEMS), was highlighted as critical for facilitating effective DSM implementation. These technologies enable real-time monitoring, automated control, and integration with dynamic pricing schemes. Despite their benefits, DSM adoption faces barriers such as limited user participation, data privacy concerns, system complexity, and interoperability challenges.

Future research should focus on hybrid modeling approaches, privacy-preserving algorithms, scalable real-time solutions, and user engagement strategies, as well as integration with renewable energy and storage systems. Addressing these areas can enhance the efficiency, reliability, and acceptance of residential DSM programs. The findings suggest that combining advanced computational methods with emerging technologies and user-centric strategies is essential for achieving sustainable, intelligent, and resilient energy management in residential settings.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the author(s) used Grammarly to assist in improving grammar, language quality, and overall readability of the text. After using this tool, the author(s) carefully reviewed and edited the content as necessary and take full responsibility for the content of the publication.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

Author 4: Formal analysis; Methodology; Writing - original draft.

Author 5: Supervision; Validation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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