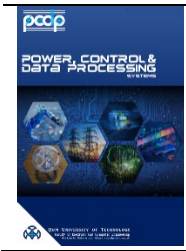
DOI: 10.30511pcdp.2025.2072667.1045 - ISSN: 3060-8376 - Vol X3(1), 2026



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A Review of Game Theory-based Approaches for Demand Side Management in Smart Energy Grids

ARTICLE INFO

Article Type
Original Research

Authors
A. Sina Samadi Gharehveran[1]*
B. Kimia Shirni[2]
C. Mohammad Sarhangzadeh[3]
D. Sana Gholinavaz[4]
*[1] Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz, Iran, s.samadi@tabrizu.ac.ir
[2] Department of Electrical and computer engineering, Qom University of Technology, Qom, Iran, k.shirini@tabrizu.ac.ir
[3] Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz, Iran, m.sarhangnote@gmail.com
[4] Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz, Iran, sanagholinavaz83@gmail.com
**** Correspondence***
Address: Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz, Iran, *Phone*: -
Fax: -
s.samadi@tabrizu.ac.ir

Article History
Received: Sepetember 24, 2025
Accepted: October 15, 2025
ePublished: March 01, 2026

ABSTRACT

Smart grid and demand side management have increased the interaction between energy suppliers and consumers. Energy savings are possible through optimal resource allocation and energy utilization. This interaction helps reduce grid dependency, optimize resources. This paper reviews the socio-economic and reliability benefits of smart grid and focuses on the classification and analysis of recent studies that propose game theory approaches for optimizing demand side management. The analysis of each application, including cooperative and non-cooperative games, is carried out by analyzing the mechanisms and solution methods. Based on the review of these studies, game theory applications on the demand side can be beneficial for the grid and the consumer. Classification and review of recent works, proposing game theory approaches for optimal demand side management are considered in this paper. Applications of different cooperative and non-cooperative games are analyzed by reviewing their mechanisms and solution methods. It is concluded from the review of these works that game theory applications on demand side is beneficial for both grid and the consumer.

Keywords: Renewable energy, load forecasting and planning, demand side management, game theory.

1 Introduction

Deregulation of the electricity industry and increasing environmental concerns over global warming and greenhouse gas emissions are increasing the installation and use of renewable energy sources. Renewable sources are made up of several technologies that include photovoltaic cells, biomass power plants, wind turbines, and geothermal power plants. The coordinated operation and control of these distributed energy sources, as well as energy storage systems, like batteries, are the fundamentals of the smart grid concept. An electrical system that can use information for computational purposes over secure cyber communication links and is integrated throughout electricity generation, transmission, and distribution to design and operate a financially and environmentally sustainable system [1]. As energy demand continues to increase, smart grid technology has evolved from its original scope, utilizing all modern technologies to provide services with high quality to the grid and make the electricity grid a grid with "intelligence." The National Institute of Standards and Technology has listed six functional areas of a smart grid that are critical to the technology's development.

The use of energy-efficient smart devices with communication capabilities will decrease dependency on fossil fuel-based electricity generation and will lead to the reduction of greenhouse gas emissions. Integrating renewable electricity generation from on-site solar and wind generators and energy storage systems such as batteries and electric vehicles into the grid, as well as integrating distributed renewable energy generators into a centralized system can be used to work towards sustainability. The smart grid infrastructure is, of course, without a smart meter. Advanced metering infrastructure is a key part of the smart grid infrastructure. The metering network's capacity for security and privacy, on which smart metering relies [2].

In the smart grid, the management of distributed energy resources (DERs) becomes the key to running the grid smoothly. These distributed energy resources could be distributed energy generators that produce energy, renewable sources or energy storage devices, such as batteries. Distributed management of energy resources aims to manage distributed energy resources over a large geographical area and interact with building energy management systems or community energy management systems for the benefit of all the smart grid entities. In a smart grid, each portion can be classified as a player who has a distinct role to perform in order to accomplish the group's goals. Although they all act separately and have different goals, the choices one player makes influence the other players' strategy/decisions. Some of these decisions may be operational planning and real-time event management to ensure the network is reliable [3].

Figure 1 illustrates the conceptual framework of demand-side management in smart grids, highlighting the main stakeholders—utilities, aggregators, consumers, renewable generators, and electric vehicles—and their game-theoretic interactions through pricing, incentives, and load-shifting mechanisms.

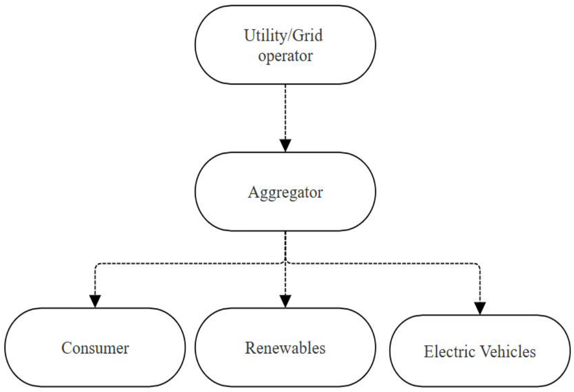

Figure 1: Conceptual framework of demand-side management with game-theoretic interactions in smart grids

The above framework shows the major stakeholders in demand-side management, including the utilities, the aggregators, the consumers, the renewable generators, and the electric vehicles. Game-theoretic interactions like pricing, incentives and loads shifting mechanisms among the involved players. The main contributions and innovations of this review are summarized as follows:

(1) A systematic, historical, and analytical review of game theory–based demand-side management (DSM) methods in smart grids, emphasizing their socio-economic and reliability aspects;

(2) The introduction of a novel multi-criteria comparative framework to evaluate existing approaches in terms of accuracy, stability, computational cost, and adaptability;

(3) A detailed analysis clarifying the transition from classical optimization-based DSM models to recent learning-driven and hybrid game-theoretic approaches; and

(4) The identification of key research gaps and future research directions to guide the development of next-generation DSM strategies.

2 Main components of the smart grid

The high price and the volatility of the availability of fossil fuels and the increase in environmental pollution have resulted in a global paradigm shift from the use of fossil fuels to renewable sources of energy for energy production. Distributed energy sources are complementary to conventional fossil fuel-based power plants. Distributed renewable energy sources relieve pressure on fossil fuel-based energy sources while contributing to economic development and sustainability. Solar energy is the most common renewable energy source for electricity generation followed by wind, biomass, and hydroelectricity[4]. Distributed energy sources provide a backup system for the distribution company and a system that can supply electricity in areas where connection to the electricity grid is impossible or very expensive. The lower startup costs of renewable energy generators compared to conventional power generators and the short time they take to be deployed are their competitive advantages over conventional central power plants [5].

Advanced metering infrastructure acts as a bridge between the distribution company, consumers, loads, distributed energy sources, and energy storage devices. Advanced metering infrastructure refers to a smart meter with communication links that can be remotely configured, apply real-time tariffs, monitor power quality, and perform load control [6]. The communication link between the consumer energy meters, the substation, and power plant control room, and the distribution companies' metering data centers, must be reliable. The various entities connected through the link include customers, distribution companies, network operators. Information and communication technology has the potential to allow the integration and interoperability of previously disparate systems to better levels. From the point of view of the distribution companies, the ability to predict energy consumption and identify and correct network problems leads to cost and energy savings. The control system has evolved from a centralized architecture to a decentralized, autonomous, flexible, and robust structure due to the intermittent nature of renewable energy sources, the complexity of the smart grid, and the presence of distributed generation. Consumers are active in demand-side management through the advanced metering infrastructure and the market mechanism.

Table 1 presents a comparative summary highlighting the main distinctions between the present review and previously published review articles on game theory-based DSM in smart grids.

Table 1. Comparison between the present review and other related review articles

Main Focus / Scope	Methodology	Evaluation Criteria	Novelty / Contribution	Reference
General review on DSM methods in smart grids	Descriptive survey	Economic efficiency only	Lacks historical or comparative analysis	[18] E. Nekouei et al., IEEE Trans. Smart Grid, 2014
Game theory for energy trading	Conceptual and qualitative	Cost-benefit and stability	No focus on learning-based approaches	[19] R. Heidarykiany & C. Ababei, Energy AI, 2024
Cooperative game theory in DSM	Thematic classification	Participation rate, fairness	Limited to cooperative games only	[12] Z. Zhu et al., IEEE Trans. Ind. Inform., 2015
Demand response and pricing models	Comparative review	Cost optimization and response rate	Does not integrate socio-economic or reliability criteria	[15] K. Shirini et al., 2024
Game theory–based DSM approaches in smart grids	Systematic, historical, and analytical review	Accuracy, stability, computational cost, adaptability, and socio-economic impact	Introduces a multi-criteria comparative framework; bridges classical and learning-based methods; outlines future research directions	This Study (Present Review)

3 Demand side management

Demand-side management has been considered as a key component in the planning methodology adopted by electricity distribution companies which is also referred to as integrated resource planning. Integrated resource planning refers to the modification of consumer demand for energy by various approaches such as financial incentives and voluntary behavior changes, with the desired effects being a general reduction in the peak load of the network. Demand-side management involves incentivizing consumers to use less energy during peak hours or to shift their load to off-peak hours; therefore, the strategies in this category do not aim to reduce energy consumption, but rather to reduce investments in the network and the energy distribution network's capacity to meet peak demand. Demand-side management strategies assist in enhancing the stability of the network since they enable it to strike a balance between the demand and supply, therefore, the average peak ratio is improved; hence, the demand-side management strategies improve energy efficiency while load response programs focus on reducing the peak load and on energy saving [7]. On the other hand, distribution companies have resorted to smart pricing alternatives to encourage voluntary changes in the consumers' energy activities towards reducing their energy costs. In the scheduling algorithm described in [8], consumers have the ability to shift the starting times of their household appliances depending on the daily energy prices set by the distribution companies while considering the uncertainty in the electricity prices and solar energy production. The reduction in household energy consumption can be implemented by controlling the demand of the transferable load without compromising the comfort of the user. The real-time pricing described in [9] provides incentives to consumers to plan their consumption in order to improve their cost efficiency.

The two-level hierarchical algorithm [9] put forward a demand response program that was aimed at the consumers who were to be rewarded both for their level of demand transfer and for the extended support of the network due to the shift in the energy consumption. Figure 2 presents the taxonomy of game-theoretic approaches applied to DSM in smart grids, categorizing them into non-cooperative, cooperative, Stackelberg/hierarchical, evolutionary, and hybrid frameworks based on interaction type, solution method, and application domain.

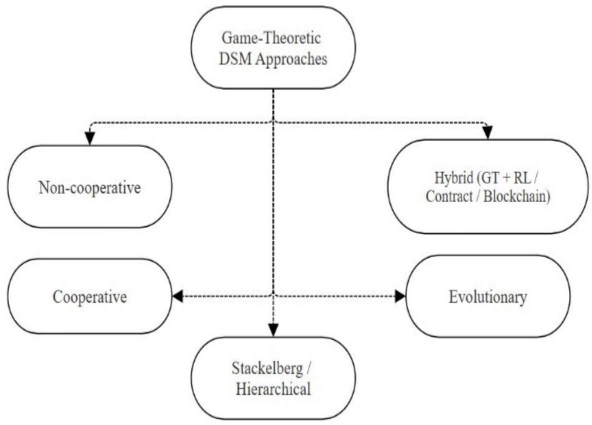

Figure 2: Taxonomy of game-theoretic approaches applied to demand-side management in smart grids

The taxonomy categorizes DSM approaches into five primary groups: non-cooperative, cooperative, Stackelberg/hierarchical, evolutionary, and hybrid frameworks. These categories represent various interaction rules, solution methods, and application scenarios within smart grid contexts.

4 Game theory

Consumers are considered self-interested, they will act in ways that improve their individual interest. Game theory is a mathematical study of decision makers who interact in such a way that the decision of one player in the game may affect the other players. It mathematically models the strategic interrelationships among intelligent and rational decision makers with a set of rules, constraints and outcomes [10]. Multiobjective optimization problems are very much like games, game theory methods are gaining popularity to solve them. However, it is obvious that these methods usually satisfy only Nash equilibrium and not Pareto optimality. However, Pareto solutions and Nash equilibriums are different. In Pareto optimal solution, everyone (except one of the agents) can get a better payoff; In Nash equilibrium, no one can improve their payoff, Therefore, Nash equilibrium is more useful in energy management solutions.

4.1 Non-cooperative game

A non-cooperative game is a game where individual players compete to gain maximum payoff on their own assumptions or beliefs about how other players will play. Coalitions can occur only if there is a credible threat. Non-cooperative game theory studies the strategies of individual decision makers who have conflicting preferences. The lack of an external authority that enforces the rules diminishes the potential for coalitions, so the players all compete independently of each other. If the players find a solution point in the game, if one player departs from the solution point then he should not get any incentive, because it does not increase the payoff of the player. Not more than two players can leave; the point at which neither player can improve his payoff by a unilateral move is a Nash equilibrium [11]. In a Nash equilibrium, no player can unilaterally increase his payoff by changing his strategy if the actions of other players are fixed. So the mutually optimal response is reached by all players.

4.2 Cooperative game

In a game theory where competition takes place between groups of players rather than individual players is called a cooperative game or a coalition game. This is possible only when a game can be played under the control of a central authority and the contract of cooperation can be legally enforced by the center [12]. As in a non-cooperative game, a coalition game also consists of a set N of players, but in a coalition game, different probabilities are taken into consideration for the formation of a coalition. A set K which is a subset of N is identified as a coalition. For example, a coalition N is known as a grand coalition. In this way, the set of all coalitions is the set of all subsets of N, and the number of subsets of N is N^2. A characteristic function V(S) indicates the result of interaction among the members of coalition S and also shows the net payoff during cooperation among players. If ϕ is an empty coalition, then of course, the payoff will be zero, i.e., V(ϕ)=0. Thus, a cooperative game can be defined as an ordered pair <N,v>. Equation (1) defines the characteristic function v(S) of a cooperative game, which represents the total payoff that a coalition S of players can achieve through cooperation, where N is a set of players and v is a characteristic function defined as [6]:

$$v: 2^N \rightarrow \mathrm{R}, V(\phi) = 0 \qquad \text{Eq 1}$$

Figure 3 shows a collaborative microgrid model demonstrating how different energy entities—such as households, renewable generators, and storage units—form coalitions to optimize local energy management under a cooperative game framework.

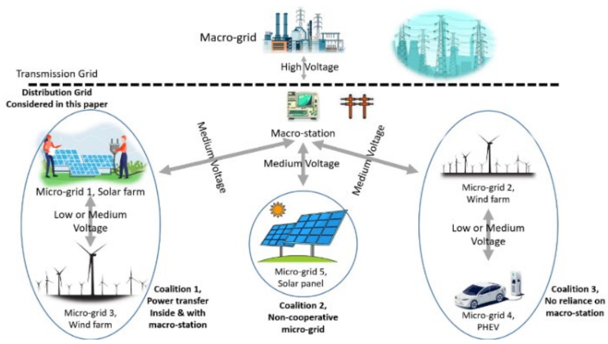

Figure 3 : Image of a collaborative microgrid model

4.3 Profit matrix

Players follow strategies which are improvements in their payoffs in a particular situation. Payoffs are mapped to the choices of a player and is the quantified amount of change, increase or decrease, of “value” in a value system. Payoffs in a game are represented in the form of a matrix, and the payoff of a player in a particular situation is given by the choices made by other participants in that same situation. The payoff matrix for a 2 player game is a tabular representation in which the strategies of one player are given by rows and the strategies of the other by columns. The cells of the table are the payoffs of each player and the first row in the cell represents the payoffs of that player. A simple example of a payoff matrix is shown in Figure 4. In this game, the game represents two players X and Y and the symbols inside represent the payoff of the players. The choice of strategy by each player is independent of the actions of the other players.

Y \ X	Strategy 1	Strategy 2
Strategy 1	$P_{X(1,1)}, P_{Y(1,1)}$	$P_{X(1,2)}, P_{Y(1,2)}$
Strategy 2	$P_{X(2,1)}, P_{Y(2,1)}$	$P_{X(2,2)}, P_{Y(2,2)}$

Y \ X	Strategy 1	Strategy 2
Strategy 1	1 , 5	2 , 4
Strategy 2	3 , 1	0 , 3

Figure 4: Payoff matrix for a two-player game

4.4 Nash equilibrium

A Nash equilibrium is a solution proposed for a non-cooperative game and named after the mathematician John Forbes Nash Jr. If each player's equilibrium strategies are known to every other player, then the players have no incentive to deviate from the accepted strategy. [12] Each player chooses his actions from a set of strategies, either based on past experience or by watching the progression of the game. If no player can increase his expected payoff by changing strategy when the other players do not change their strategies, then the current set of strategy choices is a Nash equilibrium. In a Nash equilibrium, the strategy of each player is optimal given the decisions of the other players. Each player wins because all receive the maximum expected payoff for the strategies used by the other players. Equation (2) formulates the set of joint actions A that includes all possible combinations of strategies chosen by every player participating in the game [8]. A normal-form game is a multiplayer game (N,A,C,f,u), in which:

- N is a set of players, and iii denotes a participant in the game such that $i \in N$.
- Each player has a set of actions A_i
- The set of joint actions is defined as:

$$A \coloneqq \{a | a = (a_i)_{i \in N}, a_i \in A_i, \forall i \in N\} \qquad \text{Eq 2}$$

where each player can choose from among their actions.

Each vector $a = (a_1, a_2, \dots, a_n) \in A$ is called an action profile. For every action taken by a player, there exists a corresponding consequence CCC. For each action taken by a player, a related outcome will exist. Equation (3) expresses the relationship between players' actions and the resulting consequences or outcomes C of the game [9].

$$f: A \to C \qquad \text{Eq 3}$$

In a game, players will have preferences and these can be represented by a utility function u:C→R. The utility function (payoff function) can represent a cost-minimization problem (loss reduction) or a profit-maximization problem. For x,y∈A, we say that a player prefers action x over action u(x)≥u(y). In this case, the player chooses strategy X. Not every action taken by a player is necessarily optimal. Any subset A'⊆A of actions which represents feasible actions for a player, is called the feasible action set in the game. Equation (4) defines the feasible action set A′ and illustrates how each player selects an optimal action x* that maximizes their own utility function. [11].

The player chooses an optimal action x*⊆A' such that :

$$f(x*) \geq f(x), \forall x \in A' \qquad \text{Eq 4}$$

This implies that in each round, a player picks a solution to maximize their own objective function (5). That is, when a player chooses an action from A*, he keeps his priority unchanged from the previous round. Equation (5) presents the optimization objective of each player, showing that a player continuously chooses strategies that maximize their expected payoff during each iteration of the game [11].

$$\underset{\{x \in \boldsymbol{A}\}}{max} u(f(x)) \qquad \text{Eq 5}$$

Support is the subset of actions which are assigned positive probability by the mixed strategy. It is a set of pure strategies. Equation (6) calculates the expected utility of a player when adopting a mixed strategy profile, reflecting the probabilistic combination of different pure strategies [11].

$$u_i(s) = \sum_{a \in A} u_i(a) \prod_{j=1}^{n} s_j(a_j) \qquad \text{Eq 6}$$

Were a player in the game to know the answers of all the other participants, he would only have one (utility maximizing) strategy for the game left. Equation (7) specifies the strategy profile of all players except player iii, which is used to analyze the best-response behavior of each participant [13].

$$us = (s_i, s_{-i}) \qquad \text{Eq 7}$$

Equation (8) defines the best-response function of player i, identifying the strategy that maximizes their utility given the strategies of all other players [14]. The best response of player i to the strategy profile s_{-i} of the other participants is a strategy $s_i^* \in S$ such that:

$$u_i(s_i^*, s_{-i}) \geq u_i(s_i, s_{-i}), \forall s_i \in S_i \qquad \text{Eq 8}$$

That is, the best response of player iii is always the action that maximizes their utility given the strategies of the other players. The best response s_i^* of player iii is not always unique, unless the strategy is a pure strategy. When the support of best responses includes multiple actions, the player may mix indifferently among these, and therefore any mixture of such actions may also be a best response.

In practice, since other players' strategies are unknown, the best response is defined only over the set of possible outcomes. To illustrate Nash equilibrium: if s_i^* is the best response for all players, then the strategy profiles $(s, s_1^*, s_2^*, \dots, s_n^*)$ form a Nash equilibrium.

5 Game theory in demand side management

Consumers and their interactions under various circumstances can be modeled, and various decentralized platforms can be analyzed using game theory. Game theory, therefore, has been extensively applied in energy management platforms in which demand side management is of great importance. In [15], game theory is used to attain a reduced peak consumption ratio. The interaction between the distribution company and consumers is employed in such a way that the consumers make their consumption plan in a manner that minimizes the difference between the energy cost and the energy value. Figure 5 illustrates the convergence behavior of the proposed game-theoretic DSM algorithm, showing how the peak-to-average load index and producer price stabilize after several iterations for 50 participating users.

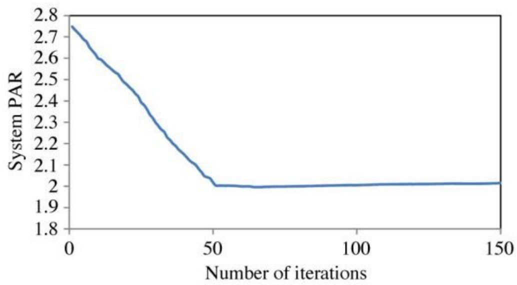

Figure 5: Convergence of the peak-to-average index of the proposed game theory method system [15]

The distribution companies compete to sell energy to a buyer and the buyers compete to minimize their total cost. The game among the distribution companies is modeled as a non-cooperative game while the consumers play an evolutionary game. Authors in [15] review two game theory frameworks very similar to this work. Authors in [16] proposes a two-stage, two-level model for the energy pricing and distribution problem of a smart grid retailer[17-23]. A retailer is in between the wholesale energy market and the consumers. A game theory framework is based on mixed integer linear programming. The model that schedules the energy consumption profiles of consumers and the existence of Nash equilibrium of the game exists and the optimization converges to an equilibrium where all the consumers can benefit from participation. Figure 6 demonstrates how a serious game-based interaction between consumers and the distribution company can improve demand-side participation and promote more efficient load management in the network.

Centralized scheme may lead to privacy leakage, and the transmission overhead to transfer data in real time is huge. On the other hand, the game theory, due to its local computation, can alleviate the negative impact of the centralized mechanism. In addition, the two schemes above have the same advantages. In [17], a decentralized collaborative algorithm is designed to control the operation of the player distribution system, which can increase the incentives of users when their actions can enhance the social welfare.

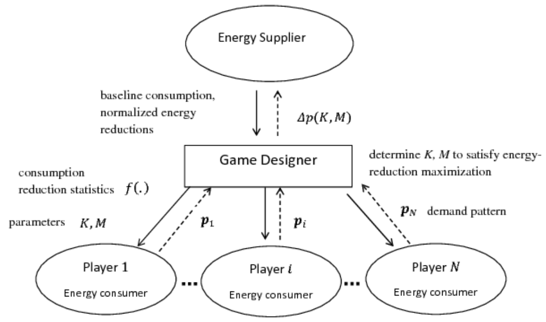

Figure 6: How serious game interaction between customers and distribution company [16]

An extended comparison is presented in Table 2. It shows the diversity of game-theoretic paradigms used for DSM. The prevalence of non-cooperative and Stackelberg games is consistent with the current trend, due to their ability to model strategic interactions between customers and utilities. However, scalability issues and privacy concerns are common problems in these frameworks. Cooperative and coalition games are useful for ensuring social welfare and fairness, but they often need a central coordinator and good communication infrastructure to work properly. Hybrid frameworks that incorporate game theory with other techniques such as reinforcement learning and contract theory are growing in interest. These approaches are good at managing uncertainty and adapting to the behavior of users. But they also face high computational complexity. P2P trading, as a promising way to apply game theory to decentralized microgrids, provides examples of the energy sharing and self-consumption for DSM applications, but the challenges of regulation and market design are not addressed. In general, game theoretic methods can provide solid theoretical support and good performance for DSM, but they mostly lack real-world deployment and are often limited to simulations. There is a lack of benchmark datasets for DSM with game-theoretic methods, which should be the future research directions to validate the algorithms in real-world scenarios[24-33].

The analysis of challenges and opportunities in Table 2 shows that although game-theoretic approaches offer a solid theoretical basis for modeling consumer–utility interactions in DSM, their practical implementation remains in its early stages[33-41]. Scalability, privacy, computational complexity, and uncertainty from renewables are the most urgent technical challenges, while real-world validation and regulatory barriers are the primary obstacles to widespread adoption[41-46]. However, emerging technologies like reinforcement learning, blockchain, privacy-preserving computation, and robust optimization offer promising solutions to address these issues. In addition, policy support and pilot projects can help bridge the gap between theory and practice to enable market-ready solutions. Table 2 summarizes recent studies that apply various game-theoretic models to DSM, listing the approach, solution method, application domain, and performance metrics used in each work.

Table 2: Summary of game theory approaches to demand side management in recent studies

Ref	Year	Approach	Solution method	Application domain	Performance metrics
[10]	2024	Stackelburg Game Theory	Stackelburg equilibrium, energy management optimization	Residential DSM	Energy costs, user satisfaction and renewable energy integration
[11]	2024	Game Theory, Reinforcement Learning, Contract Theory	Nash equilibrium, Stackelburg equilibrium	Residential & EV charging	Demand response, energy costs and social welfare
[12]	2024	Game Theory, Contract Theory	Nash equilibrium	EV charging coordination	Demand response, energy costs and electric vehicle charging
[13]	2024	Game Theory, Reinforcement Learning, Contract Theory	Nash equilibrium, Stackelburg equilibrium	Mixed DSM (households + renewables)	Demand response, energy costs, social welfare and emission reduction
[14]	2024	Game Theory, Contract Theory	Nash equilibrium	EV charging + DSM	Demand response, energy costs and electric vehicle charging coordination
[15]	2024	Game Theory, Contract Theory	Nash equilibrium, Stackelburg equilibrium	Residential DSM with storage	Demand response, energy costs, renewable energy integration and use of energy storage
[16]	2024	Game Theory, Contract Theory, Reinforcement Learning	Nash equilibrium	Energy pricing & scheduling	Demand response, energy costs, social welfare and emission reduction
[17]	2024	Game Theory, Peer-to-Peer Energy Trading	Nash equilibrium, Stackelburg equilibrium	Community microgrids	Energy costs, energy sharing and self-consumption
[18]	2024	Game Theory, Contract Theory, Reinforcement Learning	Nash equilibrium	Smart grid DSM	Demand response, energy costs, social welfare and emission reduction
[19]	2024	Stackelburg Game, Robust Optimization	Nash equilibrium, Stackelburg equilibrium	Energy market integration	Energy efficiency, carbon emissions, renewable energy integration and energy market development

Table 3 outlines the main challenges faced by game-theoretic DSM frameworks—such as scalability, privacy, and computational complexity—and proposes possible solutions and opportunities for future research.

Table 3: main challenges faced by game-theoretic DSM frameworks

Challenge	Description	Opportunities / Possible solutions
Scalability	Most game-theoretic models work only for small-scale simulations and face difficulties when scaled to thousands of users.	Use hierarchical or multi-level games; employ approximation and decomposition techniques; integrate reinforcement learning for scalability.
Privacy concerns	Many DSM schemes assume full data sharing (consumption, preferences), which may violate consumer privacy.	Apply privacy-preserving mechanisms such as differential privacy, blockchain, or secure multi-party computation.
Computational complexity	Iterative algorithms and equilibrium computations can be too slow for real-time DSM.	Develop lightweight heuristics, distributed algorithms, and online learning-based solutions.
Uncertainty from renewables	Intermittent solar and wind generation introduces unpredictability that affects equilibrium stability.	Incorporate robust optimization, stochastic game models, and predictive machine learning for uncertainty handling.
Real-world validation	Most studies are purely simulation-based, with no large-scale field trials.	Design pilot projects and industry collaborations; establish benchmark datasets for reproducibility.
Regulatory and market barriers	Peer-to-peer energy trading and decentralized DSM often face unclear regulations.	Propose policy frameworks, regulatory sandboxes, and hybrid market mechanisms.

6 Discussion

By comparing the previous game-theoretic DSM studies, several common limitations are still observed, despite the encouraging outcomes. First of all, the non-cooperative frameworks based on Nash equilibrium are still preferred due to their conceptual simplicity and applicability to selfish consumers, but their assumptions of rationality and complete information are often violated in practice, and their scalability is limited for real-world applications with thousands of heterogeneous players.

On the other hand, the cooperative and Stackelberg models achieve higher efficiency and fairness by incentivizing coalitions and hierarchical relationships between utilities and consumers. These frameworks are commonly used for energy pricing and scheduling problems, as they can enforce stability and optimality of social welfare with the support of an aggregator. However, their centralized data collection and control can raise privacy issues and communication overhead. Moreover, the recently proposed hybrid models that combine game theory with reinforcement learning, contract theory, and robust optimization show the potential of improving the adaptability of DSM schemes in dynamic environments with renewable energy sources. These frameworks can leverage the learning-based approaches to adjust to the real-time variations in the consumption and generation patterns, but their computational complexity is high, and they often rely on extensive simulations without clear evidence of real-world impact.

Finally, the game-theoretic DSM models are starting to be applied to the emerging area of peer-to-peer (P2P) energy trading, which can offer new opportunities for decentralized energy markets and communities. While these models can support energy sharing and self-consumption among peers, they are still facing regulatory uncertainty and lack of standardized market mechanisms, which hinders their real-world validation and deployment as more than just conceptual solutions.

In general, the game-theoretic approaches have established themselves as a solid analytical foundation for DSM, but their real-world impact is still limited by their assumptions and challenges. To fully unlock the potential of these models, the issues of scalability, privacy, computational feasibility, and regulatory support should be addressed, which will require not only technical innovation but also interdisciplinary collaboration with economics, law, and behavioral sciences.

7 Research Gaps and Future Directions

First, while most DSM studies have focused on small scale simulations with a small number of users and a simple system model, the application of game theory in large-scale and realistic smart grid environments is a considerable challenge. The scalability gap becomes evident when considering thousands of consumers, distributed energy resources, and dynamic market conditions in real-world smart grids. In this regard, future works should focus on the hierarchical game and multi-level game formulations for large-scale DSM with heterogeneous players under guaranteed computational tractability.

The second research gap is concerned with the lack of privacy and data security. The existing game-theoretic frameworks in DSM assume that complete information about users' preferences, costs, and consumption patterns is available. This information transparency is usually not possible in practical systems and may lead to privacy violations. The integration of privacy-preserving mechanisms such as blockchain-based energy trading, differential privacy, and secure multi-party computation in DSM is still an open problem without sacrificing efficiency.

The third gap is related to uncertainty and its effects on the equilibrium stability. The presence of renewable energy sources makes DSM highly susceptible to the variability of supply-demand equilibrium. In particular, the existing DSM models in the literature assume a deterministic environment with fixed solar, wind, and load profiles. However, in real-world environments, these profiles are subject to stochastic fluctuations. Robust optimization, stochastic game models, and predictive machine learning should be considered in future works to address the DSM problem in the presence of uncertainty and ensure its resilience.

The fourth gap in existing research is related to the computational complexity of proposed models and their real-time implementation. The iterative algorithms for Nash or Stackelberg equilibrium may not be scalable or responsive in large-scale or fast-changing environments. In this regard, lightweight heuristic methods, distributed algorithms, and online learning approaches need to be considered to enable near real-time DSM with acceptable quality of solution.

Another gap in the field of game-theoretic DSM is a lack of real-world validation. The large majority of the existing works are based on simulations, and there is a need for large-scale field trials, benchmark datasets, and cross-country comparative studies to validate and compare the effectiveness of the existing and future DSM approaches. This is another problem that can be addressed with collaborative pilot projects and research conducted in close cooperation with utilities, regulators, and research institutions.

The last identified gap is related to regulatory and market barriers. The application of some advanced DSM schemes, including peer-to-peer energy trading and decentralized market designs, is not possible in many jurisdictions due to the existing electricity market regulations. However, these regulations were often designed without considering the decentralized, game-theoretic energy exchanges that modern DSM systems make possible. In this regard, future works should be more interdisciplinary in their nature and also address the issues of policy design, regulatory sandboxes, and socio-economic analyses of DSM and consumer behavior.

In general, the multi-disciplinary future work is required to address most of the existing gaps in the game-theoretic DSM literature, as the problem is not purely mathematical but also involves other engineering fields such as machine learning, optimization, cybersecurity, etc. Moreover, a lot of the identified gaps still have policy and regulatory-related aspects, which can be further studied in an interdisciplinary manner. By addressing scalability, privacy, uncertainty, computational efficiency, real-world validation, and regulatory frameworks, the next generation of DSM research can contribute to the development of scalable, secure, and market-ready DSM solutions for the smart energy grid.

8 Conclusion

The paper presented in the document offers a detailed summary and critique of existing literature on game-theoretic approaches to demand-side management (DSM) in smart grids. The proposed taxonomy, which categorizes the literature into non-cooperative, cooperative, Stackelberg/hierarchical, evolutionary, and hybrid models, provides a clearer understanding of the range of techniques and their specific applications. The comparison tables and the diagram give an overview of how different game formulations are used to address the fundamental DSM challenges, including cost reduction, peak-to-average load minimization, social welfare maximization, renewable integration, and customer participation.

The summary shows that non-cooperative games and Nash equilibrium are still the most popular, mainly due to their simplicity and the wide range of existing solution algorithms. However, their applicability to large-scale systems with realistic user behavior remains limited. Cooperative and Stackelberg/hierarchical models have been shown to yield more efficient and fairer solutions but require strong centralized control and complete information availability. Hybrid models that combine reinforcement learning, contract theory, and robust optimization are emerging as a new frontier that can address uncertainty and dynamic system conditions but at the cost of increased computational complexity. Peer-to-peer trading models and frameworks have shown significant promise for decentralized DSM but face regulatory and market structure challenges in real-world deployment.

Beyond classification and summary, this paper also helps in identifying important research gaps and directions for future work. These include: (1) the need for scalable and computationally efficient game-theoretic algorithms that can manage thousands of users in real-time; (2) the integration of privacy-preserving techniques like blockchain, differential privacy, and secure multiparty computation; (3) the development of robust and stochastic models that explicitly consider the uncertainty of renewable energy sources; (4) the creation of benchmark datasets and standardized testbeds to enable reproducibility and fair comparison of different approaches; and (5) the need for more collaboration between academia, industry, and regulators to develop DSM frameworks that are not only technically effective but also practically implementable, considering legal, economic, and social aspects.

In terms of real-world applicability, the insights and overviews provided by this review can help utilities and system operators in selecting and implementing suitable DSM mechanisms tailored to their specific goals and constraints, whether those are cost minimization, emissions reduction, or community-based energy sharing. Regulators and policymakers can also find opportunities to design regulatory incentives and testbeds that would facilitate the deployment of the identified solutions.

In summary, it appears that game-theoretic DSM is quite mature in terms of theoretical and modeling work but in its early stages with regard to large-scale, real-world deployment. There is significant opportunity for future work to address this gap by leveraging recent advances in game theory, machine learning, cybersecurity, and policy design to create innovative, scalable, and privacy-preserving game-theoretic DSM mechanisms that can have a real-world impact. In the long run, such mechanisms will be a critical component for the development of intelligent, resilient, and sustainable smart grids.

Disclosure of Potential Conflicts of Interest

The Authors declare that there is no conflict of interest

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