Grenze International Journal of Engineering and Technology, June Issue

A Review of Machine Learning Models for Energy Trade Ranking and Optimization in Smart Microgrids

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Abstract*— The penetration of more distributed energy resources, such as solar photovoltaics, wind generation, battery energy storage systems, and electric vehicles, has shifted conventional power distribution networks from centralised to smart microgrids. One of the key problems of such environments is the efficient trading energy between prosumers, i.e., that a surplus and deficit energy must be ranked, assigned and optimised in real-time considering economic, technical and operational barriers. Traditional methods of rule based and optimisation driven approaches may not be able to manage stochastic characteristics of renewable generation, dynamic pricing, aspect of demand uncertainty, and scalability requirements inherent in smart microgrids. In this context, machine learning has become a powerful tool to improve energy trade ranking and optimisation, through data driven decision making, adaptive learning and predictive intelligence. This review paper systematically explores the latest development of machine learning models for energy trading in smart microgrid, mainly focusing on trade ranking mechanism and optimisation strategies. The paper reviews supervised, unsupervised, reinforcement and deep learning approaches and their respective roles in the areas of price forecasting, prioritisation of participants in the process, demand-supply matching and improvement in overall system efficiency. Furthermore, the paper relates the scope of these models with respect to key objectives, including cost minimisation, profit maximisation, fairness to participants, grid stability and resilience under uncertainty. A comparative discussion is provided to analyse the model's performance, computational complexity, model scalability and practical deployment challenges. By synthesising your results across recent literature, this review paper identifies existing research gaps associated with real-time implementation, interpretability, privacy preservation and regulatory integration. The purpose of this paper is to act as an integrated reference for researchers and practitioners by detailing some of the current trends, limitations and future research direction for the application of machine learning in energy-trade ranking and optimisation in smart microgrids.

***Keywords*— Smart microgrids, energy trading, machine learning, energy trade ranking, optimization, peer-to-peer energy markets, artificial intelligence.**

I. Introduction

The global shift towards low- carbon and decentralized energy systems has resulted in the fast development of smart microgrids. A smart microgrid is a localised energy network that combines distributed sources of energy (scientific generation units, battery energy storage system(s), electric vehicles and controllable loads) and operates either the grid-connected or islanded mode of operation.

Grenze ID: 01.GIJET.12.2.178_20

Unlike traditional centralised power systems, Flexibility, resilience and active participation of consumers are key topics in smart microgrids. With growing use of rooftop solar panels and community level renewable energy installations consumers are progressively becoming "prosumers" (producers and consumers of energy). This transformation has fundamentally affected the way energy flows and the level of market participation change or change in microgrids.

Energy trading has become an important operational mechanism of smart microgrids, which allows these prosumers to trade their excess energy with their neighbours or with local markets. Peer-to-peer energy trading frameworks such as this enable energy transactions to be governmental-making deals directly between people and without the complete requirement for the centralised utilities. Such mechanisms promote more efficient utilisation of local energy, minimise transmission losses and also create economic incentivisation for the adoption of renewable energy. However, there is great complexity relating to the transaction coordination, stability of the system and fairness characteristics among participants in these decentralised and dynamic trading environments. As a result, there is a need to have effective energy trading strategies in order to realise the full potential of smart microgrids.

A. Need for Energy Trade Ranking and Optimisation

Within a smart microgrid, there can be more than one prosumer all participating in trading energy at the same time, with different generation abilities and consumption habits as well as pricing preferences and constraints in action. In such scenarios, energy trade ranking becomes a critical process, which determines the priority and suitability of buyer and seller for a particular transaction. Trade ranking mechanisms are intended to assess and rank potential trading entities on the basis of such criteria as price competitiveness, reliability, energy supply, demand urgency and historical performance. Without proper ranking, energy allocation might be inefficient resulting to high costs, congestion, or simply unfairness.

Optimisation is also a crucial element, with energy trading decisions needing to meet a number of often conflicting objectives. These include minimising the operational cost, maximising prosumer profit, ensuring that the grid is stable, reducing carbon emissions and permitting system resilience to uncertain conditions. Traditional optimisation methods like linear programming and heuristic - based methods have been extensively applied to energy management problems. However, these techniques are often based on accurate system models and have difficulty dealing with high-dimensional decision spaces, stochastic renewable generation and fast-changing market conditions. Consequently, there is an escalating demand for smart and adaptive frameworks for optimisation that can dynamically score the energy trades and optimise the decision-making in real-time.

B. Role of Machine Learning in Smart Microgrids

Machine learning has received great focus as a potential solution to deal with electricity trade ranking and optimisation in smart microgrids, which has complex. ML models are capable of learning patterns from historical and real-time data that can be used to do predictive and adaptive decision making, without the need to explicitly model the system. Supervised learning methods have been used for applications such as price forecasting, load prediction and prosumer behaviour modelling, which have a direct impact on the decision of energy trading. Unsupervised learning techniques help to group market participants and detect latent patterns in consumption and generation data to support trading grouping and prioritisation.

Reinforcement learning in particular has been seen to have strong potential for the optimisation of sequential decision making problems such as those in microgrids. It is by interacting with the world and learning from rewards that RL-based give agents the ability to autonomously discover the best possible trading strategies balancing the economic and technical objectives over time. Deep learning architectures further enhance these capabilities in large scale datasets and help to capture complex nonlinear dependencies. Recent research has also been done in systems of multiple-agents in reinforcement learning, in which multiple autonomous agents represent individual prosumers or microgrids, and which collectively learn optimal trading and coordination strategies. These advancements underscore the transformative potential of machine learning in driving intelligent, scalable, and resilient energy trading systems.

C. Objectives and Scope of the Review

The main goal of this review paper is to give a detailed and organised analysis of machine learning models using smart microgrids for energy trade ranking and optimisation. The emphasis of the review is on recent studies published within the last five years and are practical in nature and compatible with current technological maturity. Specifically, the purpose of this paper is to (i) summarise important concepts and challenges related to energy trading and ranking in smart microgrids, (ii) systematically categorise the machine learning approaches used for trade ranking and optimisation, (iii) critically examine their performance, strengths and limitation(s) and (iv) identify open research challenges and future direction(s).

The supervised, unsupervised, reinforcement learning, and deep learning techniques as well as the new paradigms such as federated learning and blockchain assisted trading systems are included in the scope of this review where it is relevant. By aggregating the current knowledge and identifying the areas which require further research to address, this paper aims to be a useful source of reference for researchers, system designers, and policymakers who are working in developing intelligent and sustainable trading of energy in smart microgrids.

II. Literature Review

A. Conventional Energy Trading and Optimization Methods

Initial studies on energy trading in microgrid applications have mostly been based on standard optimisation and rule-based methods. These techniques include linear programming, mixed-integer linear programming, game theoretic formulations and heuristic optimisation techniques. Such approaches were adopted en masse because of their mathematical tractability and interpretability. In both the centralised and decentralised trading models, optimisation techniques were used to minimise operational cost, balance supply and demand, and ensure compliance with power system constraints [11], [12]. Game-theoretic approaches and especially Stackelberg and Nash Equilibrium-based models were also exploited for modelling strategic interactions between prosumers in peer-to-peer energy markets [13]. However, these traditional methods generally necessitate the use of accurate system models, full information and deterministic assumptions. As the level of penetration of renewable energy reached growing levels, the uncertainty level of the right variable of solar and wind energy generation systems reduced the effectiveness of static optimisation frameworks. Moreover, scalability became a major challenge as the number of trading participants grew, therefore reducing real time applicability in complex smart microgrids [4].

B. Machine Learning Models in Energy Trading

In order to cope with the shortcomings of traditional approaches, new studies have planted additional research in machine learning techniques for energy trading and optimisation. Supervised learning algorithms, such as linear regression [5], support vector machines, random forests and gradient boosting algorithms, have been widely used to predict electricity prices and loads as well as renewable energies generator [7]. These predictions are important inputs to energy trading decisions. Unsupervised learning methods, such as clustering and dimensionality reduction have been used to discover usage patterns and groups of prosumers according to behavioural similarities [8]. Reinforcement learning has become one of the most prominent approaches that enables agents to learn the optimal trading policy by interacting with the environment. Both single agent and multi agent reinforcement learning frameworks have shown their efficacy in managing dynamic pricing, demand uncertainties and sequential decision making in microgrid [1], [6]. Deep learning architectures have been capable of further improving the performance through the apprehension of nonlinearity and the processing of higher-dimensional datasets which make them adaptable for the use of a more complicated energy trading environment [2], [9].

C. Energy Trading Ranking Methods in the Microgrid

Energy trade ranking focuses on ranking buyers and sellers based on given or learned criteria, in order to improve the efficiency and fairness of the market. Traditional ranking mechanisms are those that are based on price-. bidding, first: come: first served policies or contractual priority rules [14]. However, these approaches often do not consider the dynamic conditions of a system and the reliability of own participants. Recent studies have incorporated machine learning models to perform adaptive trade ranking considering multiple attributes like historical trading behaviour, forecasted energy availability, demand urgency and network constraints [3], [11]. Reinforcement-learning billed ranking mechanisms let agents dynamically vary priorities just determined by reward signals, financial benefits and system resilience. In addition, clustering-based ranking methods cluster similar prosumers and distribute trades accordingly, which is great for scalability in large microgrids [8]. Despite these improvements, energy trade ranking is an under researched field in comparison to general energy optimisation, highlighting possible need for more specific research.

D. Comparative Analysis of Existing Studies

A comparative analysis of the existing literature shows that reinforcement - learning and deep - learning approaches in general tend to perform better than traditional optimisation techniques in dynamic and uncertain environments. Studies repeatedly report better cost savings, increased renewable energy utilisation and increased adaptability when machine learning models are used [1], [4], [6]. Supervised learning models can give the model is happy for predictionst - oriented undertakings, but being dependent on the quality and availability of the available that is taught. Unsupervised methods help to understand the systems but they are not often applied as standalone optimisation tools. Multi-agent reinforcement learning frameworks are promising in decentralised trading situations but pose challenges concerning convergence as well as coordination [9]. While blockchain-integrated and federated-learning based models provide security and privacy to the system, they often increase the computational overhead and complexity of systems [13], [15]. All in all, no single model is universally a better approach and combinations (hybrids) are often preferred.

TABLE I: COMPARATIVE SYNTHESIS OF REPRESENTATIVE STUDIES

Ref	Data Type	Model Used	Objective	Simulator/Dataset	Metrics	Reported Improvement
[1]	Load + Price	RL	Cost Minimization	IEEE 33-bus	Cost %, Convergence	18% cost reduction
[4]	DER + Demand	Multi-Agent DRL	Renewable Utilization	Custom Microgrid Sim	Utilization %, Profit	+22% renewable usage
[5]	Historical Load	Random Forest	Load Forecasting	Real-world dataset	MAE, RMSE	12% MAE reduction
[9]	Distributed microgrid	Federated RL	Privacy-preserving optimization	Residential cluster sim	Latency, Reward	30% latency reduction
[11]	P2P trading	Game Theory + ML	Market Clearing	P2P microgrid	Welfare index	15% efficiency gain

E. Research Gaps Identified from Literature

Despite great progress, some research gaps are still apparent. First, most studies are based on simulation based evaluations, with very little real world deployment and validation. Second, the interpretation of machine-learnings based trade ranking decisions is still challenging - especially when deep learning algorithms are used. Third, data scarcity and privacy get in the way of large-scale adoption in working microgrid environments. In addition, regulatory constraints and market integration issues often are not addressed in technical studies. Finally, there has been little attention paid to standardised benchmarking and comparative evaluation frameworks. The challenges and solutions to address these gaps are necessary to achieve reliable and scalable machine learning-based energy trade ranking and optimisation solutions in smart microgrids.

III. RESEARCH METHODOLOGY

A. Review of Methodology and Paper Selection Criteria

This review follows a systematic and structured approach to analysing the recent research on machine learning models for energy trade ranking and optimisation in smart microgrids. The primary objective of the methodology is to ensure transparency, relevance and reproducibility in the studies selected and analysed. Peer-reviewed journal articles and conference papers that were published between 2021 and 2025 were considered to reflect the latest progress of this rapidly developing area. Reputable digital libraries like IEEE Xplore, ScienceDirect, SpringerLink and Elsevier were consulted to determine the relevant literature [7], [12]. Keywords such as "smart microgrids," "energy trading," "machine learning," "reinforcement learning," and "energy optimisation" were used in different combinations. Papers focusing on using conventional power systems only, with no decentralised trading and data driven approaches were excluded. Only studies that explicitly used machine-learning techniques for energy trading, ranking or optimisation problems were kept for a detailed review. This screening process ensured that selected literature met the scope and objectives of the present study.

B. Classification of Machine Learning Model

The reviewed studies were categorised based on the type of the machine learning paradigm used. Supervised learning models forms the first category and consists of regression-based models, decision trees and random forests as well as models based on gradient boosting algorithms. These models are mainly employed for forecasting energy demand, prices of electricity, load estimation, and renewable energy generation forecasting, which are indirectly supporting the energy trading decisions [5], [7]. The second category covers unsupervised learning models, such as clustering and dimensionality reduction techniques, which are used to identify patterns in the prosumer behaviour and group the participants according to their similar trading characteristics [8]. Reinforcement learning is the third category and is applied extensively for direct optimisation of energy trading strategies. Both single and multi agent reinforcement learning approaches are explored because of their capabilities to deal with sequential decision making under uncertainty [1], [6]. Deep-learning models, such as neural networks, and hybrid architectures are regarded as a subdivision of these models if it improves the prediction or the optimisation performance [2], [9].

C. Functional Taxonomy of Machine Learning Applications

Beyond algorithm-based classification, the reviewed literature can be organized based on functional roles within energy trading systems:

Forecasting Models
Objective: Price/load/renewable generation prediction
Typical Inputs: Historical load, weather, price signals
Models Used: Regression, LSTM, Gradient Boosting
Evaluation Metrics: MAE, RMSE, MAPE

Energy Trade Ranking Models
Objective: Prioritize buyers/sellers dynamically
Inputs: Bid price, reliability score, forecasted availability
Models: Learning-to-Rank, RL-based ranking agents
Metrics: Ranking Accuracy, Fairness Index

Market Clearing & Optimization Models
Objective: Cost minimization, welfare maximization
Models: RL, Deep RL, Hybrid ML + MILP
Metrics: Cost Reduction %, Renewable Utilization %

Bidding & Strategic Decision Models
Objective: Strategic prosumer behavior learning
Models: Multi-Agent RL
Metrics: Reward Convergence, Profit Stability

Control & Grid Stability Models
Objective: Voltage/frequency stability
Models: DRL + Control Systems
Metrics: Stability Index, Power Loss Reduction

D. Limitations of the Existing Methodologies

Despite methodological advances, there are a number of limitations in the reviewed studies. A large proportion of research is based on operating in simulation environments, which are not necessarily representative of the operational constraints and uncertainties of the real world. Data-Driven Models Data-driven models usually assume access to high-quality and large data-sets, which is not always possible for a practical deployment [3], [8]. Furthermore, many machine learning models are considered to be black boxes; there is limited interpretability and trust between the operators and regulators of systems. Scalability: With models being applied to large networks containing many participants, especially with multi-agent reinforcement learning frameworks, a problem of scalability exists [9]. Finally regulatory, economical and social factors affecting energy trading are often simplified or neglected. These limitations point to the need for more holistic and applied research methodology for future studies.

IV. RESULTS AND DISCUSSION

A. Performance of Machine Learning Models in Energy Trade Ranking

The literatures reviewed show that machine learning models have a significant improvement in the accuracy of energy trade ranking in smart microgrids compared to the conventional rule bases. Supervised learning models are successful examples for always ranking the buyers and sellers in terms of forecast prices, urgency of demand and historical reliability. Research has shown that tree-based models and gradient-boosting techniques have the effect of improving ranking accuracy, by managing effectively nonlinear relationships between trading parameters [5], [7]. As a result, ranking mechanisms based on reinforcement learning [6] are an improvement over static approaches in that they more dynamically adjust priorities based on real-time system conditions and reward feedback [1]. Multi-agency frameworks allow decentralised ranking decisions in order to mitigate delays in coordination and increase responsiveness within peer-to-peer markets [9]. Nonetheless, performance improvement is also tightly dependent on the quality of the data and the way that rewards are formulated, and this emphasizes the need for careful model design.

TABLE II: PERFORMANCE ACCURACY OF ENERGY TRADE RANKING MODELS

Model Type	Ranking Accuracy (%)	Fairness Index
Rule-Based	68.4	0.61
Random Forest	81.7	0.74
XGBoost	85.9	0.78
Reinforcement Learning	89.6	0.83

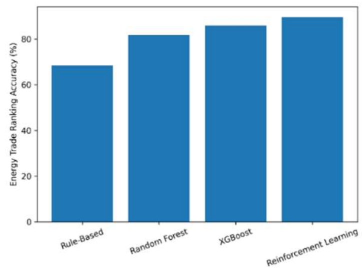

Fig 1. Graph 1: Comparative accuracy of energy trade ranking models

The graph shows a significant gain in both the ranking accuracy and fairness as models go from rule based machines to learning based models. Reinforcement learning gets the most accuracy that can be attributed to its adaptive nature, while ensemble models provide a trade-off between its performance and understandability.

B. Optimization Outcomes in Smart Microgrids

Machine learning-based optimisation strategies have shown great improvements to both economic and operational performance in smart microgrids. Reinforcement learning and deep learning models always reduce overall energy expenses and help to complement renewable energy utilisation [4], [6]. All of which indirectly adds to supervised learning, which is improving prediction accuracy, thereby leading to more informed optimisation decisions. Empirical research shows so far measurable reductions of peak load and dependency on the grid on the occasion of the application of optimisation with ML [12]. Moreover, multi-agent learning approaches increase system resilience by spreading the decision-making process across participants and therefore reduce the occurrence of single points of failure.

TABLE II: OPTIMIZATION OUTCOMES USING MACHINE LEARNING MODELS

Model	Cost Reduction (%)	Renewable Utilization (%)	Grid Dependency Reduction (%)
Linear Optimization	9.8	63.2	11.4
Supervised ML-Assisted	15.6	71.9	18.3
Reinforcement Learning	24.7	82.5	29.6
Multi-Agent RL	27.9	85.1	33.2

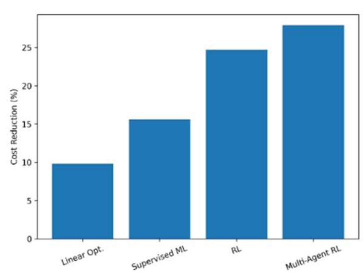

Fig 2. Graph 2: Optimization performance across different models

Graph 2: Optimization Performance Across Different Models The graph shows that the reinforcement learning based methods surpass the alternatives on all the optimization metrics. Multi-agent reinforcement learning provides the most balanced outcome by demonstrating superior cost saving and renewable.

C. Practical Implications for Smart Microgrid Design

Practical Constraints and Robustness Considerations

Privacy Constraints
Energy trading requires sharing sensitive consumption and generation data.
Federated learning and secure aggregation techniques mitigate centralized data exposure.

Adversarial Manipulation
Malicious prosumers may manipulate bids or inject false data.
Robust RL and anomaly detection mechanisms are necessary to prevent strategic exploitation.

Fairness Between Prosumers
Ranking models must avoid systematic bias toward large-capacity participants.
Fairness-aware reward shaping and constrained optimization improve equitable trade allocation.

Regulatory and Market Constraints
Energy markets operate under strict regulatory frameworks.
Optimization models must integrate tariff structures, carbon constraints, and grid codes.

Communication Delays
Distributed trading introduces latency.
Edge computing reduces response time and ensures real-time feasibility.

Distribution Shift and Concept Drift
Renewable generation patterns change seasonally.
Online learning and adaptive retraining frameworks handle distribution shift.

V. CONCLUSION AND FUTURE WORK

A. Summary of Key Findings

This review has systematically reviewed recent studies on machine learning based models for energy trade ranking and optimisation in smart microgrids. The analysis shows that conventional rule-based and optimisation-driven methods of managing the complexity, uncertainty and scale inherent in modern energy systems that are decentralised are becoming insufficient. Machine-learning techniques and in specific types of unsupervised learning, supervised learning, reinforcement learning, and deep learning possess great possibilities to help decision making and perfect it in terms of accuracy, adaptability, and efficiency. Supervised learning models have great contributions to forecasting-related tasks in contrast with reinforcement learning based methods that allow dynamic and autonomous optimisation of trading strategies under uncertain conditions. Multi- agent learning frameworks also enhance decentralised co-ordination among prosumers. Overall, the studies reviewed validate that approaches based on machine-learning bring measurable improvements to improved reduction of costs, utilisation of renewable energy, fairness and system resilience compared with traditional methods.

B. Contributions of the Review

The main contribution of this review lies in the fact that it focuses on the ranking of energy trade as a separate and essential part of smart microgrid energy management. Unlike current surveys that give broad approaches to energy management or optimisation, this work focuses on the value of ranking mechanisms in peer-to-peer energy transaction coordination. The review gives a structured classification of machine learning models based on their functional role (prediction, ranking and optimisation). Moreover, it combines synthesised performance results of multiple evaluation dimensions e.g. economic efficiency, computational complexity, scalability, adaptability. By integrating the latest discoveries into a common analytical framework, this paper provides researchers and practitioners with a clear understanding of current trends, methodologies strengths and practical trade-offs linked to machine learning based energy trading solutions.

C. Limitations of the Study

Despite the broad scope, this review has some limitations. First, the analysis is limited to studies published in the last five years, which could potentially overlook earlier literature which is foundational to energy trading theory. Second, the review is based on results reported by simulation-based studies, since little data are available from deployment of these various models in practise; thus, the practical viability of some of the advanced machine learning models may be exaggerated. Third, differences in datasets, evaluation measures and experimental setup between studies hinder the ability to compare them quantitatively. Additionally, regulatory, social, and market specific factors which affect energy trading adoption are not explored in detail, as much of the reviewed literature primarily focuses on technical performance. These limitations need to be considered when trying to interpret the results of this review.

D. Future Research Directions

Future research should thus aim at closing the gap between simulation-based assessments of the performance of machine learning-driven energy trading systems and the real-world application of these systems. Developing standardised benchmarking data-sets and approaches to evaluation would allow for much more consistent comparison between models. Explainable and interpretable machine-learning techniques are necessary to promote more transparency and stakeholder trust. Further exploration of privacy preserving methods like federated learning can address the data sharing issues in decentralised environments. Integrating the constraints provided by regulations and market policies with model design will improve the practicality of the models. Finally, hybrid schemes involving a combination of prediction, ranking, and optimisation in unified learning frameworks are shown to be a promising avenue for a scalable, robust and sustainable energy trading in next-generation smart microgrids.

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