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Integrating Multi-Carrier Flexibility and Uncertainty: A Systematic Review of Hybrid MCDM-Optimization Models in Local Energy Communities

Mubarak Sani[1] and Pramod Kumar[2]

M. Tech Scholar, Vivekananda Global University, Jaipur, Rajasthan, India[1]

Professor, Department of Mechanical Engineering, Vivekananda Global University, Jaipur, Rajasthan, India [2]

Abstract: *This systematic review summarizes the current state of the art on the application of Multi-Carrier Energy Communities (LMCECs) that incorporate operational flexibility and multi-dimensional uncertainty into the energy system by using Multi-Criteria Decision Making (MCDM) and mathematical optimization models. The shift towards decentralized, multi-vector energy networks including electricity, thermal energy, and green hydrogen present a challenge to effectively balance competing economic, environmental, and technical considerations as energy systems evolve from centralized fossil fuel-based to decentralized multi-vector networks. This paper collates the literature obtained from the peer reviewed and available databases, and examines the evolution of decision frameworks from static modelling approaches such as MCDM (AHP, TOPSIS) to dynamic and stochastic hybrid approaches (MEREC, RAFSI, IGDT-MCDM). Key findings include the importance of hybrid architectures in the mitigation of rank reversal, market price volatility and the integration of flexibility up the supply chain.*

Lastly, the paper discusses the existing structural shortcomings and offers directions for future studies in real-time, AI-supported energy management.

Keywords: Multi-carrier energy communities, multi-criteria decision-making, operational flexibility, uncertainty quantification, hybrid optimization.

I. INTRODUCTION

The global need for deep decarbonization has also driven the shift from a traditional and centralized power system to multi-vector and localized power systems [1]. Local Multi-Carrier Energy Communities (LMCECs) are a combination of different energy carriers such as electricity, natural gas, district heat and cooling, and green hydrogen to increase energy system efficiency, resilience and sustainability [2, 3]. These systems enable considerable flexibility from the demand side of interconnected microgrids [2,4] when combined with short term battery storage and long-term thermal/hydrogen storage. But there is a considerable complexity in the operation of LMCECs [3]. The multi-dimensional decision making in a system with deep parametric uncertainties due to the variability of renewable energy resources, variable energy market prices and changing consumer demand patterns must be made by system operators [4, 5].

The traditional optimization models are mainly single objective optimization models such as economic dispatch [6] or minimization of operational cost. On the other hand, classic Multi-Criteria Decision-Making (MCDM) methods give attention to the preferences of the various stakeholders based on conflicting economic, environmental and technical indicators, and are mainly used with fixed parameters [7, 8]. To fill this gap, in recent years, hybrid MCDM-optimization frameworks have been adopted more and more in the literature [9, 10]. These integrated approaches rely

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on the preference ranking ability of MCDM, and the strict constraint-handling ability of mathematical programming and uncertainty quantification approaches [9, 11]. The combination of the distributionally robust optimization and fuzzy interval optimization with hybrid architectures allows the operator to study a more complex trade-off without being overly conservative [5, 10]. Moreover, such multi-stage frameworks can respond flexibly to intra-hour fluctuation in the grid in real time implementations at the edge [9].

This paper conducts a systematic review of the hybrid MCDM-optimization methods that have been used for solving LMCECs. This review follows a literature-based approach, integrating cutting-edge research from different jurisdictions around the world, to capture the development of decision models, to classify the essential criteria and uncertainty methods and to pinpoint future research directions.

Integrated Workflow of Hybrid MCDM-Optimization Frameworks

The operational decision pipeline of a hybrid optimization-MCDM framework for LMCECs is executed across sequential stages, as detailed in **Fig. 1**:

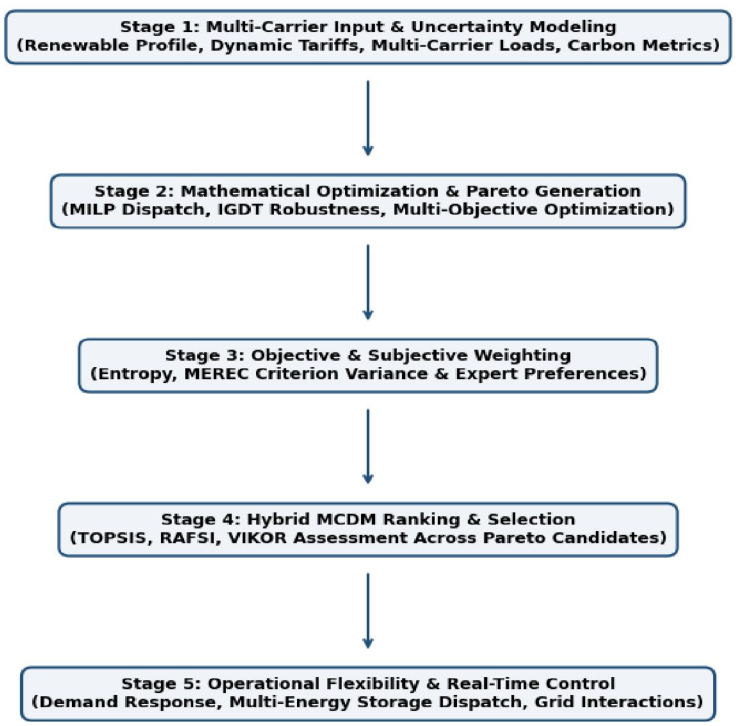

Fig. 1 Complete execution pipeline of the proposed hybrid optimization-MCDM decision framework in local multi-carrier energy communities

The mathematical optimization models in Stage 2 find non-dominated Pareto trade-offs between conflicting operational parameters (e.g. hourly cost vs. CO_2 emissions) as shown in Fig. 2.

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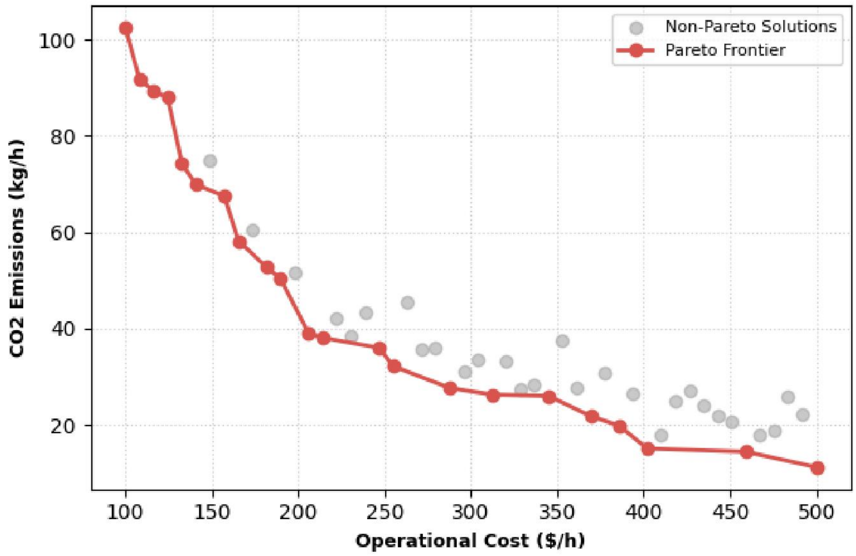

Fig. 2 Mathematical optimization output (Stage 2) mapping non-dominated Pareto trade-offs between operational costs and carbon emissions.

For Stage 4, we use a hybrid MCDM ranking method (MEREC-RAFSI or TOPSIS) to assess the Pareto front candidates using objective criterion variances and preferences of decision-makers to get the best operational dispatch, as can be seen in Fig. 3.

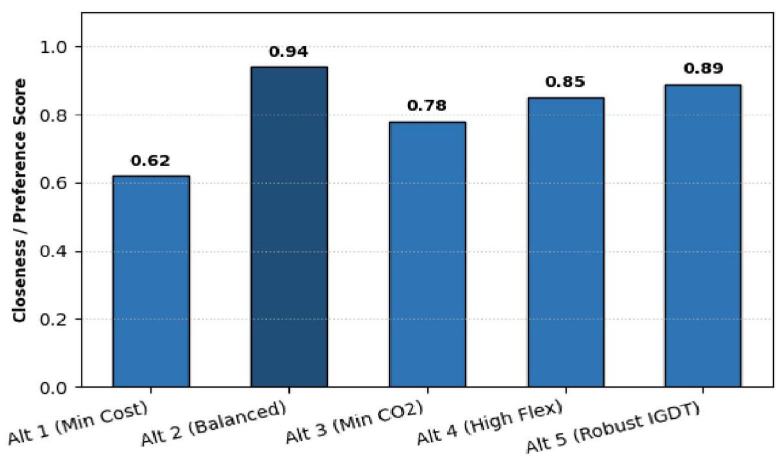

Fig. 3 Hybrid MCDM decision evaluation (Stage 4) ranking Pareto-optimal operational configurations based on criterion variance and multi-dimensional preference scores.

Objective vs. Subjective Weighting Trade-Offs

One of the important results of the literature synthesis is that there is a clear trade-off between the subjective and objective weighting methods in Stage 3:

Subjective Weighting (AHP, ANP, SWARA): Is based on expert judgment and pairwise comparisons. It is a good way to capture high-level strategic priorities (e.g. political feasibility, or policy alignment), but is still subject to cognitive bias, inconsistent consistency ratios and skepticism by reviewers.

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Objective Weighting (MEREC, Entropy, CRITIC): Computes the weights of the criteria solely based on variations of data and variance of removing effects. MEREC, especially, reduces the human subjectivity from uncertainty driven operational dispatch and is very effective to price the market dynamically and to manage the variability of renewable generation. Modern third generation models feature
Hybrid Weighting Integration which incorporates both objective variance and subjective preferences, making sure that the empirical data rigor and stakeholders' alignment are maintained

Methodological Comparison of Recent Literature

Table I is used to compare 18 representative studies for energy management decision models in the last 10 years (from 2016 to 2025) across energy management paradigms of smart homes, multi-carrier homes communities, industrial energy efficiency and macro-policy frameworks.

Table I: Comparative Analysis of Representative MCDM Energy Management Literature

Authors	Year	System Context	MCDM/Optimization Method	Criteria	Primary Research Findings
Anjum et al. [12]	2025	Smart Factories	MEREC, RAFSI, Intuitionistic Fuzzy	8	Effectively ranked 5 energy-saving alternatives under uncertainty and avoided rank reversal.
Lamfermann et al. [13]	2025	Building Energy Systems	AHP, ELECTRE III, Pareto Filtering	10	Extracted interpretable trade-offs across 20,000 Pareto-optimal configurations.
Sobhan et al. [14]	2025	Multi-Carrier Communities	TOPSIS, IGDT, Probabilistic Optimization	22	Reduced operational cost by 29.64% in high flexibility default scenarios via incentive optimization.
Aparisi-Cerdá et al. [15]	2024	Decentralized Renewables	ANP	27	Identified political will and tech maturity as top drivers accounting for 41% of total weight.
Anbazhagu et al. [16]	2023	Smart Homes	Hybridized Neuro-Fuzzy, AHP	5	Achieved 94.17% decision accuracy and 93.16% energy savings over standard TOPSIS-AHP.
Wen et al. [17]	2023	Demand-Side Management	TOPSIS, VIKOR	5	Identified 13 load clusters to optimize net metering and dynamic tariff options.
Janjić et al. [18]	2023	Smart Grid HEMS	Fuzzy AHP	4	Determined technology improvement as the highest priority driver for HEMS adoption.
Akçaba et al. [19]	2022	Regional Energy Strategy	SWOT-ANP, Fuzzy TOPSIS	4	Ranked mainland grid interconnection and natural

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					gas pipelines as top strategic choices.
Kabir et al. [20]	2021	Smart Power Systems	SWOT-AHP, WASPAS, TOPSIS	12	Identified Advanced Metering Infrastructure (AMI) as the highest priority implementation.
Ziemba et al. [21]		Energy Security Risk	Fuzzy Weighted Sum Method (FWSM)	29	Projected national energy security risks up to 2030 under dynamic fuzzy uncertainty.
Wang et al. [22]	2021	Integrated Energy Systems	Single-Valued Neutrosophic TOPSIS	12	Evaluated complex construction schemes equipped with smart management platforms.
Mishra et al. [23]	2020	Bioenergy Production	Intuitionistic Fuzzy SWARA–COPRAS	11	Ranked agricultural and municipal biogas waste as the most sustainable bioenergy options.
Kaveh et al. [24]	2020	Smart Home Scheduling	Multi-Objective Antlion, Evidential Reasoning	5	Optimally scheduled home electrical loads using bio-inspired optimization and decision reasoning.
Cocaña-Fernández et al. [25]	2019	HPC Computing Clusters	Genetic Fuzzy Systems (GFS)	3	Maximized eco-efficiency and reduced power consumption in high-performance computing clusters.
Vié et al. [26]	2019	Macro Regional Sustainability	Fuzzy Goal Programming (FGP)	5	Assessed long-run sustainability targets for EU nations under the Europe 2020 Strategy.
Nguyan Son [27]	2018	Maritime Energy Efficiency	AHP, Fuzzy-TOPSIS	17	Facilitated low-carbon shipping technology selection across multi-criteria maritime operations.
Sadeghi et al. [28]	2018	Power Generation Mix	Fuzzy ANP (FANP)	7	Formulated an optimal sustainable electricity generation mix considering inter-criteria dependencies.
Neol et al. [29]	2017	Industrial Multi-Site GEMS	AHP, Fuzzy Logic, TOPSIS	4	Developed a global energy management framework for non-energy intensive multi-site facilities.

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Uncertainty Quantification and Criteria Selection

Flexibility in LMCECs needs to be managed by taking into consideration different technical and socio-economic dimensions. Based on the literature review, the following are some key evaluation criteria that were identified:

Economic Metrics: Levelized cost of energy (LCOE), operational expenditure (OPEX), investment cost and flexibility incentive prices (upstream).

System Resilience, Load shedding ratio, prediction accuracy (MSE/RMSE), Grid interaction stability.

EBM's include Direct CO_2 emissions, Land use efficiency, Technological maturity and Social adoption barriers.

II. CONCLUSION & FUTURE RESEARCH DIRECTIONS

It is shown that the hybrid MCDM-optimization models can offer a comprehensive, scalable solution for dealing with flexibility and uncertainty in LMECs. Based on the review of the literature, it is observed that there is a trend from static weighting approach to dynamic approach in which objective weighting (MEREC), novel interval aggregation operators (RAFSI) and uncertainty quantification (IGDT and neuro-fuzzy logic) are included. In the multi-objective operational space, these hybrid methods are able to solve critical decision-making problems, such as rank reversal and Pareto-solution selection.

Key research gaps, methodological proposals, and potential impacts are broken down into Table II, to inform future developments in this area.

Table II: Future Research Roadmap for Hybrid Energy Decision Frameworks

Research Domain	Existing Structural Gap	Proposed Methodological Solution	Expected Operational Impact
Real-Time Execution	High computational latency of multi-objective Pareto solvers.	Integration of Deep Reinforcement Learning (DRL) with online MCDM engines	Enables sub-second automated flexibility dispatch at the edge-computing layer.
Cross-Vector Coupling	Over-reliance on power-only or dual thermal-electric models.	Expansion to dynamic green hydrogen, district cooling, and e-fuel vectors.	Unlocks multi-carrier storage synergies and deep seasonal decarbonization.
High-Dimensional Uncertainty	Standard fuzzy models struggle under extreme, non-Gaussian market events.	rid IGDT-Distributionally Robust Optimization (DRO) with RAFSI ranking.	Ensures high operational resilience without overly conservative cost penalties.
Multi-Agent Coordination	Centralized decision-making fails to scale across peer-to-peer (P2P) networks.	Decentralized Federated Learning integrated with consensus-based MCDM.	Preserves prosumer data privacy while optimizing community-level flexibility.

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