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Review

From Design to Deployment: A Comprehensive Review of Theoretical and Experimental Studies of Multi-Energy Systems for Residential Applications

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Abstract: Multi-energy systems (MESs) use more than one energy vector to fulfil users' electrical, thermal, and cooling demands. This paper examines the recent developments in the design, optimisation, and implementation of MESs, focusing on residential applications. Firstly, recent advances in the design and optimisation of MESs are explained and analysed. The field is characterised by the proliferation of bespoke optimisation methods suitable for this kind of problem. Secondly, practical implementation in the laboratory of MESs and microgrids supplying electrical and thermal loads is discussed. The hardware requirements, in terms of controllers and converters, are critically analysed. This is contrasted with the real-world implementation of MESs or multi-output microgrids in the real world. A description of the communication infrastructure required for real-world implementation is discussed. Finally, a critical review of the entire process, the areas of challenge, and potential research opportunities are presented.

Keywords: multi-energy systems; integrated energy systems; battery energy storage system; building integrated photovoltaic; IoT in multi-energy systems; multi-energy system optimisation; energy management

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1. Introduction

In recent years, there has been a growing emphasis on sustainable energy solutions for residential and industrial applications, driven by the need to enhance energy efficiency, reduce energy costs, and alleviate environmental impacts. Buildings are responsible for a significant fraction of 40% of the total energy consumption in Europe and 32% globally [1]. In contrast, the heating and cooling demands of the residential energy sector consume 55% of the total energy consumed. They are responsible for 17% of total carbon emissions in the building sector in Europe [2]. Given the current environmental impact of the energy demand in the residential sector, numerous research works and strategies are proposed to promote decarbonisation and enhance energy efficiency [3].

Renewable energy systems are presented as a crucial alternative to fossil fuel-based energy systems that solve the growing environmental and energy challenges sustainably. Therefore, renewable energy systems have become an urgent solution to the difficulties related to the global energy demand, rising emissions, and increasing energy costs. With the introduction of sophisticated simultaneous control and management technologies, the operation of various distributed generation (DG) systems as a unified architecture is becoming popular in the literature. These DG systems are often deployed close to consumption sites (small scale) and referred to as microgrids, which are locally controlled architecture and customised following consumer demand. The architecture of microgrids mainly consists of renewable energy system (RES)-based resources for energy production and intelligent control centres capable of enhancing consumption and supply interaction [4]. Intelligently controlled microgrids are considered one of the key pillars of smart grids, which, along with advanced monitoring and control technologies, can guarantee the efficient operation and management of energy networks [5].

Significant progress has been made in the decarbonisation of electrical power. However, the decarbonisation of thermal demands, such as hot water and space heating, is lagging. A promising remedy is the integration and interaction of thermal and electrical systems with simultaneous control, which can be beneficial for achieving decarbonisation and economic and technical goals [6]. Integrating multiple energy generation resources is often termed an MES—involving integrated and hybrid energy systems, etc. [7]. Multi-energy generation systems are developed by integrating RES-based heat pumps (HPs), boilers, and electric and absorption chillers to generate various forms of energy including thermal, cooling, and electricity. MESs can exhibit significant advantages, such as improving efficiency and economic performance with reduced emissions [8]. The MES topology integrates diverse energy sources, including electrical, gas, and thermal generators. These energy sources are interconnected at multiple levels, such as generation and demand. A unified operational management framework is utilised for this complex network to control and optimise these energy sources at numerous levels simultaneously. The energy sources utilised at the generation side mainly comprise RES-based thermal energy production and storage systems (i.e., HPs, boiler, thermal energy storage, etc.), and electrical generators and storage systems (i.e., photovoltaics (PVs) and wind turbines (WTs), etc.) [9]. A combined heat and power (CHP) system is one of the earliest examples of "multi-energy systems" and is often deployed on a smaller scale. It is based on fossil fuel technology, such as natural gas, and it produces electricity via a generator while a heat recovery system collects heat [10]. In the residential sector, thermal energy production is usually achieved through burning fossil fuels, such as the natural gas used in a boiler, which presents a significant challenge in transitioning to low-carbon alternatives [11]. Decarbonising the domestic heating sector is the most challenging obstacle in achieving zero-emission targets. Therefore, the integration and unified interaction of different energy carriers offer excellent potential energy systems and end users, which is usually termed sector coupling [12]. Sector coupling focuses on coupling the electric supply with other sectors, e.g., gas and hydrogen, which promotes using RESs to reduce emissions and costs with increased efficiency and self-consumption of RES resources [13]. Sector coupling is also considered crucial for integrated and hybrid energy systems, which facilitate the flexibility and stability of the overall energy system. These systems are developed on a larger scale and provide alternative use options to store, deliver, and transform multiple energies, such as gas, electricity, cooling, etc. [14]. The residential sector's thermal demand electrification using RES-based electric HPs, efficient boilers, and multi-energy storage systems can also be considered a cost-effective way of decarbonising and reducing costs [15]. HPs operated by RESs can replace the presently installed fossil fuel-based conventional heating systems, which can exhibit higher efficiency with fewer emissions [16].

The coupling of the multi-energy sectors and components increases the complexity of energy systems, which can be resolved using a sophisticated energy management strategy (EMS) [17]. Optimisation algorithms are the backbone of these strategies, optimising the scheduling of generation units and consumer load, component selection, and sizing [18]. Design, size, and planning optimisation can significantly reduce the initial investment costs with a shorter payback time for the generation site. The component selection, capacity, location, scale, variables, and other parameters of energy systems are also optimised using these techniques [19]. To make the energy system model more realistic, various variables, constraints, and energy flow criteria of generation components are considered [20]. Energy dispatch optimisation requires various real-time monitoring and control systems deployed using communication infrastructure to ensure optimal energy management [21]. Therefore, an optimised energy system is economically, environmentally, and technically more efficient and provides economic benefits.

Modern energy systems need to intelligently meet a wide range of requirements and integrate multiple microgrids with a high penetration of RESs, storage systems, and multi-energy production capabilities [22]. These energy systems are mostly called smart grids and aim to manage supply and demand, ensuring optimised energy generation, distribution, and user consumption [23]. These functions are carried out by deploying smart metres at consumption sites, which provides a bi-directional communication flow and helps in achieving an efficient energy supply and management [24]. The communication flow among the components of a smart grid can be used to achieve demand control through demand-side management models and techniques. DRPs can also be implemented, through which users' demands can be shifted from peak to off-peak hours, and they can be rewarded with incentives or low-priced energy [25]. The efficient and intelligent implementation of smart grids with communication flow can also manage prosumers' supply and generation. Prosumers are energy users and producers who can produce and sell excess energy to the main grid. Various complexities arise when a smart grid interacts with multi-energy-producing microgrids, prosumers, and consumers. Therefore, supplying economical and sustainable energy with efficient supply and demand balance infrastructure is important when transitioning towards the smart grid paradigm [26].

Recently, multi-energy microgrid EMS have been studied extensively in the literature. A list of recent review papers covering some aspects of MES microgrids is shown in Table 1 below. These studies highlighted and reviewed various architectures and optimisation-based control strategies proposed for the multi-energy management of residential users. Many alternative designs and architectures are available in the literature to provide consumers with energy demands. Such designs have been studied by Liu et al. [27], who focus on different aspects of MESs, including planning and operation using multi-objective algorithms. Bozgeyik et al. [28] reviewed the sub-system design of RES-based MESs and compared performances using energetic and exergetic analyses. To further discuss the integration of RESs with MESs, Wu and Skye [29] and Nazari et al. [30], investigating the integration of PVs with a heat pump (HP) to supply multi-energy demands to buildings, concluded that such a combination could lead to 50% lower costs with high self-consumption, a 70% emission reduction, and energy savings. Pathak et al. [31] reviewed the various solar energy-based heating systems to analyse the environmental, economic, efficiency, and exergy-economic performance. The authors conclude that solar-based heating systems can achieve the highest reduction in carbon emissions of up to 70%, with a shorter payback time when optimal sizing is considered in the design process. Bazdar et al. [32] presented a detailed review to evaluate the energy storage devices used in MESs.

Table 1. Comparative analysis of various review studies on MESs.

Ref.	Year	Architectures	Optimisation Techniques			Loads			Implementation Discussed?	IoT/ICT	Contributions
			Conventional	Heuristic	AI	Electrical	Thermal	Cooling			
[27]	2022	PV/WT/GB/GT/FC/AC/EC/CHP/HP/ESS TES/ISS	✔	✔	✔	✔	✔	✔	✗	✗	Reviewed various studies to reduce the carbon emission life cycle using optimisation techniques.
[28]	2022	PV/WT/CHP/PVT/AC/GT/FC/HP/GB/ESS/TES	✗	✗	✗	✔	✔	✔	✗	✔	Reviewed various architectures supplying CCHP loads to the multi-energy user and evaluated the performance of each architecture.
[29]	2021	PV/WT/ESS/GT/CHP/FC/HP/PVT	✔	✔	✗	✔	✔	✔	✔	✗	Reviewed PV module-based HPs, which are operated to supply multi-energy demands to buildings.
[30]	2023	PV/WT/HP/TES/ESS	✔	✔	✗	✗	✔	✔	✗	✗	Reviewed various architectures and configurations of RES-based HP to supply heating and cooling demands to residential buildings.
[31]	2023	PV/PVT/PCM/TES	✔	✔	✗	✔	✔	✗	✗	✗	Configurations for solar thermal collectors to meet thermal and electrical demands based on 4E with and without PCM.
[32]	2022	PV/WT/CHP/ESS/TES/CAES	✔	✔	✗	✔	✔	✗	✗	✗	Reviewed various architectures with CAES to meet the multi-energy demands of residential consumers.
[33]	2022	PV/WT/ESS/EB/EV	✔	✔	✔	✔	✔	✗	✗	✗	Reviewed various studies providing electrical energy to fulfil the demand of a smart home or residential building.
[34]	2018	PV/WT/CCHP/EB/AC/GB/HP/TES/ESS	✗	✔	✗	✔	✔	✔	✗	✗	Reviewed various studies implementing heuristic algorithms only for the management of CCHP systems.
[35]	2023	PV/WT/ESS/DG/FC	✔	✔	✗	✔	✗	✗	✗	✗	Reviewed the applications of hybrid optimisation algorithms and individual algorithms in hybrid RES-based energy systems for residential users.
[36]	2022	PV/WT/ESS/EV/EB	✔	✔	✔	✔	✗	✗	✗	✗	Carried out a review study on applying optimisation techniques adopted for energy management in smart microgrids.
[37]	2023	PV/WT/FC/HP/ESS/TES/DG/	✔	✔	✔	✔	✔	✔	✗	✔	Reviewed the applications of optimisation algorithms in MESs.
[38]	2022	PV/WT/ESS/DG/FC/CHP	✗	✗	✔	✔	✔	✗	✗	✔	Reviewed the various applications of AI-based optimisation in energy systems providing only thermal and electrical energy, primarily via electrical energy generators.
[39]	2022	PV/WT/ESS/CCHP/TES/GB/AC/EC/FC/HP/GT/CHP	✗	✗	✔	✔	✔	✔	✗	✔	Reviewed studies considering AI-based techniques and their applications in MESs, reducing emissions and increasing efficiency.

Table 1. *Cont.*

Ref.	Year	Architectures	Optimisation Techniques			Loads			Implementation Discussed?	IoT/ICT	Contributions
			Conventional	Heuristic	AI	Electrical	Thermal	Cooling			
[40]	2022	PV/WT/ESS/FC/DG CHP/EB/	✔	✔	✔	✔	✔	✗	✗	✗	Reviewed various architectures to achieve multiple objectives by providing energy demands to residential consumers.
[41]	2022	PV/WT/ESS/GT/FC/CCHP/AC/EC/TES/ISS	✔	✔	✔	✔	✔	✔	✗	✔	Reviewed the applications of optimisation algorithms in energy hubs, providing CCHP loads to residential users participating in the energy markets.
[42]	2022	PV/WT/ESS/TES/CHP/FC/HP	✔	✔	✗	✔	✔	✗	✗	✔	Reviewed various DRPs implemented for the users with thermal and electrical loads operated by electrical and CHP units.
[43]	2023	PV/WT/CCHP/EB/AC/GB/HP/TES/ESS	✔	✔	✔	✔	✔	✔	✗	✗	Various policies for implementing CCHP systems were adopted by countries and reviewed by multiple architectures.
[44]	2021	PV/WT/ESS/EB	✗	✗	✔	✔	✔	✗	✗	✔	Reviewed various studies based on AI-based self-management systems presented for buildings.
[45]	2023	PV/WT/CHP/H2/GB/ESS/TES	✔	✔	✔	✔	✔	✔	✗	✔	Reviewed various studies with architectures providing thermal and electrical demands and networks facilitating multi-energy microgrids. However, the implemented work and optimisation algorithm classification and their application are not fully covered.
[46]	2023	PV/WT/PVT/CHP/HP/FC	✔	✔	✗	✔	✔	✔	✗	✗	Reviewed various architectures utilising waste energy to produce heating, cooling, and electrical energy for the multi-energy user.

The optimisation strategies utilised for the optimal operation scheduling, planning, and design optimisation of compressed air energy storage in energy systems for various applications are studied in detail. The authors concluded that compressed air storage has a longer time span of 40 years, which makes it suitable for integration in large-scale energy systems. Ali et al. [33] reviewed various studies considering home energy management using optimisation techniques in smart homes with multi-energy demands. While extensive simulation-based studies have been conducted tackling multi-energy demand management, there remains a notable gap in comprehensive studies addressing the practical implementation of these frameworks. Nazari et al. [34] presented an extensive review of the use of optimisation algorithms in the modelling process of MESs, whereas Gusain et al. [35] focused on metaheuristic algorithms specifically utilised for optimising size and design. In another study, Thirunavukkarasu et al. [36] concluded that MILP-based algorithms can optimise microgrids and models due to their simplicity and effective performance in obtaining optimal solutions. Thirunavukkarasu et al. [37] evaluated the optimisation-based techniques for optimal sizing considering RES-based multi-energy structures with various constraints and decision variables. The authors concluded that AI has more advantages than heuristic and conventional algorithms in achieving objectives via fast convergence and global optimisation with high-precision calculation. However, the training data required for AI are highly complex, which limits its applicability. Liu et al. in [38] and Alabi et al. in [39] also evaluated studies focused on applications of AI in the different sectors of MESs. The studies assessed AI's use in uncertainty modelling, forecasting techniques, and sizing optimisation approaches. Ammari et al. [40] also reviewed only AI-based algorithms, ignoring other conventional and heuristic algorithms for MES optimal energy management. Studies related to implementing control strategies for MESs have also been ignored. Ding et al. [41] and Tiwari et al. [42] reviewed the communication infrastructure required to realise smart MESs. Alabi et al. [43] highlighted challenges in the adoption of MESs. They evaluated various policies Europe, Asia, and North America adopted to implement RES-based MESs to decarbonise multi-energy production. EV integration is also recommended as a flexible and economically feasible energy storage device.

Comprehensive literature studies have been conducted on MESs, focusing on various aspects of MESs, such as optimisation techniques for MES energy management and operation planning, sizing, modelling, and scaling. These studies focus mainly on theoretical and simulation-based studies; hence, there is a need for a study focusing on the simulation, deployment, and practical implementation of the strategies and covering various aspects of the modelling and realisation of a residential MES microgrid. In addition, there is a lack of comprehensive review studies on the strategy implemented in hardware in laboratories, showing their effectiveness when deployed. In this study, we focused on highlighting theoretical, simulation, laboratory deployment, pilot studies, communication infrastructure, and DRPs. Furthermore, a detailed understanding of the overall functionality of various technologies, including multi-energy input and output vectors, energy storage systems, and controller mechanisms, is discussed in detail. In summary, the main contributions of the current review study are itemised below:

1. A comprehensive and detailed overview of technologies, laboratory developments, and practical and real-world implementation, including pilot studies, is presented;
2. Various optimisation techniques, including conventional, heuristic, and artificial intelligence-based residential multi-energy management strategies, are reviewed, evaluated, and classified;
3. Configurations and architectures with intelligent energy management techniques adopted to simultaneously provide power, heating, and cooling demands are discussed and presented in detail.

This field of study contains a plethora of phrases and names that are either interchangeable or signify adjacent concepts/technologies. For clarity, here, we explicitly mention terms that are interchangeable or distinguish between different terms. In this study, specific terminologies are employed to describe various energy generation and distribution architectures. The term "MES" is utilised to define an architecture that incorporates more than one energy input (electricity and gas) to fulfil multiple energy demands (heating, power, and cooling). This architecture is also known as integrated energy systems, energy hubs, and hybrid energy systems, among other terms. However, in this study, the term "MES" is used. RES refers to integrating and utilising one or more renewable energy resources or conversion systems, such as solar or wind sources, PVs, or WTs, for energy production. CHP refers to the use of gas-based combined heat and power generation units. However, in several studies, CHP terminologies have also been used to represent solar-based power and heat generation, fuel cell-based power and heat generation. Unlike CHP, the term "CCHP" describes the combined cooling, heat, and power generation process, which involves various input vectors and conversion units that can simultaneously generate cooling and heat power.

Table 1 presents a comprehensive summary of the existing review studies, outlining the architectures, techniques and methodological frameworks, loads met, and contributions. The methods and methodological frameworks consist of optimisation technique-based energy management strategies and applications in MESs, which are categorised into three distinct columns: conventional algorithms, heuristic algorithms, and AI-inspired algorithms. Additionally, the table includes a comprehensive summary of the types of loads analysed by the recent studies, specifically electrical, thermal, and cooling loads. The scope of the current study is also extended to hardware-based implementation in the existing literature, which has not been focused on in the recent review studies. Most studies concentrate on or are limited to numerical simulations and modelling-based studies. Therefore, the table also gives insight into practical implementation discussions in each existing review study. Furthermore, the table highlights the contributions and scope of each study, providing insights into the scope of the existing review study.

The remainder of the work is organised as follows: Section 2 delves into the technologies employed in MESs to generate multiple forms of energy, including thermal and electrical energy. It also thoroughly examines the integration and coupling architecture of MESs, detailing the energy input and output vectors and the storage of these energies as heat and electricity. Energy management and dispatch strategies, utilising optimisation techniques focusing on DRPs, are also discussed. Section 3 outlines the widely used tools and software, physical technologies, controllers, implemented energy management strategies, and communication infrastructure necessary to realise a practical MES architecture. Section 4 describes the MES architecture developed in practice as part of a pilot study or a complete project. This section also highlights key pilot projects that have been recently completed or will be completed in the near future. Alongside these projects, it provides an in-depth discussion of key analyses related to cost and feasibility measures, reliability and operability measures, and the commercial prospects of various MES architectures. Finally, Section 5 concludes the study with future recommendations.

2. Sizing and Optimisation

2.1. Technologies

This section outlines the technological architectural framework adopted to realise a typical MES. These systems are often designed to integrate and manage multiple energy production systems, including electricity, gas, and interaction with the district heating networks. The input vectors are utilised to operate the DG systems and conversion units, which are capable of concurrently providing electrical power, heating, and cooling demand. Figure 1 shows a typical MES framework—the selection of architectural frameworks utilised depends on the input vectors' availability and user demand. The green colour arrows represent the flow of electricity, blue for cooling, red for heating and yellow for natural gas flow. The core components include energy input vectors, production, conversion, and storage units. To balance the energy flow, an intelligent controller is utilised to monitor and manage the multiple energy flows within the system.

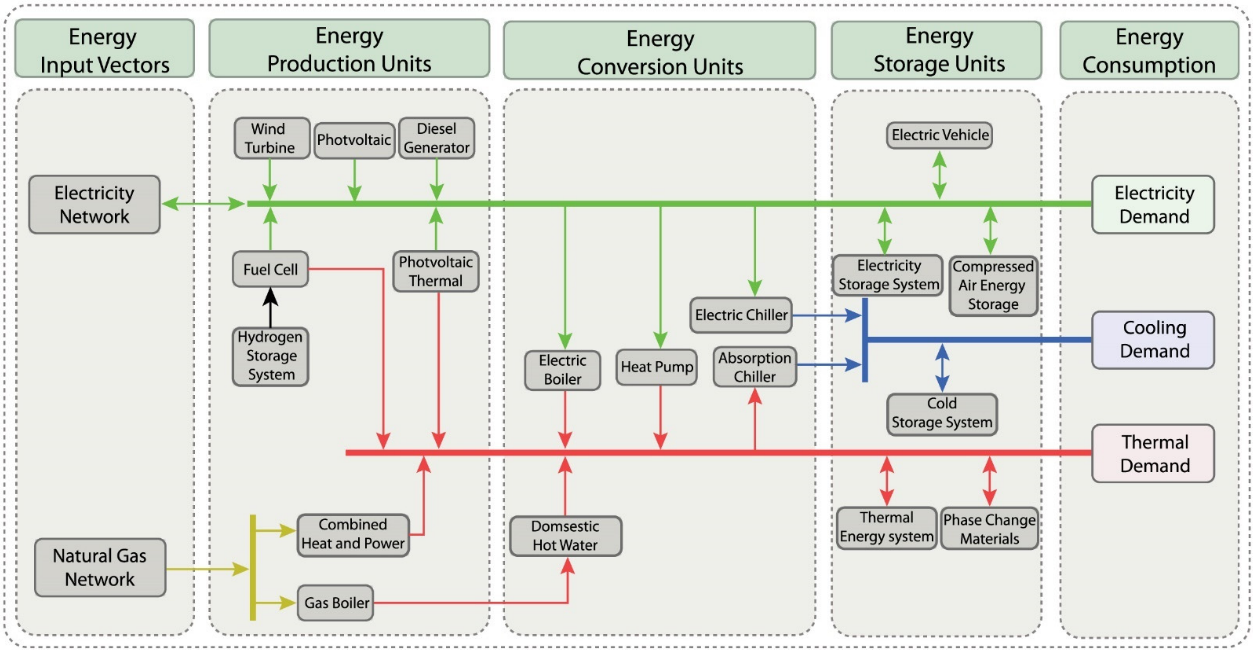

Figure 1. A typical MES framework.

2.1.1. Energy Systems

Energy Input Vectors and Conversion Units

Energy conversion units, including heat-only boilers (gas-to-heat), power plants (gas-to-power), cogeneration plants (gas-to-heat and power), HPs (power-to-heat), and technologies that convert electric energy into fuel, such as hydrogen and methane (power-to-gas), are integral components of modern energy systems. Heat-only boilers, for instance, are designed to convert gas into heat, providing a reliable thermal energy source for various applications, e.g., DHW and space heating. Conventional power plants, on the other hand, focus on converting gas or fuel into electricity, offering a direct means to generate power for use in the residential, commercial, and industrial sectors. CHP units can produce electricity and heat and are considered efficient; however, the use of fossil fuels and emissions is a big concern. The coupling of multiple energy generators becomes complex, and various equipment characteristics should be considered for the optimal size, integration, and utilisation to maximise the energy output and conversion efficiency. The components utilised are mainly PVs, WTs, CHP, FC, GTs, boilers, combustion engines, heat exchangers (HEs), HPs, and electric and absorption chillers. At present, RES-operated HPs, fuel cells, boilers, and chillers are becoming popular due to their low emissions, maximising the use of RESs. Integrating PV thermal-based (PVT) collectors within poly-generation or tri-generation systems is often carried out to enhance the utilisation of RESs, reduce operational costs, and increase efficiency. However, RES generation has reliability and intermittency issues due to weather variations, which can be resolved by installing storage devices or by robust and accurate RES forecasting of RESs. At the same time, electrical, thermal, and gas storage systems are also installed to increase the flexibility, reliability, and maximum utilisation of the available local energy. Modelling energy resource uncertainty and forecasting is crucial when designing energy systems involving AI- and ML-based mathematical and computational models. Jiang et al. [47] utilised deep learning methods for estimating forecasted energy generation systems with uncertainty. Implementing the system model increases power generation benefits by 6.18% by applying the short-term optimal load scheduling of MESs. Another challenge for MES modelling is the uncertain consumption behaviour of the user, which leads to the change and rise in the energy demand, which also needs to be mitigated in real-time. Wang et al. [48] proposed a strategy for MESs to predict and optimise the participation of the RES while considering uncertainty in a day-ahead multi-energy market. The system model effectively bids in the day-ahead energy market with risk aversion in an uncertain energy market and reduces the overall costs with the optimal operation mechanism of the integrated energy system. Wan et al. [49] proposed a combined deep learning and GA for predicting RES generation and optimising load scheduling and distribution for MES microgrids. Deep learning is used to predict energy generation, and GA is utilised for optimising consumption patterns. Deep learning exhibited a 1.3% lower prediction error and accurately predicted heat and electrical load uncertainty, which increased the revenue of the thermal power plant by up to CNY 6.26 million/yr. Stochastic and robust programming approaches are proposed in various studies related to MES energy modelling and management. Jordehi et al. [50] proposed a two-stage stochastic programming strategy for scheduling MESs, participating in the day-ahead and real-time energy market structure. The results show that the reliability increased from 90% to 95% with reduced costs. However, increased reliability increases costs in several scenarios. By incorporating historical data and statistical models, multi-energy systems can predict future energy demands, supply, and prices. Furthermore, specific methods based on game theory, fuzzy logic, and neural networks are utilised for the optimal bidding, scheduling, design, and modelling of the uncertainty related to RES production.

Energy Output Vectors

In the context of MESs, energy output vectors refer to the various energy forms produced or converted within the energy system. These output vectors include power, heat, and cooling demands, which are crucial for meeting the multi-energy demands of residential consumers. Integrating and managing these output vectors is essential for achieving efficient and sustainable energy systems. Based on the energy demands of the user, MESs can be categorised into cogeneration, tri-generation, and poly-generation. Cogeneration describes the combination of architectures that provide two energy outputs, while tri-generation is used for three energy demands. Similarly, poly-generation is used for more than three energy demands, e.g., hydrogen production. CHP units and FC units are widely utilised cogeneration systems. A similar system for the residential sector to meet DHW and space heating demands was analysed by Elmer et al. [51]. The results indicated that annual carbon emissions are reduced by up to 56% and cost by up to 177% compared to the base case scenario. The high reduction in costs occurred from exporting the energy back to the grid, as the base scenario lacks a mechanism for the export of energy. However, the dependence on export mechanisms, the high initial costs of FC, and the lack of detailed cost analysis make the fuel cell system less profitable, even after 15 years. This is due to the higher cost of the FC. Ehsan and Yang [52] presented a tri-generation-based energy system to reduce carbon emissions and costs. The study focused on optimising the size and siting of isolated microgrids powered by CHP, WTs, PVs, and electricity storage systems (ESSs). The thermal load is met through gas-fired boilers with TES, and the cooling demand is met by deploying a combination of electric and absorption chillers. The modelling of uncertainties related to generation and user demands is also considered.

Ren et al. [53] utilised a PV-based hybrid CCHP to fulfil the energy demands of a residential building. The NSGA-II algorithm optimises the multi-objective model, considering overall costs, fossil-based energy consumption, and reducing carbon emissions. The strategy outperforms the PVT framework in terms of cost, carbon emissions, and fossil-based energy consumption by 8.91%, 34.58%, and 51.99% for the case of a hotel. Tri-generation and poly-generation systems generally offer higher emissions and efficiency due to their ability to simultaneously produce electricity, heat, and cooling. These systems' economic and environmental viability also depends on factors such as the overall cost of the technology and management control strategy, etc. However, the integration of RESs, sizing, and energy flow optimisation are key strategies for enhancing the profitability and sustainability of MESs, regardless of the specific technology used.

Sector Coupling Through Electrification

The target set by the EU to cut down emissions by 80–95% by 2050 will be significantly facilitated by the decarbonisation of energy systems. Sector coupling through electrification emerges as a pivotal strategy that involves the increased use of RES-based electrical energy production resources and enhanced interlinkages among various energy components to meet multi-energy demands. The primary forms of electrification using sector coupling involve consumer-side coupling and cross-vector integration. Consumer-side coupling primarily focuses on enhancing the interactions between supply and end use and the electrification of all energy demands, such as using electric HPs' electrification of heating and cooling. Cross-vector integration aims to integrate and use various energy architectures and input vectors such as electricity, gas, and heat, which is mainly carried out on the supply side. The process involves converting surplus energy/electricity into other useful forms, which is often known as power-to-X technology. Nazari et al. [30] reviewed the potential of utilising various configurations of coupling solar energy with heat pumps. Many different configurations are suggested in the literature. PVs or PVT collectors were used as supplementary sources of heating. Air-source, ground-source, or absorption heat pumps were used to provide heating and cooling. Most studies found utilising thermal storage to be beneficial in reducing reliance on the grid. It was also found that optimising the operational schedule and control schemes helped to reduce costs by around 50% and cut emissions by 70% in some cases. The authors also highlighted some challenges in implementing the PV-HP configuration: the lack of policy incentives for such solutions, the higher electricity costs associated with PV, and the complexity of proposed controls. Patil et. al. [54] systematically discussed the key components of HP operation using PV and highlighted with such combinations costs and emissions will be reduced and further research needs to evaluate the performance and relaibility of PV-HP setups with high variations in the solar irradiance and variability.

Some of the challenges are as follows: high levelised cost of electricity for PV-operated HPs, difficulty of installation in existing residential buildings, and a lack of sufficient space for PV installation. An illustrative study was conducted by Wang et al. [55], where different sizes of PVs were coupled with reservable air-source heat pumps (for heating and cooling) installed in central south China. A heat pump with a rated power of 2.2 kW and a CoP of 3.2–3.5 for cooling and heating, respectively, was used. Five PV configurations were coupled with the HP at capacities of 1.7 kW, 2.4kW, 3.2kW, 4kW, and 4.8kW. The rated PV efficiency was 13%. It was found that the best results were achieved with a PV/HP power ratio of 1.0 to 1.10. It was also found that cooling and heating loads make the PV installation economically better.

Sorace et al. [56] analysed various combinations of energy resources consisting of HP- and FC-based systems to facilitate electrification to meet the thermal demand of the residential user. It was found that SOFC-FC with an HP system exhibits a higher efficiency of 81% and that the primary energy consumption was reduced by 30%, with reduced operating costs compared with the PEM-FC. However, the initial cost for the SOFC-FC is higher than that of the PEM-FC, thus having a longer payback time. Sector coupling through electrification offers a promising solution to decarbonise the energy sector, specifically the heating sector. It also provides a cost-effective solution for the multi-energy demand sector using various technologies. Despite the mature research and experimental advantages, there are still practical challenges in deploying and adopting sector coupling. A study by Xu et al. [57] addressed the planning of MESs, including electricity and gas networks, which improved the scalability and responsiveness to multi-energy load variations. The authors utilised an alternating direction method of multipliers to break down the planning into three stakeholder-specific problems: gas, electricity, and local MES hubs. In the context of sector coupling, Sorrenti et al. [58] presented the recent technologies of P-2-X in the context of their integration with hybrid renewable energy systems (HRES). They distinguished three main types: P-2-H_2, P-2-Gas, and P-2-ammonia. The first will convert excess renewable energy into hydrogen for fuel cells. The second will convert power into synthetic gas for current gas-burning equipment such as boilers and turbines. The third will convert electricity into ammonia, a more suitable energy carrier than hydrogen. The ammonia generated can then be used in fuel cells directly or after conversion to hydrogen.

2.1.2. Energy Storage Systems

The most common energy storage technologies used in residential MESs are battery energy storage systems (BESSs) and thermal energy storage (TES). Electrochemical-based lithium-ion batteries dominate the market due to their high energy density and efficiency, but they face challenges related to resource limitations, recycling difficulties, and safety risks. The impact of ambient temperature and degradation affects BESS performance and efficiency over time, occurring due to the chemical reactions within the BESS model. TES is utilised to store cooling and heating excess energy for the short or long term. Gas storage systems are also deployed in several architectures in the MES to store natural gas or hydrogen gas, which is produced to utilise excess energy efficiently and convert it to another useful form for later usage. Installing multi-energy storage systems raises several problems that require an energy management strategy to simultaneously control and schedule energy sharing among components to achieve technical and economic objectives. In this context, Xu et al. [59] evaluated MESs with multi-energy storage for residential buildings to reduce carbon emissions, energy consumption, and initial cost and maximise self-consumption. MILP is used to optimally utilise the DRPs to store electrical energy from the grid. The results demonstrated that thermal energy storage devices are economically better options than electrical storage devices with shorter lifetimes and high investment costs. Similarly, Marczinkowski and Østergaard [60] compared the installation of BESSs and TES in two islands (more details on this project are given in Section 4.1.1). The aim was to maximise self-consumption on the islands. They varied the system size for both BESSs and TES. It was found that for BESSs, there are diminishing returns of adding more capacity, both economically and in terms of the self-consumption ratios. This was not the case for TES, which did not show such a trend. However, to utilise thermal energy, other equipment needed to be upgraded, which affected the system's total cost. Overall, TES and sector coupling were more favourable solutions, as more energy vectors provide more flexibility. The study has limitations related to the peculiar nature of island energy systems. An analysis of national grids would be different. Ndwali et al. [61] discussed various strategies and control techniques for using thermal, ice, and electrical energy storage systems that simultaneously meet solar energy's cooling, heating, and electrical energy demands. Violidakis et al. [62] compared two technologies of latent heat storage systems powered by PVs for providing heat and electricity. The first technology involved a low-temperature phase change material-based thermal energy storage system for residential heating needs, while the second technology included an ultra-high-temperature thermal energy storage system integrated into a building, as shown in Figure 2. The systems were compared with a traditional air-to-water HP heating system, and the study concluded that the ultra-high-temperature TES was more advantageous in terms of electricity supply. Inkeri et al. [63] utilised HPs and TES architecture for DHW production. DHW is produced using HPs operated at low energy pricing for electricity or solar energy. An updated NSGA was implemented by Schmid et al. [64] to optimise the size of MESs and reduce energy costs. PVs are used as a primary energy source, and electric heaters and air-to-water HP are used to meet heat demands. The authors conducted long-term and short-term analyses considering three locations with different energy prices. They found that low-energy hoses show an additional 172% reduction in cost projection compared to low-seasonality locations.

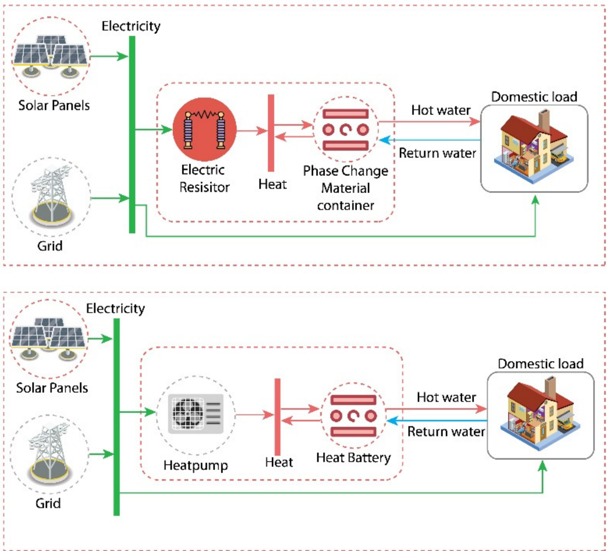

Figure 2. The schematic diagram of the proposed architecture for multi-energy storage systems was adopted from [62].

The dependence of the cost and performance of energy storage systems on their ageing process has led to the introduction of ageing considerations as optimisation objectives and constraints. A study by Neelam et al. [65] utilised differential evolution algorithms to reduce the battery degradation costs by presenting a control strategy to manage the MES demand, yielding the lowest total energy costs, battery degradation costs, and reduced total energy consumption. Sharma et al. [66] proposed a two-stage robust optimisation energy management strategy to reduce costs and enhance user comfort for a building with multi-energy demands. The simulation results were computationally efficient, had the least ESS degradation, and had a lifetime with maximum user comfort, with uncertainties considered compared to stochastic and Monte Carlo simulations.

To summarise, the limitations of BESSs include high capital costs, moderate energy and power densities, capacity degradation with cycling, thermal runaway, and environmental concerns regarding material sourcing and disposal. On the other hand, TES has different limitations based on the specific technology used. Water-based TES suffers from low energy density, necessitating a large amount of space to store adequate energy. PCM-based energy storage has a relatively high energy density but suffers from low thermal conductivity and the instability of chemical compositions with cycling. Looking ahead, technological innovations in BESSs are focusing on next-generation batteries, such as solid-state and flow batteries, which offer higher energy densities, longer lifespans, and improved safety features. TES-related innovation includes heat transfer intensification techniques, additives to improve thermal conductivity, and hybrid water–PCM systems with encapsulation solutions. Finally, hydrogen is also gaining attention for its potential to provide long-duration and seasonal storage, mainly produced through renewable-powered electrolysis.

2.1.3. Residential MES Hub/Microgrids

Residential MES microgrid subsystems can be categorised into four primary components: energy generation systems, consumption sites, energy management controllers/systems, and ESSs. In MES microgrids, grid and gas networks are widely used to meet consumer demands for power, heating, and cooling. At a small-scale residential level, gas and electricity networks are widely used energy inputs to various energy conversion units, including boilers, chillers, HPs, mCHPs, etc. These energy conversion units generate electricity, heat, and cooling energy, whereas TES can store electrical energy for DHW and ESSs. The adoption of solar and wind energy can significantly reduce emissions. However, the intermittent nature of these resources presents significant challenges in balancing the energy supply with demand. These issues are often tackled through implementing multi-energy storage systems, grid interaction via DRPs, and the design and analysis of accurate models that account for uncertainty. Introducing and integrating these solutions into energy systems necessitates management and dispatch strategies to handle excess energy effectively. Consequently, optimal strategies are increasingly valuable, particularly when considering energy storage and demand response programmes. On the other hand, the recent advancement in communication infrastructure has led to their widespread adoption in microgrids, specifically in the smart metres deployed in residential sectors. These communication technologies have significantly enhanced the information flow between the demand and consumer sides, enabling energy consumers to participate in DRPs. DRP techniques include load shifting, peak clipping, and valley filling, where the prime objective of implementation is to reduce costs and emissions and the burden on the main grid. Several research works also focused on the interaction and sharing of multi-energies, considering several buildings with MES equipment. The installation of MESs for residential applications requires design, sizing, architectural, and technological assessments, as well as optimisation, to select a feasible architecture with high efficiency and low levelised costs.

For instance, Trillat-Berdal et al. [67] presented a strategy to meet the heating and cooling demands by utilising solar energy captured through a thermal collector for water heating, where the excess thermal energy is then injected back into the ground through boreholes. This is claimed to be advantageous, as it helps to balance ground loads, increases the operating time of the solar collectors, and prevents overheating issues. However, the authors did not consider exporting or selling the excess heating energy to the neighbouring buildings, which could be profitable in terms of operating costs. Calise et al. [68] proposed a PV-, WT-, and HP-based strategy for fulfilling a building's electrical, heating, and cooling demands to reduce operational costs. The architecture consists of building-integrated PV (BIPV) modules with HPs and WTs, whereas in the other case study, the authors utilised a building-integrated PV-based thermal system (BIPVTS) with WTs and HPs. It was shown that BIPV modules have a shorter payback time of 5 years compared with the BIPVTS case, which has more than 7 years. However, in the case of the BIPVTS, 73% of carbon emissions are reduced, whereas BIPV reduced 69%.

Within residential MESs, the challenges of integrating renewables have mostly been on the electrical side. Previously, when renewable power sources constituted a small percentage of the available power on the grid, grid operators would require the disconnection of renewables in the case of fault. This allowed the operator to perform maintenance tasks safely. However, the increased integration of renewables into the grid meant that removing them from operation during grid incidents could result in further instability in the grid. As such, many countries now require renewable plants to have a Voltage Ride-through (VRT) capability and be able to withstand voltage sags (low VRT) and voltage surges (high VRT). This requirement would stipulate a maximum voltage deviation during faults (e.g., 10%) and quick recovery after fault clearing (e.g., 0.5 s). There are also requirements related to power quality, such as harmonics, flicker, and voltage imbalance. For example, the UK imposes a total harmonic distortion of less than 3% and a voltage imbalance of less than 2% at the point of standard coupling [69–71].

2.2. Energy Management and Scheduling Strategies

Enhancing efficiency and reducing the costs and emissions of MESs are key research objectives often addressed when introducing energy management strategies. Energy management strategies based on mathematical optimisation techniques are used extensively in the literature to achieve these objectives. In addition to these objectives, key focus areas include dispatch strategy, energy flow, demand forecasting, operation, grid stability, and energy balance. Optimisation strategies involve tackling these objectives based on single- and multi-objective problems. To assess economic performance, initial investment, net present value, levelised costs, operating costs, and net present value costs are some primary objectives [72]. Whilst multi-objective optimisation is applied to solve optimisation problems to provide a combination of solutions with trade-offs to keep balance among various objective functions, which can be minimisation or maximisation problems, to solve the multi-objective problem, several methods are adopted to divide the problem into a single-objective problem. These methods include lexicographic and weighting factor methods, whereas Pareto methods are deployed to generate a series of optimal solutions for a multi-objective problem. The optimised solution is then selected based on the criteria set for the optimised solution. Figure 3 illustrates and categorises the optimisation techniques evaluated in this study, which are used in finding optimal or near-optimal solutions to an energy management problem. This work categorises these techniques into four major groups: conventional techniques, AI-based techniques, heuristics algorithms, and other scheduling techniques.

2.2.1. Conventional Mathematical Techniques

Conventional mathematical optimisation techniques include mixed integer programming (MIP), model predictive control (MPC), and stochastic and robust programming techniques. These techniques are considered conventional due to their mathematical foundation, reliability, and structured methodology for solving complex optimisation problems. While solving the optimisation problems in MIP, decision variables are required to take integer values. There are two types of mixed integer programming: MILP and MINLP. MILP problems have linear objective functions and constraints, whereas MINLP problems solve nonlinear objective functions and constraints. Table 2 summarises the architectural framework, techniques, objectives, and outcomes of the studies that used these techniques to solve MES energy management problems. Ghilardi et al. [73] developed a MILP-based load control technique for 12 buildings, featuring various thermal and energy rating properties utilising RESs, HPs, and co-generation units. The strategy reduced the operating cost by 83%, with acceptable thermal comfort compared with a benchmark strategy with fixed indoor temperature set points.

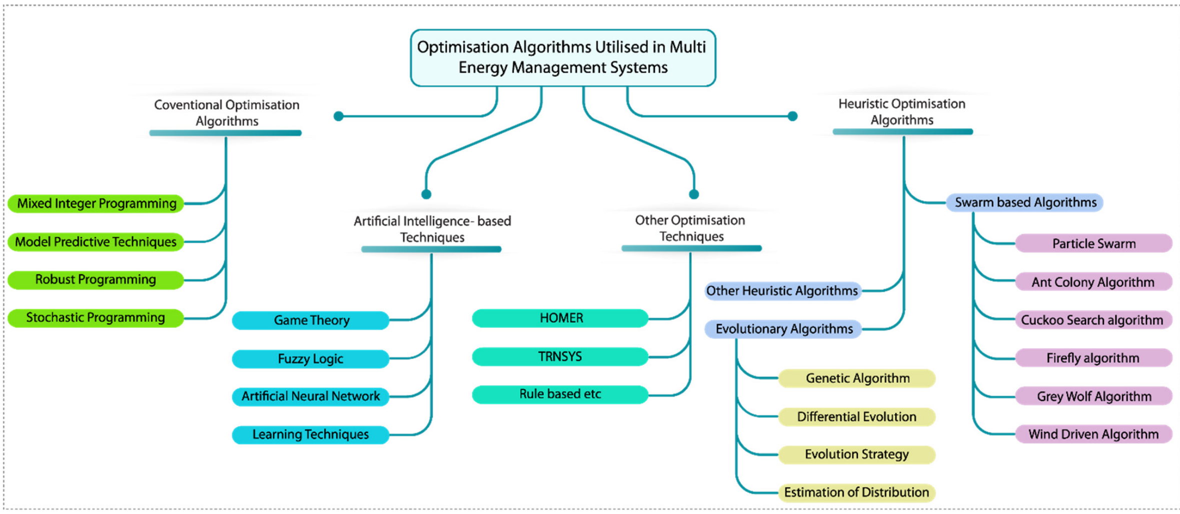

Figure 3. Classification of optimisation algorithms discussed in the current study.

Nasiri et al. [74] developed a MILP technique with information gap decision theory to handle uncertain WT-integrated MESs. The strategy is used to bid in the wholesale MES energy market to achieve particular objectives. The results show reduced user comfort and operating costs, reducing the electrical and natural gas market clearing prices by 13.32% and 5.53%, respectively. Weber et al. [75] used MILP to design and optimise DG integration with grids. The strategy reduced emissions for a town in the UK to provide multi-energy demands. Similarly, Gabrielli et al. [76] utilised MILP to optimise MESs and reduce costs and emissions. The strategy reduced the cost and carbon emissions by 22% and 73%, respectively. A multi-period MILP algorithm was designed by Kang and Peng [77] to optimise the schedule of MESs with RES penetration. The total annual cost was reduced by 11% with HSS and ESS, with a 45% increased usage of ESS and decreasing emissions, among other scenarios. Solving complex optimisation problems with MILP can lead to a long computational time due to non-integer variables. The optimal solution to a problem can become stuck in local optima, which produces suboptimal results [78]. Large-scale optimisation problems are often solved via decomposition methods, where complex issues are divided into subproblems to reduce complexity. These methods can lead to an optimal solution with high efficiency and effectiveness when solving large-scale optimisation problems [79].

MPC is another extensively utilised, sophisticated and powerful mathematical programming technique to predict future behaviour over a finite period [80]. It comprises several key steps: model formulation, prediction, optimisation, control execution, and repeating the process. Feghali et al. [81] designed a MES DSLM strategy to optimise the schedule of HPs with TES using MPC. Peak shaving and valley filling methods are used to minimise energy consumption. Guo et al. [82] used robust dynamic programming to optimise the energy flow for a prosumer with five scenarios. Stochastic dual dynamic programming is also used as benchmark algorithm for these scenarios. Robust programming solved the uncertain problems in a shorter computational time, with a suboptimality of less than 4% compared to the benchmark. Daramola et al. [83] designed a stochastic optimisation technique for integrating EV and ESS with MESs. The strategy reduced costs by 32.22%, 44.49%, and 47.20% in the first, second, and third scenarios, respectively, and emissions were reduced by 29.13%, 47.13%, and 47.90% in the first, second, and third scenarios, respectively. However, stochastic programming approaches also have a long computational time to solve an optimisation problem, which increases the sample size and makes it not scalable to obtain the optimal solution.

Table 2. A summary of studies utilising conventional mathematical techniques was reviewed in the current work.

Ref.	Year	Technique	Objectives	On-Grid?	Architecture/Topology	Loads	Implementation	Outcomes
[73]	2021	MILP	Energy balancing and overall costs	Yes	Grid/PV/WT/CCHP/NGB/HPs.	Electrical, Thermal, Cooling	No	Reduced costs by up to 80% when compared with the baseline case.
[74]	2022	MILP	Reliability and overall electrical and gas costs	Yes	Grid/WT/CAES/CHP/NGB/TES	Electrical, Thermal	No	Total operational cost was decreased by 4.7%.
[75]	2011	MILP	Reliability, costs, and emissions	Yes	Grid/HP/WT/CHP/PVT/GB/HEs.	Electrical, Thermal	No	Reduced emissions by up to 20% with no additional cost.
[76]	2018	MILP	Overall costs, operation, emissions, and design	Yes	Grid/PV/PVT/FC/MGT/NGB/TES/HP/ESS	Electrical, Thermal	No	Reduced costs by 22% and emissions by 73%.
[77]	2023	MILP	Costs, emissions, and comfort	No	PV/WT/ST/HSS/TES/ESS/GT/EC/HP/AC/GB	Electrical, Thermal, Cooling	No	Total costs were reduced by 12%, with annual carbon emissions produced higher than baseline.
[84]	2023	MPC	Costs and energy consumption	Yes	On-grid system	Electrical, Thermal	No	Electricity consumption decreased by 3% and 17% in winter and spring, respectively.
[85]	2023	MILP, MINLP, GA, and PSO	Design and size of ESS	Yes	Grid/WT/PV/PCT/CHP/ESS/TES	Electrical, Thermal	No	Up to 80% of costs can be saved when using optimisation techniques.
[86]	2018	MILP	Emissions and operational cost savings	Yes	Grid/PV/FC/TES/EC/AC/ESS/PVT	Electrical, Thermal, Cooling	No	The simulation results claim that the hybrid SOFC-CCHP-based model implemented in Beijing's hotel achieves the overall best performance.
[87]	2017	MILP	Sizing, overall costs, and energy consumption	Yes	Grid/GT/ICE/Boiler/TES	Electrical, Thermal	No	Reduced energy consumption by 64% and a 28% reduction in total annual cost.
[81]	2022	MPC	Operation and costs	Yes	Grid/HP/PV/WT/TES	Electrical, Thermal	No	The overall energy consumption is reduced during the 24 h of operation.
[82]	2022	RP	Manage and optimise the energy flow	Yes	Grid/PV/WT/ESS	Electrical	No	Improvement of 5% in all five case studies.
[83]	2023	SP	Emissions and costs	Yes	Grid/FCs/CHP/RES/ESS	Electrical, Thermal	No	Operational costs are reduced by 44% and emissions by 47.9%.
[88]	2020	MILP	Sizing and overall costs	No	PV/WT/NGB/TES/EC/DG/ESS/CHP/AC	Electrical, Thermal, Cooling	No	The authors optimised the location, size, and operation schedule with lower investment costs and uncertainty and found it less efficient in terms of cost.
[89]	2025	MILP	To reduce costs by increasing self-consumption	Yes	Grid/DHN/PV/ESS/TES/HP	Electrical, Thermal	No	In summer electric self-production is reached to 58%, and in winter self-consumption reaches 81%.
[90]	2020	ED	Efficiency and stability	Yes	Grid/CHP/PV/WT/ESS	Electrical, Cooling, Thermal	No	The efficiency and convergence time are effectively managed using the hybrid algorithm.
[91]	2015	MILP	Overall costs and utilisation of PV	Yes	Grid/DG/ESS/PV/HP.	Electrical, Thermal	No	Saved 114.06 kWh of energy and 68.09% reduced costs using DRPs.
[92]	2014	Quasi-steady-state simulation model	Costs, emissions, and savings	Yes	Grid/BCS/CHP/DHN	Electrical, Thermal	No	Saved 2010 MWh/year of energy, saving 0.81 €/MW with 38% reduced emissions.
[93]	2009	MIP	Overall costs, energy consumption, and emissions	Yes	Grid/PGU/NGB/CCHP	Electrical, Thermal, Cooling	No	Optimising one parameter may reduce or increase the other two depending on the variation in the loads, electricity, fuel costs, and environmental factors.
[94]	2021	Deterministic optimisation	Costs, emissions, and reliability	Yes	Grid/GT/AC/TES/WB	Electrical, Thermal, Cooling	No	Reduces the loss of load expectation by 108.4% and increases the annual operation cost by 110.14%.

2.2.2. Heuristic Optimisation Techniques

Heuristic algorithms are inspired by natural processes to efficiently explore the search space to obtain an optimal solution to a problem. However, finding a global optimal solution to a complex optimisation problem is not guaranteed, as most are stuck in the near-optimal solution. Figure 4 shows a flowchart of optimisation algorithms functioning for multi-energy management. Figure 4 provides a comprehensive overview of the optimisation algorithms' frameworks, designed to achieve a complex energy management problem solution. The optimisation framework utilised to solve the problem incorporates various decision variables, objective functions, constraints, and key steps of the optimisation process, as depicted in Figure 4. The process begins with initialisation and input data, including building types or consumer data, load data, temperature, and emissions, as well as the technical data of the integrated energy resources or RES-based DG systems. These inputs and their constraints are utilised to design objective functions to minimise costs, emissions, and energy consumption and optimise planning, design, size, etc. These objective functions are some of the most widely used parameters to assess the optimisation algorithm's reliability and capability in solving a complex energy management problem. Moreover, the constraints are primarily imposed on the operation strategies of the energy generation and storage units to achieve energy balance and operation schedule optimisation. Multiple optimisation algorithms are applied to explore the predefined search space and solve the optimisation problem. An iterative process is used to determine and refine the potential problem solution until an iterative process or desired optimal solution is achieved. As shown in Figure 4, each algorithm employs a specific strategy to achieve the desired optimal solution, mainly evaluating the objective function, position updating, exploration, exploitation, etc., to navigate towards the optimal solution in a predefined search space. By leveraging such optimisation techniques and algorithms, the designed framework can achieve an optimal or near-optimal solution, ensuring energy efficiency and balancing reduced costs and emissions by load and generation units' operational schedule optimisation.

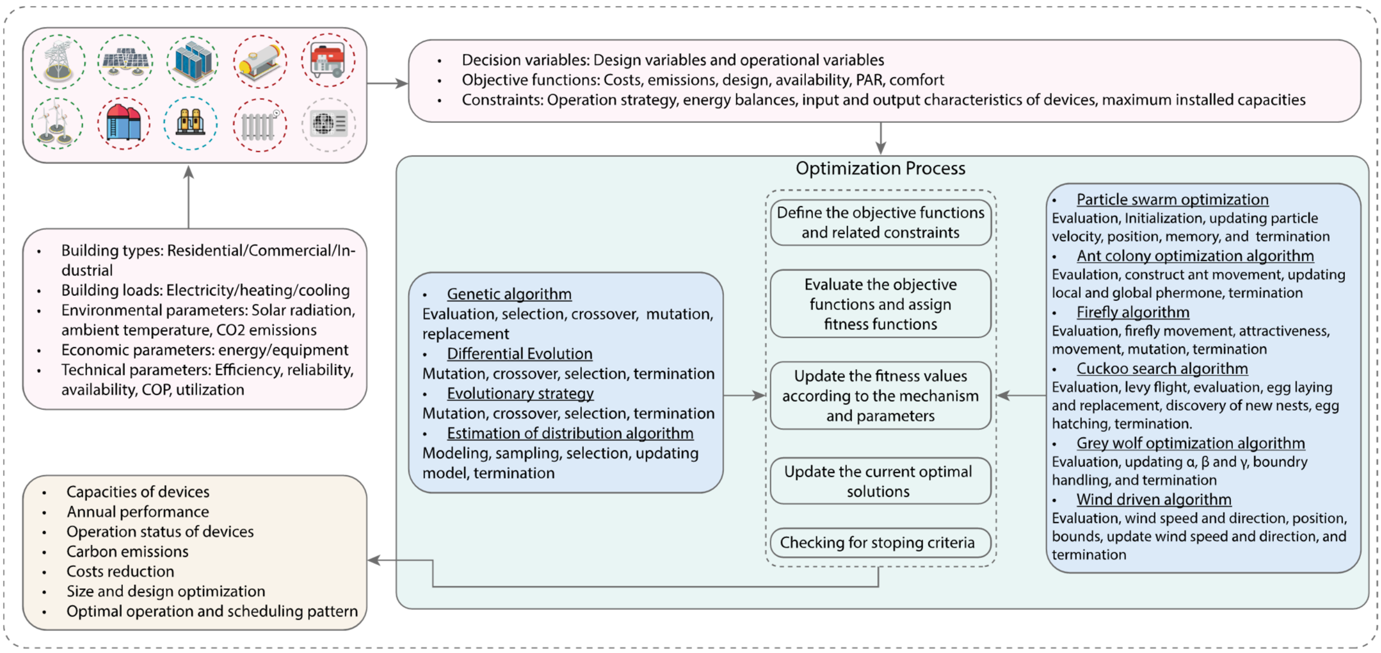

Figure 4. Flowchart of optimisation algorithms functioning for multi-energy management.

Evolutionary Algorithms

Evolutionary algorithms are a type of heuristic algorithm inspired by the process of the natural selection of various biological processes, i.e., natural selection and evolution. Selection, reproduction, mutation, and cross-over are some steps modelled mathematically to simulate the process of solving complex optimisation problems. GA has been used extensively in MESs in planning, management, scheduling, and operation. High investment costs are often considered a barrier to adopting residential MESs. Despite high initial investment and operational costs, multiple economic analyses and case studies demonstrate that implementing RES-based MESs in residential settings with optimised energy management strategies can yield favourable cost-benefit ratios and significant long-term value. Energy management and equipment operation optimisation leads to minimal operational costs. Such a detailed study was carried out by Ahmadi et al. [95], who designed a strategy based on NSGAII to reduce emissions and costs while increasing energy efficiency for a residential user. The trade-offs between objectives such as emissions, exergy efficiency, and costs are evaluated. A maximum efficiency of 33% is achieved with high costs, whereas minimising costs reduces costs as an objective function. Das et al. [96] evaluated various configurations for a MES using HOMER software. Operational costs and emissions are reduced by increasing the use of RESs and optimising the size and design of MESs. Similarly, Das et al. [97] also used GA to optimise MES operations to supply power to off-grid multi-energy users. Costs are reduced by 27–29%, with an increased reliability of 99.92% compared to not utilising excess energy and a diesel generator.

Differential evolution and evolutionary strategies belong to evolutionary algorithms, which are also extensively utilised for energy management problem solutions. Yang et al. [98] and Basu [92] formulated an energy management strategy based on DE and ES to solve problems related to MESs, aiming to reduce emissions and costs. Basu [99] evaluated three cases with different PV sizes with a benefit-to-cost ratio 1.4. The study concluded that the annual operational and maintenance costs for 130 kW are the lowest among the three cases. Arora et al. [100] designed a multi-objective ES with fuzzy logic to optimise the performance of a solar-powered Stirling heat engine. Furthermore, an NSGA-II algorithm was also used to investigate the optimal values of various decision variables to optimise the technical performance. The system's overall thermal efficiency, power output, and thermal economic ratio were found to be 35%, 17%, and 10.5%, respectively. Table 3 summarises the studies that utilised heuristic algorithms, including the evolutionary and swarm-inspired algorithms.

Table 3. Summary of studies utilising heuristic (evolutionary and swarm-inspired) optimisation techniques reviewed in the current work.

Ref.	Year	Technique	Objectives	On-Grid?	Architecture/Topology	Loads	Implementation	Outcomes
[95]	2014	NSGA II	Costs, emissions, and exergy efficiency	Yes	Grid/FC/BCS/MGT/TES/AC/DHWH	Electrical, Cooling, Thermal	No	The results showed that the authors had an essential effect on the trade-off between different objectives.
[96]	2021	HOMER	Optimal sizing, emissions, and utilisation of RES	Yes	Grid/PV/WT/MGT/Li-Ion ESS	Electrical, Thermal	No	Emissions were reduced by 40%, with a 33% higher consumption of RESs.
[97]	2021	HOMER and GA	Reliability, overall costs, and optimised sizing	No	PV/WT/ESS/TLC/NGBs/DG	Electrical, Thermal	No	Reliability is increased to 99.92%. The energy cost is 0.255 $/kWh for the case of utilising PV, WT, and ESS.
[98]	2022	DE	To optimise the economic dispatch strategy	Yes	Grid/CHP	Electrical, Thermal	No	The hybrid technique is utilised to enhance the dispatch strategy.
[99]	2019	EA	Overall costs and emissions	Yes	Grid/PV/CHP	Electrical, Thermal	No	The benefit-to-cost value is 1.4 at a PV capacity of 130 kW.
[100]	2019	EA	Efficiency, power output, and thermal economic ratio	Yes	Grid/PV/CHP/TES	Electrical, Thermal	No	Efficiency, power output, and thermal economic ratio increased by 35%, 17%, and 10.5%, respectively.
[101]	2019	Gradient descent algorithm and PSO	Overall cost, reliability, and optimal sizing of RES	No	PV/WT/BCS/ESS	Electrical	No	A combination of 300 Ah ESS, 0.25 kW PV, and 1 kW WT was selected as cost-effective and reliable on a chosen site.
[102]	2019	MOPSO	Design of HP, energy consumption, and operational cost	Yes	Grid/HP	Thermal, Cooling	No	HP dual mode is 27% more efficient in terms of cost than single operating mode.
[103]	2019	ACO	Sizing and operation scheduling	Yes	Grid/WT/PV/CHP/AC	Electrical, Thermal, Cooling	No	Enhanced energy utilisation rate and economic performance.
[104]	2022	Hybrid ACO	Cost and operation scheduling	Yes	Grid/PV/WT/CCHP/TES	Electrical, Thermal, Cooling	No	Costs are reduced by up to 40–47%.
[105]	2017	Multi-objective firefly algorithm	Operation optimisation	Yes	Grid/PV/WT/NGB/CHP/IEEE bus 39	Electrical, Thermal, Cooling	No	Enhanced results with better trade-offs.
[106]	2017	Modified firefly algorithm	Costs and emissions	Yes	Grid/PV/WT/GB/AC/CHP	Electrical, Thermal, Cooling	No	Lowered costs and emissions when compared with the benchmark.
[107]	2021	Modified firefly algorithm	Design, operation strategy, costs, and emissions	Yes	Grid/FC/GB/AC/HE/TES	Electrical, Thermal, Cooling	No	Emissions and fuel consumption reduction by 10.06% and 8.15%, respectively.
[108]	2021	Cuckoo search algorithm	Costs and emissions	Yes	Grid/SG/MT/PVT/AC	Electrical, Thermal, Cooling	No	The tri-objective optimisation problem is achieved and outperforms the NSGAII algorithm.
[109]	2015	Cuckoo search, PSO, GA, DE, and mPSO	Optimisation of operation	Yes	Grid/CHP/PV/WT	Electrical, Thermal	No	Computational performance is 135 times faster than dynamic programming.
[110]	2024	Hybrid GWO and Local search heuristic	Enhanced economic efficiency and System reliability	Yes	Grid/PV/WT/Super capacitor	Electrical	No	Reduced costs by 9.5% and enhanced reliability by 0.3% when compared wolf search optimisation algorithm

Table 3. *Cont.*

Ref.	Year	Technique	Objectives	On-Grid?	Architecture/Topology	Loads	Implementation	Outcomes
[111]	2022	Cuckoo search and GWO	Frequency regulations	Yes	Grid/PV/CHP	Electrical, Thermal	No	The Cuckoo search tuned the PID controller's performance, outperforming the other algorithms' performance.
[112]	2021	Modified GWO	Costs and emissions	Yes	Grid/PV/WT/DG/CHP/TES/ESS	Electrical, Thermal	No	Overall costs, emissions, and comprehensive costs are reduced by 1.2%, 11%, and 3.27%, respectively.
[113]	2021	Hybrid GWO	Costs, emissions, PAR, and comfort	Yes	Grid/CHP/PV/WT/ESS	Electrical, Thermal	No	Costs, emissions, and peak-to-average ratio are reduced by 25%, 20%, and 36%, respectively.
[114]	2021	GWO	Costs and emissions	Yes	Grid/PV/WT/ESS	Electrical	No	Costs are reduced by up to 21% under a 200 MW system.
[115]	2020	PSO	Generation utilisation and reliability	Yes	Grid/WT/PV/CCHP/ESS/TES	Electrical, Thermal, Cooling	No	The generation rate increases by up to 50% during the peak demand hours.
[116]	2019	GA	Overall costs and energy consumption	Yes	Grid/HPs	Thermal	No	HP's performance increased during cold weather.
[117]	2015	Fuzzy logic control with GA	Emissions, NPC, payback, and excess energy	No	PV/WT/FC/ESS/HESS	Electrical	No	Optimised NPC is $192,485, % excess energy of 26%, and 274 kg/yr annual carbon emissions.
[118, 119]	2020, 2022	Optimisation	Emissions, costs, and computational time	Both	Grid/HP/TESS	Thermal	No	The study concluded that net-neutral decarbonisation can be achieved, and various modelling approaches can present computational benefits and high-accuracy results.
[120]	2021	PSO and machine learning	Overall costs, operation, and reliability	Yes	Grid/WT/PV/FC/ESS/EZY/MT/HSS/EV	Electrical	No	An 8% cost reduction in the multi-energy microgrid scenario.

Swarm-Inspired Algorithms

Swarm-inspired algorithms are inspired by the collective behaviour of social animal organisms such as elephants herding, birds flocking, insects searching for food, and fish schooling. PSO, ACO, and other swarm-based optimisation algorithms have significant applications in MES energy management. For instance, Patel et al., in [101], evaluated various techniques utilised for optimal design and size to reduce the costs and emissions of an off-grid MES with a RES. However, these optimisation algorithms can become stuck in their local optima while exploring the search space. These limitations are resolved by carefully selecting the design parameters of the algorithm. Kavian et al. [102] utilised a MOPSO algorithm to optimise the schedule of a vertical ground HP system, which operates in three modes: heating, cooling, and multi-usage. The irreversibility rate is related to the efficiency and energy losses, which account for the amount of exergy (available energy and useful work potential) destroyed in a closed system, representing the wasted work potential. The irreversibility analysis is an important parameter, because the lower the irreversibility rate, the higher the efficiency [121]. The results showed that the average electricity cost per operation time in the multi-usage mode was 27% higher than in the single heating mode and 8% higher than in the single cooling mode. The hourly costs for these modes of operations are USD 0.139, USD 0.143, and USD 0.117 for multi-usage, cooling, and heating, respectively. ACO is inspired by the movement of ants to find the shortest possible path towards food from their nest using their pheromones for communication. A primary limitation of the ACO algorithm is that it can be trapped in the local optima due to excessive pheromone accumulation on suboptimal paths. Zhou et al. [103] used ACO as a benchmark to validate their MES sizing and operation scheduling results. The authors concluded that their proposed discrete immune parallel evolutionary algorithm outperforms the benchmark algorithms, exhibiting an enhanced energy utilisation rate and economic performance. The ACO algorithm's complexity level is not high due to its efficient convergence with an optimal solution within an acceptable computational time, which makes it feasible for use with other optimisation algorithms. ACO-based hybrid algorithms utilise one algorithm for global searches and ACO for local searches. For instance, Ye et al., in [104] designed an ACO and PSO hybrid to solve a nonlinear planning and scheduling problem for MESs. The study was carried out both in the grid-connected and islanded operation modes. The results concluded that the hybrid algorithm is feasible for solving the optimisation problem. The costs of supplying energy in both operation modes are reduced by up to 40–47%. The ACO algorithm is considered slow in starting the search for optimal solutions, whereas the PSO algorithm also has problems with premature convergence towards the optimal solution. ACO often underperforms in real-time applications, where a faster response with optimal results is needed. These individual limitations of each algorithm necessitate the design of a hybrid algorithm to keep a balance between exploration and exploitation dynamics, with higher efficiency in providing optimal solutions.

Wang et al. [105] proposed a multi-objective firefly algorithm, which also belongs to swarm algorithms and is inspired by firefly foraging and these insects' attraction towards a flashing light. The algorithm was applied to optimise the operation of MESs on an IEEE 39 bus system. A series of subproblems are developed, which helps in achieving the optimisation problem effectively. The operational costs with this strategy are reduced by 4.97%, whereas with other techniques, they are reduced by 5.74% and 6.20%. Abdelaziz et al. [106] modified the firefly algorithm for MESs to reduce costs and emissions. The results suggest that the strategy reduced costs and emissions compared to a conventional mathematical dispatch strategy. However, the population and iteration values for the firefly algorithm are usually higher, which increases the computational time. Guo et al. [107] proposed a hybrid algorithm comprising key steps from the firefly algorithm, GA, and PSO algorithms to optimise the system design and operation strategy and reduce costs and emissions. The control strategy decreased emissions and fuel consumption by 10.06% and 8.15%, respectively, with reduced computational time.

Naeimi et al. [108] utilised the cuckoo search algorithm to optimise the design and energetic, economic, and environmental performance. The configuration of the proposed architecture consists of gas turbines, steam turbines, solar thermal collectors, heat exchangers, and absorption chillers, whereas the simulation environment is built in Thermoflow software. The results demonstrated that the tri-objective optimisation problem is achieved and outperforms the NSGAII algorithm. This outperformance of the NSGA II is mainly due to the slower convergence in complex search spaces. Ikeda et al. [109] utilised a metaheuristic algorithm to optimise ESS and TES operation scheduling in an MES for a building. The authors concluded that the metaheuristic algorithms, including the cuckoo search algorithm, are around 135 times computationally faster than dynamic programming for their type of problem.

Hu et al. [110] presented a hybrid grey wolf algorithm inspired by grey wolves' social hierarchy and hunting behaviour to reduce costs and enhanced reliability by managing power fluctuations and optimising consumption. The results demonstrates that costs are reduced to 330595 USD when hybrid GWO was utilised, whereas simple PSO and WSO exhibited around 350694 USD and 344974 USD, respectively. Similarly, reliability is also increased to 0.8985 compared to 0.8930 for GWO and 0.8928 for PSO algorithm. Khadanga et al. [111] developed a hybrid of GWO and CSA to tune the PID controller parameters used for frequency regulation in MESs. Individual CSA and GWO algorithms are used as benchmark techniques. However, various parameters related to CSA affect its scalability, convergence speed, and limited exploration due to memoryless searching. Simple GWO can suffer from limited adaptability and be trapped in local optima. Therefore, to resolve these limitations, several hybrid optimisation techniques based on combining two algorithms are developed, whereas the slight modification and proper tuning of the optimisation techniques can also force the algorithm to perform better in several scenarios. Another hybrid composed of GWO and TLBO was developed by Roustaee et al. [112] for the multi-objective optimisation of multi-microgrids to reduce emissions and costs. The proposed strategy outperforms the benchmark technique regarding costs, reliability, and reducing emissions. Liu et al. [122] proposed a modified GWO to reduce the emissions and costs of MESs. Compared with the conventional GWO, the daily economic costs, emissions, and comprehensive costs of microgrid are reduced by 1.2%, 11%, and 3.27%, respectively.

WDO is another nature-inspired algorithm based on air parcels' motion in the earth's atmosphere. Like ACO, its structure is simple and demonstrates effective results in solving optimisation problems compared to other swarm-based algorithms. Rehman et al. [113] presented a modified WDO algorithm for a smart home load scheduling operated by a RES with ESS. The results were compared with the GA, WDO, PSO, and GWO algorithms. The strategy reduced costs and emissions and peaked at the average rate of 25%, 20%, and 36% compared to the benchmark. Comparatively, WDO is considered more robust and efficient, effectively finding solutions to complex optimisation problems. Another combination of the WDO and water wave algorithms was designed by Krishnan et al. [114] to solve the scheduling problem of RES-integrated microgrids. Using the proposed strategy with PVs and WTs as the input, the costs are reduced by 21% compared to the conventional WDO.

In conclusion, swarm-inspired techniques share similar limitations, such as being trapped in local optima. This limitation can be overcome mainly by fine-tuning the search parameters. This is usually carried out based on experience, by performing meta-optimisation (optimising search parameters) or through trial and error. In all cases, tuning is time-consuming and reflects that improved performance comes at the expense of less robustness in handling complex problems.

2.2.3. Artificial Intelligence Algorithms

AI-based methods are extensively used in the design of MESs. They can be classified into five families: fuzzy logic, game theory, multi-agent, neural networks, and Reinforcement Learning [36]. Figure 5 demonstrates the diverse and impactful role of AI in various sectors of energy systems, whereas Table 4 summarises the studies that adopted AI-based techniques for the energy management of MESs. One of the techniques based on AI, game theory (GT), is widely used to model and predict consumers' behaviour in DRPs. A GT-based MES operation strategy was proposed by Liu et al. [123] to reduce emissions and costs (fuel costs) by promoting the penetration of RESs. The strategy cut 10.5 kton of emissions per year with 100% RES energy production and reduced the use of fossil fuels. Wu et al. [124] proposed a two-stage GT model for MESs consisting of smart metres to participate in energy markets. The proposed strategy is compared with the time of use of a tariff-based system. The results confirm that the proposed strategy effectively reduces energy costs and the peak-to-average ratio. Mitridati et al. [125] presented a strategy for decentralised energy systems to balance the energy used by prosumers. The strategy effectively performs energy trading and demonstrates the trade-off between the efficiency stability and incentives provided by energy operators.

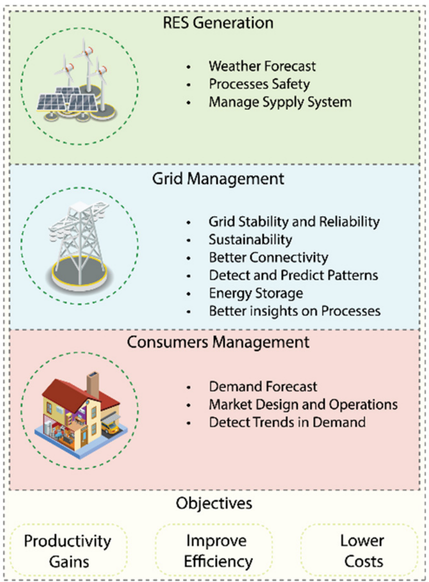

Figure 5. AI applications in MESs [126].

A fuzzy controller energy management and frequency regulation system in MESs is proposed by Yu et al. [127]. The results show that the system's production costs are minimised, and revenue is increased. In another work, a fuzzy controller is proposed to utilise the waste heat produced during the FC electrochemical reactions by Ma et al. [128]. The results show that the FC with the fuzzy control-based strategy works efficiently and reduces the operation time of the CHP unit for a household.

Coccia et al. [129] proposed an MPC-ANN-based management strategy to increase the self-consumption of RESs in grid-connected scenarios. With the use of MPC-ANN, up to 70% of energy consumption is reduced compared to the rule-based technique. In another work, Buffa et al. [130] presented an MES management strategy for large-scale residential users based on an MPC-ANN to reduce energy consumption in peak hours. Advanced controllers utilised DRPs from the grid to use low-price electricity for hot water tanks. The strategy rescheduled the operation time from peak hours to off-peak hours, resulting in a 3.5% reduction in utility bills. Figure 6 illustrates the functioning of the strategy utilised by Luo et al. [131] to solve energy management problems related to the design and operation of MESs with RES to increase computational efficiency and accuracy. The problem is modelled as a bi-multi-objective strategy where the government determines the optimal subsidy policies (upper level), and the residents optimise the HRES design and operation (lower level). ANN data are trained using the results from lower-level optimisation, which further enhances the accuracy while supporting decision-making and system design. The strategy utilised 57.01% of the solar energy of energy consumption in the standalone mode.

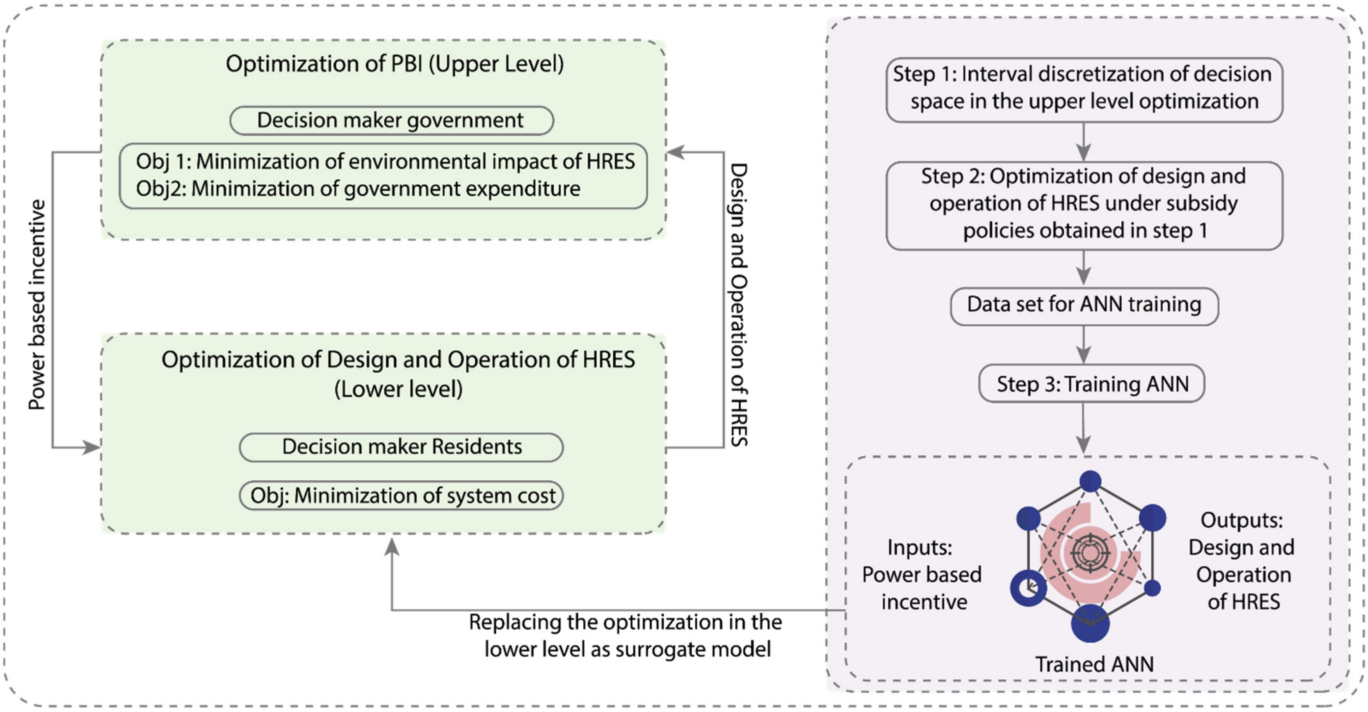

Figure 6. Flowchart of ANN-based hybrid algorithm for multi-energy management [130].

Q-learning falls into the reinforced learning category, enabling its capability of iterative learning over time with improved results. A Q-learning-based algorithm is proposed for balancing power and reducing the load fluctuation and peak load regulation cost for residential homes in a coastal area by Lingmin et al. [131]. The strategy outperforms the GA- and PSO-based techniques in balancing power and load fluctuations. However, the peak load regulation cost is higher when compared to the PSO- and GA-based results. Chen et al. [132] proposed a strategy based on a reinforced learning multi-objective optimisation algorithm for 140 generating units of MESs. For this purpose, the authors considered and applied the reinforced learning-based multi-objective optimisation algorithm to determine and adjust the control parameters. The results suggest that the control strategy reduced the overall costs and emissions compared to other multi-objective optimisation algorithms deployed in the same scenario. These analyses highlight that while implementing MESs requires a significant initial investment, long-term operational savings, increased revenues, and environmental and social co-benefits can lead to attractive returns on investment and greater economic resilience for residential stakeholders.

Heuristic algorithms like GA or PSO, which efficiently provide near-optimal solutions, are nonetheless sensitive to parameter tuning and may converge prematurely. AI-based approaches dynamically adjust to evolving operational contexts and implicitly handle complex constraints through learned representations [133]. Empirical studies in microgrid energy management and multi-energy system scheduling demonstrated that AI-based optimisation achieves a solution quality comparable to or exceeding that of conventional and heuristic methods and significantly reduces computational overhead in real-time applications. Consequently, integrating AI-based optimisation is increasingly recognised as a critical enabler of the next generation of MESs. The computational complexity of the AI-based framework for energy management depends on several factors, including the dataset's dimensionality, the model framework's design, and the specific objectives related to energy tasks (like demand forecasting or grid optimisation). To evaluate this complexity rigorously, it is essential to quantify the efficiency of algorithms in terms of runtime, memory usage, and scalability, especially when dealing with large-scale energy systems. More specifically, AI techniques are used for optimising energy-efficient navigation routes for autonomous agents, dynamic resource allocation in smart grids, or deploying infrastructure in distributed renewable networks. AI can make a decision ensuring low latency and high robustness to changing factors, such as varying energy prices or intermittent RES generation. Therefore, the framework's ability to adapt to these trade-offs is crucial for its effectiveness in operational environments, where computational efficiency directly affects system responsiveness and economic outcomes [134].

Table 4. Summary of studies utilising AI- and machine learning-based optimisation techniques reviewed in the current work.

Ref.	Year	Technique	Objectives	On-Grid?	Architecture/Topology	Loads	Implementation	Outcomes
[123]	2021	GT	Emissions and costs	Yes	Grid/PV/ET/CHP/HP/EC/AC/ESS	Electrical	No	Cut 10.5 kton of emissions per year with 100% RES energy production.
[124]	2018	GT	Emissions and costs	Yes	Grid/GB/HE	Electrical, Thermal	No	Effective in reducing the energy costs and peak-to-average ratio.
[125]	2021	GT	Efficiency, stability, and costs	Yes	Grid/PV/WT/CHP/EB/HP/ESS/TES	Electrical, Thermal	No	Reduced costs via trade-offs among the key objectives while participating in energy markets.
[126]	2019	FLC	Frequency oscillations	Yes	Grid/PV/FC/WT/CHP	Electrical, Thermal	No	Effectively controlled the frequency oscillations of each component of MESs.
[127]	2022	FLC	Efficiency and utilisation of FC	Yes	Grid/FC/ESS/TES/CHP	Electrical, Thermal	No	Efficiently increased the operation time of the CHP unit.
[128]	2022	ANN	Energy consumption and costs	Yes	Grid/CHP/PV/HP	Electrical, Thermal	No	Reduced energy consumption by 70%.
[129]	2020	ANN and MPC	Energy consumption and costs	Yes	District heating network with various MES	Electrical, Thermal	No	Reduced energy consumption by 3.5%.
[131]	2023	ML	Load fluctuations, peak load regulation, cost, and balance of power	Yes	Grid/WT/PV/CHP/TES/ESS/EV/HP.	Electrical, Thermal	No	Achieved balanced power and load fluctuation with a higher cost than the PSO- and GA-based algorithms.
[132]	2023	RL	Emissions and costs	Yes	Grid/CHP	Electrical, Thermal	No	Control strategy reduced the overall costs and emissions.
[133]	2019	Exergo-economic optimisation	Design and overall costs	No	PVT/CCHP/TES/HP/HE/CE	Electrical, Thermal, Cooling	No	Reduced specific cost of the system products by 6.4%.
[134]	2020	Modelling in TRNSYS	Operational cost, emissions, and efficiency	Yes	Grid/PVT/MGT/GG/GT	Electrical, Thermal, Cooling	No	Efficiency of 34% and 0.12 ton/MWh of emissions is achieved with a cooling capacity of 4906 kWh.

2.2.4. Other Scheduling Techniques

Optimisation studies that used techniques other than those presented earlier are grouped here and summarised in Table 5. These techniques include rule-based optimisers, exhaustive search, and proprietary solvers embedded in commercially available software. These techniques have limited customisability but are general enough to be applied to different problems without much tuning [135]. The downside is that they can be computationally expensive for large problems [136]. These optimisation techniques main aim is to utilise RES and increase self-utilisation of local RES generation [137]. techniques Facci et al. [138] utilised the PV-HPs system to fulfil the heating and electrical demands of the residential consumer. Reductions of 41% in energy costs and 73% in CO_2 emissions were achieved compared to the benchmark system using natural gas heating. Wu et al. [139] presented a two-stage rolling dispatch strategy to reduce energy consumption and address the scheduling problem. The operation costs are reduced by 14.55%, and the utilisation of renewable energy is increased by up to 13.3%. Mago et al. [140] proposed the following (thermal or electrical) load-based strategies to reduce energy consumption and carbon emissions. The system is designed to meet the electrical, heating, and cooling demands of a building through a grid, fuel-based power-generating unit, boiler, chiller, and heating coil. The system models are tested in different cities with different climatic conditions. Following thermal loads reduced the primary energy consumption, energy costs, and emissions compared to the electric load. This is due to the waste heat utilisation in the CCHP and CHP modes. Patteeuw et al. [141] designed a load scheduling strategy for improving the electric grid flexibility and operation of residential buildings. MPC is leveraged to manage the operation of HPs and thermal load. Each user can participate in DRPs. Two DRPs—direct load control and the dynamic time of use tariff—are used to evaluate the effectiveness of HPs powered by RESs. The strategy achieves a reduction of 5% in operational costs and a 6.6% reduction in emissions. Kumar and Tewary [142] conducted a techno-economic assessment of standalone hybrid energy systems using a HOMER simulation toolkit. The authors utilised an optimisation-based strategy for the operation of RESs with BSS and diesel generators to meet the electrical energy requirements of the off-grid consumer. The strategy generates 19.3% excess electricity of the required amount of energy annually, thus reducing the overall operational costs and increasing the reliability of the standalone urban hybrid generation system. Wang et al. [143] proposed an operation mode-based strategy for MESs to reduce emissions and improve energy saving, exergy, and efficiency. These operation modes include thermal and electrical demand management modes. Each mode of operation can produce the required energy to meet the thermal and electrical load. Considering the case of a commercial building in Beijing, China, simulation-based environments are studied. The results indicate that the performance of the system model is more effective and efficient in winter than in summer because of the use of heating energy. The exergy efficiency is improved by 16.1–19%, emissions reduced by 25.1%, and energy savings of 42.7% are recorded. The application of optimisation techniques is not limited to the on-site MES; Yang et al. [144] introduced a two-stage robust planning method designed to maximise the net present value. The optimisation-based strategy leads to a 10–15% reduction in energy costs for the MES hub within a cruise ship.

Table 5. Summary of studies utilising other rule-based optimisation techniques reviewed in the current work.

Ref.	Year	Technique	Objectives	On-Grid?	Architecture/Topology	Loads	Implementation	Outcomes
[138]	2019	Optimisation	Cost, emissions, and energy consumption	Yes	Grid/PV/GB/AC/HP/TES	Electrical, Cooling, Thermal	No	Energy cost savings of 41% and up to a 73% CO_2 emission reduction.
[139]	2023	Second-order cone relaxation method	Utilisation of RES and overall costs	Yes	Grid/PV/WT/nGT/ESS/FC/DG	Electrical, Thermal	No	HRES utilisation increased by 13.3% and 14.55% reduction in operational costs.
[140]	2009	Load following method	Costs, emissions, and energy consumption	Yes	Grid/PGU/GB/AC/HC	Electrical, Thermal, Cooling	No	CHP-FTL-based mode reduces the energy consumption, emissions, and costs.
[141]	2016	Day-ahead optimisation	Costs and emissions	Yes	Grid/HP/PV/WT/EV	Electrical, Thermal	No	Operational costs were reduced by 0.9% and 5.5%, and emissions between 0.4% and 6.6%.
[142]	2022	Optimisation using HOMER	Costs, efficiency, and operation optimisation	No	PV/WT/DG/ESS.	Electrical	No	Excess electricity of 19.3% is generated annually.
[143]	2011	Operation mode-based strategy	Emissions, energy saving, and exergy efficiency	Yes	Grid/CHP/GB/HC/CCHP	Electrical, Thermal, Cooling	No	The exergy efficiency is improved by 16.1–19%, and emissions are reduced by 25.1%, with 42.7% energy saving.
[145]	2023	Optimisation and designing	Efficiency and COP of the air-source HP	No	Grid/PV/HP/TES	Thermal	Yes	Yearly self-consumption, self-satisfaction rates of PVs, and the COP of the air-source HP increased by 131.25%, 10.53%, and 9.56%, respectively.
[146]	2021	HRES energy management using TRNSYS	Energy consumption and efficiency	Yes	Grid/PV/TES/TLC/HP DWH/ESS	Electrical, Thermal	No	Energy consumption is reduced by 13%, and electricity purchased from the grid for water heating is reduced by 90% while using PV-HP.

2.2.5. Comparative Analysis

As discussed earlier, the optimisation techniques used to solve problems related to energy management in MESs mainly include mathematical programming-based techniques. Each method exhibits distinct strengths and limitations concerning complexity, sensitivity, and solution quality. Methods like MILP are valued for their ability to ensure global optimality and manage complex constraints, which makes them suitable for MES optimisation related to design, operation, and dispatch strategies. However, the computational complexity of MILP increases exponentially with problem complexity, size, and constraints. Due to these limitations, MILP becomes impractical for solving large-scale and highly nonlinear problems, increasing computational time and complexity. In contrast, metaheuristic algorithms such as GA and PSO can effectively explore large, non-convex and multi-model solution search spaces to find an optimal solution to a complex problem. Delivering nearly optimal solutions in significantly shorter time frames often comes at the expense of guaranteed optimality and requires careful tuning of the parameters and constraints. The quality of Pareto fronts produced by these methods is typically inferior to those generated by MILP, especially as the constraints become more complex or numerous. Advanced control techniques, such as MPC, strike a balance by excelling in real-time operational control. They incorporate forecasts and adapt to uncertainties. However, their effectiveness is highly sensitive to the prediction horizon, the models' accuracy, and the computational burden they impose. Reinforcement Learning (RL) strategies, while promising for adaptive and data-driven control, still encounter challenges in handling constraints and managing high-dimensional state-action spaces. In many realistic scenarios, they often underperform compared to MPC. Case studies in residential energy systems consistently show that while mathematical optimisation provides the most robust and cost-effective solutions under strict constraints, metaheuristics and hybrids of RL and MPC offer practical alternatives for faster, scalable, and adaptive control, incredibly when computational resources or model accuracy are limited.

Ultimately, the choice of optimisation technique depends on the trade-off between computational tractability, sensitivity to model and parameter uncertainties, and the rigour needed for constraint satisfaction. Hybrid and decomposed approaches are increasingly preferred to leverage the advantages of each method in complex energy management applications.

2.3. Demand Response Programmes (DRPs)

Demand-side management strategies are widely utilised in the field of residential MESs. DRPs' prime objective is to manage or modify the energy consumption pattern of the user by offering a price or incentive to shift loads to a more convenient time for the provider. There are two primary types of DRPs: price-based DRPs and incentive-based DRPs. There are various types of DRPs, which are discussed below. In price-based DRPs, consumers are charged differently multiple times to encourage the change in consumption patterns during the peak demand hours. Using incentive-based DRPs, users are incentivised by energy operators to change their energy consumption patterns during peak demand hours. These incentives are usually adjusted as bill credits or discounts on future electricity bills. DRPs have been effectively implemented in residential MESs, significantly reducing energy consumption and costs. For instance, a real-world implementation in a UK neighbourhood with 66 homes showed that DRPs, managed through a cloud-based AI framework, allowed for the automated scheduling of controllable appliances like dishwashers, washing machines, and dryers. This strategy prioritised locally installed PV generation over importing from grids with variable energy pricing tariffs. As a result, the community experienced an average reduction of 30% in energy costs and a 25.5% decrease in the daily peak load, all while ensuring grid stability and complying with low-voltage constraints [147].

2.3.1. Price-Based DRPs

Real-Time Pricing

Real-time pricing (RTP) adjusts the energy prices for the consumers following the market prices; it is communicated in real-time to the consumers' smart metres. For competitive energy markets, RTP is considered one of the appropriate IDRPs because of real-time energy market price signal regulation. Therefore, various recent studies adopted this type of IDRP in the field of multi-EMS, which led to significant reductions in peak demands and operational costs [148]. Jin et al. [149] implemented real-time IDRPs for optimal MES operation management for residential buildings, reducing the peak load demand by 17% and energy costs by up to 8.8%.

Critical Peak Pricing

Operators use critical peak pricing to manage energy demands by charging significantly higher prices to reduce electricity usage during peak demand periods, typically lasting 4–5 h. Consumers are encouraged to shift their energy usage to non-peak hours, thereby reducing the load on the grid, which helps stabilise the grid, reduce the risk of blackouts, and contribute to a more efficient and reliable energy system. Wang et al. [150] conducted a study related to the residential EMS to reduce energy demand during peak hours. The mechanism connects the user and supply via communication infrastructure for energy price regulation. It was shown that energy consumption during critical hours decreased and that the supply-demand balance increased. Lin et al. [151] also utilised a critical peak pricing DRP to reduce the grid peak load and enhance reliability and security, reducing energy bills by scheduling the loads to low energy pricing hours.

Time of Use

Time of use is one of the most widely used IDRPs. Tariffs are changed at different time slots, and consumers are encouraged to utilise the low energy prices. The consumers adjust the loads following the energy price, which leads to reduced energy consumption and, eventually, lower energy bills. Qi et al. [152] demonstrated dynamic control of the DG systems with DRPs, which leads to reduced operational costs and energy savings for consumers. Sichilalu et al. [84] and Firouzmakan et al. [153] demonstrated that leveraging TOU, real-time pricing (RTP), and the inclining block rate (IBR) can effectively reduce energy consumption and costs compared to RTP and IBR.

Extreme Day

The extreme day tariff resembles critical peak pricing; however, an extreme day tariff is leveraged to lower the energy demand during critical situations such as energy market or grid instability. This is also utilised when there is a risk of system failure due to intense weather conditions. Extreme day tariffs can motivate consumers to invest in energy-efficient technologies and practices, as doing so can help them avoid high energy pricing periods and reduce their overall energy bills [154].

2.3.2. Incentive-Based DRPs

Incentive-based DRPs have two major types: market-based and conventional DRPs, which are discussed below.

Market-Based DRPs

Energy Bidding

In energy bidding, the consumers give the control of loads to the operators to reduce the load during peak hours, and in return, consumers receive revenue, perks, and incentives.

This DR programme can benefit the consumer, as depending on the market conditions, the energy price increases, and in this way, consumers can earn more when actively participating in energy markets. Several research works utilised market bidding DRPs; for example, Ostadijafari et al. [155] proposed a strategy for residential consumers to participate in the wholesale energy market. Further, a stochastic optimisation technique is utilised for the day-ahead demand bids, and the system is tested on the IEEE-123 bus system to evaluate performance based on demand bidding for energy consumption cost reductions.

Ancillary Service Market

In this demand response scheme, the consumers suggest the threshold to which they can reduce or curtail energy consumption to receive a market clearing price from the providers. The energy management controllers installed at the user's premises should quickly respond to the changes required by the operators during peak demand hours. Canizes et al. [156] utilised such DRPs to mitigate grid flexibility, voltage, and congestion issues through the participation of residential consumers in a low-voltage distribution network.

Conventional Incentive DRPs

Curtailment DRP

The curtailment demand response scheme is a load scheduling strategy where a group of users apply and then select the load, and later, the operator provides directives to the users to limit or reduce the energy consumption in certain hours to reduce the peak demand periods for the operator [157]. In this way, the users can earn incentives, operators' grid reliability is increased, and the risk of system failure is mitigated [158].

Direct Load Control

Direct load control scheme users give the energy supplier access to appliances' operation schedules, which enables the supplier to control the operation of user loads during peak hours or critical events. This strategy reduces the user's energy consumption, mitigating blackouts and load shedding and increasing grid flexibility and reliability during peak hours. Calver et al. [159] demonstrated that HPs installed at the users' premises can be controlled by energy operators to manage their energy consumption. The users are also offered additional benefits besides the reduced monthly energy bills. Sridhar et al. [160] also demonstrated the effectiveness of the direct load control scheme considering residential consumers, which showed that consumers' participation could yield enhanced flexibility of the power systems.

3. Laboratory Deployment

3.1. Energy System Tools and Software

The technical and economic evaluation of microgrids with various energy inputs and conversion units is crucial for effectively assessing the overall system. This requires using software tools for modelling to evaluate multiple topologies economically and technically. Several software tools are mentioned in the literature to study and assess various aspects of the MES. HOMER, TRNSYS, EnergyPlan, energyPro, MATLAB, Dymola/Modelica, RETScreen, BALMOREL, BCHP Screening Tool, SOLSIM, Invert, and HYBRID2 are some of the most widely used mathematical and model-based software tools for the evaluation of MESs. Prefeasibility studies, sizing, integration, simulation, and comprehensive economic, technical, and environmental analyses of an MES architecture were carried out. HOMER is widely used to determine optimal sizing and energy flow within an energy system for a standalone or grid-connected microgrid [161]. Technical and economic assessments can be carried out for various combinations of generation, conversion, and storage units. Similarly, TRNSYS has become a hybrid simulator that models and simulates electrical, thermal, and cooling systems. Its library comprises RESs, building models, HVAC systems, and optimisation models, facilitating comprehensive MES analysis. EnergyPlan is a tool used to design and simulate MESs from a smaller scale to a larger scale, exploring scenarios for transitioning to a 100% RES. It is mainly known as a simulation tool rather than an optimisation tool. Similarly, energyPro is also used to design and model single or thermal MESs. This tool can also be useful for designing and analysing DHN integrated with various RES resources [162]. MATLAB/Simulink is a high-level programming language and numerical computing environment that provides a powerful platform for designing and optimising MESs. A wide range of optimisation, control, and electrical power system components are available, which can be used to model MESs and conduct various analyses. Modelica can be useful to handle the complexities of MESs, including the integration of optimised RESs. A toolkit of Modelica, OPTIMICA, offers advanced features for the automation, simulation, and optimisation of energy systems [163]. BALMOREL, developed using the GAMS language model, also can analyse MESs. DHN, CHP, storage, and RES-based generation units can be modelled and analysed [164]. The BCHP Screening Tool and SOLSIM are also specifically designed and developed to analyse small-scale projects, including commercial ones, to fulfil combined heat and power [165]. Large-scale MES implementation and analysis cannot be carried out using the BCHP Tool. Hybrid2 was developed to analyse the MES's performance in the long term and to provide insights into various performance indicators, including costs, emissions, and efficiency [166]. Furthermore, forecasting and probabilistic techniques can also be used to predict energy demands and generation. However, this software tool also has limited access to adding various parameters and, hence, less flexibility.

3.2. Choice of Physical Technologies

The design and deployment of MESs require various component analyses based on the capacity requirements, availability of the required sizes, project goals, capital costs, etc. The choice of physical technologies can also be significantly affected by the type of energy the consumers demand. A detailed description of the required multi-energy microgrid equipment and standards can be found in [167]. RES-based multi-energy generation systems can also provide electrical and thermal energy simultaneously, including PVT collectors. Detailed studies were carried out by Herrando et al. [168] and Sirin et al. [169], demonstrating that installing PVs and WTs for electrical energy greatly facilitates electrified heat production using electrical boilers, HPs, FC, etc. The cost of installing PVs is lower than that of PVT collectors, as they are not yet as mature a technology as PV. Energy storage units have also been installed to improve MES operation. ESS can help avoid peak demand, schedule the load effectively, and reserve energy for peak tariff price periods. However, installing these generators and storage systems can be costly for laboratory deployments and experiments; therefore, to lower the costs of experiments, various studies utilised signal generators to mimic the energy output of energy input vectors, e.g., FC and WTs, etc. [170]. A study by Cagnano et al. [171] explains the key characteristics and structure of the PrInCE Laboratory [172], developed at the Polytechnic of Bari, to carry out various simulations related to the MES. The laboratory includes multiple energy inputs, including electrical, thermal, and cooling. The electrical and thermal components consist of 120 kW NG-CHP, 30 kW NG-MT, 50 kW PV, a 60 kW wind simulator, 210 kW of ESS with a maximum charge/discharge capacity of 60 kW, 120 kW of programmable loads, and a V2G mode of operation as well. The modelling of the overall system is greatly facilitated using simulation models, which include the white box, black box, and grey box modelling. While the white box modelling approach considers the detailed energy dynamics, black box modelling is data-driven and mostly takes data profiles as the input and grey box modelling combines both white box and black box modelling approaches to facilitate the simulation process and get close to the real-life implementation and behaviour of the simulation model. For instance, Ghillardi et al. [73] demonstrated using a single-state grey box model derived from [173] for a building load to lower the computational time and operation control using a TRNSYS white box model. Johnson et al. [174] modelled and simulated a grid connected hybrid RES using TRNSYS to supply load to multi energy user. A multi objective optimisation-based energy management strategy demonstrated achievement of 80% solar friction with 6.9 years of payback time for whole investment. The challenges related to implementing MES energy management include modelling and testing the technologies and replicating the behaviour of the energy conversion and generation systems.

3.3. Choice of Controller

Sophisticated control strategies are adopted to maximise the efficiency and self-utilisation of RES-integrated MESs. Hardware-based implementation is used to validate the control topologies. The laboratory setup can be classified into four categories, namely the hardware-in-the-loop (HIL) microgrid, hybrid microgrid, real microgrid, and simulation-based microgrid. The HIL microgrid architecture involves the real-time simulation of the microgrid using physical components, e.g., ESS, RES modules, loads, etc. A hybrid microgrid scenario refers to using various physical components integrated for experimentation. It can be a valuable tool for assessing microgrid functioning on an experimental scale. Small-scale real microgrids are developed to facilitate the experimental validation. Some examples of real microgrid facilities for research can be found in [175]. The simulation-based microgrid is a mathematical modelling-based representation of a real microgrid. This type is the initial setup of microgrid experimentation, which is later deployed using physical controllers and hardware. A detailed study on microgrid development can be found in [176,177]. The two most common setups used for laboratory experiments are hardware-in-the-loop and hybrid microgrids. These setups present balanced approaches that ensure reliable outcomes during the practical implementation of microgrid setups. MATLAB/Simulink is the most common software used in the hardware-in-the-loop and hybrid microgrid setups. The software interacts with the hardware connected with it in real-time using a control system such as dSPACE, PLC, or FPGA [178], which are popular hardware-based controllers and are widely used in the industry. The dSPACE control system serves as a real-time interface between the simulated microgrid setup (e.g., on Simulink) and hardware components (e.g., converters and programmable loads) [179]. Donoso et al. [180] used a dSPACE ds1103 controller with a SPARTAN 3 FPGA control system for a grid-connected microgrid. The MPC-based algorithm produces a fixed switching frequency for a grid-connected three-level neutral point-clamped converter. The controller maintains a fast dynamic response in the presence of uncertainties, limiting the total harmonic distortion to under 2% for the current supplied to the grid. Arafa et al. [181] utilised the dSPACE ds1202 controller for the real-time implementation of the GWO optimisation algorithm with the PID and fuzzy logic controllers to carry out the real-time implementation of the algorithm with the hardware. Along with the dSPACE controller, several other controllers are also utilised to implement the control strategy practically using hardware. Gundogdu et al. [182] used an FPGA, dSPACE, and Altera DE2-115 control board to implement an algorithm for direct torque control of a three-phase induction motor as hardware-in-the-loop. The authors used MATLAB/Simulink for the simulations and performed the practical implementation using the FPGA control board. The developers of dSPACE continuously update the documentation about implementing various models through manuals for implementation purposes. However, there is limited information regarding the practical implementation of real-time simulations, especially in a hybrid multi-energy microgrid. Therefore, there is a need for further exploration and documentation in the area of MESs' practical implementation and energy management.

3.4. Energy Management Strategy Implementation

Modelling and simulation-based theoretical study are essential in evaluating system model performances. Theoretical study implementation into actual hardware-based setups is often considered impractical or expensive. Research studies often focus on theoretical validation; however, several studies practically implemented their proposed strategies, which are discussed in the current section. Li et al. [183] demonstrated that optimal sizing, planning, and investment costs for the system model's deployment and implementation result in increased profits with low investment costs. Various uncertainties related to the energy balance are added to the system's design. The MES consists of PVs, WTs, CCHP plants, electric boilers, and a supply from the utility grid. ESS and TES are installed to manage the energy flow during critical hours. The profits gained using the proposed control strategy were three times more than those gained using the benchmark strategies, where ESS and TES are controlled separately. With uncertainty added, the system model exhibited a total of a 2.47% increment in profit with MESs and demand-side management. Tiar et al. [170] designed an intelligent fuzzy controller-based strategy. They demonstrated its performance using hardware to switch the mode of operation between the local hybrid microgeneration system and the grid. A back-stepping technique-based inverter was used to control the front-end single-phase inverter. The fuzzy logic-based intelligent controller was deployed with the PV to maximise the extracted power from the PV. The work was implemented in a lab with a test system consisting of dSPACE 1104. The FC stack supply was reproduced using a continuous DC supply with boost choppers and grid-connected voltage-source inverters. An interface card was employed to connect the convertors and controller and to sense voltages and currents. The results show that the maximum power was extracted from PVs. The excess power was sold back to the grid, and the invertor-based strategy was optimally utilised for switching purposes. However, the authors did not consider uncertainty in the load. In another work by Elsied et al. [184], the dSPACE 1104 controller is used for practical implementation in a laboratory with a GA optimisation technique connected with MATLAB and ZigBee as a communication network. Li-ion batteries and four DC supplies with variable energy supplies are used to replicate the energy output of the generation architecture. Two programmable DC loads are connected to the system, and the demand profile can be added accordingly. The work demonstrates the performance of the control strategy in utilising low-price electricity from the grid and exporting the excess electricity from the RES back to the grid to gain more profit. Pean et al. [185] presented an experimental control strategy based on the MPC controller to minimise energy costs and emissions and increase thermal comfort in a residential building in Spain. The costs, flexibility, emissions, and thermal comfort of the user are considered in the study. Flexibility is achieved via the optimised shifting of the thermal loads of the building towards periods of lower electricity prices or grid CO_2 emissions. TRNSYS is used to model the building, MATLAB is used for the MPC algorithm, and LabVIEW is used to exchange commands and information as the main simulation software. The HP produces the required energy for the DHW by charging a 200-litre TES. The HP can produce 11 kW of heat with a COP of 3.9 in the heating mode and 7 kW of energy produced in the cooling mode. The operational costs and emissions are reduced by 7% and 17%, respectively. Simko et al. [186] demonstrated PV-powered HP operation, which produces thermal energy stored in a TES for space heating and DHW. The energy system consists of a 6.5 kW inverter powered by 20 PV panels of 325 W each, with a payback period of 7 years. The air-to-water HPs can operate in the cooling or heating mode. The excess heating and cooling energy is stored in TES. A similar study was also carried out by Velasco et al. [187] to meet the DHW and space heating demand using a water-to-water HP with a TES. LabVIEW software is used for data acquisition. The results showed an increase of 12.4% in the system's global COP and a reduction of 16% in the compressor's energy consumption compared to other strategies.

Atienza-Marquez et al. [188] conducted a comparative study considering a hospital producing and distributing hot water using electricity from a grid and an RES installed locally. The authors considered a 440 kW gas-fired boiler that could boil the water to 90 °C to limit the rise in harmful bacteria. The model was built using TRNSYS software, and techno-economic analysis was carried out. The model reduced the thermal losses by up to 70% and the overall hot water production cost between 15 and 45%. In contrast, the cost-optimised strategy increases the solar caption area by up to 45–50%. Jahanbin et al. [189] demonstrated a practical study to assess the production of DHW and storage using TRNSYS and MATLAB, followed by implementation. The annual energy cost was reduced by up to 5.2%, whereas the thermal losses occurring at different components were also enhanced by up to 4%. Brka et al. [190] used an ANN for the power management of the consumer, supplied by a PEM FC integrated with HSS. This system model was implemented practically in a laboratory. The results of the experiments demonstrated that the implemented system model prevents the loss of power supply during the transient start-up time.

3.5. Communication Infrastructure

The communication infrastructure installed for achieving intelligent operation within a smart grid paradigm is powered by the IoT and ICT, which enables real-time monitoring, control, and the reporting of energy interruption and abnormal events. Figure 7 shows the role and importance of using a communication network in different smart grid sectors to ensure that the energy is balanced via the bidirectional flow of power using red arrows and communication flow using blue arrows. These components are connected by a centralised/master controller capable of managing the operation schedule. The controller functions include monitoring, logging, and executing the control strategy. The monitoring phase is used to monitor the users' demand and energy availability information, the logging phase processes the data, and controlling deals with load operation management.

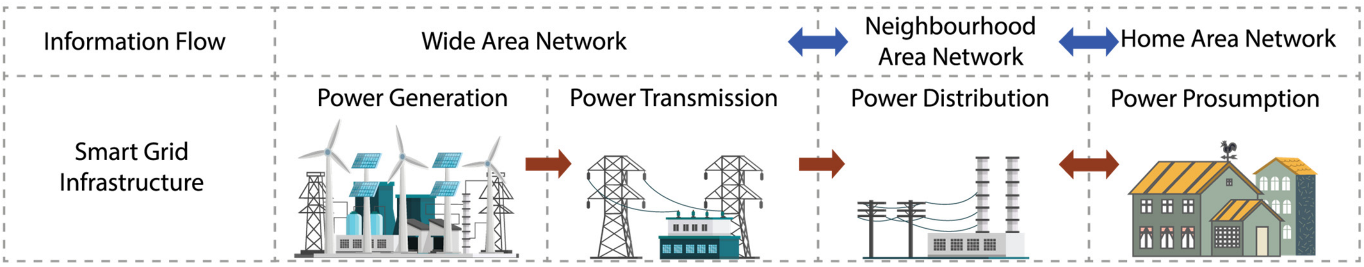

Figure 7. Role and importance of communication in the smart grid infrastructure.

The residential EMS works as a closed-loop system with the input signal (generation data) and output signal (demand data). Energy balancing in the residential EMS is achieved by taking the users' energy demand signals. IoT infrastructure has three layers, which together make a network that can communicate and monitor the components of MESs to facilitate an intelligent EMS. Communication infrastructure is categorised into the following technologies.

There are multiple protocols and several ongoing developments in communication and interoperability technologies. A multi-energy smart grid was constructed at the University of Bari in Italy [172,191]. The pilot project uses the SCADA platform to carry out tasks related to power management and implementing control strategies. The hardware is connected through a three-level control. The first level uses local controllers, which can receive control signals and execute functions. The second layer ensures the optimal operation of the microgrid, which uses fibre optics as the communication medium, with two programmable logic controllers responsible for executing control functions. The second layer's communication is mainly carried out using Modbus/TCP IP protocols. The communication and information flow received at the second layer from the first layer uses Ethernet. The third layer is designed to connect with the MATLAB/Simulink to design and evaluate hardware in the loop simulation. These protocols and standards are adopted to ensure reliability and security in energy and power management within a smart grid through interoperability, advanced cyber security mechanisms, and robust data handling. Some of these standards and protocols are also adopted within a pilot developed under the InteGridy project [192] to install smart metres to support DRPs (see more details in Section 4.1.7). The smart metres are installed using several protocols, including the following: IEC 61970 for standard information model and energy management, IEC 61850 for power utility automation, IEC 61968 for standard information model and distribution management, IEC 62351 for ensuring security, and IEC 62056 for data exchange for metre reading and tariff and load control.

3.5.1. Home Area Network (HAN)

The HAN typically involves a communication framework between smart metres, the master controller, and appliances. This communication is usually done using standardised protocols, such as Zigbee, Z-Wave, a wired network, and Wi-Fi. Zigbee, Z-wave, WiFi, and 6LoWPAN are some of the wireless networks used to facilitate the communication infrastructure for the HAN. Danbatta and Varol [193] compared the wireless technologies in smart home energy management and operation. These technologies facilitate reductions in costs and energy consumption and ease real-time information sharing among components. A comparison of the different wireless technologies used in energy management within the residential sector is shown in Table 6. Advanced metering infrastructure (AMI) along with the HAN can optimise the operation of MESs. Pandraju et al. [194] utilised the HAN and the AMI to ensure the monitoring and transferring of power between the energy supplier and user. The smart metres enhance the performance of the AMI in monitoring the low-voltage networks. Energy providers can control the energy loads to reduce the user's costs. The authors concluded that the system model can effectively reduce the network loss rate by up to 0.155%.

HomePlug

HomePlug is a technology widely adopted in smart homes for high-speed wired communication across appliances. It enables the transmission of Ethernet data through an existing electrical system, allowing devices to communicate with each other and the Internet. Sensors are usually installed to monitor and control the temperature for DHW and space heating, lighting, door locks, and smart appliances. Jin and Kunz [195] utilised a HomePlug and Zigbee based on IEEE 802.15.4 to receive and deliver information on appliance usage patterns. Zigbee and HomePlug are spread out across an entire home through sensor nodes to share information with the master controller. Rehman et al. [196] utilised the wired HomePlug system for smart appliance management and communications with the controller. Various electric appliance operation patterns are optimised using optimisation algorithms. The optimised scheduling pattern is then communicated with the appliances to achieve multiple objectives concerning costs, emissions, and the peak-to-average ratio.

Ethernet

Ethernet is a common technology widely used in household appliances, including laptops, servers, printers, audio-video (AV) equipment, and game consoles. Ethernet supports a range of data rates (10 Mbps–1 Gbps) via optical fibres up to 10 Gbps. Considering the high costs of the equipment and installation, which make it a less suitable option for communication technology for a smart home, Sisavath and Yu [197] presented a smart home model to make smart homes easy to use, utilising IoT applications and technologies. The authors used an ethernet service controller, LPC 1769, embedded in an ethernet module for building communication infrastructure. This layer of communication was used for the controller and appliances.

Insteon

Insteon is a wired technology that can transmit and receive data on appliance operations without a master controller and can manage the scheduling of appliance operations. Insteon is utilised by Khan et al. [198] for communication between appliances and components to build infrastructure for a smart farmhouse. This communication technology is employed to monitor and control the environment and appliances of the farmhouse remotely.

Table 6. Comparison of different wireless connection technologies for smart home energy management [199].

Indices	Z-Wave	Zigbee	Bluetooth	WiFi
Standard	IEEE 802.15.4	IEEE 802.15.4	IEEE 802.15.1	IEEE 802.11
Power Consumption	1 mW	100 mW	10 mW	High
Scalability	>6000	6000	20	32
Cost	High	Low	Very low	Medium
Range (metres)	30	100	10	1000
Frequency band	868.4 MHz	2.4 GHz	2.4 GHz	2.4/5 GHz

Finally, in the context of smart buildings, emerging technologies for structural health monitoring are becoming more critical in optimising the operations of MESs, both from the source and load sides. They provide capabilities for real-time assessment, predictive maintenance, and operational optimisation [200]. Recent advancements in digital twin technology enable continuous synchronisation between an energy generation system and its digital counterpart. This allows for proactive energy management and rapid response to real-time load variations and generation variations. Sensor fusion in energy systems, especially those using local DG systems and storage, involves integrating data from various sensors to offer a more accurate, comprehensive, and actionable understanding of the system's performance and environmental conditions.

Additionally, AI-powered anomaly detection employs machine learning algorithms to automatically identify patterns indicative of damage or degradation [201]. This method often surpasses traditional threshold-based techniques in both sensitivity and specificity. Including these technologies in smart building management systems improves safety and resilience, enhances energy efficiency, and reduces lifecycle costs by enabling data-driven decision-making and timely interventions.

3.5.2. Neighbourhood Area Network (NAN)

The neighbourhood area network (NAN) facilitates and communicates information exchange between the wide area network (WAN) and various HANs installed and utilised at the power generation site. The NAN connects the HAN with the generation site through

AMI installed in smart meters and enables electricity monitoring and control of the loads on the user side. The NAN can cover large areas and facilitate the transmission of data from energy components to a data centre or substation. Various wired and wireless technologies are used based on the coverage and application, including Ethernet, ZigBee, Wi-Fi, and PLC [202]. The NAN is mainly utilised in the implementation of DRPs [203], metre readings [204], energy price regulation [205], distribution automation [206], and the outage and restoration management of power [207]. ZigBee is widely utilised along with the HAN to facilitate networking and establish the remote controlling and monitoring of smart appliances and other electronics and components [208]. However, it can also be exposed to the distortion of different technologies working on the home premises, including WiFi and Bluetooth, which operate in the same frequency band as the ZigBee network [209]. Various appliances, including smart water heaters [210] and electrical space heaters [211], are deployed with WiFi connectivity to monitor their usage patterns, which will essentially contribute towards implementing smart controlling strategies. Power Line Communication (PLC) technology is utilised to transmit information using existing power transmission lines and high-frequency signals (kHz to MHz). This technology can be broadly used in almost all areas of implementing modern power systems, from smart homes [212] to high-voltage grids [213].

3.5.3. Wide Area Network

The wide area network (WAN) is a communication network with multiple HANs that covers a broader area. It is considered a fundamental communication infrastructure in energy systems and is usually installed for real-time communication, control, and monitoring. Depending on the specific requirements, the WAN can be wired or wireless and transmit data over longer distances. It establishes communication between substations, control systems, protective equipment (e.g., SCADA, PMU, and RTU), and utility operators [214]. The WAN can provide data rates from 10 Mbps to 1 Gbps and coverage between 10 and 100 Km. The WAN requires other technologies such as PLC, optical fibre communication, WiMAX, Ethernet, and satellite communication [215]. Optical fibres provide high bandwidth and data, but the installation cost can be higher compared with other alternatives. Communication between the substations and main utility [216] and modern district heating systems [217] can be executed using optical fibres.

3.6. Microgrid Laboratories

Several universities and companies have developed laboratory-based microgrids to evaluate the performance of novel architectures and control strategies on hardware. A microgrid in KEPRI and Seoul National University was developed using IoT-based models and energy architectures to assess and implement various energy management strategies. The modules consist of PVs, ESS, WTs, and V2G as DG systems, with grid connection [218].

The PrInCE–Electrical Energy System Lab was developed at the Polytechnic University of Bari, Italy. This microgrid has the capability of five different modes of operation. The laboratory also has various RES-based generation systems and the ESS, CHPs, FC, and V2G modes. This microgrid can also conduct multi-EMS lab experiments [206].

The Kythnos microgrid [219] developed in Greece is also utilised for electrical engineering-related model testing. The microgrid was developed in 2001, and it is the first microgrid laboratory facility in Europe. Later, the microgrid was updated by installing various RES modules.

The University of Genoa, Italy, also developed a smart poly-generation microgrid laboratory. This smart grid can operate in conjunction with the grid or be landed. Along with electrical energy production components, thermal energy generation DG systems are also installed to facilitate the MES model's validation, testing, and research developments within the smart grid realm. The detailed structure and specification of the microgrid test bed can be found in [220].

The Perfect Power System at Illinois Institute of Technology [221], The Brons Bergen Holiday Park microgrid [222], the residential microgrid of Am Steinweg in Stutensee, Germany [223], and the energy lab at Savona University campus [224], mainly used for teaching are some of the key microgrid test facilities for MESs. Table 7 summarises the laboratory studies evaluated/considered in the field hardware deployment of MESs.

Table 7. Summary of studies that considered laboratory and hardware deployment.

Ref.	Year	Field	On-Grid?	Architecture	Controller	Network/Sensors	Implementation	Outcomes
[170]	2017	Residential	Yes	Grid/PV/FC/ESS	Fuzzy logic	HAN	Yes	The results show that the maximum power is extracted from PVs. The excess power is sold back to the grid, and an inverter-based strategy is optimally utilised for switching purposes.
[183]	2021	Residential	Yes	Grid/PV/WT/EC/EB/ESS/CCHP/IEEE 33 Bus	Computer-based	HAN	Yes	Total of 2.47% increment in profit.
[184]	2016	Residential	Yes	Grid/MT/WT/PV/FC/Li-Ion ESS	dSPACE 1104	HAN with Zigbee	Yes	Provides an economical solution for residential energy management.
[185]	2019	Residential	Yes	Grid/HP/HEs/TES	dSPACE 1104	HAN with sensors	Yes	Operational costs were reduced by 7%, and emissions reduced by 17%.
[186]	2021	Residential	Yes	Grid/PV/HP/ESS/TES	Computer-based	HAN	Yes	Implemented to provide cooling, heating, and electricity to a house.
[187]	2022	Residential	Yes	Grid/HP/CSS/TES	Computer-based	HAN and NAN	Yes	COP of the overall system increased by 12.4% and a reduction of 16% in the compressor energy consumption compared to other strategies. COP is increased by 59% and reduces the heating time by 40% whilst increasing the evaporator inlet water temperature from 5 °C to 20 °C.
[188]	2022	Commercial (Hospital)	Yes	Grid/PVT/TES/HPs/GB	Computer-based	HAN	Yes	Reduced the thermal losses by up to 70% and overall hot water production cost by 15–45%.
[189]	2023	Residential	Yes	Grid/PV/HP/TES/HEs/CSS		HAN and NAN	Yes	Total annual electricity cost was reduced by 5.2% and enhanced thermal losses by up to 4%.
[190]	2015	Residential	No	PV/WT/ESS/PEM FC/TES	Computer-based LabView and MATLAB	HAN and NAN	Yes	The implemented system model prevents the loss of the power supply that occurs during the transient start-up time, and a delay of 3 s will lead to a total loss of the load and change conditions.
[194]	2022	Residential	Yes	Grid/PV/WT/ESS/DG	Computer-based	HAN, NAN, and WAN based on LTE	Yes	The network loss rate is up to 0.155%, and the success rate is increased by up to 90%.
[195]	2011	Residential	Yes	Grid only	Smart home controller	HAN based on HomePlug and Zigbee	Yes	Increased security and reliability for a smart home user.
[196]	2021	Residential	Yes	Grid/PV/WT/ESS	Computer-based	HAN with HomePlug	Yes	Reduced costs and emissions and increased thermal comfort by 33.6%, 91%, and 54%, respectively.
[197]	2021	Residential	Yes	Grid only	NPC's LPC1769 and NB-IoT module	HAN with Wi-Fi and Zigbee	Yes	To make the smart home more convenient and easier to use.
[198]	2022	Residential	Yes	Grid only	Gateway Interface	HAN with Insteon, ZigBee, and Z-wave	Yes	To enable remote monitoring and control of the farmhouse.
[206]	2023	Residential	Yes	Grid only	Gateway Interface	HAN, NAN, and WAN with ZigBee and WiFi	No	Effectively utilised for cost and energy savings.
[207]	2023	Residential	Yes	Grid only	OPNET Modeler 14.5	HAN and WAN with PLC	Yes	Highly scalable and achieves full network bandwidth utilisation.
[225]	2023	Smart Buildings	Yes	Grid/PV/WT/EV/CHP/TES/ESS/AC/HE/FC	Computer-based	HAN, NAN, and WAN	Yes	Electricity and market clearing prices were reduced by 17.5% and 8.8%, respectively.
[226]	2019	Residential	Yes	Grid/PV/WT/ESS	Computer-based	NAN and HAN	Yes	Utilised the RESs efficiently, which leads to more than a 100% reduced energy consumption of grid energy.
[227]	2019	Residential	Yes	Grid only	STM32 as the central processor	HAN with ZigBee and Wi-Fi	Yes	ZigBee technology can make a remote-control system for the smart home.
[228]	2023	Residential	Yes	Grid/GB/CHP/HE/TES	Computer-based	SCADA	Yes	Successfully detects anomalies and anticipates SCADA alarms.

4. Laboratory to Real World

4.1. Recent MES Projects in Europe

This section summarises some recent projects developed around residential MESs. Most of these projects are funded research projects from the EU. Moreover, each project usually consisted of multiple work packages spanning several years. Hence, this section will inevitably be omitted. Interested readers should refer to the main web pages provided for each project to see the complete list of documentation. The date mentioned in each sub-section is the end date of the project. The country is the country of the coordinating organisation.

4.1.1. SMILE (UK 2021)

The SMILE project [229] aimed to validate various technological and non-technical solutions within distribution grids for islands. These solutions facilitate DRPs, implement smart grid functionalities, integrate energy storage, and promote multi-energy coupling. Three project demonstrations were conducted in the Orkney Islands (UK), Samsø (Denmark), and Madeira (Portugal). The objectives were to (i) minimise the energy exchange with the mainland for Orkney and Samsø; Madeira has an independent grid; and (ii) maximise the generation and utilisation of renewables. BES and TES are combined with AS-HP, smart metres, and communication systems. One of the studied systems is shown in Figure 8 below. These configurations were established in various setups, including the operation of this setup and the existing heating systems. The core aim is to reduce RES curtailment and increase self-consumption. The Kaluza Platform from OVO Energy is a cloud-based control aggregator responsible for the functionality and control of all equipment installed in the consumer's premises developed under the SMILE infrastructure. The remotely controlled infrastructure provides the grid with intelligent control of the equipment installed at the consumer's premises, which is used to manage flexibility issues and reduce the curtailment of RES. The infrastructure developed and installed in the consumer's premises for MES energy management, with details of the equipment installed, are listed in Table 8.

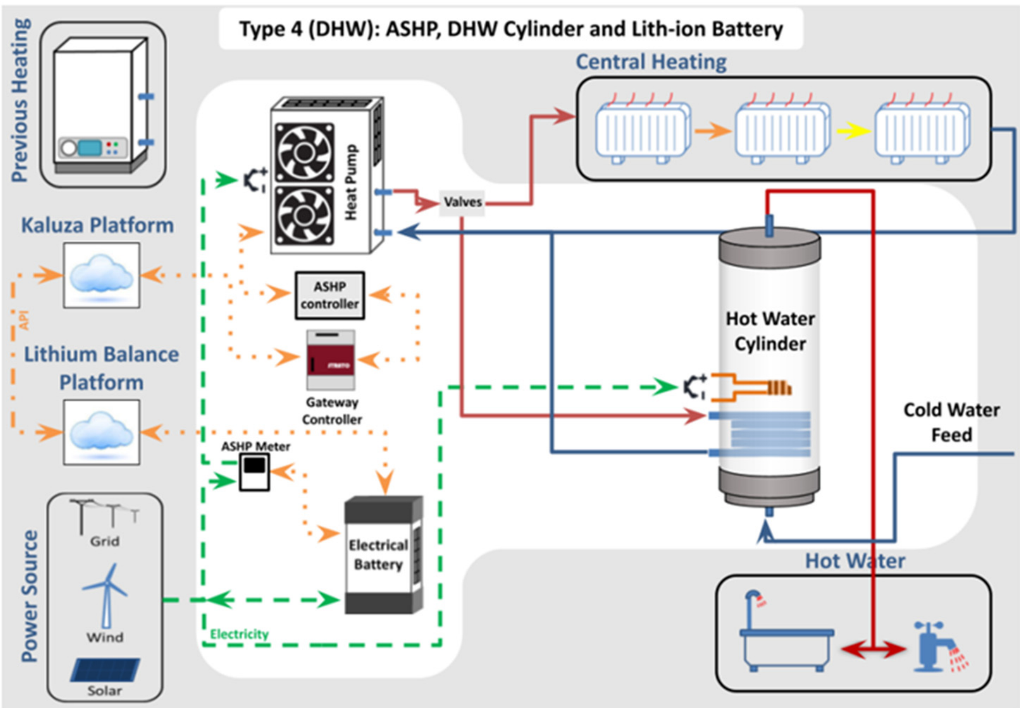

Figure 8. One of the system topologies installed under SMILE project for residential application [229].

Table 8. Equipment details were installed at various properties under the SMILE project at Orkney Island.

Component	Description	Connectivity	Installation Site
VSCON	To monitor and transmit RES curtailment information to the local smart grid	Modbus-RTU for wind turbine and Ethernet to onsite router	Wind turbine site
LiBal	To remotely control the battery's charging and discharging control	TCP internet link between battery and internet router	Lithium Balance data centre
Kaluza Platform	Cloud-based control infrastructure for controlling generation and demand infrastructure within SMILE project sites	TCP connection over internet routers' location at generation site and consumer's premises	Kaluza data centre
Kaluza Gateway	To provide on-site control and bidirectional flow of communication	Ethernet from onsite router to MODBUS-RTU	Consumer's premises
Hot water Boiler	3 kW of 100–300 L hot water storage heated directly from ASHP	Closed-loop water connection with ASHP	Consumer's premises
ASHP	Daikin Altherma 4–6 kW input and 11–16 kW output	Gateway and Daikin Controller	Consumer's premises
Daikin Controller	To control the ASHP and respond to the Kaluza Platform to control the hot water flow	Modbus-RTU comms connection between Daikin Controller and Daikin ASHP	Consumer's premises
Local smart metre	A 100 A smart metre is also installed to measure the power consumption of heating components.	MODBUS-RTU to the Kaluza Gateway	Consumer's premises
Li-Balance Li-ion ESS	3.5 kW/7.5 kW is installed to manage the mismatch	Connected to the Li-Balance data centre through the internet	Consumer's premises
Indra smart+ Charger	A 7 kW charger using the Kaluza Platform for communication	Connected through a LAN or WiFi	Business, tourist, and domestic site

4.1.2. RES4BUILD (Germany 2023)

The RES4BUILD project [230,231] aimed at decarbonising heating and cooling in buildings with a combination of PVT collectors, a multi-source HP, borehole thermal energy storage, and a building energy management system. A pilot case was studied in Greece, and the system configuration is shown in Figure 9. This system provided heating and cooling to a single-floor building with a 103 m^2 surface area. One of the main innovations is the multi-source HP, which can select different sources and sinks through several three-way valves. However, the borehole heat exchanger was emulated with a large tank kept at 18C, the underground temperature on site. The project outputs were implemented in refurbishments of three different buildings in the Netherlands.

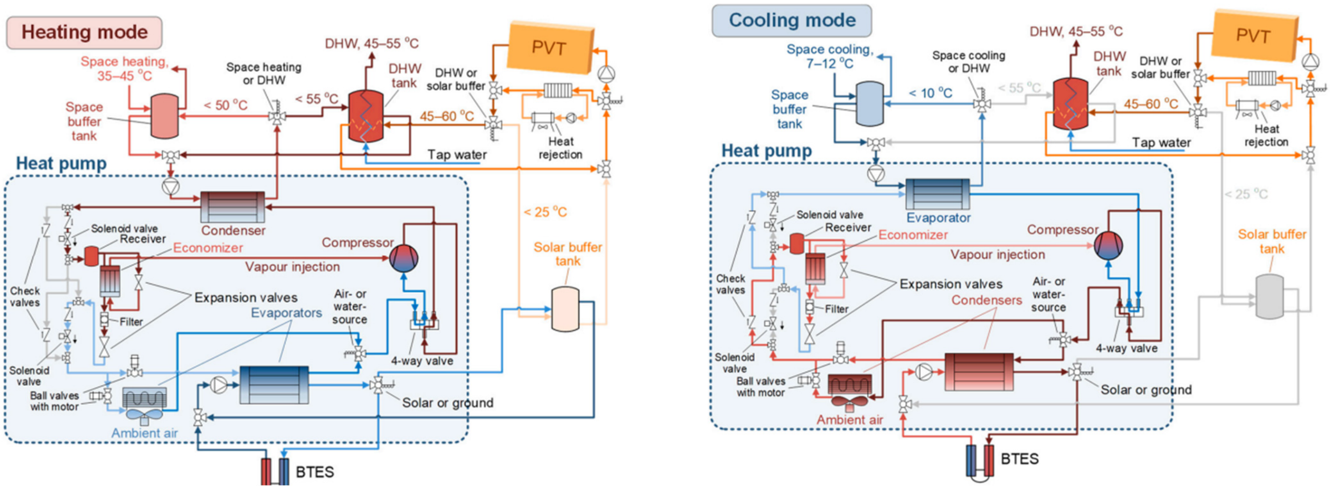

Figure 9. The proposed system layout for heating and cooling [231].

4.1.3. TRI–HP Project (Switzerland 2023)

The TRI–HP project [232] is related to developing and demonstrating tri-generation systems operated by RES-based HPs with cold storage (ice slurry), TES, and ESS. The HP uses natural refrigerants (CO_2 and propane). The aim is to provide heating, cooling, and electricity to multi-family residential buildings with a RES share of 80% of the total energy consumption. An overview of the system is shown in Figure 10 below.

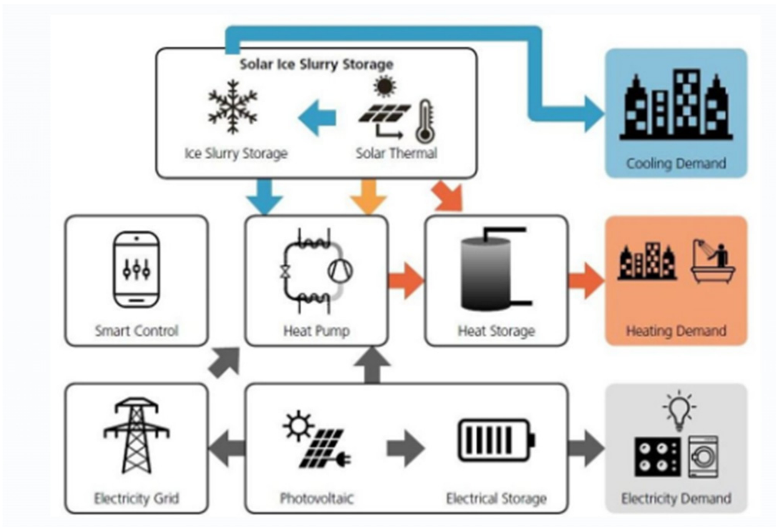

Figure 10. HP tri-generation system topology, adopted from [232].

Intelligent and smart control strategies are implemented to manage electricity, heat, and cold. The projects aimed to reduce energy consumption costs by 15% and carbon emissions by up to 75% for residential buildings. The project will evaluate two architectures of the energy model, one consisting of dual ground/air sources and another incorporating PVs with an ice storage system. The project also produced a detailed economic analysis of the main components and compared prices between Spain and Switzerland. Linear equations were derived for the main components as a function of the nominal size.

4.1.4. SolBio-Rev (Greece 2024)

The SolBio-Rev project [233] aims to cater to the multi-energy demands of residential buildings with a 70–85% RES share. The system topology consists of a reversible HP combined with an Organic Rankine Cycle, a cascade chiller, PVT collectors paired with thermoelectric generators, and a low-emission biomass boiler that operates in the CHP mode, as shown in Figure 11 below.

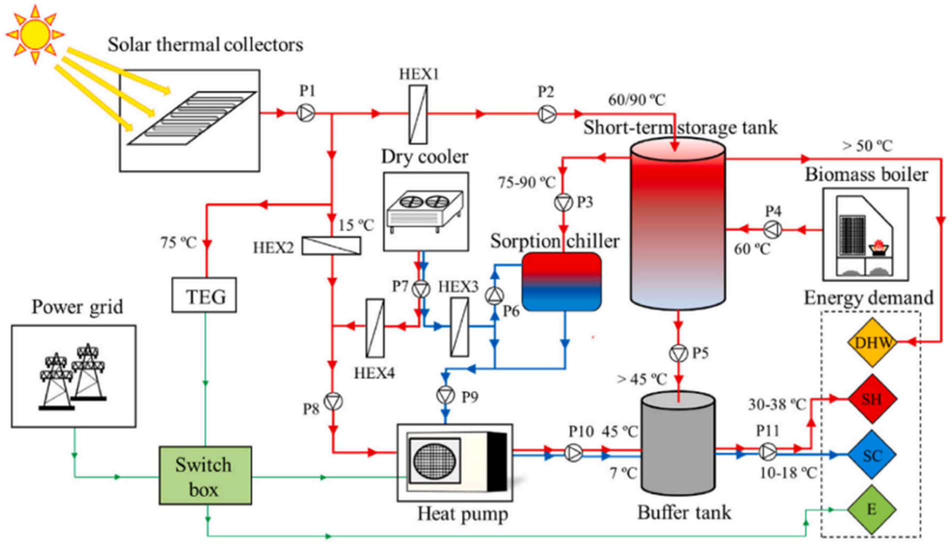

Figure 11. SolBio–Rev system topology adopted for a Mediterranean climate [234].

An advanced controller was designed and implemented using deep learning techniques to minimise operational costs. A cost reduction of around 35% was achieved via comparison with a rule-based controller.

4.1.5. SERENE Project (Denmark 2025)

The SERENE project [235] is related to implementing smart metres in the residential sector, using communication infrastructure to enable users to participate in the electricity market. This is achieved through implementing advanced EMS and smart control algorithms. These systems enable the optimal balancing of local energy production and consumption, dynamic pricing integration, and the maximisation of the self-consumption of RESs. The participating consumers can reduce their annual energy-saving costs by 10–20% with a payback time of 8–10 years. Demonstration projects and experiments are being conducted in three European communities— Skanderborg (Denmark), Olst (The Netherlands), and Przywidz (Poland)—where “energy islands” are being established to showcase the optimal integration of multi-energy carriers, smart control, and local energy balancing.

4.1.6. FLEXMETER Project (Italy 2017)

The FLEXMETER project [236] focused on developing a flexible smart metering architecture for multiple energy vectors. A multi-utility, multi-service metering architecture was designed and deployed in two demonstrations. The proposed architecture enables innovative services for prosumers, operators, and the retail market, including demand-side management, fault detection, network balancing, storage integration, and analysis of energy consumption. As seen in Figure 12, Device Integration Adapters are used at the bottom layer to enable the interoperability of heterogeneous measuring devices. The measurements are sent to a cloud infrastructure. The project succeeded in developing an IoT-oriented smart metering infrastructure connected with smart metres—both commercial and prototypes—to provide new services currently unavailable (detailed visualisation of consumption curves, aggregations, breakdown into appliances, and grid management functionalities).

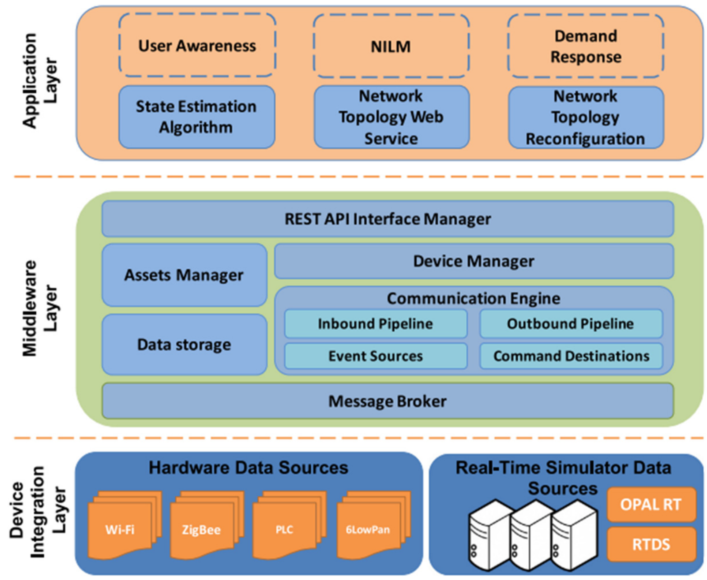

Figure 12. FLEXMETER software architecture [236].

4.1.7. InteGRIDy (Spain 2021)

This project evaluated the performance of various DRPs and demand-side management schemes [192]. Initially, 85 houses were considered for DRP installation. Furthermore, five houses were selected to install them with ESS to completely utilise the DRPs and benefit from the low energy price. The project also considered commercial buildings and selected various offices to implement DRPs and direct load control with ESS. To implement DRPs, several communication protocols and standards were adopted while installing smart meters within the consumers' premises. These protocols facilitate secure two-way communication between utilities and consumers. The project also presented a framework for implementing and installing smart metres to facilitate DRPs. The interoperability standards and functioning of smart metres are also introduced within this project and are listed in Table 9.

Table 9. Main Communication protocols and technologies adopted within InteGRIDy to install smart metres, adopted from [192].

Protocol/Technology	Description
PLC IEC 61334	Used for low-speed PLC applications and suitable for command and control.
PLC Prime	It stands for power line-related intelligent metering evolution and is also used for command and control.
PLC G3-PLC	A digital multi-carrier modulation method carries data on several parallel data streams. This includes Echonet Lite for Japan's home energy management systems (HEMSs), metering and prepayment standards, etc.
PLC Metres and more	It can support a bidirectional data flow, making it suitable for command and control applications.
Open Smart Grid Protocol	Finland proposed it, and is currently deployed in various countries. It can support large-scale smart metering projects.
PLC CX1	Austria proposed it and used a fast-frequency hopping spread spectrum technique with differential phase shift keying.
Wi-SUN	Provides a wireless field area network for AMI, EMS, and distribution automation. Can link smart metres with the cloud.
Metre-Bus	Based on European standards, a reduced OSI layer stack is often used for measured units, information about tariffs, etc.
IEC 61850	An application layer often used for V2G covers DG systems, storage, communication among wind turbines, etc.
DLMS/COSEM	It has also been developed for direct information access from smart meters and is widely used within smart grids.
CIM	EPRI South America developed an open standard for representing power system components. It provides a common control centre within power systems for energy management.

4.1.8. RE-COGNITION (Italy 2022)

The RE-COGNITION project [237,238] aims to develop and deploy building-integrated RES technologies. Five technologies have been developed up to the prototype scale: a vertical axis wind turbine (VAWT), a building-integrated PV, a hybrid solar-cooling system, a latent heat thermal storage unit, and a biogas-fuelled micro-CHP. These conversion units were connected as shown in Figure 13. Furthermore, a gateway system and three dedicated software types are developed to help with planning, data visualisation, and the operation of the technologies. The combined cost savings and improved efficiency of each component helped to reduce the system cost by around 50% from the baseline at the beginning of the project.

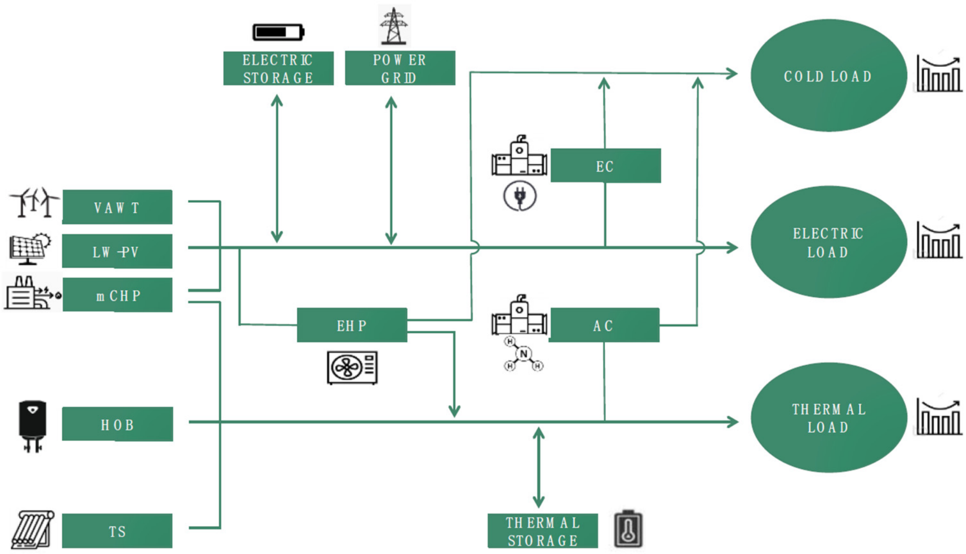

Figure 13. RE-COGNITION project MES topology [239].

The new technologies were tested in UK, Italy, Romania, and Greece considering a typical multi-family residential building of 15 dwellings. The developed optimisation procedure configured different topologies for various sites to suit local conditions, resulting in cost savings of between 11 and 42% from the reference scenario. This was achieved despite higher investment costs, 47% to 124% compared to the reference case. The daily operating costs were reduced by 15% and 48%.

4.1.9. Build Heat Project (Italy 2021)

The Build Heat project [240] aims to develop renovation frameworks for old buildings involving RESs for cooling, heating, and electrical demands. The studied buildings are multi-family houses across Europe. The project aims to control and manage DG systems practically, resulting in reduced costs and losses and high energy conversion efficiency. The energy architecture uses an HP, PVT collector, TES, and ESS. The configuration is applied practically to various climatic zones and buildings. In total, 16 cases with various locations and RES architectures were evaluated. The strategy can reduce the primary energy consumption by 30 to 50% for a given thermal demand, and when coupled with the RES, an additional reduction in the primary energy consumption of up to 27% is achieved. Moreover, using RES-based PVT collectors and PVs also results in a 40–80% reduction depending on the location and building type.

4.2. Costs and Feasibility Measures

Cost and feasibility analysis are important in the MES's architecture design. Various factors should be considered to ensure the practicality of the architecture. These factors include capital costs, operational and maintenance costs, lifecycle costs, payback time, levelised costs of energy, and governmental subsidies. For instance, the UK government provides up to GBP 7000 for installing low-carbon heating such as heat pumps. A case study was carried out by Braunholtz-Speight et al. [241], where a range of UK residential and community-scale MESs were evaluated, with a key focus on initial investments, operational savings, and payback periods. The study considered technologies such as PVs, HPs, and BESSs managed by a smart EMS controller. It was found that the integration of RES resources along with BESSs can present significant economic outcomes and high cost-benefit ratios. In the recent literature, along with operation management and optimisation, cost-related objectives were evaluated to achieve certain economic and environmental objectives. For instance, Ma et al. [242] analysed combined cooling, heating, and power provided by solar-assisted architecture. They evaluated its performance based on energy levels, costs of products, and environmental performance. Using the architecture saved 11.3% of natural gas, with reduced emissions and payback time. The feasibility and cost-effectiveness of these combinations depend on factors such as the availability and variability of loads (electric, thermal, and cooling), the maturity and cost of storage technologies (batteries, hydrogen, and thermal), and the degree of sector coupling enabled by the regulatory and market frameworks. Governments worldwide offer incentives for various energy components that are operated by RESs and have fewer emissions. The studies above demonstrate that despite high initial investment, MESs can offer favourable cost-benefit ratios over an operational lifetime. Ma et al. [243] compared MESs for residential heating with coal-fired, electric, and air-source heat pump systems. The results demonstrated that MESs had the lowest annual energy consumption costs and nearly zero emissions. The payback period for the initial investment has been determined to be 9.73 years. This system generated 62.35% of its heat from solar energy and 37.65% from backup sources. This reduced payback is due to the utilisation of solar energy. In the European project BuildHeat [240], a 17-storey residential building with 100 flats in Salford, UK was studied. The project utilised HPs along with RES resources and efficient EMS infrastructure. The installation of the project reduced the energy costs by up to 60–80% compared with the newly built houses with comparable loads. Similarly, case studies from the residential sector evaluated in the earlier sections further substantiate these findings. Implementing and installing RES-based HPs in the residential sector has resulted in significant savings annually. Obalanlege et al. [244] conducted a techno-economic analysis of the HP operated by a hybrid RES for the DHW and space heating purposes. The strategy incentivised the electricity and heat generation of 5 p/kWh and 21 p/kWh, respectively, with a payback time of 14 years. A study by Elkadeem et al. [245] considered the CHP, along with PVs and storage devices for residential buildings. It addressed the net present costs, energy costs, annual bills, and emissions, which were reduced by up to 9%, 10%, 45%, and 16%, respectively. However, CHP units' maintenance and operating costs are important due to the use of fossil fuels, which depends on energy market fluctuations. A brief description of the cost analysis of the architecture can also be found in the study. The electrification of thermal demand is considered an important way to decarbonise heat. In this regard, Sorace et al. [55] also conducted a long-term economic analysis of the FC and HP-based CHP for 2030. The authors considered various component parameters during the economic analysis, which included the net present values of the components to be installed, including boilers, FC, HPs, TES, and other costs taken from [246]. However, the installation costs of HPs to produce thermal energy are one major reason for their slow progress and adoption.

For instance, the costs of installing and setting up HPs to produce enough energy for the DHW and space can cost between GBP 400/kW$_{therm}$ and GBP 400/kW$_{therm}$ [247], when on the contrary, normal oil and gas boilers cost between GBP 70/kW$_{therm}$ and GBP 90/kW$_{therm}$ [248]. For residential consumers around the UK, adopting efficient air-source HPs can be considered a low-carbon thermal energy generation system. In the context of the electrification of heat demands, the installation of HPs can produce 3.1 kWh$_{therm}$ of energy when 1 kWh of electricity is utilised; with a boiler efficiency of 90%, HPs' coefficient of performance is kept at 3.1 or higher. In conclusion, the initial investment is often perceived as a barrier to adopting MESs; however, the cost savings realised during the operational period effectively offset the payback period.

4.3. Reliability and Operability Measures

The high complexity of MESs necessitates paying particular attention to reliability. Ensuring the reliable operation of MESs starts at the design stage, during which the optimisation of system components is carried out with some reliability measure, either as a constraint or as an objective [112]. Energy management system design also plays a vital role in operational reliability. During the operations of MESs, common reliability issues mainly stem from the electrical side of the system. High power ramping rates of renewables could lead to large voltage swings and potential instability. Keeping MESs running during maintenance, system restoration in case of faults, and switching between grid-connected and islanded modes are other challenges facing the designer and operator of MESs.

Potential solutions found in the literature include forecasting demand and supply, regular maintenance of the system, and redundancy in the communication system. For example, in the PrInCE Lab [171,172], a fully redundant communication system is constructed between the SCADA system and the PLCs controlling the equipment. Fibre optics organised The field communication with three gateways redundantly connected to the PLCs. This level of redundancy was needed due to the centralised nature of the microgrid controller and because it is a research microgrid. In MESs that have the functionality of the islanded mode of the electrical side, reliability issues arise during the switching between the grid-connected and islanded modes, and in reverse, When the microgrid is in islanded mode, the phase angle deviates from that of the grid-phase angle. Therefore, a robust resynchronisation strategy should be implemented before reconnection back to the grid to ensure a smooth transition without any transient current, which may trip the protection relays [249].

Acuna et al. [250] analysed the hybrid RES-based energy system's reliability using probabilistic approaches based on stochastic and deterministic methods. Furthermore, the authors also consider various economic and environmental indicators; however, multiple uncertainties must be considered when designing the systems to achieve economic, reliability, and environmental goals. These uncertainties are essential when developing an energy system with a high penetration of RES-based energy generators. For instance, recent studies evaluated the reliability of the designed energy systems using various indicators, including the loss of load probability [251], loss of power supply probability [252], expected energy not supplied, and level of autonomy [253]. Therefore, considering these indicators and uncertainties in the design and sizing of the energy systems can make the system more reliable, which can eventually make the system cope with increased energy demands. The fluctuations and intermittent behaviour related to RES utilisation are addressed by Qiu et al. [254] by carrying out a study to evaluate the performance of energy systems with the high penetration of RES based on operational risk assessment. They identified risk factors like component failure, extreme weather events, and cyber-attacks. Another risk to system reliability arises when there is a power ramp from renewable generators, like wind and solar. This ramping is high in magnitude and fast, which could cause stability issues, especially in systems with high renewable penetration. Roustaee and Kazemi [112] used a voltage deviation function to quantify such large power injections into the system. This function was used as a constraint in optimising the studied microgrid. Li et al. [255] developed a secondary controller for a DC microgrid to reduce the communication burden and monitor the trigger condition using a self-trigger mechanism to increase reliability. The method could achieve proportional load sharing within the multi-bus DC MES. The method's efficiency was similar to the baseline, but the sampling rate was higher.

4.4. Commercial Prospects

Coupled multi-energy architectures possess an economical solution for the electrification and decarbonisation of thermal energy demands. The recent rise in interest in decarbonisation and the net zero goals set by developed countries for achieving net zero emissions will increase the adoption of clean resources for the residential, commercial, and industrial sectors' energy demands. For instance, the UK government adopted certain policies to reduce emissions via various measures, including electrifying thermal demands. Adopting this strategy will yield reduced carbon emissions, as most emissions are associated with conventional boilers used for heating in the residential sector. The UK government aimed to provide and install 0.6 million/yr to execute this strategy. HPs by 2023 and 4 million houses' thermal demands should be fulfilled by 2035. A recent study conducted by Renaldi et al. [256] evaluated the performance of HPs and compared them with conventional thermal energy generation systems to meet thermal demands with TES. The authors found that installing TES with the HP reduces the operational costs; however, the investment costs are still high. The UK government has implemented many grants to widen the adoption of RESs and efficient heating systems. Furthermore, deploying and realising various sophisticated control strategies for combined heat and power can provide many benefits, from generation dispatch to energy savings, enhanced efficiency and reliability, and reduced costs and emissions with balanced supply and demand. Furthermore, if these control strategies are deployed with the implementation of DRPs, having a high penetration of RESs can also lead to controlled energy demands on the user side. Various architectures adopted in recent studies, including FC, HPs, PVs, and WTs, are presented in the literature. These are technically feasible; however, the investment, maintenance, and operational costs remain concerning. Effective multi-energy demand management with sophisticated control strategies and forecasting of RES energies can produce significant economic and environmental goals. A study by Hobley [257] compares two scenarios of the decarbonisation of energy systems using nuclear RESs in scenario one and natural gas with hydrogen and carbon capture storage systems for scenario two. The author conducted techno-economic and feasibility evaluations of both scenarios for the UK 2050 target for emission control. As a result, the nuclear and RES-based scenarios were found to be economical and environmentally friendly and have high energy production. However, uncertainty in energy demand is not considered in the survey for either scenario. Apostolou and Enevoldsen [258] also presented a comprehensive study evaluating various energy conversion systems adopted for energy curtailment using hydrogen storage systems. The authors concluded that the unpredictability of wind energy and its high investment costs can affect the production price of hydrogen. Using energy storage with the MES can enhance the flexibility in user demands. The energy stored can reduce energy consumption during peak hours, benefiting both energy providers and users. To further enhance flexibility, operators implement various DRPs to facilitate consumer and operator interactions, which can reduce costs with peak demand. Several limitations still exist in the wide adoption of these technologies: high investment costs, optimisation, sizing, the operation scheduling of energy resources, and immature control architectures with a lesser focus on user participation and reliability. Furthermore, the electrification of thermal demands will influence electricity demands, affecting stability and reliability during peak hours.

Various combined heat, power, and cooling (CHPC) technologies and modelling techniques have been extensively discussed in the literature. These include integrating gas-based combined heat and power (CHP) units with renewable energy sources (RESs) and using HPs. However, certain architectural configurations often encounter challenges in fitting within existing buildings or at residential scales due to constraints such as high costs, design limitations, and environmental factors. Consequently, the practical deployment of such systems confronts numerous design hurdles spanning energy resource allocation, conversion unit design, storage system implementation, demand management, and energy flow optimisation. Integrating diverse energy resources, including solar, wind, fuel cells, and grid connections, necessitates sophisticated technologies and management systems capable of optimising operations to achieve economic and environmental objectives. Despite advancements, the practical deployment of such strategies via hardware-based designs encounters various challenges. Pilou et al. [230] examined a RES-based HP system designed to provide heating, cooling, and power to buildings throughout the seasons—the architectural design comprised HP, PVT panels, borehole energy storage, and water tanks for DHW. The HP was strategically deployed to enhance the efficiency and self-consumption of installed solar modules. The theoretical data was validated by comparing them with the results obtained from a pilot study on a similar hardware-based architecture conducted in Greece as part of the RES4BUILD project. The results found variations ranging from 5% to 10% between experimental and simulation-based studies, mainly due to energy flow losses within the thermal network and dust accumulation on solar panels. To improve the accuracy and effectiveness of simulation models in replicating real-world behaviour, it is essential to incorporate the hardware considerations into mathematical modelling. Additionally, studies have explored the integration of PVT modules for combined heating and electricity production alongside HPs. Such systems, designed and demonstrated using hardware, offer simpler structures, higher efficiency, and increased self-consumption of RES resources. Ji et al. [259] conducted an experimental study utilising a hardware-based solar-assisted HP to supply electrical and thermal loads and DHW to small-scale users. These straightforward architectures are widely adopted due to their simplicity, efficiency, and enhanced self-consumption of RES resources.

5. Conclusions and Future Work

In this paper, we presented the latest developments in the design, optimisation, and deployment of MESs in the residential sector. In Section 1, the topic and scope of the paper were introduced, and relevant review papers were presented. Section 2 discussed the different technologies that constitute MESs, from generation to conversion and storage. Energy management studies and the different optimisation techniques used to achieve optimal results were presented in detail in Section 2.2. Section 2.3 presented the different demand response methods in the context of residential MESs. Sections 3 and 4 presented some of the deployments of MESs in laboratory and pilot projects in Europe over the past 10 years.

Some of the insights gained from this survey are summarised below:

- There is no single system topology that emerged as having a clear advantage. The large number of technologies deployed and the different contexts are largely the reasons for this. However, the combination of solar energy (PV and/or thermal) with heat pumps and storage seems to be quite an important combination. In cold locations, most of the time, they are not enough in the winter. However, in more temperate climates with

a need for heating and cooling, this combination works very well due to the match between the high solar irradiance and cooling load.
- The role of energy management systems is becoming more important due to the increased complexity of MESs. Several studies showed significant cost savings when adopting advanced optimisation techniques for power dispatch.
- The role of energy storage is interesting: adding BESSs or TES will inevitably increase the complexity of the controller and protection schemes. However, the larger the share of RESs in the system, the more important it is. A trend in the literature is towards maximising self-sufficiency and minimising the interaction with the grid. This is often due to the unfavourable conditions for exporting energy back to the grid. This is also particularly important in the context of islands, where abundant energy is produced and transmitted to the mainland at a cheap price, such as the situation in the Orkney islands of the UK.
- Several studies found that TES is better economically than BESSs in cases where there is a large enough heating demand. However, BESSs provide more flexibility. Also, most studies incorporated both, which could provide significant flexibility, especially with accurate demand and supply forecasting. This balance is expected to tip in the near future, as the advances in BESSs are rapidly outpacing the advances in TES.
- In terms of cost, several surveyed studies agreed that a high initial investment cost is still an obstacle to the wider adoption of MESs. However, operational savings could sometimes outweigh the higher capital and produce savings in the long run. Furthermore, the complexity of the installation creates a wide range of costs depending on the specific project. Even within the EU, similar technologies were installed simultaneously, and there was around a 20% difference between different countries.
- Surveying optimisation techniques was challenging due to the large number of studies in this space and the difficulty of classifying the methods used. However, in general, it was found that AI-based methods are suitable for optimising MESs. Heuristic and evolutionary methods were also extensively used. They performed well, although careful parameter tuning is needed to avoid them being trapped in the local optimum.
- Real-world MES projects tended to have a hierarchical control structure with local controllers for each major component, then a top layer for supervision and dispatch. Some systems even had three layers of control.
- Reaching zero emissions from MESs seems to be more challenging than initially thought. Most real-world projects achieved significant CO_2 reductions but did not reach zero. Decarbonising heating and cooling is a particularly stubborn problem.

Finally, some of the key recommendations for future research are mentioned below:

1. As the penetration of RESs into the energy systems is being paid more attention, an intelligent and advanced forecasting model is required to forecast multiple uncertainties within the energy system, including user demand and DRPs. The existing models focus only on generation prediction or user demand. Therefore, a unified forecasting mechanism is required to efficiently analyse and predict multiple uncertainties simultaneously in real time to address uncertainty related to wind and solar energies.
2. A unified framework for MESs is required to manage electrical and thermal energy simultaneously, and flexible energy load schedules must be scheduled in accordance with energy availability. Intelligent and optimal technology should be developed to manage excess energy locally in case of high energy generation; it can either be used for fuel cell operation, stored as hydrogen or thermal energy, or exported to the grid. Thus, techno-economic evaluation is required with certain DRP implementations so that the user can fully participate in various DRPs implemented by the energy operator.

3. More efficient and comprehensive technological improvements should be made to the existing technologies to reduce and manage the waste of heat energy via several components in the architecture. Using excess energy can increase the overall system efficiency with reduced costs.
4. Integrating several electrified thermal generation systems with a sophisticated control strategy should be practically evaluated to enable the widespread deployment of HPs and FC. There is a gap between these technologies' theoretical and practical implementation, which can become a new frontier in research and address the real-world implementation of electrified multi-energy generation systems.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

BIPV	Building integrated photovoltaic
BESS	Battery energy storage system
BIPV	Building integrated photovoltaic
BESS	Battery energy storage (electrical)
CCHP	Combined cooling, heat, and power
CO2	Carbon dioxide
COP	Coefficient of performance
CHP	Combined heat and power
CAES	Compressed air energy storage
CSS	Cold storage system
CE	Combustion engine
DGs	Distributed generation systems
DG	Diesel generator
DRPs	DRPs
DHW	Domestic hot water
ESS	Energy storage system (multi storage)
EMS	Energy management system
EB	Electric boiler
EC	Electric chiller
EU	European Union
EV	Electric vehicle
FC	Fuel cell
GT	Gas turbine
GG	Gas generator
GWO	Grey wolf optimisation
GA	Genetic algorithm
GSHP	Ground source heat pump
GB	Gas boiler
HP	Heat pump
HAN	Home area network
HEMS	Home energy management system
HE	Heat exchanger
IoT	Internet of Things
MES	Multi-energy systems
ML	Machine learning
MIP	Mixed integer programming
MILP	Mixed integer linear programming
MINLP	Mixed integer nonlinear programming
mCHP	Micro combined heat and power
MPC	Model predictive controller
MINLP	Mixed integer nonlinear programming
MOPSO	Multi objective particle swarm optimisation
NGB	Natural gas boiler
NSGA-II	Non-dominated sorting genetic algorithm
NAN	Neighbourhood area network
NG	Natural gas
PV	Photovoltaics (electrical)
PVT	Photovoltaics (thermal)
PID	Proportional integral derivative controller
PSO	Particle swarm optimisation
PCM	Phase change materials
PGU	Power generation unit
PI	Proportional integral controller
RTP	Real-time pricing
RES	RES
SOFC	Solid oxide fuel cell
SOC	State of charge
TOU	Time of use
TES	Thermal energy storage (thermal)
WDO	Wind-driven optimisation
WT	Wind turbine
WAN	Wide area network
HRES	Hybrid renewable energy system

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