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Strategic potential of multi-energy system towards carbon neutrality: A forward-looking overview

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ABSTRACT

Carbon neutrality is an ambitious goal that has been promulgated to be achieved on or before 2060. However, most of the current energy policies focus more on carbon emission reduction, efficiency and high penetration of renewable energy. Thus, this paper presented a review strategy towards carbon neutrality by presenting the concept of a multi-energy system (MES) in terms of its technologies, configuration, modelling and feasibility as zero-emission equipment. The paper addressed some prominent challenges associated with zero-carbon multi-energy systems (ZCMES). Various proven solutions in the extant studies that have been affirmed to alleviate some of these challenges were presented. In the end, we identified and summarised the current research gaps, and the future directions to ensure the feasibility of ZCMES as a primary strategy towards the actualization of carbon neutrality. Hence, this review work serves as a reference for revising the current energy policies to incorporate a carbon neutrality framework.

1. Introduction

The universal recognition of global carbon emissions following the implementation of the Paris Climate Agreement cannot be overstated. This immerse awareness through various strategies followed by different carbon emission reduction activities yielded a remarkable achievement in 2020 by achieving a 5.8% reduction in global (carbon dioxide) CO_2 emission [1]. Meanwhile, despite the CO_2 emission decrement in 2020, an enormous energy demand increase has been recorded in recent decades due to the rise in economic growth, population increase, and the recent pandemic that escalated the demand for oil and gas [1]. Hence, the global energy-related CO_2 emission is currently at 31.5 GT, the highest ever CO_2 concentration in the atmosphere since the industrial revolution. Meanwhile, the ardent ambition to achieve a carbon-free environment has been the primary target of many developed nations [2]. For instance, through the introduction of the European Green Deal, the European Union (EU) commission aimed to make the continent climate-neutral by 2050 [3].

Decarbonization of the energy sector by substituting conventional power generation with renewable means has been the primary approach towards the CO_2 emission curtailment in the energy sector. According to International Renewable Energy Agency (IRENA) latest information, about 261 GW of renewable energy plants were commissioned in 2020, and 91% of the new installed capacity is shared between wind power and solar system, making the total global renewable energy capacity to be 2799 GW [4]. Fig. 1 illustrates the renewable energy capacity of each region, with Asia, North America and Europe having the highest global capacity share growth in 2020. On the other hand, Fig. 2 presents the contribution of CO_2 emissions in each region. Interestingly, most regions with the largest renewable energy capacity share are the major CO_2 emission contributors, implying that focusing on power sector decarbonization alone is insufficient to achieve the zero-emission target.

The transportation sector is another primary driver of greenhouse gas (GHG) emissions. The International Energy Agency (IEA) reported that the transportation sector is responsible for 24% of direct CO_2 emissions, chiefly through direct fuel combustion and road vehicles that account for 75% of transport sector CO_2 emissions [5]. On the contrary, sustainable transport systems such as an electric vehicle (EV), hybrid electric vehicle (HEV), and hydrogen vehicle (HV) deployment have grown tremendously in the recent decade, yet, the total replacement of combustion vehicles with these sustainable transport systems is still an ambitious goal [6]. Similarly, the generation of thermal demand, which

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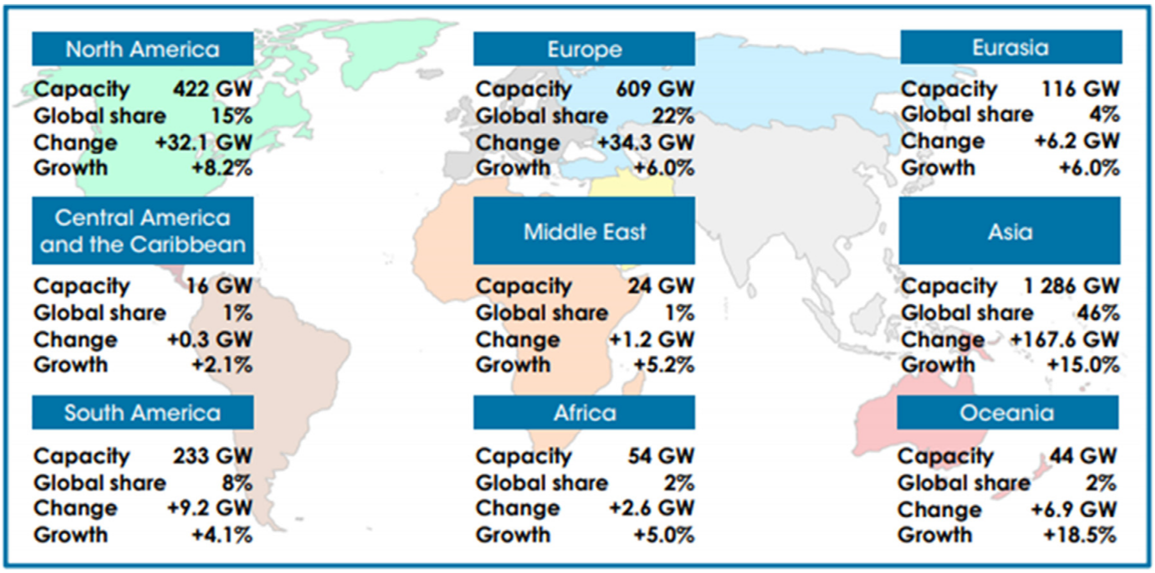

Fig. 1. Renewable energy global capacity installation [4].

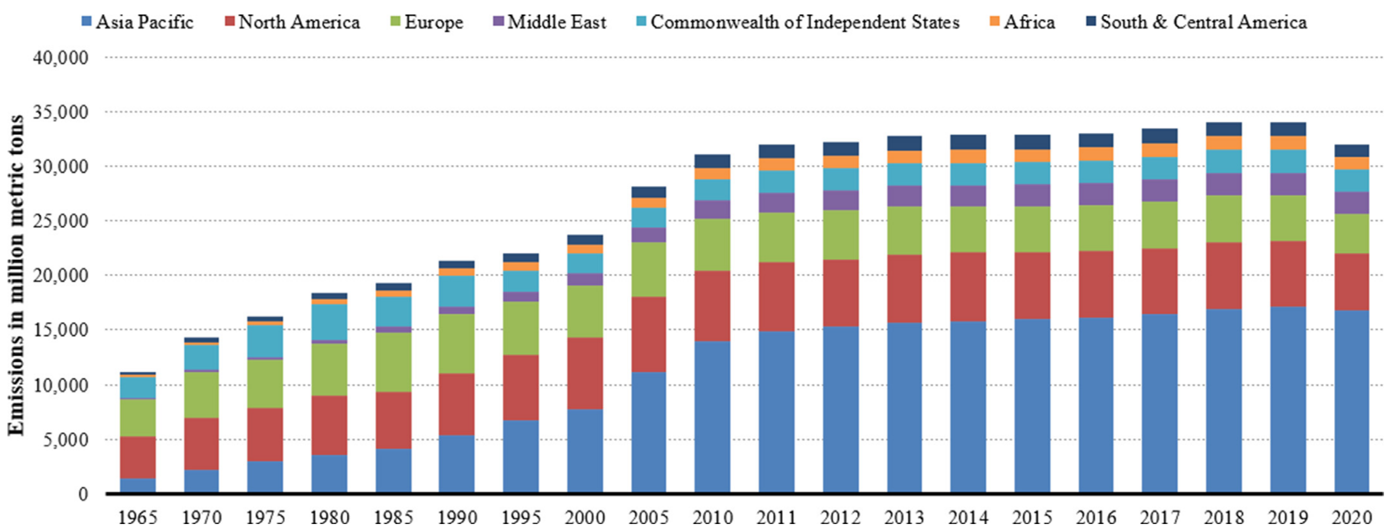

Fig. 2. Global carbon emission [1].

is another form of energy demand, is another emission activity; district heating and production of thermal energy for hot water requirement are usually produced through natural gas consumption and fossil fuel burning, which is the most significant energy consumption in the industrial sector and building energy demand [7].

Multi-energy systems (MES) have been the current trend in the recent decade due to their holistic approach features in decarbonizing power, thermal, and transportation sector while minimizing associated economic implications and reasonable utilization of energy efficiency [8]. MES is also defined as integrating energy generation, transmission, storage, distribution, and consumption under a unified framework [9]. Without hesitation, numerous contributions have been made in the research communities towards the efficient planning, sizing, operation, and energy distribution of MES [10]. Notably, Geidl first introduced the MES concept in 2007 to coordinate energy systems "as a whole" across multiple energy carriers, infrastructures, and consumption [11].

Nonetheless, while MES has been recognized as the pathway towards achieving the Paris Agreement, i.e., the regularization of the energy sectors to ensure the limit of global temperature below 1.5 °C, the feasibility of MES towards achieving carbon neutrality promulgated by most developed countries continues to be a difficult challenge. Thus, this review considers MES from a zero-carbon perspective, evaluates some of the research works in these regards, the challenges, and some unique solutions provided in the literature. In the end, the pathway towards its feasibility in terms of recommendation and future perspectives are presented.

The remaining part of the paper is organized in this section. The concepts of MES and its benefits are presented in Section 1. Section 2 presents the overview of MES in terms of its configuration and its modelling. Section 3 introduces MES as a zero-carbon system, followed by some of the challenges of operating MES and the proven solutions in the literature. The future direction and recommendation are presented in Section 4, while Section 5 concludes the study.

1.1. Why multi-energy system?

First and foremost, some other names have been used to describe MES in the literature, such as integrated energy system (IES), integrated electricity and gas system (IEGS), multi-carrier energy system (MCES), and energy hub (EH). Moreover, it is noteworthy that the energy component goes beyond electricity alone; it encompasses electricity, heat, cooling, and gas demand. Besides, most energy consumers are heterogeneous in demand. Thus, the primary idea of MES is the wholesome synergizing of all energy infrastructure which comprises energy generation, conversion, energy storage, and distribution to meet the multi-energy demands of consumers or prosumers economically and sustainably [198]. The associated benefits of MES are elaborated below:

1.1.1. Decarbonization of overall energy sector

Numerous efforts have been made towards the decarbonization of the power sector; nevertheless, the prime focus on electricity decarbonization alone without considering other energy sectors thwarts the efforts of achieving global CO_2 elimination. This is evident by the present 31.5 Gt of energy-related CO_2 in 2020 despite substantial renewable capacity installation in the same year [1]. MES has been identified as the main strategy towards deep decarbonization of all energy sectors through the electrification of other sectors, high penetration of renewable energy systems, the production and use of low carbon and carbon-free fuels [12]. For instance, replacing the combustion transport system with EVs and HVs with the integration of the charging station and gas stations as an integral component of the distributed energy system (DRES), the electrification of the heat production process for heavy industries using electric furnaces that are powered by sustainable means, and the generation of synthetic fuel from renewable electricity for maritime and aviation transport. Finally, optimal exploitation of the synergy between the electricity sector, thermal sector, gas sector, and other considered end-use sectors.

1.1.2. Efficient use of energy resources and circular energy system

Energy losses, especially thermal loss, accompany power generation. For instance, most gas turbines and steam engines have around 30% electrical efficiency, while the remaining conversion efficiency is wasted as heat [13]. The emergence of MES has enabled the reduction in waste energy through a recovery process that is usable for other purposes. For instance, the 29% of industrial waste energy that is dissipated as waste heat can be captured by a heat recovery system and utilized to heat room space, hot water production, or serves as input for absorption chiller for a cooling generation [14]. Furthermore, the power loss during energy transmission and distribution, approximately 5–10% [15], can be reduced to a negligible level since MES close the transmission gap between energy generation, transmission, and distribution. Thus, MES contributes to energy resources' efficient and effective utilization while minimizing energy loss.

1.1.3. Strengthened economy

The economic benefits of MES cannot be overstated. At the lowest level, MES contributes to reducing operation cost through waste minimization, efficient utilization of resources, and reduction in transmission energy losses [16]. Additionally, it contributes to a decrease in the curtailment cost of the renewable energy system. For example, the California Independent System Operator (CAISO) curtailed 1.5 million MWh of solar and wind generation in 2020 [17]. This curtailed power can be harnessed, converted to other energy products, and exchanged for monetary benefits where the power to hydrogen (P2H), power to gas (P2G), and power to anything (P2X) are some prominent approaches to achieve this. Furthermore, at the regional level, MES contributes to economic growth by promoting the development of sustainable and efficient technologies related to the energy transition, thereby providing competitive economic growth amongst specialized companies that develop smart grid technologies and complex technologies [18].

1.1.4. Reduced air pollution and energy-water footprint

Air pollution is another major global environmental crisis. According to World Health Organization (WHO), it contributes to 4.2 million premature death every year [19]. Thermal power plants contribute 54%, 26.6%, and 6.5% of the global SO_2, NOx, and PM2.5 respectively, which are the main components of air pollutants [20]. Thus, due to the high renewable energy penetration and thermal energy generation via sustainable manners which are the primary features of MES, it contributes to air pollution reduction. The energy-water footprint is another critical issue that has contributed to water scarcity. The energy sector has been identified as the most significant consumption; thermoelectric power consumes 0.47 gallons of water for every 1 kWh of electricity produced [21]. Similarly, according to the EU report, reservoir hydropower consumes 9.1 million litres to produce 1 TJ of electricity, and this occurs due to an artificial evaporative flux caused by reservoir/dam construction. In contrast, a renewable energy system consumes 1 thousand litres of water to produce the same energy quantity [22]. Hence, the adoption of MES also alleviates the water scarcity challenge.

1.1.5. Bolsters energy system flexibility

MES also enhances the flexibility of various energy systems coordinated in one-fold. Integrating different shares of renewable energy production to complement each other is one of the primary benefits. For example, during insufficient solar generation, the wind turbine is available to meet the power demand, while the solar power is stored during the abundance solar period when demand is low and will be discharged to complement wind power generation. Combining different storage technologies such as pumped hydro storage, static electrical storage, and mobile electrical storage boosts system flexibility due to their unique dynamic characteristics [23]. Furthermore, EV is another flexibility booster if power flow is designed bi-directionally. Admittedly, it has been asserted that EV could contribute up to 20% of energy flexibility by 2050 [24]. Moreover, thermal energy storage and P2G via electrolyser provide long-term energy storage potentials and buffering capability [25].

1.1.6. Increased resilience and security of energy supply

The self-dependency feature of MES through utilizing localized resources for power generation, efficient energy distribution, optimal system integration, and synergy exploitation contribute to an increase in the systems' resilience due to minimal dependency on external supply. Similarly, the energy network has been susceptible to various attacks such as natural disasters, vandalization, and accidents [26]. Whereas reducing the complexity of energy networks through MES increases energy supply security and minimizes unexpected blackouts.

1.2. National policies towards multi-energy systems (MES)

Numerous policies have been promulgated and enacted by policymakers to promote sustainable development in the energy sector. Since the advent of MES, most of the policies have been invigorated to accelerate its acceptance and implementation. In this context, this section presents some of the endorsed energy policies and projects in diverse global regions that contribute to MES enactment.

1.2.1. Europe

The EU has made tremendous efforts to achieve the Paris climate agreement in the last decade. In 2019, an earnest aim of achieving carbon neutrality by 2050 was enacted by the EU through European Green Deal (EGD) [3]. The framework set up 50 actions to broader the decarbonization of the EU economy. Some of the proposed actions of the EGD are; increasing renewable energy share, decarbonization of the heat and transport sector, and technology development. Trans-European Network in Energy (TEN-E) framework is another EU innovative plan for regulating the electricity, gas and CO_2 network infrastructure projects, which are currently undergoing revision to be synergized with Trans-European Transport Network (TEN-T) [27]. Furthermore, Renewable Energy Directive and Energy Efficiency Directive are other plans proposed by the EU commission to accelerate smart and highly efficient district heating and cooling networks that are renewable based [28]. Remarkably, the EU has also set up some funding schemes for the research and development towards achieving the 2050 carbon neutrality target. Some of the notable schemes are Horizon Europe, with a budget of €95.5 billion to support research and development and implementation of EU policies to tackle climate change [29]. Others include the Innovation Fund, one of the most extensive funding programmes to support the development of innovative low-carbon technologies [30], and the Modernisation Fund that is dedicated to support low-income EU member states towards carbon neutrality transition [30].

1.2.2. North America

The United States of America (USA) and Canada are the leaders of energy decarbonization policies in the North America region. In 2001, the USA department of energy (DOE) proposed an Integrated Energy System development strategy [31]. The California Energy Commission also published a comprehensive report on the state Integrated Energy policies in 2007, intending to address major energy trends and issue facing the states [32]. Similarly, the DOE also provides some dedicated services to foster the implementation of MES. A typical example is the DOE's Office of Distributed Energy Resources that anchors the awareness of cogeneration equipment regarding their energy, economic, and environmental benefits. The department also provides support at regional and national levels through dialogue, international meetings, and the provision of education materials [33]. DOE also provides different facilities to grant an enabling environment for the research and development of IES. Some notable ones are Oak Ridge National Laboratory (ORNL), DOE National User facility, and IES test centre at the University of Maryland [34].

The Canadian government published a comprehensive report on the feasibility of MES in 2009, titled "Combining our energies: integrated energy systems for Canada communities." The city of Guelph's community energy plan was used as a case study to evaluate the various benefits of energy integration. Some recommendations for implementing an integrated energy vision for Canadian communities were suggested in the report [35]. The Canadian Council of Energy Ministers also published a report on the integrated energy solutions' roadmap for the feasibility of the targeted carbon-neutral Canadian communities by 2050, and various strategies, key players, and enabling roles for its feasibility are described [36].

1.2.3. Asia

The Asia region has been at the forefront of decarbonizing the power sector, which is evident through their large renewable capacity shares. On the other hand, the region is the major contributor to global CO_2 emissions due to rapid industrialization and huge population density [1]. In 2014, the Chinese government introduced the Energy Internet policy, which comprises three core ideas: *energy networks, information networks,* and *energy management and trading* [37]. The Indian government also developed an Integrated Energy Policy in 2004, which received the government cabinet's approval in 2008. The policy provides a pathway on energy security, integrating various energy networks, and the feasibility of achieving deep penetration of renewable energy in the Indian power sector [38]. Moreover, the Singaporean government enacted the Energy Conservation Act in 2012 that was amended in 2014 and assuredly promotes energy conservation, improved energy efficiency, and reduced environmental impact associated with energy use [39].

2. Multi-energy system overview

This section demonstrates the general overview of MES. Firstly, the MES technologies and various configurations are illustrated. In the second part, we described the MES modelling, further subdivided into the Decision-making model (DMM) and modelling approach (MA).

2.1. Technologies and configurations for multi-energy systems

Fig. 3 illustrates a typical MES technologies integration. The technologies are classified into four (4) categories, which include 1) **Energy input:** this is the entry port of the system and mainly consist of energy supply from the power grid via a transformer, renewable energy system, and gas (natural gas or hydrogen) supply. A typical scenario was proposed in ref [40] where hydrogen, derived from a PV-fed electrolyser, is combined with natural gas to achieve a building's thermal needs via boiler combustion or by switching to a combined heat and power (CHP) unit. 2) **Conversion technologies:** these are energy equipment that converts energy input to other energy forms depending on the requirement of the prosumers or consumers, e.g., gas turbine that converts natural gas from the energy input into electric power and thermal energy; an electric boiler that converts electricity to thermal energy (heat); and absorption chiller that converts waste heat to cooling power. For instance, de Santoli et al. [41] combined natural gas CHPs and back up boiler, two-stage electric heat pumps (EHP) and transcritical CO_2 EHP to develop an hybrid solution for high-temperature heat production and power generation in a building. 3) **Storage technologies:** these are equipment that serves as energy backup during insufficient power generation or peak demand and stores energy during excess power generation or low energy price. In MES, the major storage technologies are electrical energy storage (EES), thermal energy storage (TES), and gas storage (GS), and this can be achieved in buildings in a few cases. For example, authors in ref [42] developed a conceptual framework where buildings can act as vital EES and TES while being enablers for establishing positive energy building nets. 4) **MES networks:** these are interconnection devices, cables, and pipelines that connect each equipment in MES. Jing et al. [43] applied this technology to create an optimization-based multi-energy trading aiding tool for heat and power that allowed for peer-to-peer energy trading between prosumers. For more information on MES technologies, readers can consult [44].

MES configuration depends on the expected multi-energy demand of the consumers or prosumers, the available renewable energy technologies, and the available energy conversion equipment. The consumers' energy demand usually comprises electric or power, heat, cooling, gas, and X. The X denotes other demands by the consumers that can also be provided within the MES framework; such examples include captured CO_2 and ammonia that are useful for manufacturing processes. Since MES is known for its multi-energy production, the possible configuration is categorized into cogeneration, trigeneration, and polygeneration. These configurations are described in detail below.

2.1.1. Cogeneration

Cogeneration is used to describe an MES configuration that generates two energy outputs which can be any combination of the consumers' energy demand mentioned in the preceding section. The cogeneration configuration is usually a combination of electricity and heat load or electricity and cooling load in the literature. Fig. 4 illustrates MES cogeneration output (electricity and heat demand obtained from the literature). In Fig. 4a, the energy inputs are from wind turbines and conventional energy units, while a carbon capture system (CCS) is integrated to capture the associated carbon emission. Power-to-gas (P2G) technology is also introduced to utilize the captured CO_2 to generate synthetic methane gas for users' consumption purposes. On the other hand, the MES in Fig. 4b is modelled to meet the electricity and heat demand of the end-users with the aid of gas boilers, gas turbines, and energy storage.

2.1.2. Trigeneration

Trigeneration is another category of MES configuration that describes three (3) energy outputs based on the consumers' or prosumers' demand. It is achieved by introducing an additional energy converter to the cogeneration MES configuration. This approach was adopted in [47], where an absorption chiller is introduced to enable the production of cooling energy using the thermal (heat) output of CHP. Consequently, this changed the system to a combined cooling, heat and power (CCHP) system. Apart from the usual electricity, cooling, and heat production, a

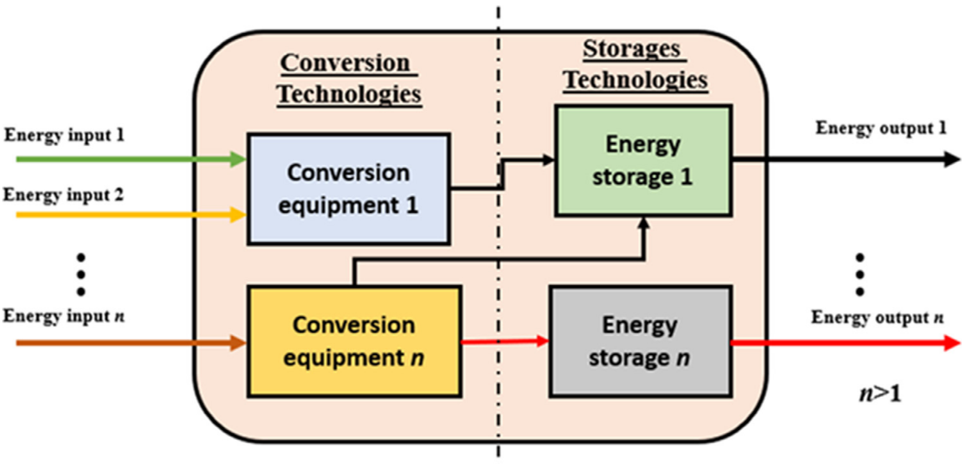

Fig. 3. Multi-energy system configuration.

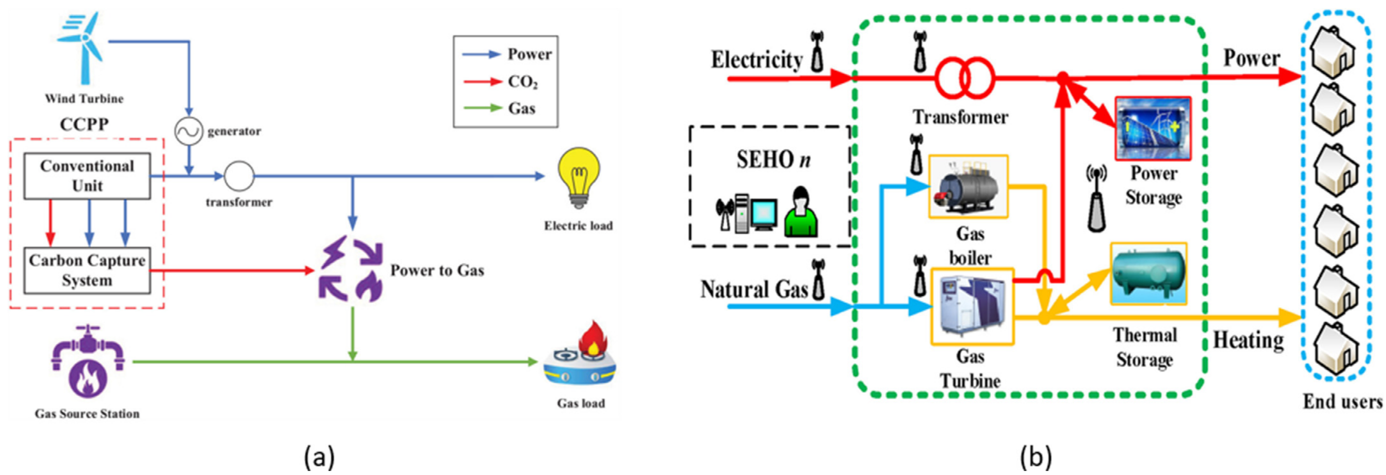

Fig. 4. Cogeneration [45, 46].

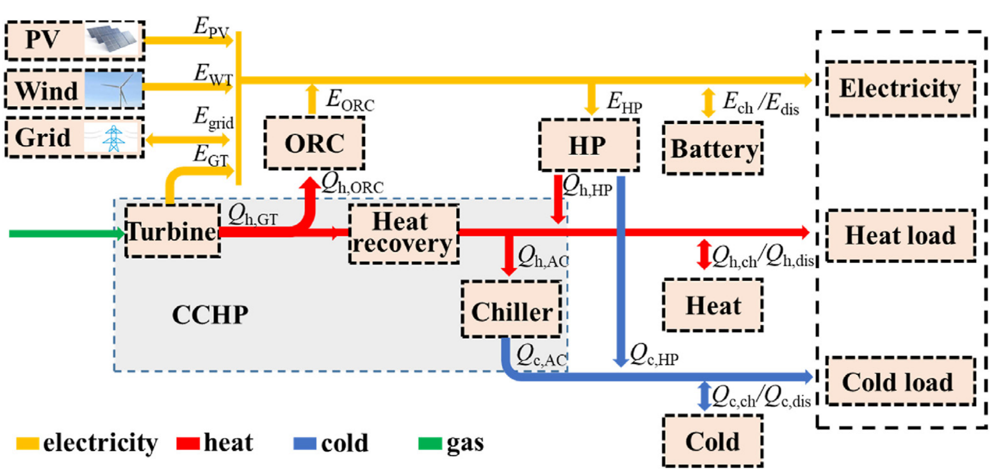

Fig. 5. Trigeneration [51].

trigeneration can also be configured to generate different energy combinations. Xi et al. [48] configured MES to meet electricity, gas, and heat demand, and a similar approach was also adopted in [49] with the aid of P2G.

On the other hand, Fakhari et al. [50] proposed a trigeneration model for the simultaneous generation of power, heat, and potable water by introducing a water desalination system into the model. A typical schematic representation of trigeneration is illustrated in Fig. 5. The system is configured to provide electricity, cooling, and heat demand with energy input from renewable resources and thermo-generation plants. A heat recovery system is used to harness the waste heat, which is used for meeting heat demand and cooling production via an absorption chiller system.

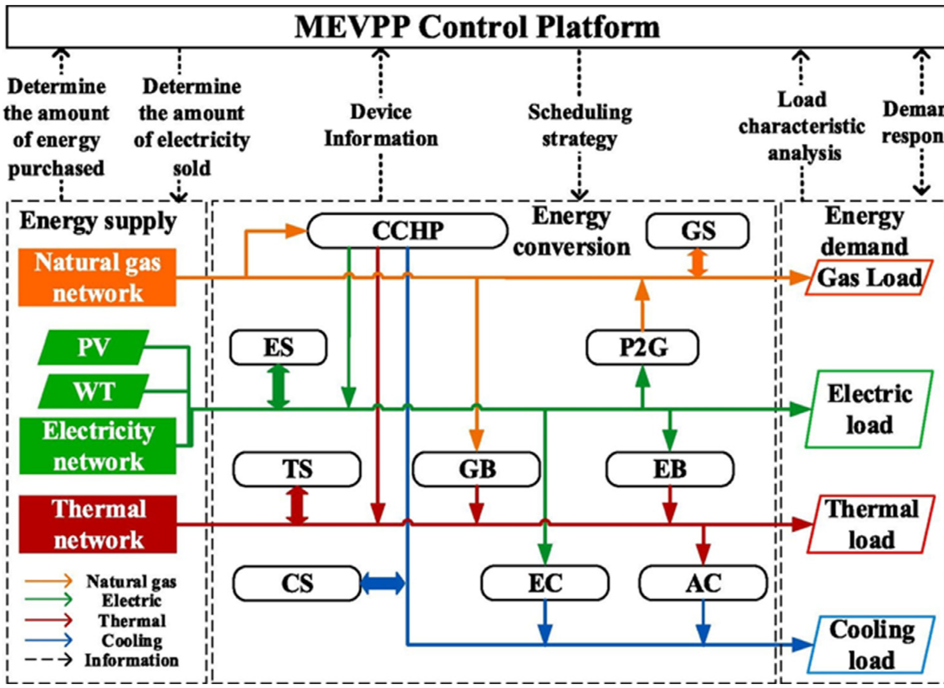

Fig. 6. Polygeneration [53].

2.1.3. Polygeneration

An MES that is designed to generate more than three (3) energy output is categorised as polygeneration, and the system is usually designed for commercial, industrial, and district buildings due to huge multi-energy demand. The concept of polygeneration emerges from modelling a system that will supply all the energy-related demands of a consumer or prosumer, Li et al. [52] modelled an MES to supply combined electricity, heat, cooling, and natural gas (for cooking purposes), simultaneous production of electricity, heat, water, and gas load was developed in [53]. Meanwhile, it is worth mentioning that the output of polygeneration is a different combination of energy vectors, that is, MES that has an energy output of heat load for a room(heat), hot water heat load(heat), cooling, and electricity, is not a polygeneration. Fig. 6 describes a polygeneration MES with four outputs using applicable energy converters. An electric chiller supplies the cooling load, CHP and gas boiler provide the required heat demand, and P2G i.e., the electrolyser is introduced for hydrogen production.

2.2. MES modelling

In this study, MES modelling is categorized into a decision-making model (DMM) and modelling approach (MA), which are further described in detail under this section.

2.2.1. Decision-making model (DMM)

The main goal of energy planners or modellers is to achieve optimal planning and smooth operation of the system without violating applicable constraints. In this regard, DMM is further classified into planning and operation modelling. MES planning can be defined as the optimal selection, site location, sizing, and configuration of energy equipment within MES. Numerous contributions have been made in this area via a mathematical programming/optimization approach that involves formulating the planning model to minimize the objective function (usually economic cost and carbon emission) while obeying the governing physical and technical constraints within the feasible region. e.g., capacity limit, space or area constraint, available resources constraint, and energy policy limit. Fan et al. [54] explored the expansion planning of MES considering the coupling characteristics of electricity, heat, and natural gas infrastructure, Wang et al. [55] evaluated the effect of investment constraints on the MES equipment selection and sizing. The obtained results validate the influence of optimal economic cost. Similarly, Wang et al. [56] proposed an expansion planning model for district MES considering active distribution network constraints.

On the other hand, the optimal energy despatch, scheduling, energy flow regulation, switch control, and unit commitment of MES equipment at each timestep is described as the optimal operation or schedule decision-making. The approach is also referred to as day-ahead scheduling since the decision for the next timestep is primarily decided earlier. Like the planning model, operation decision-making is mostly modelled using a mathematical programming approach to minimize the scheduling cost/operation cost while ensuring energy balance optimally at each timestep without violating the specified constraints [57]. The scheduling or operation costs usually consist of the systems' maintenance, fuel, energy purchase, and carbon emission costs. In contrast, the applicable constraints primarily consist of energy balance, energy network parameter constraints, energy flow constraints at each timestep, ramp limit, the systems' governing unit commitment constraint, and some flexibility or reliability constraints specified by the modeller. A comprehensive review on the modelling and solution methods of MES optimal operation scheduling is provided in [57,58].

Notably, most of the recent studies on MES adopted the co-optimization of planning and operation in their model. The advantage of this approach is the consideration of schedule decisions on the capacity sizing and selection at the planning stage. Mittelviefhaus et al. [59] developed an integrated optimal planning decision and scheduling model for residential MES to mitigate climate change's effect on the economic cost. Similarly, Li et al. [52] proposed a bi-level optimization model to coordinate community MES's synchronized planning and scheduling. Alabi et al. [60] also proposed a co-optimization model that is efficient for the optimal investment decision and scheduling influence on capacity sizing of MES with zero-emission potentials. It is worth mentioning that the mathematical programming approach, which has been the primary tool for optimal decision making, is also affected by some factors such as convexity of the problem (i.e., convex or non-convex), the nature of the decision variables (i.e., linear, non-linear, or bilinear) and the type of objective functions (single or multi-objective). These factors determine

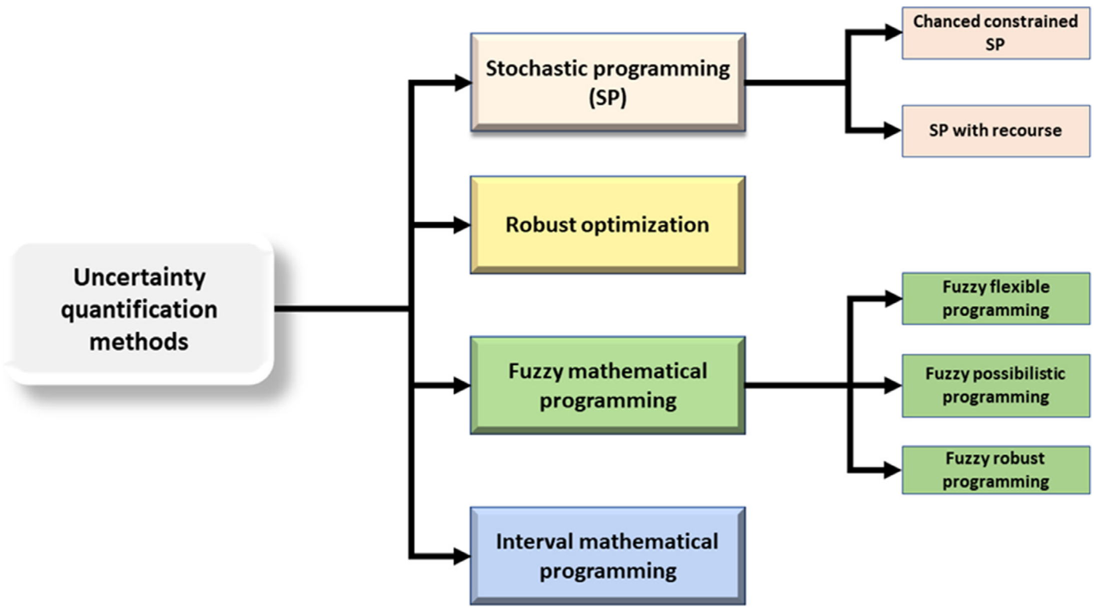

Fig. 7. Uncertainty quantification methods.

the complexity of the problems, which can be addressed using appropriate mathematical techniques such as linearization and decomposition methods and the use of appropriate optimization solvers [61,62].

2.2.2. MES modelling approach

The modelling approach (MA) describes how the data and the parameters needed for optimal decision making are handled. This study categorises the approach into a *Deterministic* and *Uncertainty* model. A deterministic model entails using exact data and parameters without considering any variation. Cheng et al. [63] applied a deterministic approach to evaluate the relationship between MES performance and thermal storage effect. Gotze et al. [64] proposed a novel MES modelling approach validation using a deterministic approach. Similarly, Cao et al. [65] applied a deterministic approach to model MES integrated with EV to achieve a low-carbon community. The deterministic approach is used chiefly for planning decision-making or evaluating new algorithms, and the approach is not considered suitable for a scheduling model. Any scheduling model that adopts a deterministic approach is deemed to be unrealistic due to renewable resources volatility that is inevitable.

MES encourages high penetration of renewable resources due to stochasticity caused by weather variation. Another challenge is the unexpected changes in consumers' behaviour that may influence the energy demands and variation in equipment real-time performance. In this regard, the uncertainty modelling approach has been the primary MES modelling approach. Many uncertainty quantification models have been proposed in the extant studies, as shown in Fig. 7. However, the most adopted methods are stochastic optimization (SP) and robust approach (RO). SP is an uncertainty quantification approach that involves the generation of multiple scenarios of data using appropriate probability distribution functions (PDF). The PDF parameters are obtained from historical data then used with random variables either through Monte Carlo simulation or Latin hypercube sampling (LHS) for multiple scene generations [66]. SP is applied for the optimal scheduling strategy in [67] while considering energy network dynamism and psychological preference. Zhang et al. [68] proposed a two-stage stochastic optimal operation for MES considering power reserve influence, and Mei et al. [69] developed an SP model for optimal operation of MES based on multiple scenario simulations.

On the contrary, RO eliminates the need for multi-scene generation by assuming the data variation ranges within an uncertainty set [70]. It has a computational advantage over SP, but its main challenge is its conservative nature which may be uneconomical [71]. Yan et al. [69] developed a multi-objective MES robust planning method considering multi-demand uncertainty influence. Lekvan et al. [49] applied RO for the optimal despatch of the MES system. Similarly, a robust MES scheduling model with the evaluation of heating network uncertainties was developed in [72].

3. Zero-carbon multi-energy systems (ZCMES)

In this section, we presented the main driver behind modelling MES as a zero-carbon system, its feasibility based on the proposed configuration in the extant studies, followed by challenges related to operating MES with zero-emission potentials and some proven solutions.

3.1. Rationale for ZCMES and its feasibility

The impassioned goal of achieving carbon-neutrality is the primary driver for considering zero-carbon multi-energy systems (ZCMES). Based on the information retrieved from Energy and Climate Unit, as illustrated in Fig 8, 137 countries have pledged towards net-zero carbon achievement [73]. Most of these countries proposed to achieve this goal on or before 2050, while Ukraine, Kazakhstan, and the largest carbon emitter, i.e., China, proposed 2060 as the target. Unfortunately, Bhutan and Suriname are the only countries that have achieved carbon neutrality, which is understandable due to their low population density. Only six countries have enacted a law to fast-track the feasibility of this goal, including Denmark, Hungary, France, New Zealand, and the United Kingdom (UK). Twenty-four countries have set official carbon neutral policies, including China and the US.

In comparison, the remaining countries that constitute 72% (99 out of 137 countries) of those that pledged on zero-carbon are still at the discussion stage without any official statement. Meanwhile, the energy sector (power, thermal and gas) and the transportation sector are the major carbon emission contributors. Although the synergy of these sectors in an optimal manner has been validated to be effective, ZCMES creates a pathway towards carbon-neutral feasibility.

3.2. MES as zero-carbon systems

Recent advancements in energy systems have enabled the feasibility of modelling MES as a zero-carbon system. ZCMES can be categorised

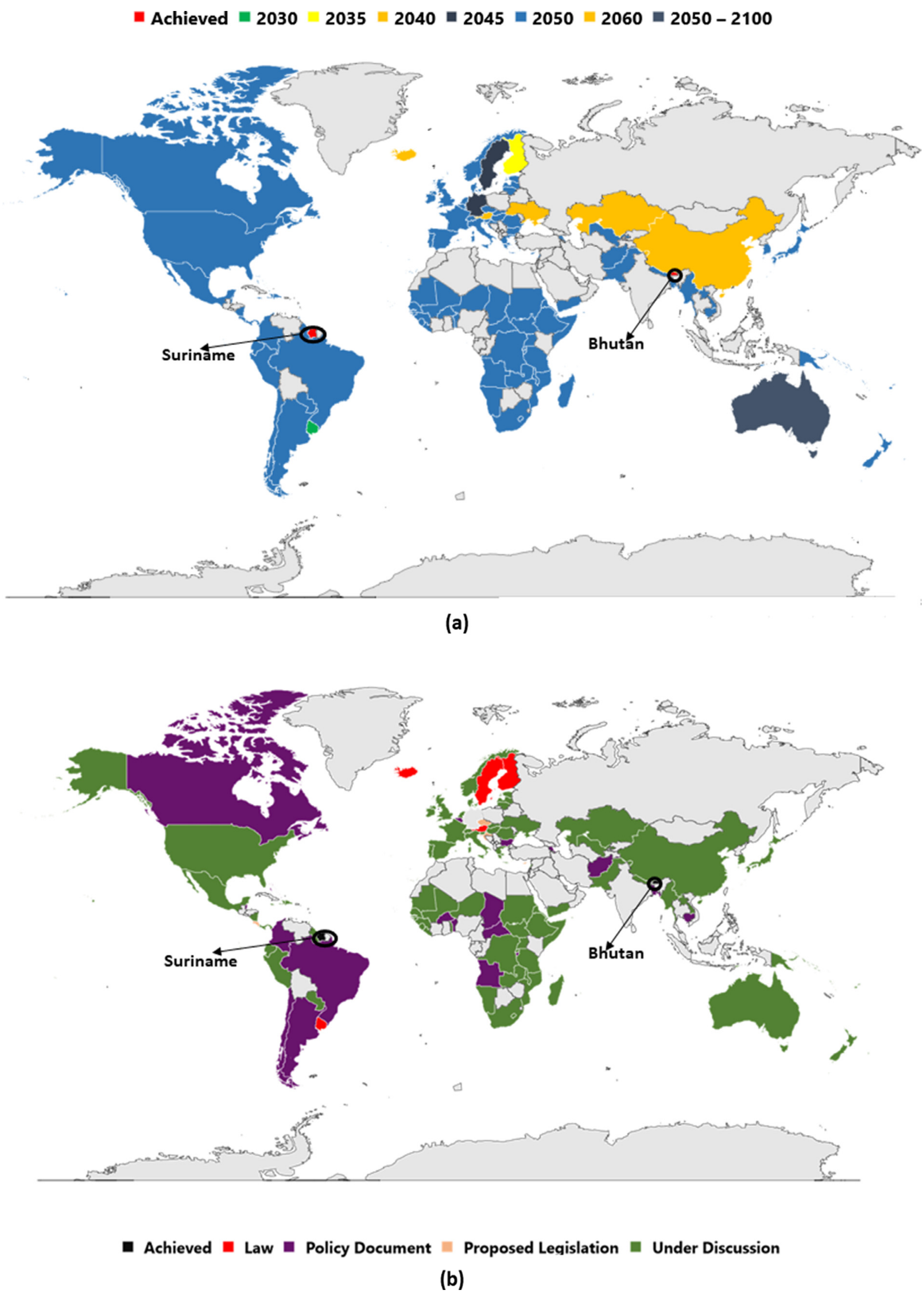

Fig. 8. Net-zero carbon race (a) target year (b) strategy.

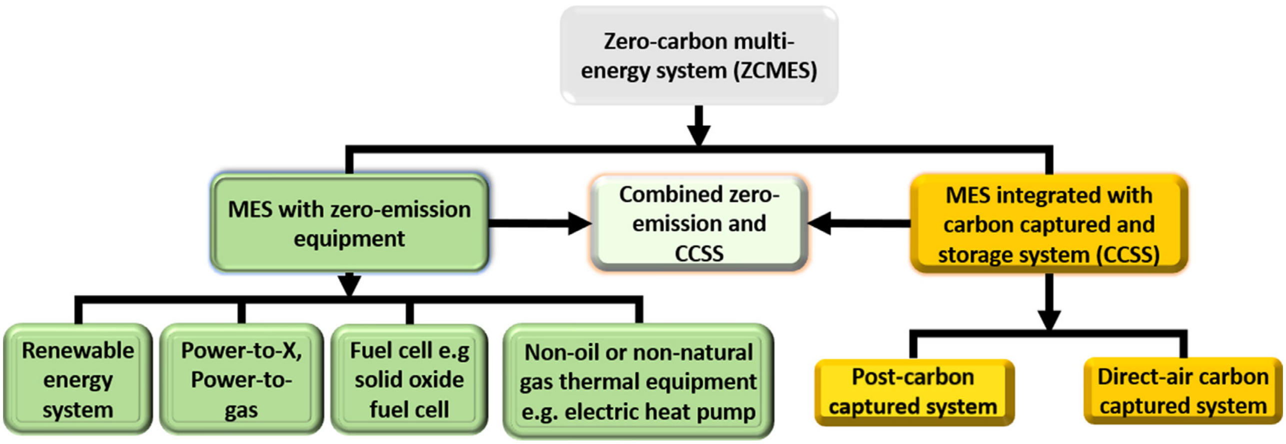

Fig. 9. Zero-carbon multi-energy system (ZCMES) components.

into two components, as described in Fig. 9. Further details are described in the following section.

3.2.1. MES with zero-emission equipment

The ongoing evolution of interconnected clean energy sources via zero-emission equipment (ZEE) has been identified as an ideal avenue to boost the potential of ZCMES and the realization of a carbon-free world. Simply put, ZEE refers to such energy infrastructure with little or no reliance on the upper grid, non-discharge of global pollutants and ability to achieve total decarbonization. The new normal is to introduce ZEE, including renewable energy sources (RES) (solar and wind energy), P2X/P2G and fuel cell (FC), to the planning, design and operation strategies of MES modelling. The high penetration of RES as ZEE in MES has been considered in ref [74,75]. However, its erratic nature and difficult curtailment can be catered for when combined with P2G, hydrogen gas (H_2), solid oxide FC (SOFC), and this has been recognised as a promising approach by several scholars. For instance, in [76, 77], micro-grid and grid-connected infrastructure comprising wind power, P2G, SOFC were proposed for MES multi-objective optimization. Fu et al. [78] developed a model that minimized the overall cost and maximised the operating synergy of MES via H_2 generated P2G. Furthermore, Chen et al. [79] developed a probabilistic modelled solar-powered P2G and FC electric vehicle network for an optimal MES operation that maximises daily profit. More studies on diverse ZEE equipment in ZCMES are extensively discussed in [80–85].

On the whole, most proven researchers have considered the combined ZEE as a burgeoning approach to optimize the feasibility of ZCMES, with intensified interest emerging from H_2 due to its clean harness, production, deployment, high storage density and long storage time. The major drawback of the ZEE lies in the enormous considerable investment cost in their development.

3.2.2. MES with carbon captured and storage system (CCS)

CO_2 emissions are usually released freely into the atmosphere and are dangerous to human health and the environment. The primary approach in the energy field is to reduce the emission to a minimal level, which hinders the feasibility of achieving a carbon-free environment. Meanwhile, recent research progress and technological development on carbon capture and storage systems (CCS) have confirmed the feasibility of carbon neutrality. CCS has been incorporated as part of MES, as illustrated in Fig 9. The captured CO_2 can also be recycled by utilizing it to produce synthetic gas through the methanation process, which is then feedback into MES to produce electricity and thermal energy [86]. CCS technology is classified into post-carbon capture systems (PCCS) and direct-air carbon (DAC) carbon capture, as shown in Fig 9. A detailed description of these technologies is illustrated below:

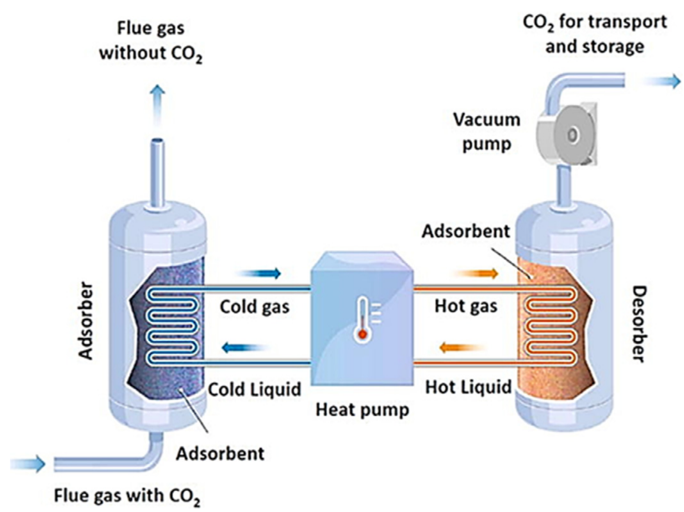

Fig. 10. Post-carbon capture system (PCCS) [87].

3.2.2.1. Post-carbon capture system (PCCS).

PCCS is a carbon-dioxide removal (CDR) technology for capturing flue gas from fossil combustion equipment such as gas turbines and gas boilers. PCCS requires minimal retrofitting of the existing energy equipment; the exhaust chamber of the energy equipment is connected directly to the PCCS with the aid of a connection pipe as shown in Fig. 10. The flue gas passes through the adsorber chamber, where it contacts a chemical solution that can remove 85%–90% CO2 that is present while the flue gas that is free of CO_2 is released to the atmosphere [87]. The chemical solution can either be a liquid solution or solid sorbent, and the CO_2-rich solution is then passed through the desorber or regenerator, where the CO_2 is stripped from the solution using thermal energy. The CO_2 is subsequently compressed, cooled, stored, or transported, while the lean chemical solution is recycled in another capture operation.

Few studies on MES have considered the integration of PCCS to achieve carbon neutrality; Ma et al. [88] proposed an integrated model of PCCS and P2G for the feasibility of MES, the P2G model consists of electrolyser (ELZ) and a methanation part. The ELZ aid the H_2 production, which is then combined with the captured CO_2 for the synthetic methane gas production that is utilised by a gas turbine. Their obtained results show that their proposed configurations enhanced renewable energy and contributed to reducing operation cost and carbon emission. Zhang et al. [89] also developed integrated CCS-P2G for the optimal economic scheduling of MES, and they concluded that the produced synthetic gas reduces dependency on external gas. Moreover, a comparative

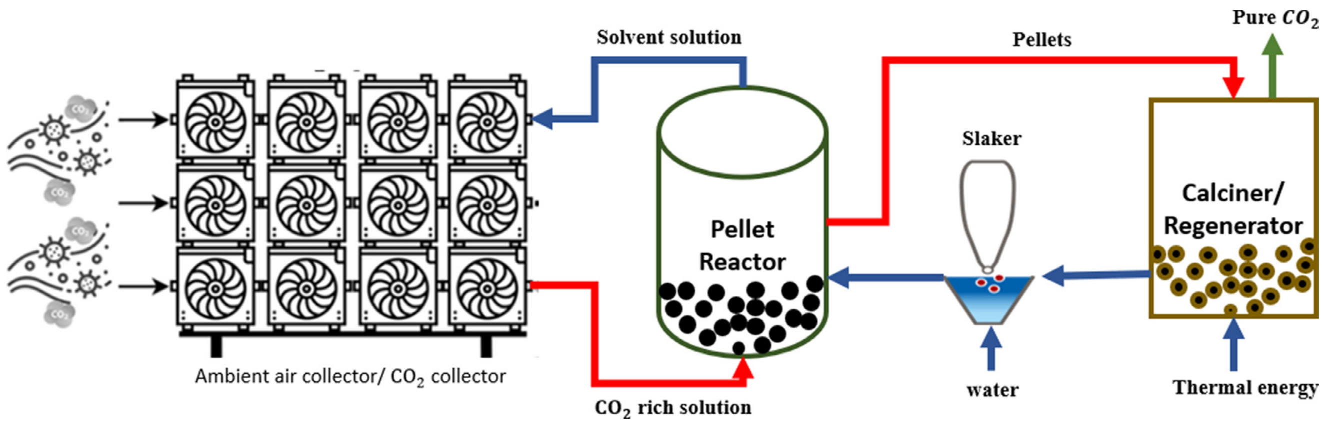

Fig. 11. Direct-air carbon (DAC) capture system.

analysis between gas-to-gas (G2G) with CCS and P2G was evaluated in [78] for the decarbonization of MES through hydrogen penetration. The authors asserted that G2G provides more cost savings than P2G and reduces renewable energy capacity.

3.2.2.2. Direct-air carbon capture system (DACS). DAC is another CDR technology with the idea of capturing the CO_2 present in the atmosphere. Compared to PCCS, the system required an extractor fan to harness the surrounding air, as shown in Fig. 11, while other components and the CO_2 capturing process are similar to PCCS. One of the benefits of DAC over PCC is the capturing of environmental CO_2 such as transportation system emissions and other activities associated with CO_2 release into the atmosphere. Deutz et al.[90]. presented a life cycle assessment of DAC on an industrial scale using the pilot study project in Hinwil and Hellisheiði that Climeworks operates as a case study. Their findings confirmed that a large-scale deployment of DAC is required to achieve meaningful global carbon reduction. Tom et al. [91] also evaluated the life-cycle assessment of DAC when integrated with low-carbon energy sources, and they proved that the system is cost-effective because it utilizes waste heat to regenerate the CO2 stripping process. Despite the potentials of DAC in achieving a negative carbon environment, the system has rarely been integrated with the energy generation system. Berger et al. [92] compared PCC, DAC, and P2G as the primary influencing systems in achieving deep decarbonization in the energy sector. Their findings suggest that CDR technologies, such as PCC and DAC, serve an enabling role but that DAC can only supplement PCC and not replace it. The vast amount of power and heat energy needed by CDR systems, especially at a large scale, is a significant disadvantage of the technology. Keith et al. [93] estimated that 366 kWh of electricity and 3.5 GJ of natural gas is required to captured 1 ton of CO_2, although waste heat can be used for the thermal demand if low-temperature sorbent (mostly in solid form) is used as the absorber. However, the leveraged cost (LC) of the system is another drawback, the present LC per ton of DAC is 94$–232$/t-CO2 which depends on the energy cost and the materials cost.

3.2.3. Combined zero-emission equipment and CCS

Integrating zero-emission equipment and CCS is another economically viable approach for decarbonizing the energy sector. As stated in Section 3.2.1, the fundamental challenge of most existing zero-emission equipment is their high capital and operating costs, while reliability issues caused by uncertainty impact the renewable energy system dependency. Also, sole dependency on CCS is uneconomical due to the colossal power demand that may surge fossil fuel consumption [92]. The integration of the two approaches bridges the gap between decarbonization, reliability, and economic viability. Ma et al. [88] optimised the configuration of MES with the integration of CCS and P2G. Due to the magnitude of the case study's thermal and power demand, renewable energy was proposed as the principal energy source. CHP and thermal boiler were introduced while CCS is responsible for capturing the associated system's CO_2 emission and P2G enables the utilization of the CO_2 within the system. A similar approach was also proposed in [94], which involved incorporating the renewable energy system, conventional power generation, and CCS. The obtained simulation results of the proposed approach enhanced renewable energy penetration and restrained carbon emission. The utilization of captured CO_2 within the MES framework was evaluated in [95] by integrating the supercritical CO_2 cycle that consumed CO_2 and coal to generate electricity and thermal energy.

3.3. The challenges of operating MES as zero-carbon systems

As detailed in the preceding section, operating MES as a zero-carbon system (ZCS) is a principal strategy for achieving carbon neutrality. Its feasibility has been affirmed through zero-emission equipment adoption or developing a capture and storage strategy for the emitted carbon. The primary difference between MES and ZCMES is the technologies introduced, while the modelling approach is similar, as described in Section 2.2. Nevertheless, some challenges arise when operating MES as ZCS due to total independence. Some of the possible challenges are described below:

3.3.1. Influence of uncertainty

The two prominent renewable energies, i.e., solar and wind energy, are called variable energy generation (VEG) due to their variability with time and climate data variations. This variability feature is also considered as uncertainty since the exact variation at each time step cannot be accurately predicted. MES modelling has been studied extensively, and uncertainty influence has been identified as a critical aspect that cannot be overlooked. Without its consideration, the MES model is considered infeasible due to frequency imbalance problems associated with uncertainty, resulting in energy equipment breakdown or total blackout. The National Renewable Energy Laboratory (NREL) evaluated the impact of photovoltaic and wind energy variability at multiple timescales, and it was concluded that various mix of energy reserves technique is needed to alleviate the uncertainty impact [96]. Zhou et al. [97] optimised MES operation under strong uncertainty influence, and P2G mitigated the possible impact of the renewable uncertainty on the operation. Notably, the multi-energy demand fluctuation due to changes in consumers' behaviour is another crucial uncertainty influence on the performance of MES. Alabi et al. [98] examined the impact of multi-energy demand and renewable resources uncertainties on MES planning. Their results asserted that each multi-energy demand affects the selected energy equipment capacity size, and their proposed model reduced the operation cost by 10%.

Meanwhile, since uncertainty is a major consideration for renewable resources, modelling MES to achieve zero-emission will transit to significant dependency on renewable energy at the upstream, i.e., the energy input side. Even if fuel cell is selected as the primary power generation device, hydrogen production via electrolysis must be generated through renewable and sustainable means. Hence, the influence of uncertainty is inevitable. Although some innovative approaches have been proposed in the literature, as described in section 2.3.2, to quantify uncertainties, with more details in [99], the increase in renewable energy dependency contributes huge uncertainty impact which the contemporary uncertainty quantification methods may not be suitable.

3.3.2. Reliability and security

The reliability of MES and energy security is another crucial challenge that may hinder the effectiveness of ZCMES. Reliability is described as the ability of an energy system to meet the consumers' demand with a high degree of confidence [100]. The reliability standard recommended by National Electricity Rules (NER) stipulated that the energy system must meet at least 99.998% of the forecasted consumers' demand [101]. Energy security refers to the uninterrupted energy supply from the generation sources to the consumers' side. It describes the ability of energy networks to transport energy safely without uneven distribution [101]. It is expected that an electricity network must transmit the power generation within the stipulated voltage range and frequency value. Energy security has been a significant concern in the power sector. For instance, the Australia Electricity Market Operator (AEMO) affirmed that 95.6% of blackout experienced in Australia between 2009 and 2018 was caused by energy network disruption, while reliability events only account for 4.1% [101].

Energy reliability is a significant concern for ZCMES; despite the supply of energy reserves to minimize outages, the existing power infrastructure still has reliability issues. Although energy storage technologies such as EES and TES are provided to deliver energy backup during insufficient power generation, Luo et al. [102] evaluated the impacts of multiple energy storage on the operational benefits of regional MES and a precise energy storage economic model for MES was proposed by Cong et al. [103]. Alabi et al. [104] went further by considering the degradation effect of EES and TES on the optimal planning and operation of MES, and their proposed model outperformed the conventional model. Nonetheless, any discrepancy in the expected performance of any ZCMES components may hinder the systems' reliability. The energy security potential threat is already minimised by MES architecture since the distributed energy resources (DRES) is located close to the consumers/prosumers.

On the other hand, as the complexity of ZCMES increases, especially for the regional district, energy security become a concern to avoid uneven distribution, voltage and frequency spike, and current undulation. Also, the thermal and gas networks are other concerns that must not be overlooked to ensure optimal regulation of the mass flow rate, temperature effect, and pressure regulation. It is worth mentioning that tremendous contributions have been made on MES energy networks modelling in the literature. The established model uses alternating current (AC) or direct current (DC) power flow model to describe MES electric network while thermal-hydraulic model and Weymouth formula are used for thermal and gas distribution networks, respectively [105,106]. Junjie et al. [67] considered the dynamic characteristics of the MES energy network for the optimal scheduling of the system. The effects of ambient temperature, temperature drop coefficients of thermal networks uncertainties on the operation performance of MES network, and scheduling were evaluated by Huansheng et al. in [69]. It was affirmed that their proposed method could improve the robustness of the network. J. Wang et al. [56] took a step further and proposed active network management (ANM) for MES by integrating smart devices. However, most of the works were not based on a zero-emission target.

3.3.3. Physical and cyber-attack threat

Physical disruption of energy systems through natural disasters such as windstorms, earthquakes, typhoons or vandalization has been a significant threat to the power grid. California in the United States (US) recently experienced a power outage due to an increase in the heatwave in the region [107]. A similar event occurred in Texas due to extreme weather, which caused the energy demand to exceed supply and the shutting down of wind turbine farms [108]. Cyberattacks of the energy sector is another threat that has made headlines recently. According to World Economic Forum's Global Risk 2020, the energy system was ranked fifth amongst the critical infrastructure susceptible to cyberattack [109]. Although there is a lack of comprehensive statistics on energy infrastructure hacks, a massive energy system cyberattack on the western Ukraine power grid occurred in 2015, affecting 30 substations. [109].

Due to the isolating nature of ZCMES to curb national grid and gas grid carbon emission, physical attacks, especially unpredicted climate changes, is a significant concern. ZCMES will encourage high renewable energy penetration, whereas shutting down a renewable energy plant due to extreme weather conditions may result in a state of emergency in some regions. The vandalization of power grid components can also be a substantial threat from an enemy of states, a common incident in the African region [110]. The effects may be worsened for ZCMES since there is no connection with external power sources, and the rectification may take a more extended period. Furthermore, while the Internet of Things (IoT), communication networks and smart devices, cloud services, and internet facilities all support the feasibility of ZCMES, all of these facilities are vulnerable to cyberattacks without physical interruption.

3.3.4. Economic implication

High energy efficiency with low or zero-emission potentials has become the major goal of energy researchers and energy equipment manufacturers. Auspiciously, there has been a skyrocketing achievement in this area, especially with the recent development of some novel energy equipment such as hydrogen catalytic boiler, heat pump, fuel cell, electrolysers, etc. Meanwhile, the major challenge of these devices is their economic cost compared to conventional energy equipment due to some scarce materials used for their development. Alabi et al. [60] conducted a comparative analysis on MES carbon minimization and zero-carbon target, and their results depicted that the investment cost of the zero-carbon target increases by 40.14% in comparison with the carbon minimization target. Berger et al. [92] presented a comprehensive evaluation of CCS as a decarbonization strategy. According to their findings, CCS is economically feasible on a broad scale. Hence, without providing an incentive program, possible investors will be reluctant to invest in ZCMES.

3.3.5. The complex energy management task

Energy management is a proactive measure and the systematic energy production and consumption management optimally [111]. In MES, energy management is usually categorised as scheduling or optimal operation. It is described mathematically by introducing all the possible governing constraints of each energy equipment, in terms of their minimum and maximum output, unit commitment (UC) constraints, energy balance at each specified time step, and other applicable phenomena constraints. A flexible UC scheduling model for the optimal scheduling of combined heat and power (CHP) was presented by Gonzalez et al. [112]. The proposed model optimally scheduled the operation of CHP in terms of thermal load filling while meeting the electricity demand. The optimal operation of MES was proposed in [113] while considering the influence of thermal storage capacity, the constraints of the cogeneration, energy networks, and thermal load balance. Similarly, a distributionally robust optimization (DRO) was introduced by Chen et al. [114] for the optimal day-ahead scheduling of regional MES. The proposed DRO considered the worst-case uncertainties that influence MES energy storage and other equipment scheduling.

On the contrary, the implementation of ZCMES may increase the number of devices, which will increase the complexity of the mathematical expressions and the intricacy of achieving optimal scheduling. Besides, to ensure realistic operation, some optimization properties such as non-linear relationships, bilinear terms, and non-convexity may arise, requiring reformulation or the use of a specialized solver. Combining this with the possible increase in ZCMES components complicates the energy management task. The difference in dynamic characteristics and the response time of different energy systems is another challenge. For instance, the response time of the electricity energy carrier system is fast and is near the speed of light (3×10^8 m/s), compared to thermal energy system carrier with large inertia, characterised by a low response time that is not more than 1.2 m/s [58].

3.3.6. Rapid degradation of energy equipment

Energy system degradation refers to the reduction in the system's actual performance due to irreversible physical or chemical alteration [115]. Degradation in performance usually occurs after the service life when the equipment is due for replacement. However, the environmental conditions and utilization rate lead to a rapid degradation scenario, which is more evident in energy storage technologies, especially chemical storage due to chemical reactions. [116]. The effect of battery degradation on the operation performance of energy storage was studied by Aramis et al. [117]. Their results indicated that the state of charge (SOC) of the battery and the ambient temperature are the main factors that contribute to energy storage degradation. Conversely, only a few studies have considered the degradation effect on MES optimal scheduling. Chen et al. [103] designed a co-optimization model for MES by incorporating BES and TES degradation model, the effect of the energy storage ageing model on the optimal planning of ZCMES was studied by Alabi et al. [104]. Their findings confirmed that energy systems are overdesigned without considering degrading effects.

ZCMES requires a robust approach to ensure adequate energy supply and reliability without relying on external power sources. The study in [104] illustrated that ZCMES is accompanied by selecting a large energy storage capacity and high charging cycle of ESS. This attribute contributes to rapid system degradation and early replacement before the expected service life.

3.3.7. Precise day-ahead prediction challenges

The feasibility of smart grid and smart energy systems has been reinforced with the availability of powerful algorithms to predict future scenarios. The research communities have made tremendous contributions using either machine learning (ML) or deep learning (DL) techniques for energy prediction and renewable resources future forecasting [118]. Meanwhile, as a result of correlated properties and time-series events of energy and renewable resources, DL techniques which comprise of recurrent neural network (RNN), long short-term memory network (LSTM) and its variants, convolutional neural network (CNN), and customised deep learning methods have been the most adopted techniques [118]. The application has also been extended to MES; a multi-task DL technique that comprises the integration of gated recurrent unit (GRU), which is a variant of LSTM and CNN was proposed in [119] for multi-energy load prediction of MES; the proposed model has better prediction applicability than other models. Wang et al. [120] developed a novel multi-energy load forecasting for regional MES considering the data's temporal dynamic and coupling characteristics. The model was developed using an encoder-decoder model and LSTM, which are then fused to form an ensemble model and retrained using a gradient boost decision tree (GBDT).

ML or DL accuracy depends on achieving the least predictive error obtained by evaluating the differences between test data and the predicted values. The commonly used evaluation metrics to examine the accuracy of any ML or DL performance are root mean square error (RMSE) and mean absolute percentage error (MAPE). However, the main challenge of this forecasting technique is that the forecasted future event cannot be exact or 100% guaranteed. Another view is the possible deviation in the prediction model's performance during the real-time event due to uncertainties influence. This shows that a highly independent ZCMES with deep renewable energy penetration that is highly affected by stochastic parameters requires precise prediction for efficient and optimal economic decision making.

3.4. Some proven solutions in the literature

The challenges mentioned above are the possible hindrances that may affect the feasibility of ZCMES and complicate the possibility of achieving the carbon neutrality goal. Nonetheless, efforts from relentless researchers in the energy field have provided some unique solutions to avert some of the challenges. These are described below:

3.4.1. Hybrid uncertainty model

SP and RO are the established uncertainty quantification methods. However, they have their pros and cons. SP has been proven to quantify the uncertainties effectively with the availability of historical data and understanding the PD attributes, whereas it is difficult to establish the PDF stochastic parameters in a real-world application, and it is computationally intensive [66]. RO eliminates the need for PDF estimation, but its main rip-off is the conservative nature which usually results in economic disadvantage [71]. Hence, hybrid uncertainty that involves the combination of two or more uncertainty quantification approaches to complement each other weaknesses has been proposed [121]. Fig. 12 illustrates the possible combination of the hybrid uncertainty approach; it involves careful analysis of the modelling uncertainties and selecting a suitable uncertainty model that applies to each uncertainty parameter. For instance, with the availability of historical data, an SP can be applied to the data, while with inadequate historical data, a robust optimization is suitable for the data with the specification of deviation value. Some studies on MES have also applied the approach; A robust-stochastic model is applied for MES optimal despatch in [122]. A distributed robust optimization (DRO) that integrates ambiguity set and the confidence band construction is proposed to quantify the wind power stochasticity. Likewise, Alahyari et al. [123] applied hybrid uncertainty that combined scenario generation using Monte Carlo and a classic robust method for the optimal day-ahead despatch of MES. At the same time, Alabi et al. [124] integrated Latin Hypercube scenario generation and robust optimization method. The method outperformed classical robust-stochastic due to the consideration of random variables correlation.

3.4.2. Ensemble deep learning model development

As described in Section 3.3.7 concerning the hitches of most of the proposed MES forecasting models, the current trend in this area is the application of the ensemble deep learning model [125]. It involves the combination of multiple diverse predictive models to predict a future scenario. These diverse models are termed base models, and they are modelled using different modelling algorithms or varying training datasets. Moreover, the base models are described as weak learners combined to form a strong learner [126]. Different methods are also available for integrating the base models, including bagging, aggregating, and boosting, as illustrated in Fig. 13. Readers can consult [124, 125] for more information on the ensemble model.

In addition, a few researchers have applied the technicality of the ensemble methods to increase the prediction performance and achieve near precise prediction; An empirical mode decomposition and deep belief network were ensembled for cooling load prediction model in [127]. Zhang et al. [128] developed a short-term power load forecasting model for the Australian electricity market by combining ANN and extreme learning machine, Yi et al. [125] improved on Zhang et al. model by applying clustering and grouping to generate multiple results, and then weighted them based models to obtain the final predicted power load. Whereas only a few studies have applied this innovative forecasting technique on MES. A novel deep multi-task learning was proposed in [119] for a multi-load prediction model followed by applying gradient

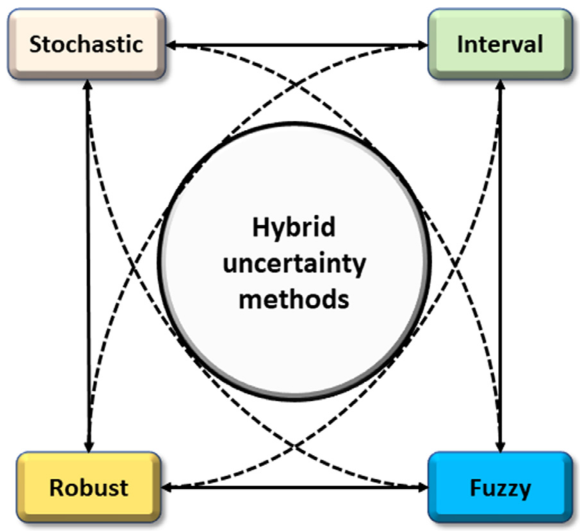

Fig. 12. Hybrid uncertainty quantifications.

boosting regressor tree (GBRT) for the final prediction of the ensemble model.

3.4.3. Hybrid flexibility approach through energy storage and building thermal inertia

The feasibility of energy flexibility has come to the limelight due to various energy storage technologies and conversion technologies. Energy flexibility is defined as the ability of the system to respond fast and react sufficiently to the energy demand without causing any instability to the system [129]. The primary purpose is to avoid energy network congestion issues, frequency imbalance, and extreme renewable energy curtailment [130]. Categorically, the primary procedure for achieving this flexibility is through the integration of hybrid energy storage technologies (combination of electrical energy storage, thermal storage and/or gas storage), advanced conversion technologies, e.g. P2G and P2X technologies [131], and the development of flexibility index to quantify the energy flexibility [132]. For instance, a typical case study is to converts excess power generation into hydrogen gas using an electrolyser, store in the hydrogen tank and utilised by a fuel cell to generate both electric power and thermal energy during insufficient power availability. Zhou et al. [133] proposed some novel energy flexibility quantification indicators for MES by considering the dynamic operation of hybrid energy storage integrated with diversified energy conversions strategies. Their proposed approach, which includes a novel control strategy, improved the system energy flexibility.

Building thermal inertia is a passive energy flexibility approach that have received immense attention. It is described as the ability of the building envelope to control its interaction with the thermal environment through transient heat flow and storage effects [134]. The property is referred to as thermal mass, and a more significant amount enables the building to time-shift and regulate heat fluctuation [134]. Li et al. [135] improved the operational flexibility of MES by leveraging the building thermal inertia. Similarly, Zhong et al. [67] considered the psychological effect of building thermal inertia on the optimal operation of MES in the presence of uncertainty.

3.4.4. Improved energy management techniques

Aside from the conventional operation and scheduling optimization approach for the optimal regulation of energy systems, some innovative energy management techniques that consider the dynamic behaviour of the energy systems have been proposed. These include **model predictive control (MPC)** and **deep reinforcement learning (DRL)**. The two techniques address the challenges associated with the traditional mathematical programming operation scheduling approach, majorly the stochasticity nature of some parameters during real-time operation, the prediction or forecasting error when uncertainty or prediction model is adopted [136], and the difficulty in real-time deployment. MPC is an advanced control method that is used to obtain the optimal control action of an energy system at each timestep while satisfying all the applicable constraints [137]. Its primary function is to ensure that the control action at each step is as close to the desired reference as close as possible.

It should be noted that while the conventional scheduling approach obtained the optimal decision variables at each time step, MPC deals with dynamic control action between each timestep. Wei at al. [138] developed an enhanced stochastic MPC technique for the optimal scheduling of MES while the authors in [139] analysed multiple uncertainties associated with the integration of power-to-X technology. In [140], a stochastic MPC was developed for Danish homes' real-time MES power imbalance management. Similarly, an MPC operation strategy that is based on the system's temperature flowrate is proposed in [141]. Table 1 illustrates some MES studies that have applied MPC, their main objectives, how MPC is applied, and their contributions.

DRL is another energy management technique that has received attention recently in MES research. The technique combined a deep learn-

Table 1
Model predictive control application in MES.

Refs.	How MPC is implemented
[142]	• An improved stochastic model predictive control MPC strategy is developed to optimise the economy, robustness, and computational efficiency of MES scheduling. • The least-square support vector machine predicts the supply and demands while the applicable constraints and cost function are described in a multi-time scale form. • The proposed method outperformed single layer and a hierarchical strategy
[139]	• Real-time scheduling of MES with multiple uncertainties and power-to-x is developed. • The formulated MPC is based on the measured state of the system and future uncertainties information, while the penalty cost to minimise the deviation between day-ahead and real-time schedules is minimized. • The developed MPC strategy outperforms traditional real-time scheduling
[143]	• A stochastic MPC is developed for real-time MES power imbalance management using Danish home is a case study • The stochasticity associated with the system was quantified using scenario generation. • The obtained results increased the systems' efficiency and facilitated cost savings.
[140]	• A non-linear economic MPC model is developed for multi-energy microgrid management. • The uncertain nature of the system is formulated using robust optimization. • The obtained results validate the superiority of the proposed strategy compared to traditional energy management.
[144]	• MPC is adopted to establish the closed-loop dynamic rolling of MES optimal despatch. • The uncertainty of the load demand and wind uncertainty were analysed using the scenario method. • The test results validate the correctness of the intraday rolling optimal despatch.
[141]	• A novel MPC operation strategy that is based system's temperature-flowrate is evaluated • The operation strategy was executed through energy forecast, scenario reduction, rolling optimization, and feedback correction. • The test results affirm that thermal characteristics affect MES reliability and economic implication.

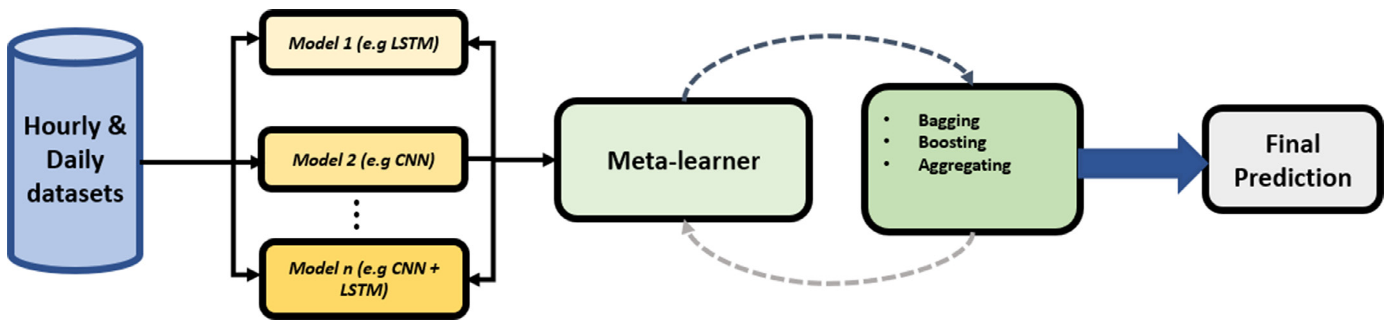

Fig. 13. Ensemble model.

ing framework and reinforcement learning RL approach. RL is a machine learning technique that dynamically learns by altering its actions based on continuous feedback from the environment to maximise reward and penalise undesired behaviour [145,146]. Generally, the main idea is for the RL agent to perceive and interpret the environment, take necessary actions, and learn dynamically using a deep learning approach. Fig. 14 illustrates the dynamic interaction of DRL components. Various algorithms have been developed in recent years for the training of DRL agents, and these algorithms are divided into model-based and model-free methods. The formal required detailed information about the environment for the learning process while the latter learns through continuous interaction with the environment while updating the learning parameters. In the energy management field, the model-free approach is the most adopted method to handle the complex and non-linear features of the energy systems interaction. The most popular algorithms are double Q-learning, deep deterministic policy gradient (DDPG), twin delayed deterministic policy gradient (TD3), soft actor-critic method (SAC), and policy proximal approach (PPO). More information on the modelling and its various algorithms can be seen in [145,147]. DRL approach was applied in [147] for the real-time energy despatch of MES using the DDPG algorithm, the proposed method achieved cost-effectiveness. Zhang et al. [148] proposed DRL as a control platform to achieve MES energy supply reliability using SAC algorithm, and their developed framework reduced the scheduling cost by 21.66% compared to a heuristic algorithm. A novel DRL approach with efficient computational speed for MES optimal despatch was proposed in [148], and this is achieved by introducing a cycling decay learning rate to DDPG training algorithm. Dawei et al. [149] deviated from the conventional way of handling systems' constraint in DRL by incorporating a safety network in the DRL framework, and the proposed method was trained and tested on MES and the approach outperformed the conventional DDPG in terms of convergency speed and optimality. In summary, similar studies on the adoption of DRL as energy management strategy are presented in Table 2 in terms of their contribution and how the DRL algorithm was applied. Fig. 14

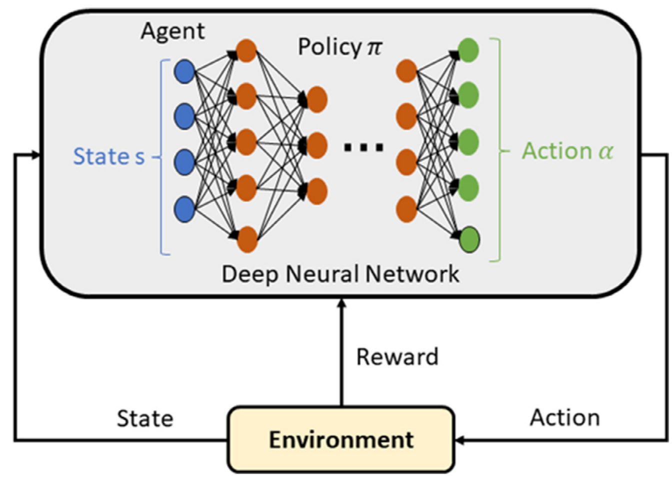

Fig. 14. Deep Reinforcement Learning (DRL) interaction.

3.4.5. Integrated demand response

In the energy management (EM) field, the supply-side and demand-side energy management are the main focus area for energy control and regulation. The supply-side EM deals with the regulation and control of energy generation and distribution at the generation source. In contrast, the consumers' regulation and response to the energy provided is described as the demand side EM (DSM). Demand response (DR) has been the primary technique of DSM. This is achieved by regulating the energy consumption pattern of the consumers either by load shedding or load shifting of flexible appliances in response to prior energy signals from the supply side [157]. The real-time pricing (RTP) mechanism is the most adopted DR technique. It enables flexible adjustment of consumers' load patterns in response to price signals from the suppliers to achieve an optimal strategy, peak shaving, and valley filling [158].

Due to the multi-energy demand feature of MES and the need for its optimal energy management, the traditional model of DR has gradually evolved to integrated energy demand response (IDR) to cope with the complex operation of MES [159]. The IDR concepts entail the extension of traditional DR to encompass the flexible adjustment of other energy demands aside from electricity in an optimal manner [160]. A typical illustration is an increased thermal energy usage while some flexible electrical loads are shifted to another period due to peak electricity prices in real-time. At the same time, the thermal energy is optimally scheduled to alleviate the possible discomfort associated with electric load shifting. Table 3 summarises some noteworthy studies that applied IDR on MES are summarised. Notably, Yuan et al. [161] developed an optimal strategy for multi-regional MES using the RTP method for IDR implementation. The peak to valley load and carbon emissions were reduced by 16.99% and 5.7%, respectively. Mirzaei et al. [162] applied IDR for the robust optimal scheduling to increase the flexibility of MES, and their results indicated that the system's performance was increased with the integration of IDR, and the operation cost was also reduced by 15%. Li et al.[163]. considered multiple uncertainties associated with MES and applied IDR as a flexibility measure for the optimal despatch of the systems using two-stage scheduling approach. A similar approach was also adopted in [164,165] using bilevel optimization method. Furthermore, Alabi et al. [104] integrated the energy storage ageing model and IDR for the co-optimization planning of ZCMES while considering uncertainties. Their results validate IDR as a promising approach for the feasibility of zero-carbon in the energy sector.

3.4.6. Electric vehicle flexibility potentials

The recent progress in the technology development and fast pace of EV adoption to replace gasoline vehicles has uplifted the feasibility of transport sector decarbonization. In addition, MES has also enabled the

Table 2
Deep reinforcement learning application in MES.

Refs.	How DRL is implemented
[150]	• A dynamic energy despatch strategy is proposed for MES using DRL. • DRL is proposed to address the randomness of renewable energy and energy demands that are limited by the accuracy of a forecasting model • The model is formulated as a Markov decision process (MDP), and the policy action is based on a deep deterministic policy gradient (DDPG) algorithm using replay mechanism and policy L2 regularization • The formulated strategy achieved cost-effectiveness and stochastic environmental adaptation
[151]	• DRL is proposed as the scheduling strategy to minimize system operation costs and ensure MES energy supply reliability • The stochastic problem is modelled as MDP, and a soft actor-critic (SAC) algorithm is developed to solve the complex scheduling problem • The proposed method reduced the scheduling costs by 21.66% compared to heuristic algorithms.
[152]	• Data-driven DRL is developed to facilitate peer-to-peer P2P transactions within MES community networks. • A deep belief network (DBN) is adopted is described the P2P transaction behaviour without sharing private data • Finally, the model is formulated by integrating MES network constraints into the DRL reward function and P2P transaction scheme. • The proposed framework achieves 7.6% energy cost savings.
[153]	• The optimal energy allocation of MES is achieved using the DRL algorithm • The associated stochasticity of the system is formulated as MDP, and asynchronous advantage actor-critic (A3C) DRL algorithm is adopted for real-time decision making, • The proposed strategy demonstrates effectiveness and superiority compared to other algorithms
[154]	• The dynamic changes of MES demand and supply are addressed using the DRL approach. • The model is formulated as MDP using applicable mathematical models and constraints. Then, the ASC algorithm is applied to optimize the control decision of asynchronous learning of agents to ensure optimal control decisions for MES demand and supply. • The training period of the proposed method is reduced by 37%, and the daily operation cost is reduced by 8.7%.
[148]	• A novel energy control method is proposed for MES using DRL, • The model is formulated as MDP, followed by applying the Cycling decay learning rate deep deterministic policy gradient (CDLR-DDPG) algorithm as the optimal operation strategy. • The proposed CDLR-DDPG algorithm outperformed other algorithms.
[155]	• The energy management problem of MES considering integrated demand response IDR and the Stackelberg game is solved by DRL. • The proposed approach reduces energy purchasing costs, and the RL algorithm exhibits a good convergence performance.
[156]	• A multi-agent distributed control strategy AGC based on DRL is developed for the optimal energy management of MES. • The control error and carbon emission are adopted as the reward function for the DRL. • The model outperformed other intelligent AGC algorithms.

charging of EVs optimally and economically. Since the electrical battery is the primary power source of EV, which needs to be charged at the charging station during the parking period, some scholars have considered the possibilities of integrating EV as part of the complex energy systems and utilising its potential flexibility economically. The flexibility provided by EV is classified into vehicle-to-building V2B, building-to-vehicle B2V, vehicle-to-grid V2G, grid-to-vehicle G2V, and vehicle-to-vehicle V2V. The combination of any of this EV flexibility has been proven to contribute to optimal operation cost and carbon emission reduction [192].

Some MES studies have considered the use of EV flexibility. Di Somma et al. [193] evaluated the optimal management of EV in a localised MES under V2G and G2V mode. The obtained results revealed that selling most of the EV flexibility to the wholesale electricity market maximized the operator's profit. Abdollahi et al. [194] evaluated the impact of smart EV charging on the optimal management of MES, which resulted to a reduction in the systems' total cost. The influence of EV parameters uncertainty about optimal scheduling of multi-energy microgrid was studied in [195]. A novel approach for optimising MES integrated with PEV flexibility was proposed in [196,197] using risk-averse and risk-seeking strategies. Remarkably, Alabi et al. [124,197] considered the EV flexibility in another dimension for ZCMES. These are; vehicle-to-electricity use V2EU, vehicle-to-cooling use V2CU, vehicle-to-heat use V2HU, and V2G as the EV multi-flexible potentials considering the multi-energy demand feature of MES, they developed an optimization model that automatically determines the suitable EV multi-flexible potentials combinations and outperformed the conventional approach.

4. Future perspectives and recommendation

Researchers have made major contributions on the actualization of MES, which has become widespread and has been implemented by many energy programs. Nonetheless, to ensure the feasibility of the carbon neutrality target, some noticeable research gaps that are needed to be explored as future research directions are recommended below:

1) The system's ability to swiftly respond or recover from destructive interruption is a significant characteristic of any energy system, especially for those operating in island mode. Various resilience approaches and methods have been proposed in the literature based on reliability and resilience metrics. Conspicuously, most of the methods were apply on MES in grid connection mode, while the external grid primarily provides their resilience and reliability. Meanwhile, most of these resilience metrics may not be effective for ZCMES since the system primarily operated as a stand-alone system to eliminate grid emission. Hence, a resilience strategy and metrics that will consider the distinct features of ZCMES is worthy of development.
2) Accurate prediction of a future event is the first step towards the feasibility of ZCMES. This enables optimal day-ahead decision making and necessary reliability measures to be executed by the management system. In this area, substantial contributions have been made by developing novel forecasting techniques, especially the ensemble modelling approach. Nonetheless, some parameters are subjected to high stochasticity during actual operation, and the forecasting model is usually evaluated using prediction or forecasting error. Hence, for the ZCMES forecasting model, the approach must factor in this stochastic influence since any slight deviation can hamper the system's reliability.
3) Sections 2.3, 2.4 and 2.5 delve into the MES energy flexibility strategies in depth. It is impossible to make a fuss about the importance of all of these flexibility measures, especially in terms of economic and technical benefits. For ZCMES, adopting a single flexibility measure may not be effective. For instance, focusing only on energy storage flexibility may result in large storage capacity sizing, which is uneconomical. Therefore, the development of a unique flexibility model that will integrate all the possible flexibility techniques efficiently

Table 3
Integrated Demand Response (IDR) application in MES. (EL: electricity load, HL: heat load, CL: cooling load, GL: gas load).

Ref	Main work	IDR EL	HL	CL	GL	Year
[114]	Development of distributionally robust optimal scheduling for the park level integrated energy system.	√	√		√	2021
[162]	A hybrid robust-stochastic optimization is proposed for the optimal scheduling of MES	√	√		√	2021
[166]	A multi-objective optimization framework is developed for the planning of energy hub while considering load flexibility	√	√	√		2021
[167]	A novel bilevel optimal despatch model is proposed for community MES	√	√			2021
[168]	An energy management method that is based on IDR is proposed	√	√			2021
[169]	A scheduling model that considers load volatility and IDR is developed	√	√	√		2021
[170]	A multi-objective optimization that integrates energy storage ageing model and IDR is proposed	√	√	√		2021
[163]	A two-stage optimal despatch method that considers multiple uncertainties and IDR is developed for MES scheduling	√	√	√	√	2021
[171]	IDR, corporative game, and virtual energy storage were integrated for the optimal day-ahead scheduling of MES.	√	√	√	√	2021
[122]	A robust-stochastic optimization that is based on IDR is developed for the optimal operation of MES.	√	√	√	√	2021
[172]	A day-ahead energy trading mechanism is developed for the MES company	√	√		√	2021
[173]	Intra-day scheduling of MES with the influence of uncertainties is proposed	√	√		√	2021
[174]	A Stackelberg game approach is applied for the optimal scheduling of IDR-enabled MES	√	√			2021
[175]	A novel energy pricing and sharing strategy is developed for virtual energy stations in MES	√	√			2021
[176]	An optimal scheduling framework for the operation of MES is proposed using IDR	√	√	√		2021
[177]	A comprehensive planning model for MES is developed by utilizing IDR flexibility	√	√			2021
[178]	A multi-task risk-averse model that considers IDR is developed for the optimal scheduling of MES	√	√			2021
[179]	A station-and-network planning model that considers IDR is developed for MES	√			√	2021
[180]	An incentive-based IDR is proposed for MES under multiple uncertainties	√	√		√	2021
[181]	Optimal scheduling of MES that is based on power Internet of Things is proposed	√	√			2020
[182]	A Nash bargaining game approach that is incorporated with IDR is developed for the MES distributed energy trading system	√	√			2020
[183]	Optimal allocation of a coupling device in MES is achieved by considering IDR and uncertainties	√	√	√	√	2020
[184]	A bilevel optimal economic despatch model is proposed considering multi-energy price uncertainties and IDR	√	√	√	√	2020
[164]	A novel optimal interval strategy considering tolerance degree and IDR is developed for household MES.	√	√	√		2020
[185]	The optimal IDR scheduling response of regional MES based on concentrating solar power is developed	√	√			2020
[186]	A medium and long-term IDR of MES that is based on system dynamics is evaluated	√	√	√	√	2020
[187]	IDR is developed for district electricity -heating network retail market	√	√			2019
[188]	A unified probabilistic energy flow analysis coupled with IDR is developed for electricity-gas coupled systems	√			√	2019
[189]	A combined optimal design and operating model is developed for MES with the incorporation of IDR	√	√	√		2019
[190]	A linearized stochastic model with IDR is proposed for MES under the influence of wind uncertainty	√	√		√	2018
[191]	The influence of IDR on the optimal operation of electricity, natural gas, and heat systems is evaluated	√	√		√	2018
[165]	Bilevel optimal despatch strategy based on IDR consideration is developed for MES.	√	√	√	√	2018

and economically will enhance the adoption and the feasibility of ZCMES.

4) The energy system operation and management are gradually revolutionizing towards a digital era, accrue to the recent advancements in information and communication technologies (ICT) and power electronics. Nonetheless, the main loophole of these technological advancements is the cyberattack infiltration, this area is still open for rigorous future research to achieve a ZCMES that is resilient to cyber intrusion.
5) Finally, the objective of carbon neutrality has become a lofty one. Nevertheless, most current energy policies do not place a premium on its implementation. The focus is more on carbon emission reduction, efficiency, and renewable energy penetration. Hence, the current energy policies need to be revised with a concentration on zero-carbon feasibility in the energy sector.

5. Conclusion

Deep decarbonization of the energy sector serves as the primary strategy towards zero-carbon environment actualization. On the other hand, MES has been proven as the right approach towards a circular energy economy and optimal energy utilization. Hence, we presented a detailed review that bridged the gap between MES and zero-carbon emission feasibility. Firstly, various MES technologies and configurations are reviewed in terms of cogeneration, trigeneration, and polygeneration, followed by the substantial benefits of MES adoption. The transition into zero-carbon multi-energy systems (ZCMES) is then presented in the second part, classified into MES with zero-emission equipment, MES integrated with carbon captured and storage system (CCS), and combined zero-emission and CCS system. In the third part, we presented some challenges that may hinder the feasibility of achieving ZCMES mainly due to lack of coverage by most of the existing energy policies, uncertainties influence, energy security and reliability issue, and the complex energy management task. Some proven solutions that have been provided in the extant studies to address these challenges were also presented. Finally, we provided some future research directions that will enhance the feasibility of the carbon neutrality target while exploiting the benefits of MES.

Declaration of Competing Interest

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

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