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Review

Future-proofing CO_2 mitigation towards a circular economy: A systematic review on process integration and advanced tools

Divya Baskaran [a,b], Hun-Soo Byun [a,*]

[a] Department of Chemical and Biomolecular Engineering, Chonnam National University, Yeosu, Jeonnam, 59626, South Korea
[b] Department of Biomaterials, Saveetha Dental College and Hospitals, Saveetha Institute of Medical and Technical Sciences, Chennai, 600077, India

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A B S T R A C T

Mitigating carbon dioxide (CO_2) emissions, which are a principal contributor to global warming, necessitates prompt and proactive measures. This systematic review evaluates advanced process integration and optimization tools, highlighting the need for a circular economy paired with efficient waste management to achieve effective CO_2 reduction. We systematically examine, for the first time, the applications and limitations of pinch analysis, Process-graph (P-graph), artificial intelligence (AI), computer-aided sustainable design (CASD), Internet-of-Things (IoT) sensor networks, and hierarchical blockchain frameworks. AI alone could save 2.6–5.3 gigatonnes of CO_2 by 2030, and its integration with CASD and IoT enables more sophisticated mitigation strategies. We recommend comprehensive carbon-offset frameworks and green-finance mechanisms to strengthen carbon-trading systems. Circular-economy measures for waste-driven CO_2 reduction remain under-represented in national climate policies owing to cross-sectoral complexity. Future work should advance interdisciplinary tools data science, system modeling, and decision-support frameworks and expand economic-feasibility studies of optimization strategies. Ensuring rigorous data quality, variability accounting, integration, transparency, and replicability is essential. Lastly, sustained collaboration among engineers, scientists, policymakers, and stakeholders is critical for developing scalable, sustainable solutions to climate change.

1. Introduction

Climate change stands as the most significant ecological and social challenge of the twenty-first century, drawing the attention of researchers globally. Countless surveys have discovered that climate change due to deforestation, fossil fuel combustion, agricultural activities, and further anthropogenic industrial actions released extensive volumes of greenhouse gases (GHG) such as carbon dioxide (CO_2), methane (CH_4), nitrous oxides (N_2O), hydrocarbons, and particular matters into the environment [1–3]. GHG emissions have prompted hasty global warming and subsequent climate changes resulting in universal emergencies. Climate change has triggered robust adverse impacts on vulnerable communities, including indigenous and underprivileged populations in stressed environments. Yet, humanity is enduring the struggles of climate change. Hence, it is crucial to take prompt and decisive action to ensure a resilient and sustainable planet. GHG emissions endanger human health, water and food security, biodiversity, and the global market [4]. It has been alarming that businesses, governments, and civil society organizations should make rigorous attempts to control GHG emissions. Corresponding to the current estimation, global GHG emissions in 2023 reached 53.0 Gt CO_2eq, an increase of 1.9% or 994 Mt CO_2eq compared to the emissions of 2022 [5]. Emissions database for global atmospheric research publicized that fossil CO_2 emissions are major contributors to worldwide GHG emissions, in that CO_2, CH_4, N_2O, and other flue gases account for 73.7%, 18.9%, 4.7%, and 2.7%, respectively (Fig. 1a). Compared to 1990, there is a major peak for CO_2, CH_4, N_2O, and other F-gases of +72.1%, +28.2%, +32.4%, and +294.1%, respectively, in 2023.

In 2024, the world's largest GHG emitters, ranked in order, are China, the United States of America (USA), India, Russia, Japan, Iran, Germany, Saudi Arabia, South Korea, and Indonesia (Fig. 1b) [6]. Typically, the severity was increased in these countries, accounting for 63.2% of gross domestic products, 49.8% of population, 62.7% of GHG emissions, and 64.2% of fossil fuel consumption.

* Corresponding author.
E-mail address: hsbyun@jnu.ac.kr (H.-S. Byun).

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China contributes the most to CO_2eq emissions at 10,667.89 Mt, followed by the USA at 4712.77 Mt, and India at 2441.79 Mt. It was observed that the absolute CO_2 emission of China increased to 784 Mt CO_2eq in 2023, a nearly 6.1% increase compared to 2022, due to the extensive generation of its energy from coal. Emissions database for global atmospheric research exposed the trend of worldwide GHG emissions across various sectors, including the power industry, industrial combustion and processes, buildings, transport, fuel exploitation, agriculture, waste, and other sectors, based on recent records for 2023 GHG emitters (Fig. 1c).

CO_2 emissions easily affect global real economic activity in the short and medium terms [7]. According to Intergovernmental Panel on Climate Change reports, the global mean concentration of CO_2 in the atmosphere was 300 ppm in 1910. This figure had risen significantly to exceed 350 ppm by 1990, reached 400 ppm in 2015, and again surpassed 420 ppm in 2021. In response, the Paris Agreement warned of maintaining global temperatures well below 2 °C of warming, with an ambition to limit them to below 1.5 °C [8]. However, comprehensive research reports indicate that the safe concentration of CO_2 is below 350 ppm [9]. Sustainable energy sources are crucial in mitigating the negative impacts of toxic emissions, which can be achieved through effective measures such as identifying renewable energy sources, promoting low-carbon transportation, enhancing energy and conversion efficiency, implementing policies and regulations, and raising public awareness.

The role of the industrial revolution towards cleaner production marked a significant impact on a sustainable world. For instance, the shift from coal to waste biomass and electric vehicles plays a decisive role in reducing CO_2 emissions in different sectors for industry, waste, energy, transportation, construction, and agriculture [10]. Later, carbon capture and sequestration (CCS) technologies have been employed to capture CO_2 from different anthropogenic activities and store it underground for future utilization [11]. This expects substantial venture in research and progress of large-scale demonstration projects; hence, further studies are urged. The execution of sustainable solutions is complex and requires international cooperation, policy frameworks, and robust political actions to achieve success in cleaner production. Many nations are fetched from fossil fuel entities and there is trivial inducement to shift to renewable energy sources. In this scenario, the policy mechanism of carbon tax can contribute to CO_2 (GHG) reduction by creating economic incentives [12].

Cleaner production is constantly worthy of competent environmental practices in manufacturing and operational processes. Especially, the process modification aims to minimize CO_2 emission through production operations (energy, water, and raw material consumption) and hazardous waste generation. The only best way is the replacement of cleaner resources in the manufacturing process, resulting in maximum output and minimum carbon footprint [13]. A circular economy, linked to waste management, is a major component of cleaner production and environmental sustainability. Statistics of different sectors (Fig. 1c) reveal that energy contributions are the main providers of carbon management. As a result, switching feedstock to bio-based resources with a cleaner alternative is decisive in mitigating CO_2 emissions for cleaner production. In this context, process integration (PI) allows a sustainable substitution to mitigate the noxious CO_2 emissions from diverse energy-intensive productions such as chemical plants, power plants, cement production, refineries, and the iron and steel industries.

Advanced tools based on process integration, such as pinch analysis or mathematical programming, encompass practices that involve merging different process components, integrating processes within heat, mass, or power total sites, and coupling processes to conserve resources and minimize toxic emissions [14,15]. Abdullah and Pauzi [16] identified that computer-based simulation models, grey models, linear regressions, optimal growth models, pinch analyses, and adaptive neuro-fuzzy intelligent system approaches have crucial advantages for forecasting CO_2 emissions. Later, a specific study was published on the mitigation of CO_2 through PI for optimization and design tools for sustainable production. Van Fan et al. [13] reported the significance and development of advanced tools such as pinch analysis, process graph (P-graph), artificial intelligence (AI), machine learning (ML), and computer-aided sustainable design (CASD) for cleaner production. The authors detailed the progress of renewable energy technology and their design for cleaner production. However, they failed to report the challenges and their development needs, and no information was provided on other advanced tools of the Internet of Things (IoT), sensor technologies, and hierarchical blockchain-based frameworks in cleaner production. Remarkably, the present study proposes to comprehensively report all advanced PI design and optimization tools, making it a valuable and first reference point for low-carbon management across various sectors. The sector-specific advantages of utilizing PI tools in CO_2 mitigation are enumerated as follows: (1) energy sector: facilitation of the optimization of energy production, transmission, and distribution; (2) industrial sector: enhancement of the efficiency of industrial processes; (3) transportation sector: support in the optimization of transportation systems; (4) agricultural sector: assistance in optimizing agricultural practices; and (5) building sector: capability to optimize building design, construction, and operation.

Circular economic contribution and its linkage with CO_2 emission mitigation policies are crucial for energy and emission management. Appropriate insight-based waste management for CO_2 emission reduction is vastly studied [17]. However, no reports have been published on PI tools with circular economy policies and waste management linkage for CO_2 mitigation. This review aims to help future readers and scientists gain a brighter understanding of the modern trend of academic accomplishment in this discipline. PI is a methodology focused on emission planning and management to save energy and carbon. Thus, this review emphasizes the extension of insight-based graphical, algebraical, and numerical advanced tools for carbon planning and energy management.

In light of the above, this review aims to contribute in three ways. First, to the best of our knowledge, the article is one of the first efforts to discuss advanced process design and optimization tools for process integration in the context of CO_2 mitigation. The challenges and limitations of each studied tool were critically analyzed. The potential transition of CO_2 into a circular economy with their policies was elucidated for carbon planning and energy management, particularly CO_2. Further, the significance of reducing the carbon footprint within waste management with future research and development needs was addressed.

2. Significance and advancement of sustainable endeavors via process integration

Various techniques and planning tools have been deployed to accomplish the carbon neutrality target by the middle of the century. Among them, PI techniques and tools have received good attention and are utilized in various countries and sectors for decarbonization efforts. Many works have been reported for these PI technologies at different scales, ranging from product carbon footprint reduction and plant-level CO_2 emission reduction to region or nationwide GHG avoidance, named a carbon management network [18–20]. The major significance (Fig. 1d) of these sustainable attempts through PI is incorporated into (1) energy efficiency: decreasing fossil fuel reliance and optimizing energy consumption; (2) resource conservation: conserving natural sources and minimizing waste; (3) climate change mitigation: slowing global warming, reducing GHG emissions and low-carbon footprint; (4) cost savings: enhances productivity, reduces operational cost; and (5) improved brand image: demonstrates commitment to sustainability. The main pillars of PI methods are pinch analysis and mathematical programming [21]. Process optimization in the efficient use of PI technologies for cleaner production hangs on some key strategies including pinch analysis to optimize heat energy networks, heat exchanger network (HEN) synthesis, and total site heat integration (TSHI) to minimize energy consumption, water integration to reduce water usage and wastewater generation, mass integration to optimize material flow and waste reduction and energy storage by incorporate batteries, thermal energy storage and other technologies [22–24]. The novel representatives of HEN considered as the shifted retrofit thermodynamic diagram were combining HEN targeting and design, pinch analysis of organic Rankine cycle, intensified heat transfer for every site process, the inclusion of environmental footprints, and integration of renewable energy sources. Several findings were reported and explored the achievements of integrating technologies into cleaner production. However, limited reviews were discussed with the extension of PI tools for the carbon footprint.

Manan et al. [25] critically reviewed the advances of PI research between 2007 and 2016 towards CO_2 emission reduction planning. The authors focused on the participation of pinch analysis PI tools in energy and emission planning. Their review may be the best reference point; however, it is limited for pinch analysis alone; hence, it is anticipated to boost their conceptual consideration and improve their decisions for the carbon management problems. A thorough assessment of the PI technologies advancements during 2013–2018 was reported by Klemeš et al. [26], who summarized the accomplishments of pinch analysis in chemical, mechanical, and environmental fields. Consequently, the sustainable PI with intensification and saving energy was analyzed and suggested for future developments in renewable reliance [27]. Optimization and intensification in HEN retrofit and operation are advantages of heat transfer enhancement [28]. Lately, the other research group critically analyzed the development of PI technologies in several thematic areas, including novel high-performance heat exchangers, heat and power integration, sustainable design of energy materials and processes, control solutions, CO_2 capture, and energy storage [29].

Very recently, the overview of progress on PI with pinch analysis and heat exchangers, extension of PI for extensive process system engineering, circular economy, and extended water-energy nexus contribution to environmental footprints was reported by Klemeš et al. [30]. The authors revealed that PI is essential for realizing necessary reductions of resource demands and minimizing environmental impacts. It was observed from the studies that the only pinch analysis tool was extensively focused on the context of advanced PI tools (Fig. 2a–c) for the mitigation of CO_2 emission, hence, further systematic review demanded other emerging tools (AI, IoT, CASD, supply chain, etc.) pointing research and development.

The application of pinch analysis to optimize heat exchange networks in established power plants, chemical processing facilities, and oil refineries presents an effective strategy for decreasing energy consumption and mitigating CO_2 emissions. The use of pinch analysis is vital for connecting processes across various industries, including cement, steel, and paper. This approach enables the recovery of waste heat, which significantly improves both heating and cooling operations. Additionally, it is instrumental in optimizing district heating and cooling systems in urban settings and enhancing overall energy efficiency in processes related to pumping and compression. Similarly, artificial neural networks (ANNs) and ML can be adapted to existing technologies through predictive maintenance, energy consumption forecasting, process optimization, energy efficiency optimization, and renewable energy integration. Integrating pinch analysis, ANN, and ML with supervisory control and data acquisition (SCADA) systems optimizes energy consumption and reduces CO_2 emissions in real-time. Applying these methods to building management systems (BMS) enhances energy efficiency and minimizes CO_2 emissions in buildings. Additionally, combining pinch analysis, ANN, and ML with industrial automation systems aims to improve energy consumption and decrease CO_2 emissions in industries such as manufacturing and oil and gas.

3. Development of advanced tools for CO_2 mitigation

Advanced tools and technologies are being utilized to both control CO_2 emissions and facilitate CO_2 capture and utilization, promoting sustainable development and mitigating climate change. According to the target fixed for 2050, to meet net zero emissions, hundreds of millions of metric tons of CO_2 should be captured and safely stored via geological storage [31]. To identify the optimal location for geological carbon storage, the CO_2 sequestration tool has been implemented. Through advanced tools, we found that each tool is responsible for individual actions for CO_2 capture and utilization optimization. Thus, PI tools have a significant role in CO_2 mitigation for unlocking resilience and sustainability on the planet. The tools are associated with process simulation and modeling, pinch analysis, exergy analysis, process intensification, optimization programming techniques, PI platforms, ML, digital twin technology, and supply chain optimization. In this section, we highlighted the potential of advanced tools with pinch analysis, P-graph, AI and ML, CASD, IoT and sensor technologies, and blockchain technology for clean technologies.

We conducted a systematic literature search using databases such as Scopus and Web of Science. The studies included in this review focused on the application of PI tools comprising pinch analysis, P-graph, AI and ML, CASD, IoT and sensors, and blockchain technology across various sectors. These sectors included energy, industrial, transportation, agricultural, and building, all aimed at mitigating CO_2 emissions. Studies that applied concepts like green banking and the circular economy, as well as those that did not utilize any process integration tools, were excluded from the review. As of September 2024, approximately 22.1% of the studies employed advanced PI tools as part of their overall CO_2 mitigation strategies. The distribution of integration tools in the studies showed that 40% used pinch analysis, 24% utilized HEN synthesis, 20% applied mathematical programming, and 16% employed other methods. The most common industries applying PI tools for CO_2 emission reduction were chemical processing (40%), power generation (24%), oil and gas (16%), and other sectors (20%). This meta-analysis highlights the importance of selecting integration tools that are tailored to specific sectors. However, the review was designed to provide a comprehensive overview of all relevant tools across various sectors, as no previous studies offered a focused review on this topic.

3.1. Assessment of CO_2 abatement using pinch analysis

For decades, the PI technique has been a successful instrument for resource conservation in the chemical industry. It began with resource use targets and was later expanded to include waste generation, emissions, and contamination of the environment.

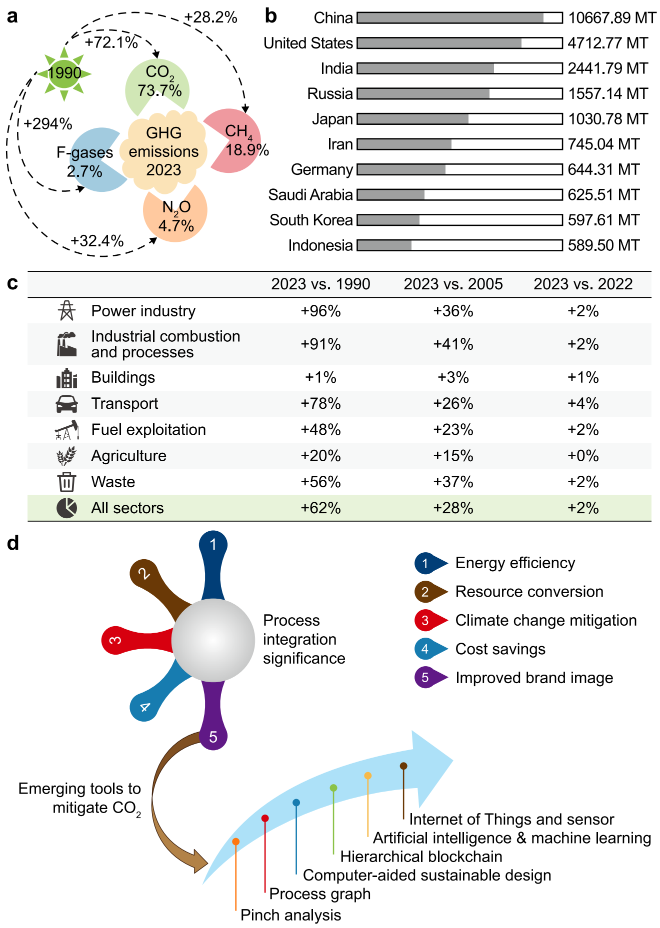

Fig. 1. a, Status of global greenhouse gas (GHG) emissions in 2023. Adapted from Ref. [5]. **b**, The top ten GHG emitters in 2024. **c**, Global GHG emission trends by sectors and key years. Adapted from Ref. [6]. **d**, Significance and emerging tools of process integration. GHG: greenhouse gas; CO_2: Carbon dioxide; CH_4: methane; N_2O: nitrous oxides; F-gases: Fluorinated gases.

Optimization is well-known for its effectiveness in leveraging the thermodynamic principle to solve resource minimization problems. Pinch analysis is a sophisticated tool designed to address macroscale carbon-constrained energy development challenges. It plays a crucial role in mitigating carbon emissions across various industries by optimizing energy utilization and enhancing heat recovery systems [32,33]. It is realistic to make adjustments to the fundamental process parameters using pinch technology to achieve energy savings. This method identifies the opportunities for energy savings by finding pinch points where energy is wasted, leading to significant reductions in carbon emissions by recognizing prospects for low-carbon energy sources. The contribution of pinch analysis has been proved by utilizing software tools, such as Aspen Energy Analyzer, HoneyWell UniSim Design, Siemens Simcenter, and pinch analysis calculators and spreadsheets. Tan and Foo [34] revealed that cleaner production with carbon emissions management is one of its primary participations and contributes to emissions mitigation. Most countries aim to reduce CO_2 emissions to a certain level each year, thereby maintaining precedence and promoting existing economic growth [35].

Most countries have put off their deployment to a later date and are not advancing in modern negative emission technologies (NET) since they have high priority in other matters. Pinch analysis is used to optimize target design for diverse resources via heat, mass, water, property, carbon, gas, production planning, and network design. Table 1 summarizes the pinch analysis framework employed for energy and carbon saving. Every study finding and limitation was emphasized for further studies. Pinch analysis involves identifying energy-intensive processes and pinch points, analyzing heat exchange networks to maximize energy recovery, optimizing process conditions to minimize energy consumption, and identifying opportunities for heat integration and energy production.

For instance, pinch analysis aids in reducing carbon emissions by optimizing heat exchanger networks [44]. The carbon emission pinch analysis (CEPA) graphical tool has developed an energy planning pinch diagram, called the composite curve, to analyze the minimum feasible renewable energy resources. If any part of the source composite curve stays to the left or above the demand composite curve, the energy planning pinch diagram is infeasible; hence, pinch analysis tools are for decision-makers. The pinch analysis has been employed to retrofit heat exchange networks in petrochemical industries, reduce carbon emissions, and achieve energy savings of 202.71 GJ h^{-1} with a cost of $2.76 million per year. Fig. 2a shows the composite curve for the retrofit HEN, observed at the minimum temperature gradient of 15 °C. The targets of hot and cold utilities are 45.67 and 32.98 GJ h^{-1} at cold and hot pinch point temperatures of 225.2 and 240.2 °C, respectively. Compared to the existing HEN, the developed network has the potential to save 35.7% for hot utilities and 43.5% for cold utilities, respectively. The Aspen Energy Analyzer tool has been utilized in many studies to compute optimum heat integration networks via pinch analysis for power saving.

In another study, a unique CEPA was applied for shipping fuel planning by optimizing fuel mixes over multiple periods, reaching up to 57.2% CO_2 reduction [45]. Designing energy-efficient processes by combining exergy analysis and pinch analysis results in a 112.12 MW reduction in utilities and a 10.9% decrease in total annual costs [46]. The application of pinch analysis to food-related CO_2 emissions in the agricultural sector can achieve a 57.2% reduction in carbon emissions by switching from meat to fish consumption [47]. Additionally, pinch analysis is applied to reduce GHG emissions by optimizing breeding policies and diet configurations [48]. The step-wise strategy has been effective in separator parameters and achieving lower H_2 depletion [49]. Their graphical architecture allows for a better conception; however, only one separator is available. Particularly in mass integration, hydrogen network design is employed for administration, waste degradation, minimizing microbial oxygen use, emergency analysis, targeting CO_2 emissions, and supply chain management. This method was first used at a chemical factory to save energy. Combining carbon emissions pinch analysis with input-output analysis broadens the scope of the analysis [50]. In the power production sector, a graphical-based pinch analysis for planning retrofitting for CCS was developed and is used to estimate carbon footprint targets [39].

Interestingly, a methodical framework was developed for a low-CO_2 industrial site plan using an integrated set of pinch analysis (a combination of algebraic algorithm and graphical representation) [36]. The case study was conducted in the proposed site plant and saved 56.7% heat, and 74.3% power, and reduced 99.8% of CO_2 emission while substituting total site heat integration, integrating renewable energy sources into a hybrid power system via power pinch analysis, and installing of heat and power for cogeneration potential in the network. Similarly, the power pinch analysis optimizes power distribution from the hybrid power system [38]. Overall, 79.95% of heat was saved by incorporating the fuel cell configuration. This will ensure that the industrial site receives a sufficient supply of carbon-neutral power. On the other hand,

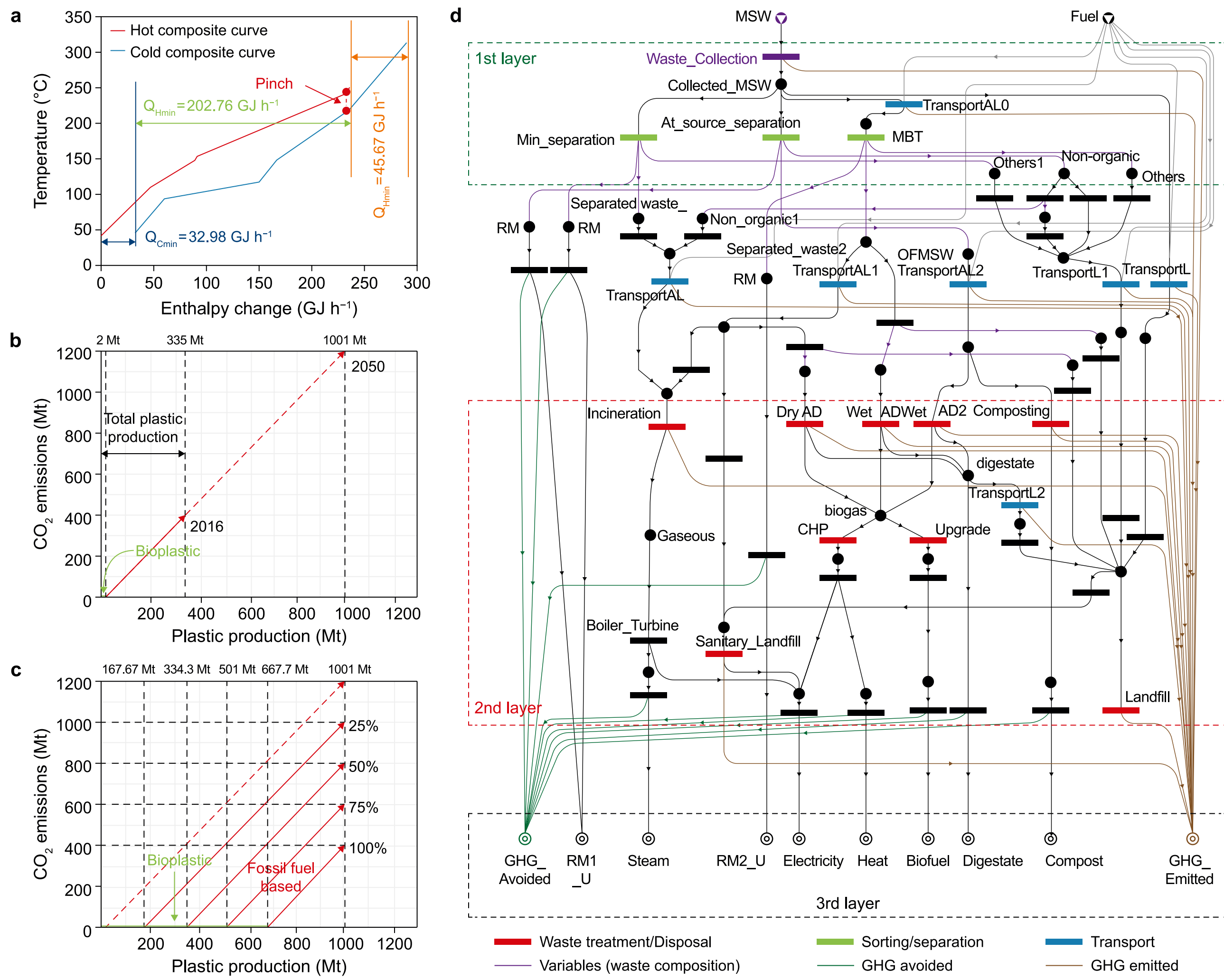

Fig. 2. **a**, Illustration of a composite pinch curve for a heat exchanger network at a minimum temperature gradient of 15 °C. Adapted from Ref. [44]. Copyright 2024. Elsevier. **b**, Illustration of the proposed plastic production for 2050 using the Pinch Analysis tool. **c**, The effect of various CO_2 emission percentages predicted using carbon emission pinch analysis. Adapted from Ref. [40]. Copyright 2020. Taylor & Francis Online. **d**, Process graph network of implemented circular economy for carbon management in the municipal solid waste treatment system. Adapted from Ref. [71]. Copyright 2020. Elsevier. QHmin: Minimum hot energy recovery; QCmin: Minimum cold energy recovery; MSW: Municipal solid waste; AD: anaerobic digestion; RM: Recycle material; MBT: Mechanical biological treatment; OFMSW: waste fraction of MSW; CHP: biogas combined heat and power; GHG: greenhouse gases; RM1_U and RM2_U: Recycling materials.

many studies have shown that plastic production alone contributes 20% of carbon emissions per year. Hence, Abdul-Latif et al. [40] summarized strategies to align future plastic production demand with CO_2 emission reduction by substituting conventional plastics with bio-based (algal biomass) alternatives through CEPA. An amount of 335 Mt of plastic was produced in 2016 (Fig. 2b), indicating that fossil fuels are major contributors, where the bioplastic CO_2 emission is assumed to be zero. Hence, an average of 1001 Mt of CO_2 emissions is anticipated in 2050. Fig. 2c shows the CEPA for various percentages (100%, 75%, 50%, and 25%) of CO_2 emission reduction. The minimum target for CO_2 reduction is 25%, while 100% indicates maintaining emissions at 400 Mt, which is the current level from plastic production. Approximately 83 Mt of algae-based bioplastic resin may be produced over the next 34 years to cut fossil-fuel emissions.

Pinch analysis is extensively accepted in the chemical industry due to its simplicity. However, some challenges still limit its applications, such as determining the exact locations of the chemical processes when optimizing the composite curves. In addition, the software may have limitations in terms of functionality, user interface, and compatibility intensive for large-scale problems. Since pinch analysis is primarily a steady-state tool, it restricts its ability to model dynamic processes. Specific technology advancements or changes can be employed to overcome these limitations, including dynamic pinch analysis, multi-variable optimization, integration with process simulations, the use of machine learning algorithms, and the development of hybrid models.

3.2. Implication of P-graph in carbon management

The P-graph is typically employed to establish the optimization and design network of new and integrated decarbonization and carbon management systems. It is open-source software that solves problems using network-like optimization techniques based on graph theory. The potential for implementation on the P-graph could also be used to solve process synthesis challenges of realistic complexity [51]. The P-graph is a mathematical tool for representing process networks unambiguously. P-graph aids in the decision-making process, similar to Pinch analysis, by determining

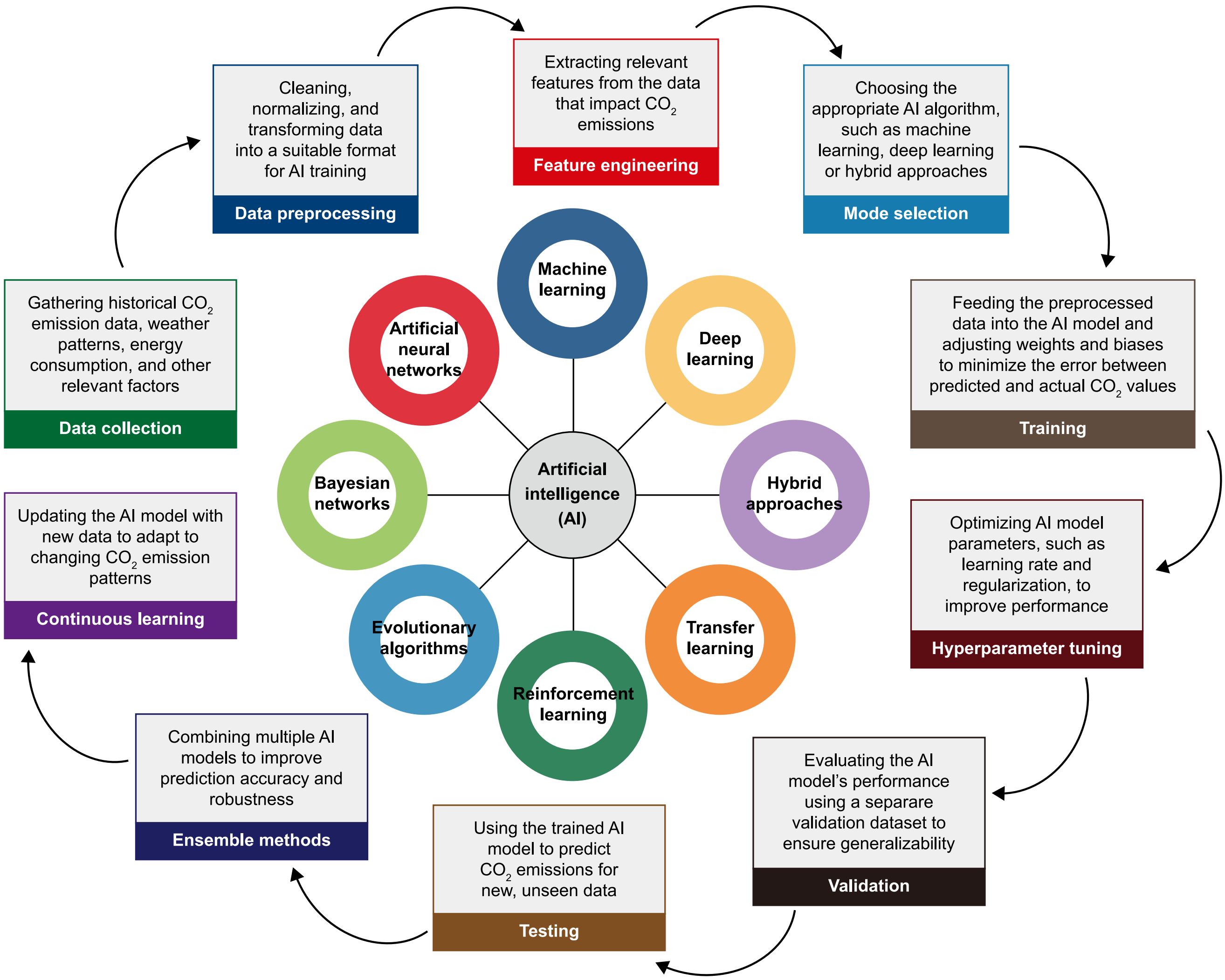

Fig. 3. A recommended methodology of artificial intelligence for CO_2 mitigation.

optimal and near-optimal network solutions [52]. Apart from other PI tools, the P-graph framework is an efficient and intense tool for resolving process network synthesis (PNS) and its issues [53,54]. The application of P-graph has grown from PNS, supply chains, reaction mechanisms, and pathways to carbon management. However, a precious number of reports have been found in applying the P-graph tool to carbon management. Table 2 summarizes the process graph analysis framework employed for energy and carbon saving. Friedler et al. [66] documented the P-graph algorithms and their applications in process system engineering. They elucidated that the contribution of the P-graph approach to decarbonization and carbon management networks is more significant than PNS and subdivided the applications to renewable energy, NET, CCS, and energy-efficient systems. According to renewable energy applications, the P-graph is employed in the design of regional biomass energy supply chains [67] and in the aid of sustainability indicators (SI) for sustainable agricultural waste-based energy supply chains [68]. It extended to the design and optimization of biorefinery to convert wood biomass residues into various products, a network of bioenergy parks, and quantification of the effect of supply-side disruption [69].

Furthermore, the most cost-effective solution for the pre- and post-pathway was optimized using a P-graph for waste plant biomass anaerobic digestion (AD) [70]. A unique debottlenecking approximate was advanced by integrating the P-graph with SI in the biomass supply chain network to identify the optimal biomass to produce syngas [56]. They found that the economic-related optimal solution is relatively low (SI < 60%) due to the high cost of CO_2 reduction technology; hence, P-graph drew the solution to integrate the CO_2 donor process with diacids production and recommended using oil palm frond from different studied biomass. In green ammonia (automotive fuel) production, life cycle optimization and considering circular economy principles in AD of municipal solid waste (MSW) were demonstrated to mitigate carbon and nitrogen footprints via P-graph models [71]. Fig. 2d shows the structure of complete waste treatment developed by P-graph. Waste is collected and separated (Layer 1) for valorization and treatment options. Treatment (Layer 2) has operating costs and carbon emissions. For a circular economy, recovered products can vary in utilization, market value, and avoided emissions credit (Layer 3).

The developed P-graph model could serve as a template for optimizing waste management. It could reduce the GHG to 411 kg $CO_2eq\ t^{-1}$ of processed MSW and achieve €42 t^{-1} potential profit. For a complete understanding of the different compositions case study and their utility, product, and emissions, refer to the

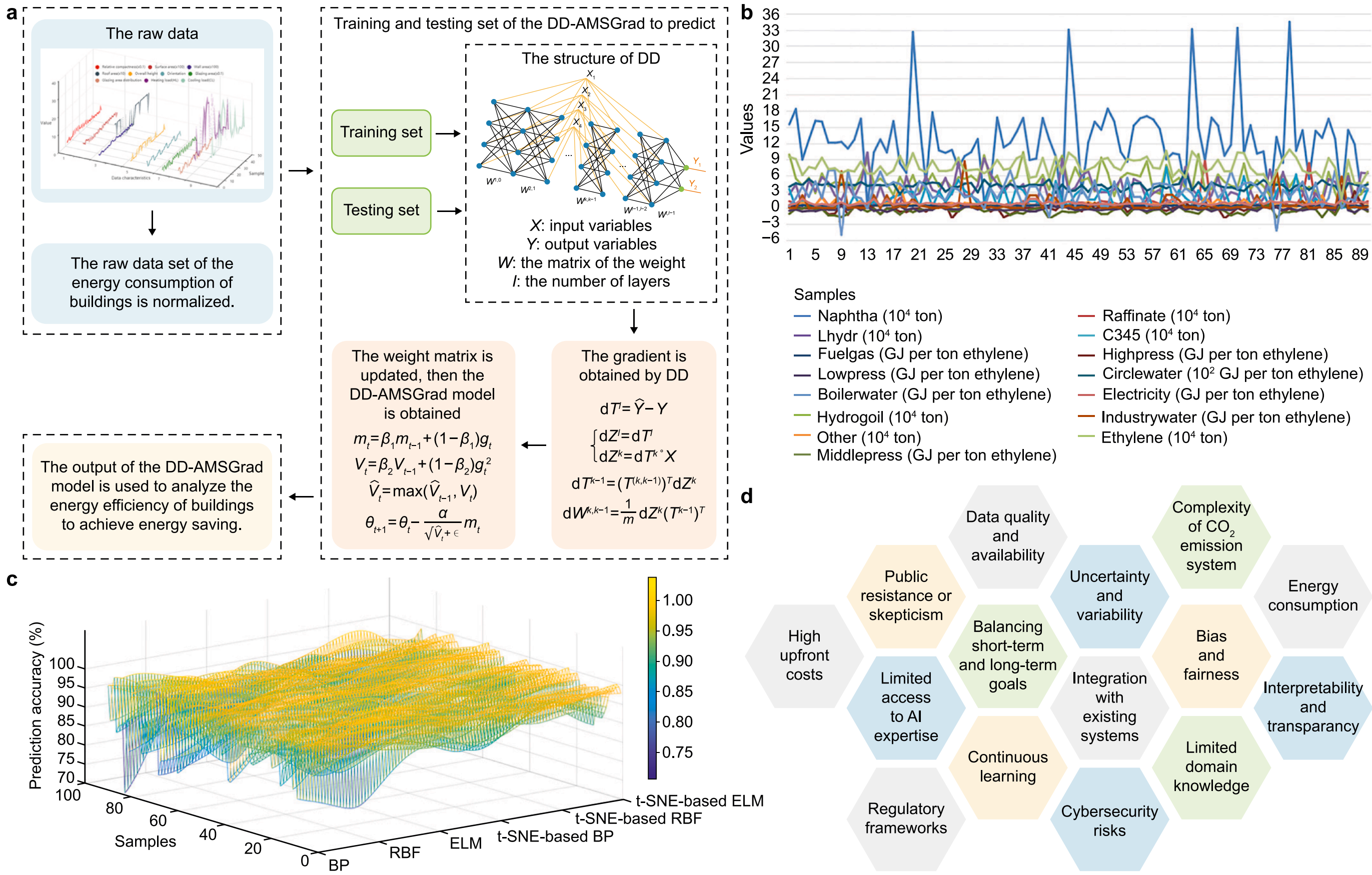

Fig. 4. **a**, Illustration for the overall process flow chart for the artificial neural network (ANN) Dendrite net-based adaptive mean square gradient prediction. Adapted from Ref. [86]. Copyright 2022. Elsevier. **b**, Illustration of specific indicators and quantities of the ethylene production process for ANN optimization. **c**, Illustration of the different ANN prediction accuracy for ethylene yield in terms of CO_2 emission reduction and energy-saving. Adapted from Ref. [87]. Copyright 2021. Elsevier. **d**, Top 15 key challenges and limitations of artificial intelligence in CO_2 mitigation. DD-AMSGrid: Dendrite net-based adaptive mean square gradient.

publication authored by Fan et al. [71]. Certainly, the bio-hydrogen network (from methane and palm oil mill effluent) was optimized using a P-graph to achieve net carbon emission [62]. P-graph helps reduce carbon production from 170,289 to 75,293 t y^{-1}, as landfill hydrogen gas emissions are lower than those from palm oil mill effluent. Currently, the application of the P-graph is being expanded to develop new pyrolysis oil refineries and integrate biorefineries for renewable energy supplies, with the goal of mitigating CO_2 emissions. Like SI, the multi-criteria decision analysis (MCDA) tool VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje) was integrated with a P-graph to enumerate the optimal and sub-optimal solutions for waste-based biorefineries. P-graph was developed for non-renewable solar energy to optimize microgrid networks with battery-hydrogen energy storage [61]. Decarbonization can be achieved by optimizing energy system designs with P-graphs, including fuel cell cogeneration with carbon constraints, efficient polygeneration, total site heat integration, heat-integrated water networks, and energy supply synthesis for manufacturing plants [59,72].

Understanding the application of P-graph in CCS and negative emission technologies is required to fulfill the part of the contribution to carbon management. The Monte Carlo simulation aided with P-graph has significant application in the development of robust carbon management networks, in the context of CCS. A multi-period P-graph model can be used to design a negative emissions polygeneration plant with a desalination network for carbon management [73]. Approximately 200 solutions were identified using P-graph analysis to mitigate CO_2 emissions by integrating the reverse osmosis process with electrolysis, with the lowest feasible limit for CO_2 emissions being 7482.04 kg CO_2eq d^{-1}. Topic coverage and impact of P-graph in different carbon management systems for various subtopics were detailed by Migo-Sumagang et al. [74]. They confirmed that the participation of P-graph methods in product design, biorefineries, uncertainty, and risk analysis has been growing continuously. Interestingly, the P-graph applied with SI utilized the concept for a non-conventional application, human resources planning in universities. Kong et al. [75] developed the P-graph energy planning (PEP) software to efficiently model multi-period Process-to-Policy energy trading and generate all possible solutions. However, the research gap is identified in the subsection of renewable energy streams, including solar, hydroelectric, green ammonia, and other products and sources. As a result, the benefits of P-graph in carbon mitigation include systematic and holistic carbon management, identification of optimal solutions for carbon reduction, integration of multiple carbon mitigation strategies, quantification of carbon emissions, and flexibility and adaptability to changing carbon regulations and prices. While P-graph is a valuable computational and powerful tool for carbon mitigation, there are challenges to its applications: data quality and availability are crucial, assumed linear relations may not always be the case, may not account for variability and uncertainty in process conditions, results need to expertise to interpret and implement, limited considerations of non-technical factors and may be integrated

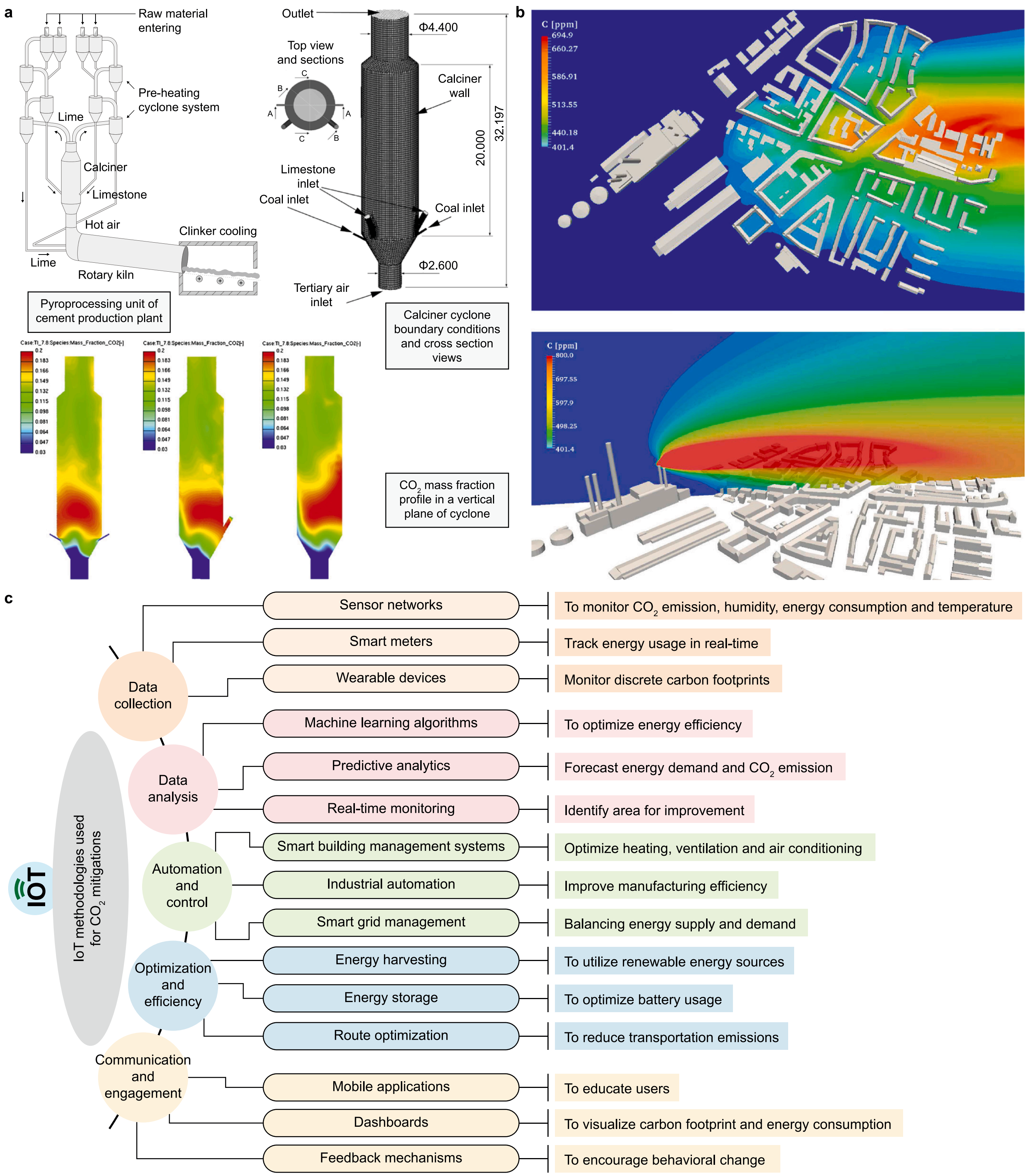

Fig. 5. **a**, Illustration of the computational fluid dynamics simulation of the calciner for CO_2 emission reduction in the cement production plant. Adapted from Ref. [106]. Copyright 2012. Elsevier. **b**, Illustration of the horizontal and vertical maps of the CO_2 spatial distribution in the metropolitan area for carbon management. Adapted from Ref. [107]. Copyright 2017. Elsevier. **c**. Advocated methodologies illustrated for an Internet of Things-based CO_2 mitigation.

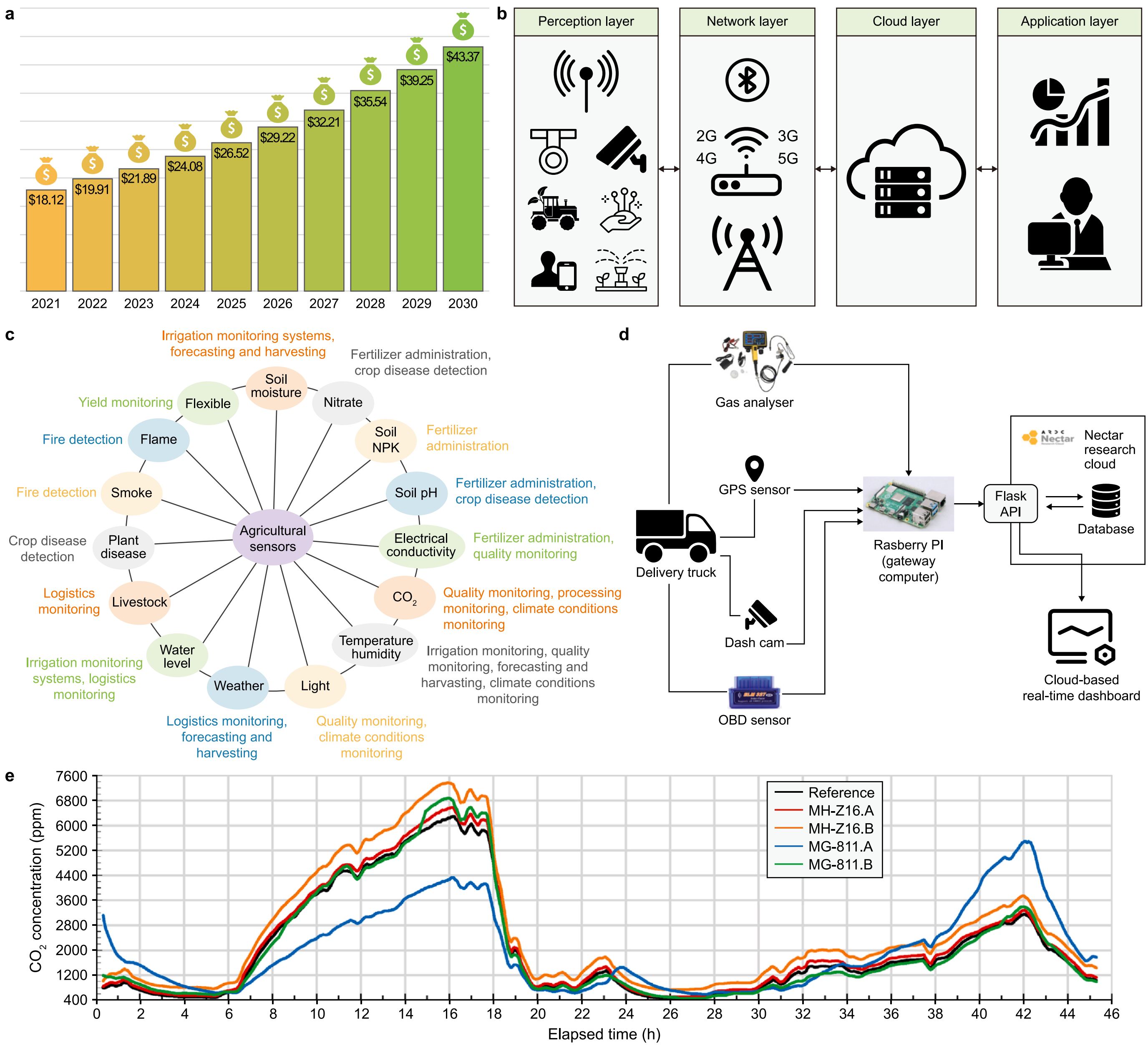

Fig. 6. **a**, The potential growth of Internet of Things (IoT) and sensor usage in the smart agriculture sector. **b**, IoT architecture for smart agricultural practices. Adapted from Ref. [120]. Copyright 2023. Elsevier. **c**, Types of agricultural sensors and their current application. **d**, A complete end-to-end IoT-and-AI-enabled testbed architecture for monitoring carbon footprint from combustion engine vehicles. Adapted from Ref. [116]. Copyright 2023. MDPI. **e**, Effect of low-cost sensors for CO_2 monitoring in the IoT context. Adapted from Ref. [117]. Copyright 2020. MDPI. GPS: Global Positioning System; OBD: on-board diagnostic data; Flask API: RESTful web service built using Flask framework in Python.

with other tools and model to result in compatibility model.

3.3. The promise of artificial intelligence

One of the finest decision-making approaches in carbon management is the analytic network process (ANP), a framework that is an extension of the analytic hierarchy process (AHP). A verdict is organized into a pecking order by AHP, which includes an objective, a verdict standard, and options [76]. The significance of AHP in carbon management includes facilitating decision-making, evaluating trade-offs, enhancing transparency, prioritizing carbon reduction projects, supporting carbon footprint analysis, integrating with other frameworks, and aiding policy development. [77]. The AHP model cannot account for interconnections, interdependencies, and responses among higher and lower-level constituents. Since it depicts the problem as a network, ANP is capable of modeling multipart associations among elements. Due to its adaptability in discovering major interconnections in "dynamic" ways, via dynamic contributions from decision-makers, ANP is an alternative to the AHP as well as other multi-objective techniques.

Several representative applications are presented to illustrate the potential of ANP in supporting CO_2 reduction efforts. These include evaluating CO_2 reduction strategies for a manufacturing plant, prioritizing renewable energy sources for a power grid, selecting sustainable materials for construction projects, estimating the carbon footprint of supply chains, detecting feasible CCS technologies, assessing the impact transportation modes on

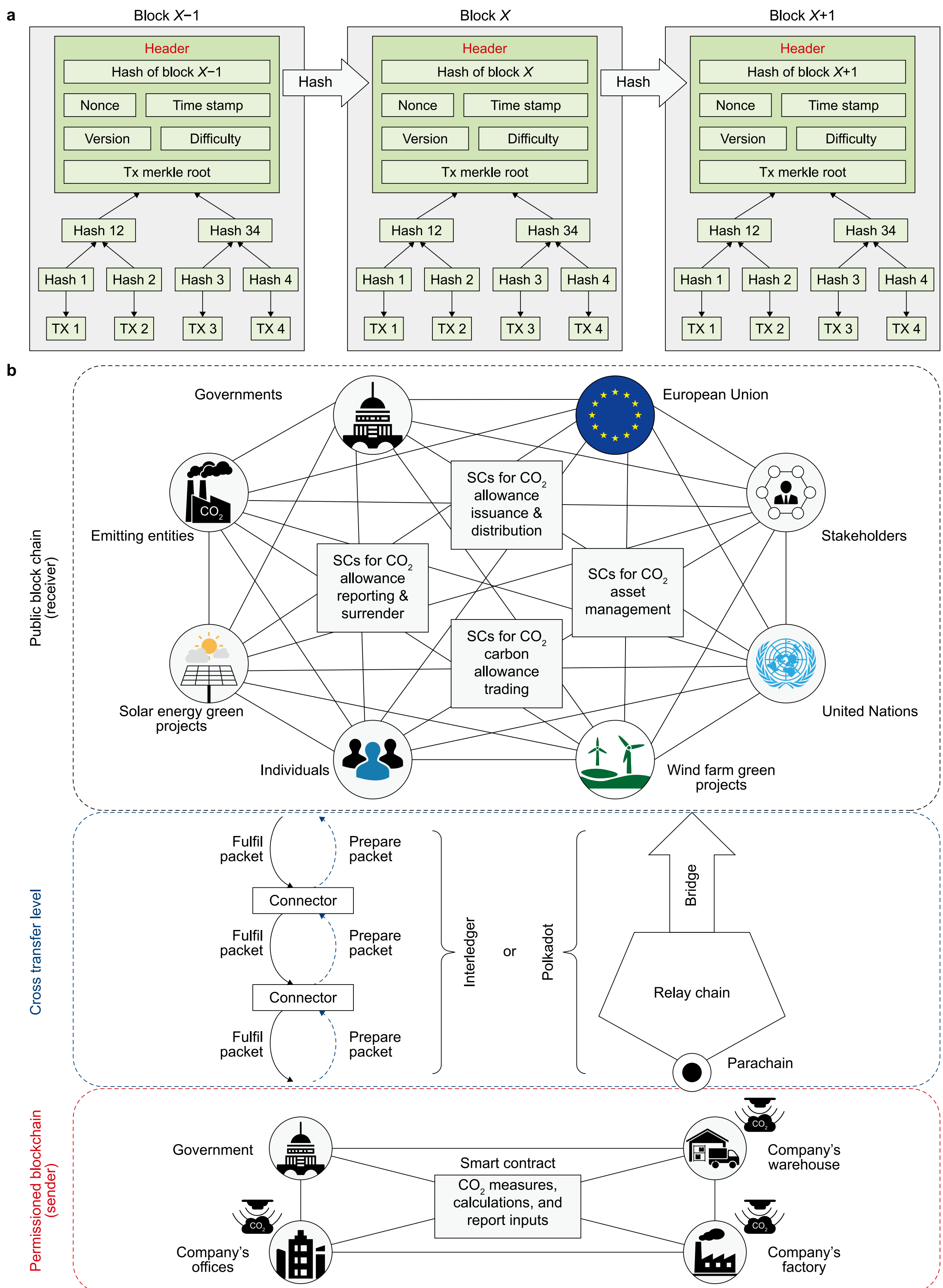

Fig. 7. An architecture of blockchain (**a**) and a framework of the carbon emission trading system (**b**) related to hierarchical blockchain. Adapted from Ref. [123]. Copyright 2021. Elsevier. SC: smart contracts.

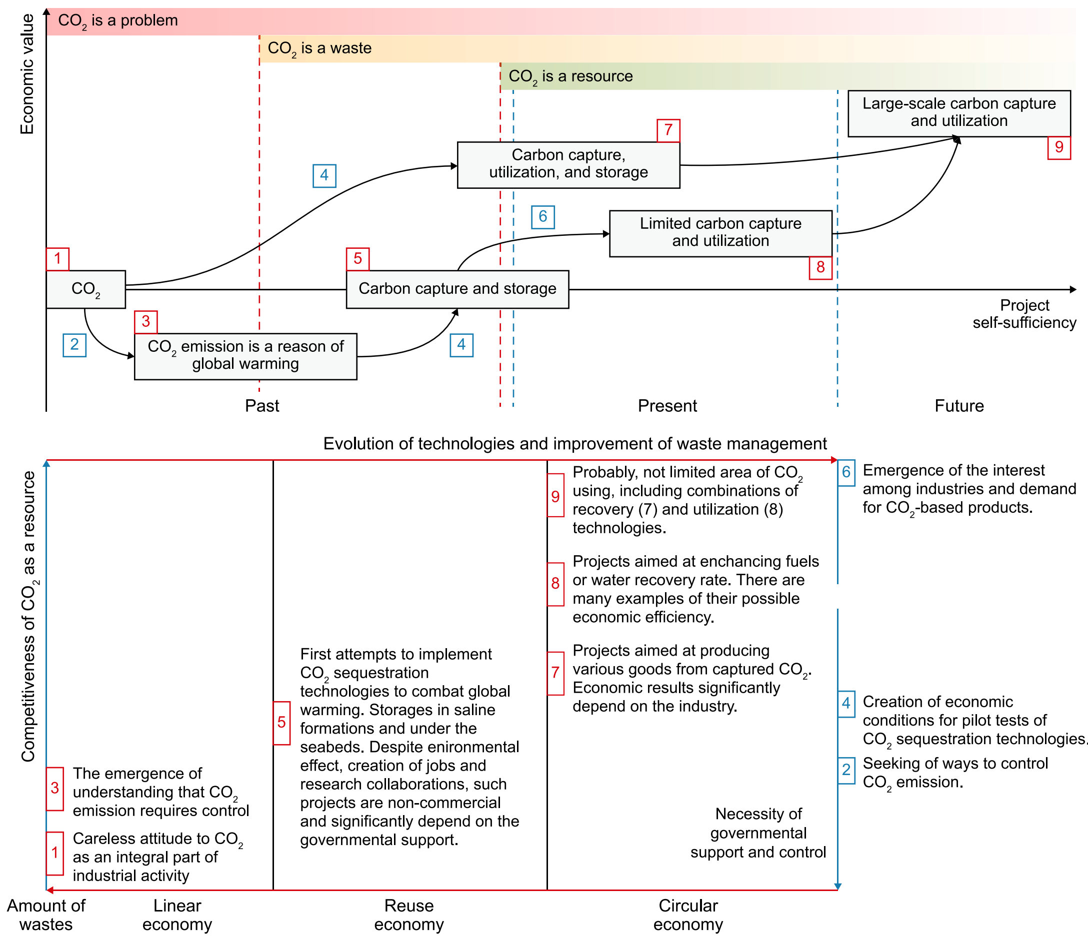

Fig. 8. Conceptual version of CO_2 transitional role in a circular economy. Adapted from Ref. [141]. Copyright 2019. MDPI.

carbon emission, developing CO_2 mitigation plan for a city or region, appraising the carbon emissions of transportation infrastructure projects and assessing the CO_2 emission of different agricultural sectors [78–81]. Interestingly, the ANP approach is supplemented with a sophisticated optimizing compiler of SI known as an optimizer for lean and green processing operations [82]. ANP was used, with an application of lean index serving as a performance measuring tool for plant practitioners, enabling periodic improvements in plant productivity. The integrated approach is incorporated with a back-propagation algorithm (feed-forward neural networks) for additional optimization of the lean and green models, directing the manufacturer towards continual development. The ANN is a well-popularized algorithm in the AI technique.

3.3.1. *Methodology of AI intrigued in carbon reduction*

Artificial intelligence has the potential to transform the game in any case. It can provide comprehensive information on the carbon footprints of companies, as well as instant cost-saving gains in times of need, making it a promising way to accelerate sustainable transformation and reduce costs [83,84]. Large firms are in an exceptionally strong position to leverage AI power, as their size grants them access to large data sets to solve specific problems. In 2030, using AI in the experience with clients can achieve a decrease of 5%–10% in GHG emissions from 2.6 to 5.3 gigatons of CO_2eq. In addition, the impact of applying AI will increase the revenues from \$1.3 trillion to \$2.6 trillion in terms of corporate sustainability, which amounts to cost savings by 2030 [85]. Hence, AI approaches will achieve greater savings if carbon offset prices rise even higher in upcoming years. Commonly, three components (monitoring, predicting, and reducing emissions) are accounted for when companies investigate reducing carbon footprints. AI can gather operational data, utilize new sources like satellites, and estimate missing data at a certain level. Predictive AI can forecast future emissions based on an organization's carbon footprint, considering current reduction technologies and future demand.

Predictive AI can optimize carbon production and achieve reduction targets more accurately. Many industries, including industrial goods, pharmaceuticals, energy and utilities, transportation, consumer, and packaged goods, can benefit from this approach to managing their carbon footprint. Reaping the benefits of AI, companies are recommended to adopt three-pronged approaches: aim superior, start modest, and scale promptly. The procedure for AI optimization for CO_2 mitigation typically involves the following steps: data collection, data preprocessing, feature engineering, model selection, training, hyperparameter tuning, validation, testing, ensemble methods, and continuous learning. The AI methodology for each step with a low-carbon footprint is elucidated in Fig. 3. Among the eight impressive methods, ANN and ML methods demonstrate effective forecasting for CO_2 emissions. The hybrid approaches can combine the strengths of ANN and ML to improve process optimization, predictive maintenance, and quality control in processing plants. The advantages of some specific learning algorithms in CO_2 prediction are significant such as random forest (RF), support vector machines (SVM), and extreme gradient boosting (XGBoost) in ML; convolutional neural

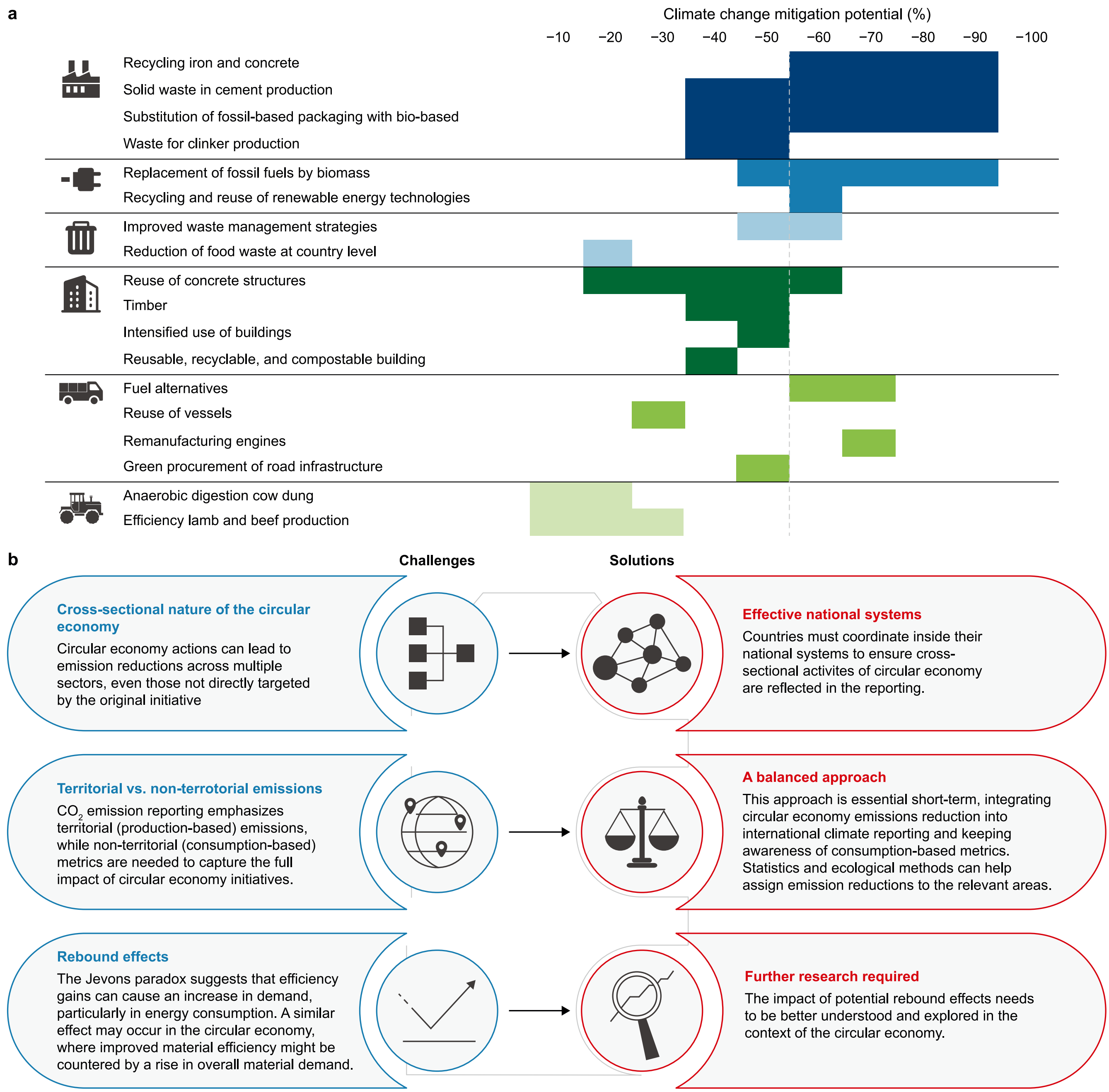

Fig. 9. **a**, Evidence of circular economic potential for CO_2 mitigation by different sectors. Adapted from Ref. [17]. Copyright 2020. IOP Publishing. **b**, Challenges and solutions for linking circular economy and CO_2 emission mitigation policies. Adapted from Ref. [187].

networks (CNN), recurrent neural networks (RNN), long short-term memory networks (LSTM) in deep learning (DL), combining ML and DL techniques in hybrid approaches; training AI agents to optimize carbon reduction strategies in reinforcement learning; leveraging pre-trained AI models for CO_2 prediction in transfer learning; modeling uncertainty and probabilistic relationships in CO_2 emissions on Bayesian networks; optimizing CO_2 reduction strategies using evolutionary principles in evolutionary algorithms; modeling complex relationships in carbon emission data in ANN. By exploring these methodologies, we could learn complex, carbon emission patterns from organizations, and it would support climate change mitigation through accurate predictions.

3.3.2. *Application of ANN and ML in low-carbon footprint*

An artificial neural network is classified as a black-box model, serving as an effective means to estimate the intricate correlations between input and output components without necessitating a comprehensive understanding of the underlying system. The optimization technique is also used to determine weight among dependent and independent parameters, with the principal goal of reducing errors between the model and the dataset. The ANN approach is less complex than conventional inventory-based models due to its prediction using small-sized datasets (ten in number). Typically, multilayer perceptron (MLP), RNN, genetic algorithm (GA), SVM, DL, RF, LSTM, CNN, autoencoder, generative adversarial network (GAN), particle swarm optimization (PSO),

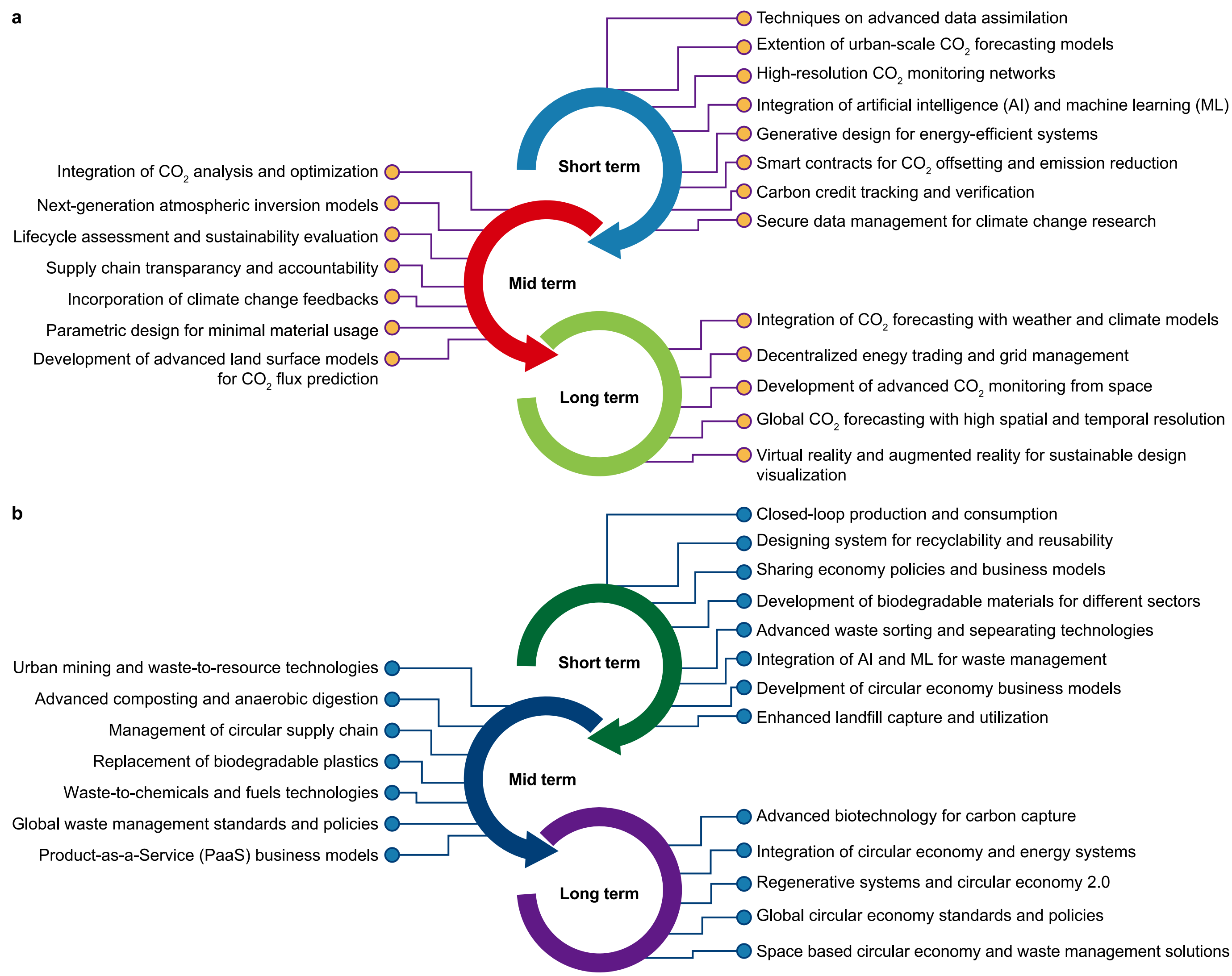

Fig. 10. Suggested research and development needs for advanced tools (**a**) and transition (**b**) to a circular economy to mitigate CO_2 emissions and promote sustainable developments.

time-delay NN (TDNN), Wavelet NN (WNN), Gaussian process regression (GPR), XGBoost, and decision tree (DT) algorithms were used in CO_2 prediction [11]. These ANN algorithms can be trained on various data sources such as weather and climate data, land use and land cover data, historical CO_2 reduction data, energy consumption patterns, and soil and vegetation data. By using these algorithms, ANN benefits in predicting the CO_2 emissions from energy consumption, forecasting CO_2 concentrations in the atmosphere, modeling CCS processes, analyzing CO_2 trends and patterns, estimating CO_2 fluxes from terrestrial ecosystems, optimizing CO_2 strategies, identifying CO_2 emission sources and sinks, developing CO_2 early warning systems and supporting climate change mitigation and adaptation efforts. Table 2 presents the available studies on CO_2 mitigation-associated uses of AI and ML.

The literature regarding CO_2 emission forecasting using ANN and ML is vigorous, with a broader range of algorithms, types of predicted CO_2 emissions from targeted regions, and fields covered in this section. The ANN–GA methodology was applied to reduce carbon emissions more cleanly in an algal biorefinery for zero waste [96]. They optimized the process condition for improved microalgal biomass production by 57% at 578.1 ± 23.1 mg L^{-1} d^{-1} of CO_2 sequestration rate. A novel hybrid model, as combined principal component analysis (PCA) with ML models such as regularized extreme learning machine (RELM), back-propagation neural network (ANN), and logistic model in terms of errors, applied to forecast the CO_2 emissions in China, published by Sun and Sun [91]. They confirmed that natural gas usage contributes to a maximum portion of CO_2 emissions compared to raw coal and crude oil, and found that the growth multiple reached 13.1 in 2014.

Many studies have demonstrated that the scaled conjugate and Levenberg–Marquardt algorithms of ANN provide accurate estimations for carbon management in Turkey. Similarly, other ANN tools have also accurately estimated carbon emissions in various countries, including the USA, China, Singapore, Malaysia, Thailand, Turkey, Bulgaria, the Philippines, California, and South Korea. ANN has been applied in the construction industry to predict the energy consumption of buildings and proposed for a low-carbon footprint. Han et al. [86] used the ANN-based dendrite net integrated adaptive mean square gradient (DD–AMSGred) method to predict energy consumption in construction buildings in China and reduce CO_2 emissions. AMSGrad was employed during DD network training to improve prediction accuracy for CO_2 emissions. Fig. 4a

Table 1
Summary of pinch analysis and process graph framework employed for energy and carbon saving.

Particulars	Findings of the study	Limitations	References
Pinch analysis framework			
Logical framework developed for low CO_2 emissions.	The integrated pinch analysis framework significantly optimizes power allocation and is used for hybrid energy systems. The framework resulted in reductions of 74.3% in power, 56.7% in heat, and 99.8% in CO_2 emissions.	The developed model is only accessible to designers, planners, and industrial site owners for optimizing integrated energy and CO_2 emissions across total sites; however, it has yet to be tested for locally integrated energy systems.	[36]
Linear pinch analysis (LPA) for GHG emission from municipal solid waste at Faridabad city, India.	GHG emissions and LPA were executed based on a 50% collection efficiency, with forecasted 20% and 30% GHG reductions in 2050, as determined using two strategies: landfilling and incineration.	Due to urbanization, the amount of municipal solid waste increasing hence, optimal waste management is demanded. Future studies should be extended to analyze GHG from sewage and wastewater in Faridabad city.	[37]
Total site heat integration technique (TSHI) is integrated with pinch analysis used for CO_2 reduction.	The technique of power pinch analysis is used to optimize power distribution from the hybrid power system (HyPS) within the industrial site. The proposed framework helped to capture 105 tons d^{-1} of CO_2 from the site and saved heat of 79.95%. The fuel cell-incorporated hybrid power system has the potential to supply low-carbon power, and the return rate was found to be 20.68%.	The framework is applicable to high CO_2-emitting industrial zones. The author does not consider the pressure drop for TSHI, the cogeneration potential for HyPS, and assumes consistent renewable energy sources while preparing the CO_2 lowering framework.	[38]
Carbon emission pinch analysis (CEPA) tool applied for energy planning and emission reduction in Canada.	Potential for energy savings of 15% through heat exchanger network synthesis achieved in the electrical sector. Optimization of energy systems through pinch analysis, reducing CO_2 emissions by 22%, indicating that the targeted emission reduction (14 Mt CO_2eq) was achieved in a lower band (3.1 Mt CO_2eq).	Limited access to detailed energy consumption data. Results may not be valid or representative of all Canadian regions. The framework focuses solely on the energy sector, excluding other sources of emissions.	[39]
CEPA tool proposed for Process-to-Policy (P2Pol) framework.	The P2Pol framework is highly constructive for carbon-constrained planning, enabling the development of strategies to reduce CO_2 emissions.	The author does not discuss the need for sustainable energy policy-making for CEPA. There is a lack of integration efforts for scaling up water and materials.	[35]
Using the CEPA tool, CO_2 emission from predictable plastic necessity in 2050.	Algal bioplastic is credited to be a replacement for fossil fuel-based plastic to reduce CO_2 emissions. About 495.524 Mt y^{-1} of seaweed and 368.224 Mt y^{-1} of total phenol are anticipated to be cultivated for bioplastic production by 2050. A complete 100% CO_2 reduction may be achieved in 2050 by utilizing 0.6 million hectares of seaweed cultivation.	The authors did not emphasize the optimization of culture conditions for macroalgae. There is a limitation to the study, particularly based on the assumption of a maximum of 75% liquid yield, 100% CO_2 reduction, and 10% bioplastic derived from other biomasses.	[40]
Waste management pinch analysis (WMPA) for association of dual-objective landfill and GHG emission reduction target.	WMPA was constructed based on the pinch point, demand curve, and supply curve. The supply curve is denoted by the landfill curve, waste-to-energy curve, and 3R curve related to reduce, reuse, and recycle. About 13.5% and 54.6% of total GHG emission reduction and landfill reduction were observed, respectively.	The authors are considered only major GHG emission contributors, such as food waste and plastics, not from metal and glass waste. In addition, they assumed that CH_4 is emitted from landfills and CO_2 is emitted from waste-to-energy technologies.	[41]
Greenhouse emission pinch analysis (GEPA) for the evaluation of GHG emission from wastewater treatment plants (WWTPs)	Different GHG-saving strategies, such as increased aeration capacity, reuse of biogas, and an external carbon source controller, were evaluated using the GEPA. Total GHG emissions from one-site, off-site, and WWTP were found to be 5.47, 0.39, and 5.86×10^4 kg CO_2eq d^{-1}.	The GHG reduction scheme for the WWTP case study is not incorporated with the Life cycle assessment, hence we could not evaluate the total environmental impact of WWTPs, apart from GHG. The optimization of each strategy is limited to the application.	[42]
WMPA proposed to explore the inference of recycling and landfill reduction target on CO_2 emission.	WMPA is capable of recognizing waste management strategies, including waste-to-energy, reduction, recycling, and reuse, as well as CO_2 reduction. The estimated CO_2 reduction is 20% from landfilling 70% of paper waste and 85% of food waste.	The authors only considered paper waste and food waste landfills; other wastes can produce CO_2 in landfills, which are not included. Lack of knowledge while developing a no-emission strategy curve for the waste-to-energy curve.	[43]
P-graph framework			
An integrated P-graph and Monte Carlo simulation methodology for carbon management systems	The generalized integrated network is employed to minimize CO_2 emissions by identifying optimal and near-optimal solutions. The carbon-constrained energy sector planning problem and CO_2 capture and storage planning issues were taken for the study to evaluate the potency of an integrated framework. The uncertainty in the capacity of 250 Mt of CO_2 to sink for two networks is 17% for optimal and 16.4% for non-optimal networks.	It has several disadvantages, including low public acceptability and limited availability. Furthermore, the lack of assumptions by decision-makers leads to an arbitrary number of near-optimal solutions being exposed.	[55]
A novel approach of integration of sustainability index and P-graph framework for the sustainable paradigm.	The proposed biomass network easily identified the bottlenecks of the research problem. Syngas production is a desired product, following the use of empty palm fruit bunches, oil palm trunks, oil palm fronds, coconut shells, oil mill effluent, and rice husks as biomass. The rice husk achieved a 90% (130 kg CO_2 t^{-1}) reduction in CO_2 emissions using a novel framework process integration.	Some other hidden bottlenecks may not be identified by the biomass framework. The omitted sustainability indicators are land footprint, mineral resource requirements, transportation safety, job creation, and food-to-energy footprint in relation to carbon management.	[56]
Automotive ammonia fuel cycle optimization using P-graph under consideration of carbon and nitrogen footprints	The optimal pathway for cyanobacteria-based ammonia manufacturing, combined with fuel cell vehicles, was identified using the P-graph model. The pathway has a nitrogen footprint of 0.325 g reactive N km^{-1} and a carbon footprint of 4.96 g CO_2eq km^{-1}.	The modeling framework was not focused on Monte Carlo simulation or possibilistic fuzzy sets.	[57]

Table 1 (*continued*)

Particulars	Findings of the study	Limitations	References
A biochar-based carbon management network developed using the P-graph approach.	The P-graph identifies both optimal and near-optimal solutions for the scale-up of biochar-based systems for carbon sequestration. The CO_2 sequestration rate reached by an optimal solution is 4.500 kt y^{-1}.	The model is limited to relatively simple static systems, highlighting a knowledge gap in multi-period planning for multi-component systems.	[58]
Optimization of heat distribution from boiler stations and thermal power plants of Tomsk city using P-graph.	The inter-cluster connection model was implemented in a district heating system. The optimized model allowed a decreased RUR 463 million h^{-1} operating cost and 500,196 t h^{-1} CO_2 emission.	Field-scale challenges with collecting and preparing data for the system. Some subgroups are identified and incorporated for optimization.	[59]
P-graph framework developed for optimizing net emission technologies (NET)	The new induction approach was implemented via a P-graph framework to determine the optimal solutions to rank new alternatives for zero carbon emission. Biochar was found to be the optimal network for feasible NET with a weight of 0.460.	The framework is limited due to decision inconsistency and data uncertainty.	[60]
Optimization of photovoltaic-microgrid for hybrid energy storage using P-graph	A framework identified the optimal and near-optimal solutions. Replacing the microgrid support for the hydrogen storage system reduces the total cost and required carbon price to \$262,334 y^{-1} and \$300 y^{-1}, respectively.	The integration approach needs to be considered for further stable energy supply.	[61]
The bio-hydrogen supply network was analyzed using a P-graph for carbon footprint reduction.	The P-graph is used to identify the supply work, ensuring that hydrogen demand is satisfied. The lowest carbon production was achieved at 75,293 t y^{-1} with a 31% reduction in total network cost.	The model is limited due to a lack of consideration for supply chain uncertainty and the use of a Monte Carlo simulation. The authors failed to consider the variations in material cost, raw material readiness, and market demand.	[62]
P-graph methodology was employed to calculate the profitability of the biorefinery concept.	Optimization of the biorefinery pathway achieved via the P-graph database. Profitability of around \$1650 to \$23,666 was achieved with optimal biorefinery configurations.	The effect of factors on the production cost is not discussed, hence the optimization may be the near-optimal solution.	[63]
Economical optimization of biomass supply network for GHG savings	Identified the optimum biomass supply network. GHG savings compared to fossil fuel comparators for heat and electricity were 210.22% and 165.06%, respectively, for manure feedstock.	Analysis of a broader range of feedstock varieties for biogas production is demanded for real GHG savings.	[64]
P-graph and analytical hierarchy process (AHP) are integrated for carbon capture in cement plants.	Retrofitting the cement plant with CO_2 capture technology and an emission trading scheme was implemented via an integrated framework. A membrane-assisted liquefaction surpassed the chilled ammonia process, and monoethanolamine showed a minimum net CO_2 avoided score of 0.7079.	Economic feasibility studies challenged the CO_2 generation process, including power stations and industrial plants.	[65]

shows the overall process of the ANN prediction chart for CO_2 reduction. The architecture of the DD model used for the prediction is presented and the learning rule used for the error MLP–BP where T^k is the output ($T^k = W^{k,k-1}T^{k-1}{}^\circ X$), $\circ$ denotes Hadamard product. For more information on the formula and process of forward BP and error BP along the process gradient of DD–AMSGrad refer to the literature by Han et al. [86]. A maximum amount of CO_2 emissions was forecasted and reduced by 158.17 kg by analyzing 50 samples while optimizing the location of the buildings.

A novel extreme learning machine (ELM) method based on t-distributed stochastic neighbor embedding (t-SNE) was applied to optimize energy and reduce carbon emissions from complex chemical industrial processes [87]. A novel approach was employed in the production of ethylene and purified terephthalic acid (PTA) to optimize resources and consequently save energy (Fig. 4b), measured in units of tons. The dataset, comprising 300 samples, refers to the monthly statistics of more than 20 ethylene plants from 2016 to 2018, along with seven strategies that were trained and validated by the planned model. The prediction accuracy of the different ANN models of BP, radial basis function (RBF), ELM, t-SNE-based BP, t-SNE-based RBF, and t-SNE-based ELM was shown in Fig. 4c. The testing accuracy of the t-SNE-based ELM model increased by 3.26%, 1.24%, and 1.21% compared to BP, RBF, and ELM, respectively. The optimized resource configuration helped reduce CO_2 emissions from ethylene plants by approximately 2.87%.

An ANN–RBF model based on an integrated multi-dimensional scaling method has been developed for assessing industrial ethylene production, achieving a prediction accuracy of 98%, a 13% energy saving, and a 39 kg reduction in CO_2 emissions [92]. At a CO_2 storage operation, ML methods were employed to enhance predictions of the long-term fate of stored CO_2. An ML and uncertainty quantification approach was used to monitor geological CO_2 sequestration risks. A multivariate adaptive regression spline has been utilized to simulate CO_2 injection in saline aquifers with multi-phase fluid flow. Reduced ANN models achieved a 24.3% reduction in cumulative CO_2 leakage uncertainty [97]. Interestingly, ML-assisted computational workflow, known as ANN-based proxy models, can optimize the hydrocarbon recovery and CO_2 sequestration efficiencies with 21.69% of the highest CO_2 leakage optimization results under 8.74% of oil production [94]. Milojevic-Dupont and Creutzig [98] conducted a methodical assessment to identify the potential of ML for climate change mitigation, focusing on areas such as urban transportation, remote sensing, and building. They revealed that meta-algorithmic architecture and framework-based ML are involved in improving planning and transforming urban infrastructure provision for a sustainable planet. Further, the power of ML in carbon prediction, optimization, and clustering data has been proved by Yan et al. [99] by harnessing the potential of ML for carbon capture, utilization, and storage effectively.

Recently, researchers developed machine learning models based on mobile observations to predict on-road CO_2 emissions ($CO_{2,traffic}$) in Seoul, South Korea. This city is the nation's largest emitter of carbon dioxide from transportation, accounting for approximately 20% of the country's total transport-related CO_2 emissions [93]. They confirmed that a regression-enhanced ANN–RF model, integrated with the Lasso model, has effectively monitored $CO_{2,traffic}$ on all roads without requiring supervisory

Table 2
Studies on CO_2 mitigation-associated relevance of artificial intelligence and machine learning.

Best algorithm/method	Model performance	Implementation source	Findings of the study	Reference
ANN: Dendrite net-based adaptive mean square gradient	Maximum CO_2 emission reduction is 158.17 kg CO_2 kg^{-1}. The heat and cold energy savings are 35.01 and 33.14 kW m^{-3}, respectively.	Building a dataset with an equal volume of 771.75 m^3, but the surface areas and sizes are not equal.	The adaptive mean square gradient method updates the dendrite net's weight matrix, reducing error and improving prediction efficiency. Based on the predicted heat and cold loads, the construction plan for the building has been adjusted to conserve energy, reduce CO_2 emissions, and enhance energy efficiency.	[86]
ML: A novel extreme learning machine method (ELM) based t-distributed stochastic neighbor embedding	The production of ethylene and terephthalic acid prediction accuracy was 96.11% and 99.38%, respectively. The reduction in carbon emissions from ethylene plants is 2.87%.	Complex industrial process of purified terephthalic acid production dataset.	A resource optimization model for the reduction of energy and carbon emissions from complex industrial processes was established. The sensible provision of raw materials for production has been successfully optimized to improve energy efficiency.	[87]
ANN: Particle swarm optimization (PSO)	The prediction accuracy for CO_2, CO, CH_4, H_2, gas yield, and lower heating value (LHV) of syngas is 99.64%, 99.38%, 99.27%, 99.88%, 99.34%, and 99.61%, respectively.	Coal gasification dataset from a pilot-scale pressurized ash agglomerating fluidized bed gasifier.	The developed model was used for predicting gas composition, gas yield, LHV, and gasification temperature from coal in the gasifier. Based on the simulation, we could increase the CO_2 content in the product gas when increasing the O/C and S/C ratio.	[88]
ANN: Levenberg-Marquardt back propagation	The prediction accuracy of (CO_2, CO, H_2, and CH_4) gas composition model is 99.8% with 7 neurons and 2-7-1 topology.	Pilot plant gasification system using palm kernel shell with Cao adsorbent and ash as a catalyst.	The model was developed for the biomass (palm kernel shell) gasification to predict product gas composition. The reduction of CO_2 content improves the H_2 content in the product exhibit.	[89]
ANN with a vector autoregressive estimator: Garson's algorithm	The maximum prediction efficiency of the CO_2 emission (USA) is 92.48% with a topology of 10–20-1.	CO_2 emissions forecasting in the USA with 4360 observations, covering the period 1984–2020.	The prediction of 14 targeted types of CO_2 emissions was confirmed by 4360 records between 1984 and 2020. The combined tool extensively predicts CO_2 emissions even during pandemic crises; hence it is a good tool in policy decisions.	[90]
ANN-ML: Principal component analysis (PCA) with a regularized extreme learning machine.	The CO_2 emission was reduced from 2.73×10^5 to 2.61×10^5 from 2010 to 2014 in China.	CO_2 emission dataset from 1978 to 2014 in China	PCA improves operational speed and forecasting accuracy. Its high precision enhances global optimization and generalization, resulting in reduced time costs, making it an advanced tool for CO_2 emission prediction.	[91]
ANN: Novel radial basis function integration multi-dimensional scaling and backpropagation.	The number of training and testing data sets is 500 and 20, respectively. The prediction accuracy reaches 98% with an increased ethylene yield of 114 t and a CO_2 emission reduction of 39 kg.	Complex ethylene production process dataset.	The model predicted ethylene plants to evaluate production capability and carbon reduction, validated by the University of California, Irvine. The reduction in base oil has since improved production capacity and carbon savings.	[92]
ML: Random forest model with a Lasso model	The training and testing data set was divided at a 3:1 ratio due to the collection information from the traffic site. About 68% of prediction accuracy was observed with an error of 0.05.	On-road CO_2 concentration in Seoul, South Korea.	Analyzed the spatiotemporal variation of on-road CO_2 concentration using a simulation model. Wind speed led to a decrease of about 20.1%, 27.4%, and 27.3% in CO_2 concentrations on major arterial roads (98 ppm), minor arterial roads (110 ppm), and urban highways (99 ppm), respectively. This model aids policymakers in developing effective CO_2 emission reduction strategies.	[93]
ANN-based proxy models: a combination of radial basis function and PSO	Cumulative CO_2 injection: 7.17 million metric (MM) tons; production: 5.05 MM metric tons; CO_2 storage: 2.16 MM metric tons; purchased CO_2 storage: 93.83%. By December 2037, cumulative oil production: 14.7 million metric barrel, oil recovery: 32.5%.	Hydrocarbon production, CO_2 storage and reservoir pressure dataset.	The model was utilized to predict cumulative CO_2 and oil recovery. The author revealed that formation injectivity may decrease over the next 20 years. Further, 77% of the CO_2 could be purchased for storage after 20 years. The optimized model case can store 94% of the purchased CO_2 within the Famsworth Unit (USA). Hence, the developed co-optimization model is more suitable for CO_2-enhanced oil recovery cases.	[94]
ANN: Levenberg-Marquardt back propagation	Solar irradiation forecasting: topology is 13–13-1 and prediction accuracy is 96.7%; Load power demand forecasting: topology is 13-6-1.	Optimize the electricity self-consumption from Renewable Energy Sources using Electric Vehicle batteries.	The proposed model is used to forecast solar irradiation, load power consumption, and CO_2 emission by optimizing the self-consumption of electricity produced from renewable sources using electric vehicle batteries. The observed peak power was below 19, 10, 3, and 2 MW, with no self-consumption optimization for the winter, autumn, spring, and summer, respectively.	[95]

Table 3
Examples of carbon management related to Computer-aided sustainable design, Internet of Things and sensor technologies and hierarchical blockchain frameworks-based findings.

Intention and Engrossment	Margins	References
Computer-aided sustainable design		
A reformulated natural gas was employed to reduce iron oxide pellets with H_2 and CO, resulting in lower CO_2 emissions. Approximately 15% of the improvements were attributed to the original carbon emissions.	The proposed optimization is not modified for the required configuration. Still, the findings on waste biomass as a replacement for reformed natural gas are a serious issue.	[102]
Computer-aided molecular and process design (CAMPD) is employed to develop the optimal solvent and CO_2 absorption–desorption process for a 400 MW combined cycle gas turbine power plant. This algorithm is beneficial for a reduction in computational cost and the total cost of \$1.2 million per year with 4% energy consumption.	No feasibility tests were reported for the solvent of CO_2. The legitimacy and pertinency of the CAMPD algorithm limit the applications.	[103]
The optimal CAMPD is used in ionic liquid mixtures for post-combustion CO_2 capture. Through simulation, the capture of CO_2 using ionic liquids reduces 16% energy losses and provides 12% of carbon footprint reduction. The designed ionic liquid mixture can recover CO_2 from 44 to 61% regarding 612 gmol min^{-1} of CO_2 in the one-stage separation process.	The study concentrated more on CO_2 solubility but failed to focus on operational and environmental factors. Lack of knowledge on uncertainty in the estimation of physical and thermodynamic properties.	[104]
The computer-aided analysis tool of ArKa-TAC^3 used to calculate both CO_2 reduction metrices and techno-economic feasibility for CO_2 feedstock capture from blast furnace gas from acetic acid production. The model benefits to fast, flexible, generic one, efficient and capable of analyzing a wide variety of carbon capture and utilization technologies. The designed process could reduce CO_2 in South Korea, the USA, China, and the United Kingdom are 65.7%, 75.4%, 75.0%, and 69.5%, respectively.	The amount of raw material for the carbon capture and utilization is restricted by its existent supply bounds. The environmental impact of lifecycle CO_2 emission and the carbon capture and utilization technology portfolio are also essential to discuss.	[105]
IoT and sensor technologies		
Developed the IoT-based air pollution monitoring device for controlling climate change, followed by CO_2 emission. Gas sensors play a major role in air analysis, and the results are sent to the Arduino Integrated Development Environment; through a Wi-Fi module, the data is sent to the monitor. This technology is easy to implement, with lower costs and high accuracy.	The proposed gas sensor is suitable for a limited number of gases to detect. The battery used in the system is limited in voltage. The functionality of the system needs future improvement for better results.	[115]
Real-time emission monitoring: developed a combined technology of artificial intelligence and IoT for GHG sensing. Coupling technology is a reliable, accurate, and cost-effective sensing technology. Further, the usage of gas sensors has been eliminated.	The author focused only on global interpretability when considering CO_2 forecasting. Failed to discuss the range of contextual statistics of geographical locations, data approximation, and computational resources.	[116]
Optimized the low-cost sensor based on the IoT to monitor weather and CO_2 emissions. Out of four CO_2 sensors, non-dispersive infra-red sensors determined accurate predictions at efficiency of 97%. The identified sensor has a virtuous sense of reality at less cost-benefit ratio.	The major challenge is identifying whether the sensor is biased or not. The optimized climate sensor is yet not proven to be critical in virtual terms. The identified CO_2 sensor still needs a long-term investigation to improve sensor data accuracy.	[117]
A real-time CO_2 monitoring architecture was developed by coupling IoT and cloud technologies. This system could deliver high accessible and real-time data visualization and benefit smart homes efficiency of analysis actualization. By using this model, 2880 CO_2 concentration data points were collected in the 16 h with 20 s intervals.	A lack of knowledge of a wide variety of sensors. The integration of any additional components and implementing sensor nodes may further improve the efficiency of CO_2 monitoring.	[118]
Developed a global model by integrating IoT and artificial intelligence to control residents' energy consumption and carbon emissions. The decision tree algorithm was used to train the model to create a unique data sequence. The integrated model contributed to reducing the carbon emission rate of 92%, an annual average reduction of 41.48 kg CO_2eq, decreasing 21%.	The applicability of the within a single country may be inconsistent, hence global political decisions are necessary instead of local activities and the efficiency should be maximized by analyzing residents' behavior.	[119]
Block-chain based frameworks		
A blockchain-enabled novel emission trading system is used to reduce emissions and simulate long-term adoption of technology. Typical market buying and selling prices offer visibility and priority. Directing fraud issues and CO_2 emission trading management emphasized by multi-criteria analysis.	Passive buyers receive no benefits because of their reputation. Uncertainties exist in the blockchain-reputation-based system. The framework lacks a reputation source, and the priority value does not accurately reflect the transaction.	[126]
Implemented computerized pollution (H_2, turbidity, CO, CO_2) monitoring scheme with Ethereum blockchains, IoT sensors, and LoRaWAN. The data integrity system operates independently, eliminating the need for trusted third-party data and allowing for automatic functionality. The system is secure, untampered, has fast data processing, and has reliable evidence for monitoring pollutants.	In most cases, a decentralized IoT and blockchain-based system is not feasible for small spaces, low consumption power, and limited power resources. Data is more susceptible when transferring to Ethereum blockchains.	[127]
Instituted a transparent, secure, and autonomous blockchain of custody for carbon and energy credits. The design is completely transparent and significantly reduces the time and cost. The network easily simplifies extremely complex trading environments that financially incentivize clean energy production.	A local platform for data transfer, a lack of trading boundaries for carbon management, revenue-centered, unclear smart contracts, and a knowledge gap in implementing credit programs.	[128]
The study highlights the similarities between blockchain and carbon trading, noting that blockchain can reliably record and transfer evidence at low cost, lowering barriers to the carbon trading market.	The framework has theoretical benefits; however, it is still at the initial stage and not yet mature, with computer response and power speed still bottlenecked. The system is merely complex and requires extensive research, specialized talents, and policy support.	[129]
Established a design to create an Australian carbon market blockchain network. The network has a significant role in existing carbon market functions. Benefits of transparency, security, reduced costs, and ease of scaling up with improved efficiency.	The blockchain design depends entirely on document analysis and lacks authenticated validation support. There is insufficient information regarding constraints imposed by existing market rules, legislation, and institutions.	[130]

(*continued on next page*)

Table 3 (*continued*)

Intention and Engrossment	Margins	References
Created a double-blockchain carbon emission trading scheme with a reputation-based transaction fee, boosting investment in carbon footprint reduction. The novel structure has better efficiency in carbon emission reduction, improved transactions, and is challenging to tamper with data because of its intense design.	The main drawbacks are data acquisition, using less precision smart meters, undecided, provision, and collection of transaction fees.	[131]
Designed a decentralized peer-to-peer trading scheme for connecting carbon and energy fairs. The new generation of transactions leads to protecting residential privacy and easily evaluating the emission behaviors of distributed prosumers. Adopting the imbalances and leakages during the transformation for energy and carbon reduction, hence, leads to reduced costs and carbon emissions.	The framework complicates carbon tracing and corrupts the accounting system for carbon emissions.	[132]
Proposed a distributed carbon ledger system using blockchain technology for corporate carbon management. The system strengthens the corporate accounting system, fitting with existing schemes and synthetic single mechanisms via integration for carbon asset management. The system is trustworthy, government roles exist, and reduce transaction costs and efficiency.	The deficiencies in integrity rules and trading boundaries, an accounting-centered approach, the absence of an input data validation system, and unexplained divisions in smart contracts are critical issues within the framework.	[133]
The study highlights the energy consumption and carbon footprint of Bitcoin's Proof-of-Work (PoW) and Ethereum's Proof-of-Stake (PoS) platforms. The PoS-based blockchain reduces CO_2 emissions by 99% and addresses sustainability issues, while the life cycle assessment supports the effectiveness of these blockchains.	The PoS-based blockchains require a vast amount of information on constraints on existing market rules. No detailed study on the provision and collection of transaction fees.	[134]
Created a Stackelberg game model using mean-variance theory to analyze blockchain adoption, demand sharing, and carbon emission reduction, yielding valuable managerial insights.	Sometimes, risk-averse retailers require the initiative to share demand evidence to advance model efficiency. Lack of information on blockchain adaptation practices of the manufacturers and sharing cost thresholds.	[135]
The work involves combining blockchain and IoT approaches on the FISCO BOS platform to examine carbon emissions and carbon credit trading using a smart contract. The framework provides the solution at a median response time.	The alliance blockchain directs trading transactions and blocks knowledge and query execution. However, integrity rules and boundaries of trading have not been discussed. The inconsistency of CO_2 emission data can easily upset the coupled technology.	[136]
Established an emission trading system powered by blockchain technology for the construction industry to reduce CO_2 emissions. The system enhances transparency and traceability, improves efficiency in tracking and verifying carbon credits, facilitates peer-to-peer transactions autonomously, and is scalable and adaptable to various construction projects.	Regulatory frameworks and standards may differ across the globe. There exists a potential for vulnerabilities within smart contracts. Additionally, transaction costs may be considerably higher when compared to traditional frameworks. Challenges regarding the integration of existing systems persist infrastructure.	[137]

surveillance, and enhances energy savings. There is an increase in $CO_{2,traffic}$ (62.9%) on urban highways due to their higher traffic speed compared to other roads and the higher traffic volume of major arterial roads and minor arterial roads. Recently, a steel production company fixed its carbon emissions by implementing AI, where nearly 230,000 tons of CO_2 (30%) were reduced with a $40 million cost reduction per annum. European oil and gas companies have implemented an ML-based predict-and-act control system, resulting in a reduction of carbon emissions by 1%–5%. This translates to a decrease of approximately 3500 to 5500 tons of greenhouse gases annually, along with cost savings ranging from $5 million to $10 million.

3.3.3. Challenges and limitations of AI function in CO_2 mitigation

Surprisingly, the use of AI solutions by companies for carbon management can actually exacerbate the issue. More than 270,000 kg of CO_2 is emitted from energy that was used to train state-of-the-art natural language processing algorithms to produce human-like texting, identified by researchers of the University of Massachusetts in 2019. In addition, ChatGPT-3, OpenAI's latest model, is more powerful than the last version; hence, carbon emissions will increase. Therefore, AI practitioners seek solutions to mitigate the technology's environmental footprint. In this view, Code-Carbon may contribute to a lower level of emissions and its future development. While applying AI in CO_2 mitigation, significant challenges and limitations are observed (Fig. 4d). High-quality data and sufficient datasets are required for AI, but this is not always possible in organizations. Many factors impact CO_2 emissions; hence, accurately predicting the complex system is challenging. In many cases, CO_2 emissions are subject to variability and uncertainty, which affect model predictions. To operate an AI system, a sufficient amount of energy is required to integrate with existing organizations, address biased data training, and overcome challenges related to interpretability and transparency in understanding policy decisions on carbon management. Integration with other existing systems and their domain-specific knowledge can be limited. AI systems can be vulnerable to cyberattacks, which can compromise efforts to reduce CO_2 emissions. A lack of clear understanding of regulatory frameworks and public expectations regarding carbon management influences AI predictions. Limited access to AI expertise and the need for continuous learning remain challenges. Based on energy consumption, developing and implementing AI solutions can be a costly endeavor. AI may prioritize short-term CO_2 mitigation over long-term sustainability. Thus, concentrating on all crucial challenges while AI predicts CO_2 emissions must be compulsory for unlocking a sustainable future.

These challenges and limitations of AI in CO_2 mitigation may be addressed through several possible actions or solutions. Data quality and availability are achieved by developing and deploying low-cost CO_2 sensors, utilizing remote sensing and satellite data, and developing data-sharing platforms and standards. AI model picture-perfect training is performed by developing explainable AI models and utilizing transfer learning and meta-learning. Integration with existing systems and infrastructure by developing data integration tools, developing digital twin technologies, and utilizing industrial IoT platforms. Furthermore, addressing cybersecurity and data privacy concerns, as well as human factors and social acceptance through the development of user-centered design approaches, is also considered a concrete solution to the limitations.

3.4. Computer-aided sustainable design for low-carbon simulation

Computer-aided sustainable design and simulation are the

Table 4
Economic prediction for CO_2-based products for 2030. Adopted from Ref. [141].

CO_2 utilized products	Manufacturing (Mt y^{-1})	CO_2 utilization in 2019 (Mt CO_2 y^{-1})	Unit price (USD ton^{-1})	Possible CO_2 utilization in 2030 (gigatons)	Potential annual revenue in 2030 (billion USD)
Methane	1100–1500	3000–4000	200–250	-	-
Calcium carbonate	180	132.3	370–450	-	-
Urea	113.9	50	30–350	-	-
Ethanol	80	152.88	480–530	-	-
Methanol	65	89.245	460–500	0.005–0.05	1–12
Formaldehyde	62	25.73	490–1000	-	-
Other value-added products	71.17	47.128	-	-	-
Aggregates	-	-	-	0.3–3.6	15–150
Fuels	-	-	-	1.07–2.1	10–250
Concrete	-	-	-	0.6–1.4	150–400
Polymers	-	-	-	0.0001–0.002	2–25

backbone of the chemical industries in this era of enhanced technology and computing capacity. It provides engineers with a better understanding of the engineering processes, enabling them to identify bottlenecks and recommend improvements. To address customer needs or solve difficulties, CASD engineering tools should be integrated with the discipline of product engineering. The prediction model-based approach is one of the software tools that can deliver new and long-term solutions that meet requirements [100]. Typically, CASD has potential applications in the simulation of CO_2 flows in pipelines, as 360,000 km of pipelines are expected to be required for CO_2 transportation by 2050. While transporting CO_2 into pipelines, it becomes damaged due to contamination of the captured CO_2 flow, which affects the flow properties and can lead to internal corrosion in pipelines [101]. Hence, a deeper understanding of the CO_2 flow dynamics using CASD is essential for carbon management. CASD is employed to optimize building design and systems for minimal energy consumption, minimize the carbon footprint, promote sustainable manufacturing, reduce waste, optimize transportation routes and modes, perform performance monitoring, and optimize the supply chain. CASD promotes the design of products for recycling, reusability, and biodegradability. CASD enables virtual testing and design optimization, thereby reducing the need for physical prototypes and associated emissions. CASD software enables developers to work efficiently, reduce production costs, and ultimately complete projects more quickly. A sufficient understanding of CASD and simulation can lead to sustainable designs that minimize CO_2 emissions and contribute to a more eco-friendly built environment. In this context, several software tools are used in CO_2 mitigation, including ANSYS Fluent, OpenFOAM, EnergyPlus, Autodesk Revit, Google's OpenStudio, Siemens NX, SolidWorks Sustainability, and Dassault Systèmes' CATIA.

Several studies have been conducted to inspect the CO_2 emission reduction using the mentioned software (Table 3). The OpenFOAM software utilized computational fluid dynamics (CFD) simulations to analyze CO_2 emissions from various organizations. Large-eddy simulation (LES) generally exhibits a superior agreement with experiments compared to the Reynolds-Averaged Navier-Stokes (RANS) equation in CFD tools for gas dispersion problems. However, RANS accounted for the attention of turbulence modeling of fluid in the system, effectively dealing with the specific problems. Many authors used the RANS turbulence model for the CFD simulation of CO_2 spatial distribution in metropolitan cities. Cement industries are leading sources of GHG, particularly CO_2 emissions; thus, considerable technological advancements are necessary to reduce energy consumption. The researchers demonstrated the competence of CFD in reinforcing the design and optimization of calciners, which is essential for lowering the carbon footprint during cement production [106]. Fig. 5a illustrates the CFD simulation of the calciner for CO_2 emission reduction in the cement production plant. Initially, the mathematical model for the calcination process was established, validated, and then implemented into a commercial CFD code. The empirical CFD model can forecast the rate of pipe corrosion and has been proven with actual measurements. The researchers have been interested in thermo-chemical reactions in a calciner cyclone, and it has been employed to optimize the calciner's geometry to accomplish higher cement production. The CO_2 mass fraction profile confirms that the CO_2 concentration is high in the region of limestone decomposition (Fig. 5a, colored in red). It was observed that the concentration of CO_2 is declining at the calciner's outlet due to a smaller limestone concentration. Applying CASD and optimization changes observed in the direct reduction route of iron ore manufacturing. A set of nearly ten operating parameters is concurrently adjusted according to the CASD optimization, achieving a 15% improvement in carbon emission [102].

Toja-Silva et al. demonstrated the CFD simulation of CO_2 distribution from fossil thermal power plants in urban environments [107]. The researchers also observed the spatial distribution of CO_2 in the city of Munich, Germany, through an analysis of turbulent Schmidt numbers and a comparison with the Gaussian plume model and measurements. Fig. 5b illustrates the CO_2 concentration CFD simulation maps for the metropolitan region. The horizontal and vertical slice views were observed for both transport and diffusion. The CO_2 concentration is higher at the ground level than above 100 m due to diffusion phenomena triggered by the turbulent eddy dissipation. Plum around 700 m downstream from the power plant, a higher concentration of CO_2 ($\geq$700 ppm) was witnessed at ground level. This punctual ground measurement of CO_2 concentration for the urban area may be interesting in further investigations. Furthermore, CFD can serve as an advanced tool to analyze and enhance the understanding of fluid (CO_2) dynamics behavior in real industrial configurations, thereby improving energy efficiency and reducing carbon or pollutant emissions. Roh et al. [105] overviewed the computer-aided analysis tool of ArKaTAC in techno-economic calculations and summarized the equations for CO_2 lifecycle emission, net emission, CO_2 avoidance cost, consumption, and reduction calculations to identify a better-designed process for a sustainable approach. A computer-aided molecular design was employed to discover a green solvent to modernize pyrolysis-based bio-oil [108]. Solvent blend B2 with 1-dodecene and 4-tert-butyltoluene was the optimal solvent which might decrease total CO_2 emissions by 3.5%. Hence, the computational approach can significantly contribute to complete lifecycle assessment for bio-oil and solvents. Similarly, computer-aided molecular and process design techniques were employed to optimize the solvent for chemical absorption of CO_2, thereby mitigating carbon emissions [103]. Most of the CASD assessments

Table 5
Reported circular economic actions from different sectors to support CO_2 mitigation.

Sector	Strategies used for circular economy	CO_2 reduction (%)	End result from the sector	Reference
Industry	1.4 kg iron ore for every one kg of steel scrap is recycled at the end of its product life	27	Approximately 34% of the research focused on the industry. Broadly, 26%, 22%, 22%, 15%, 7%, 6%, and 3% contribute to waste valorization, cross-cutting, rethinking, renewables, efficiency, reuse, and reduction principles.	[142]
	Production of one-ton marble-based geopolymer green cement instead of Portland cement	54		[143]
	Production of clinker from red mud instead of sulfoaluminate clinker	41		[144]
	Closed-loop supply chains vs forward supply chain for thermoplastic polymer waste recycling	73		[145]
	Recycling of steel and nonferrous metals	60 and 33		[146]
Energy	Wood biomass substitute to Razzaq fuel oil	75	About 23% of the research centered on energy. Broadly, 10%, 19%, 64%, 4%, and 3% contribute to waste valorization, cross-cutting, renewables, rethink, and efficiency principles.	[147]
	Wood biomass pellets substitute for coal	94		[148]
	Biofuel versus fossil fuel	60		[149]
	Residual woody biomass substitute for jet fuel	60		[150]
	Bagasse substitutes for jet fuel	47		[151]
	Anaerobic digestion (AD) bioelectrically replaced for coal generation	131		[152]
	Repurposed battery vs fresh battery in grid-connected house	58		[153]
	Reducing food waste, improving steel and material efficiency, supporting product refurbishment and life extension, upgrading vehicle lightweight, and constructing buildings in the United Kingdom.	10		[154]
	Applying biochar for soil amendment	12		[155]
Waste	A national scheme for urban Waste management	47	About 25% of the research centered on waste. Broadly, 69%, 20%, 5%, 2%, and 4% contribute to waste valorization, cross-cutting, renewables, rethink, and reduce principles.	[156]
	Sustainable waste Management	58		[157]
	Biogas production in wastewater treatment plants	43		[158]
	Production of urea from municipal solid waste	-		[159]
	Recycling plastic polymer wastes	73		[160]
	One percent increase in municipal solid waste recycling	0.285		[161]
	Recycling steel, nonferrous metal, plastic and paper wastes	43.2		[162]
	Every 1% increment in the recycling rate of municipality waste	0.06		[163]
Buildings	Wood and plastic composite for concrete production	-	About 11% of the studies focused on buildings. Roughly, 13%, 11%, 53%, 18%, 3%, and 3% contribute to waste valorization, cross-cutting, rethinking, reusing, reducing, and efficiency principles.	[164]
	Fly ash replaced Portland cement	65		[165]
	Concrete structure constructed for subsequent reuse	21		[166]
	Novel prefabricated concrete structure used	55		[167]
	Household materials are fully reusable, recyclable or compostable	40		[168]
	Composite boards made of natural fiber also biobased epoxy resin are used in place of plasterboard for drywall usage.	50		[169]
	Rethinking building materials for residential use	50		[170]
	Using concrete with recycled aggregates	43		[171]
	Design of disassembly of concrete and wooden structure	16		[172]
Transport	Electrical vehicles for fuel alternatives	64	A small fraction (<5%) of the research centered on transport. Broadly, 7%, 33%, 27%, 13%, 13%, and 7% contribute to the waste valorization, cross-cutting, rethinking, reusing, renewables, and efficiency principles.	[173]
	Ship vessel redesigned for 100% hull reuse	29		[174]
	Recycling/reuse: diesel engine manufacture	69		[170]
	Green procurement of road markings	50		[175]
	Car sharing for changing ownership models	50		[176]
Agriculture	Applied efficiency levels of the least-emitting producers of beef and lamb	31	A limited fraction (<2%) of the research is directed at agriculture. Roughly, 29%, 43%, 14%, and 14% contribute to the waste valorization, cross-cutting, rethinking, and efficiency principles.	[177]
	Recycling phosphorus from meat and bone meal, compost, and sewage sludge	28		[178]
	Closed-loop system used for pork production	11		[179]
	Cassava pulp used for ethanol production	85		[180]
	AD for cow dung to increase biogas	13		[181]
	Livestock manure-derived biogas for replacing natural gas	37.5		[182]

focus on the environmental impacts and exergy efficiency of the practice to achieve better cost savings and carbon management.

Recently, Renault attempted to optimize the CO_2 emission using Cadence CFD simulation, which has been employed to optimize turbochargers, pumps, fans, and beyond. They are still working on all existing energy solutions such as internal combustion engines, hybrid engines, and electric vehicles [109]. Cadence has been a computation software expert in electronic design and building for over 30 years. The advantages of CASD are identified as user-friendly interfaces for designers, cost-effectiveness, fast simulation and analysis, expert knowledge embedded in software, and a specific focus on sustainable design. The limitations of CASD are dependence on user expertise, limited scope beyond the design phase, and limited adaptability to new data. When compared to AI tools, CASD focuses on the design phase, requires just updates, and relies on predefined rules. Certainly, the integrated tools (CASD and AI) can create more effective CO_2 reduction strategies, such as Trimble Sketchup with AI-powered energy efficiency analysis, Graphisoft ecodesigner with AI-driven building performance optimization, and Autodesk's sustainable design toolkit with AI-powered energy analysis.

3.5. Internet of Things and sensor technologies to cut down CO_2 emissions

Transitioning to a paperless environment facilitated by IoT-enabled applications can significantly contribute to reducing the carbon footprint. IoT involves connecting a multitude of sensors and various devices through the internet, paving the way for innovative services and outcomes. Traditional sensors have localized displays while IoT sensors leverage wireless technologies to transmit collected data to the cloud for centralized storage and analysis. IoT technology benefits not only CO_2 mitigation but also concerns reducing energy consumption, enhancing efficiency, achieving cost savings, improving air quality, and facilitating better decision-making [110,111]. Fig. 5c elucidates the methodologies of IoT-based CO_2 mitigation.

Various steps have been employed to detect the carbon footprint, such as data collection, data analysis, automation and control, optimization and efficiency, and communication and engagement. By using these methodologies, IoT enables various CO_2 mitigation applications via smart cities, green buildings, transportation management, agriculture and forestry, waste management, industrial energy management, and renewable energy integration. Hence, five different ways are used by IoT to reduce carbon footprints, such as smart energy grids, smart metering, green transportation, sustainable agriculture, and smart building management. Smart electric grid technology is used to monitor and manage the storage and transportation of electricity, aiming to minimize cost and maximize reliability for renewable power. IoT solutions play a fundamental role in ensuring efficient and effective operation through constant monitoring, helping to maximize production and resource efficiency while supporting usage patterns in individual households. Real-time data collection also helps identify opportunities for grid expansion and more efficient energy use for city residents. Smart metering is a significant IoT energy solution for utility companies to predict electricity demand and consumption. Using sensors, operators can monitor energy consumption at both the city-wide and industry levels. For example, Robustel general packet radio service devices optimize energy consumption monitoring of a facility by connecting data collectors to energy meters and feeding gathered data back to the server. This benefits both the operator and the consumer by allowing dynamic adjustments to output in response to demand levels and helping consumers stay on top of their usage.

The growing world population has driven the demand for public transportation, resulting in an increase in vehicles on the road. In this context, IoT sustainability involves reducing carbon footprints by remediating faulty equipment and poor route planning, as well as enabling smart devices such as sensors, data collection systems, and maintenance, resulting in increased efficiency. In sustainable agriculture, smart sensors, drones, and temperature monitoring systems can help crop production and soil quality reduce their overall carbon emission [112]. Agriculture sensors can enhance transportation and supply chains, monitor weather and humidity, deploy robotics to carry out repetitive tasks, and use data to manage land consumption better [113]. Smart building management plays a crucial role in reducing carbon emissions by ensuring the efficient use of resources such as water and electricity, monitoring internal temperatures, and shutting down unused devices. Notably, Robustel offers a range of solutions for businesses aimed at reducing their carbon footprint. Various key technologies have been adopted for IoT, including sensor technologies, wireless communication, Arduino IDE, data analytics platforms, AI and ML, and blockchain for secure data sharing. Gas sensors analyze discharged gas and send data to the Arduino environment. This information can be displayed on a monitor via Wi-Fi, allowing for low-cost, accurate monitoring of CO_2 emissions in various cities. Table 3 presents findings related to carbon management based on IoT and sensor technologies.

IoT parking sensors contributed to reducing CO_2 emissions by optimizing parking space utilization and streamlining traffic flow [114]. These sensors use real-time parking readiness evidence to quickly locate vacant spots for parking and lower the time for seeking parking spaces. The reduction in traffic congestion led to lower fuel consumption and decreased CO_2 emissions. In addition, cities can avoid constructing new parking spots, which further reduces the environmental impact of parking sensors. Typically, CO_2 sensors include recommended components such as the MCP3008, FC-22 gas sensors, a Breadboard, an ESP8266, a HiLink, a liquid-crystal display screen, and a servo motor. Countless options for employing the IoT to today's most critical problem of climate change. Alshahrani et al. [115] outlined a model for detecting pollution using IoT. AirTick is an IoT software for smartphone cameras that employs ML algorithms and image recognition to monitor air quality cost-effectively. Additionally, ANN algorithms in networked platforms can utilize data from cameras and sensors to improve urban traffic patterns and reduce vehicle emissions. The Android platform or technology plays a more crucial role in CO_2 emissions than electrical technology. In creating IoT–Android applications, we relied on the Java programming language, the Eclipse IDE, Android application development tools, and the Android Software Development Kit for monitoring CO_2 emissions.

Agriculture plays a decisive role in controlling carbon footprint; therefore, the use of sensors and IoT technology is vital for enhancing agricultural sustainability and security. Morchid et al. [120] revealed that the IoT and sensor-related architecture enabled smart agriculture to effectively promote agricultural sustainability. Fig. 6a illustrates the global growth of the smart agriculture market, leveraging advanced technologies such as IoT, AI, and ML. In response, the market size increased significantly over time and reached $18.12 billion in 2021; therefore, it is expected to surpass $43.37 billion by 2030. The upward trend emphasizes the promising future of IoT management in the smart agriculture sector. It was observed that it is necessary to improve sustainable agricultural methods and technology to ensure sustainability and food security, since the alarming world population is expected to be 9.7 billion by 2050. Fig. 6b illustrates the IoT architecture of the smart agriculture sector, which comprises perception or sensing, actuator, network, cloud, and application layer. The perception layer incorporates the real sensors in the environment to gather and broadcast data to the IoT system. The actuator manages irrigation and fertilization while the sensor detects operating parameters, such as soil pH and soil macronutrients of nitrogen, phosphorus, and potassium. Multiple communication methods, including cellular and Wi-Fi, are integrated into the network layer for seamless data transfer among IoT components. The cloud layer processes and stores sensor and actuator data, enabling farmers to make informed real-time decisions. The application comprises several programs and apps designed to empower farmers and stakeholders, enhancing their farming operations.

IoT-enabled smart agriculture extends to irrigation monitoring systems, fertilizer administration, yield monitoring, crop disease detection, quality monitoring, processing monitoring, climate condition monitoring, forecasting, harvesting, and fire detection. Fig. 6c highlights the availability of various agricultural sensors and their application in the smart sector. Farmers can easily collect and appraise data in real-time using IoT and sensors, depending on a choice of environmental elements such as soil pH, soil macronutrients, temperature, moisture, smoke, flame, CO_2 emission, light, plant disease, water level, and weather. However, IoT and sensor technology had challenges in the smart agriculture sector, including cost and standardization, adaptability and energy optimization, heterogeneity and accessibility, superior efficiency, mobility and environmental conditions, and compatibility and reliability. Recently, researchers have developed end-to-end integrated IoT-and-AI technology to reduce the need for gas sensors in real-time carbon emission monitoring [116,121].

Fig. 6d illustrates the integrated technology testbed architecture developed for monitoring GHG emissions from combustion engines, eliminating the need for exhaust gas analyzers. The gas analyzer embedded in the delivery truck is used to measure the concentrations of emitting gases (CO_2), which are utilized to train and validate AI simulations using the vehicle's on-board diagnostics (OBD) data, such as vehicle speed, deceleration, acceleration, and engine and fuel system operating conditions. Typically, the humidity and temperature sensors are located underneath the truck to collect datasets on atmospheric conditions. The Raspberry Pi computer was global positioning system connected to both a gas analyzer and an OBD port via Bluetooth, and the IoT sensor was also linked to a dashcam and Global Positioning system device to track the vehicle's location, speed, and acceleration. The power bank and charging facilities support the IoT sensor node while cooling and environmental monitoring sensors regulate its internal temperature. In this network, a variety of machine learning methods were utilized, including Light GBM, gradient boosting, and XGBoost, to improve CO_2 emission prediction. Nonetheless, managing this sensor on moving vehicles under uneven road construction and weather conditions poses a significant challenge. On the other hand, researchers are finding low-cost sensors for CO_2 monitoring by using IoT technology [117]. There are four sensor models, MH-Z16 and MG-811, tested to analyze CO_2 monitoring in an indoor environment. Fig. 6e illustrates the impact of different brand sensors on the concentration of CO_2. The reference sensor used is the Vaisala GM70 with a CO_2 probe. It was observed that MH-Z16. A sensor achieves the best precision and acceptable results in CO_2 monitoring, due to its accurate nominal conversion curve and lower bias. It is therefore recommended for use in science and IoT applications. However, many researchers are ready to initiate appropriate input, which is inexpensive and eco-friendly, in sensor research. The ground applications of these inexpensive sensors are still challenging.

The common IoT and sensor challenges observed are interoperability, scalability, security, power consumption, accuracy, calibration, durability, cost, data analytics, and integration with existing systems. Furthermore, this advanced tool is currently constrained by several challenges: (1) data-related issues, including data quality, data management, visualization, and data standardization infrastructure; (2) deployment-related concerns, such as maintenance and public acceptance; (3) regulatory-related factors, encompassing standards, privacy, and security; and (4) technological issues, specifically energy harvesting, advanced materials, and nanotechnology. Leveraging these challenges leads to the optimization of IoT and sensor tools for effective and sustainable CO_2 mitigation.

3.6. Hierarchical blockchain for carbon emission trading system

The supply chain is a network of interconnected groups, including manufacturers, distributors, suppliers, customers, and retailers, that focuses on meeting customer demand. In the supply chain, various actions, from raw material processing to end-use by customers, collectively make a significant contribution to carbon emissions. The low-carbon supply chain management has distinctive highlights such as general environmental regulation compliance, pollution/waste reduction, overall environmental performance, and environmental reputation of the firm. Blockchain is one of the potential tools in Industry 4.0, where modern smart technology uses IoT technology. Blockchain has been pioneered as the backbone of the cryptocurrency Bitcoin for a handful of billion-dollar businesses such as Microsoft, Dell, and PayPal. Blockchain benefits include improving supply chain efficiency, reducing costs, enhancing supply chain resilience, fostering trust, facilitating data sharing, increasing supply chain visibility, and promoting interoperability.

3.6.1. Blockchain architecture and classifications

Blockchain is a secure technology that enables the exchange of evidence and simultaneous interactions among parties in a network [122]. The main benefits of blockchain are carbon footprint tracking, sustainable sourcing verification, supply chain certification, and smart contracts (SC) for emission reduction. The characterization, architecture, and applications of blockchain and its streamlined role in the carbon trading market are significant. Fig. 7a illustrates the blockchain structure adopted for the carbon trading system [123]. In the blockchain, every block has a data structure that is linked together using cryptographic hashing. Carbon-related information, including emissions sensor readings, figures from software firms, and government threshold specifications, has been stored in the blocks. The information stored in the block is authorized and included in the blockchain by identifiable nodes (minors) through the consensus algorithm. The information once validated in the blocks can't be modified or erased and becomes immutable. The vigorous assembly of blockchain has valued structures including decentralization, distribution, security, transparency, automation, traceability, privacy, and reliability, thereby demonstrating remarkable value-added roles in carbon management. The classification of blockchain (public, private consortium, or hybrid) is based on ownership characteristics and access management to customers. A public blockchain is a decentralized, open ledger. The hybrid type involves a combination of private and public blockchains, where authorized gatekeepers validate transactions rather than relying on random miners. A new way of mitigating CO_2 emissions is believed to be a blockchain-enabled carbon emission trading system.

3.6.2. Carbon trading framework and design

The recounted framework for the trading system has three levels: the upper application level of the public blockchain, the lower measurement level of the permissioned blockchain, and the cross-transfer level. Fig. 7b illustrates the comprehensive view of the blockchain framework for the carbon emission trading system. The distribution, trading, and offsetting of carbon shares are transparent, secure, immutable, and traceable since they are all documented on a public blockchain. In the public blockchain, various procedures occur, including allocation processes, SC automation, trading, auctioning, carbon asset management, carbon offsetting, and surrender processes. The upper-level blockchain was designed utilizing multichain blocks. It was made by multichain supporters of Bitcoin Core software, and other supporters are Linux, Windows, and Mac servers.

The other design method was developed by a new Ethereum project that supports SCs, providing extremely high protection [124]. Both blockchains could be open to the public. With this, a registry service can be employed to register companies, green projects, governments, and global companies to access associated SCs. In the low-level permission blockchain, initially, the carbon emission data collected from sensors can be deposited on the low-level blockchain, and then it will be allocated with budgets via a unique set of SCs. In this case, the Hyperledger project paved the way for low-level blockchain, and it was designed for enterprises that received contributions from Intel, IBM, and SP Ariba. The significant connection of low-level blockchain to CO_2 sensors and meters utilizing the IoT concept is implied in the illustrated design framework. Through IoT devices, Hyperledger Fabric receives the data and feeds and processes the information into a blockchain. Another notable design is the blockchain of things-based framework, known as IBM Bluemix-based Hyperledger services. The design encompasses two major components: the Bluemix blockchain and the Watson IoT platform, which have been handling transactions, consensus processes, and sensor data. At the third level of cross-transfer level, the carbon sensing and calculating system plays a crucial role in transferring data through either Polkadot, Interledger, or Hyperledger Grid protocols from a low-level hybrid blockchain to the higher-level public blockchain (Fig. 7b). The framework is a cycle, and the process is continuous, public blockchain has a major contribution to the system observing governments monitoring movements and taxing illegal information.

3.6.3. Blockchain technology

Blockchain in the energy supply chain offers benefits like reducing GHG emissions, promoting decarbonization, digitalization, and decentralization. The traceability of transactions performed via SCs enabled energy source identification for green sources [125,138]. Table 3 summarizes the reported studies utilizing blockchain frameworks for carbon management. A partnership between the Energy Blockchain Lab in China and IBM is creating a blockchain system for carbon trading, while the United Nationals highlights its potential for climate action. However, blockchain use in carbon management is still in the early stages. The deliberate adaptation of blockchain caused an inadequate number of studies to be encountered in the blockchain frameworks for the carbon emission trade market. The Chief Executive Officer and founder of Clean Energy Blockchain Network in the USA implemented a blockchain to optimize the supply chain to generate renewable energy credits, representing one metric ton of avoided CO_2eq [128]. The developed blockchain is transparent, fast, and secure due to the presence of SCs in generating credits. However, the researchers don't disclose the SCs program codes and details of the framework. Tang and Tang [133] developed the blockchain-facilitated distributed carbon ledger by connecting the carbon asset management system with European Union emission trading schemes. The integrated framework is utilized to create digital carbon allowances and distribute. Hence, the framework easily facilitates carbon management activities through SCs, which enhance traceability, reliability, and sustainability, tackle emission leakage issues, and reduce transaction costs. Nonetheless, the study does not account for carbon emission measurement and doesn't detail the carbon financing and assurance. A well-established framework was reported for the Australian carbon market utilizing process design [130]. The frameworks operate under four different decision platforms, including computation and storage, decentralization, blockchain configuration, and other design-related decisions. Every stage contributes to reducing transaction costs, enhancing security, improving efficiency, and increasing transparency. However, the document analysis of the framework is still limited due to a lack of validation support. To combine energy and carbon markets, the researchers have developed a blockchain framework to tackle the obstacle of disparities and leakage during energy transformation in a unified market [132]. This framework facilitates carbon emission reduction and cost; nonetheless, this peer-to-peer trading system fosters the complication of carbon tracing and debasing the CO_2 emission logging process. Further, a novel reputation-based emission trading framework was demonstrated employing blockchain technology to resolve the challenges and improve CO_2 emission trading management [126]. The framework implements strict trading rules alongside a reputation system in an algorithm for transaction regulation. While blockchain ensures data immutability, it does not guarantee credibility or transaction integrity. Therefore, smart devices or meters are recommended to reach credibility. Similarly, another novel reputation-based emission trading framework was developed by coupling two blockchain networks to enhance CO_2 emission reduction in the fame of companies' reputation [131]. This framework can handle all transactions independently of the financial chain, resulting in lower redundancy and enhanced security. The initial data acquisition, estimation, and collection of transaction fees, as well as allocation, may be limited in the developed framework. Data is transmitted through IoT sensors, blockchain, and the LoRa network, ensuring security and immutability on a local database [127].

Furthermore, the real-world applications of blockchain technology are worth reporting in this section. Veridium and ClimateTrade are carbon credit trading platforms to ensure the integrity and transparency of carbon credit transactions and are used to allow companies to buy and sell carbon credits, respectively. The Maersk and IBM platforms allow companies to track the origin, quality, and movement of goods, reducing the risks of counterfeit goods and improving supply chain technology. In addition, Walmart and VeChain platforms are involved in providing transparency and accountability in the food supply chain communications. Most importantly, Power Ledger and WePower platforms enable the trading of renewable energy between households and businesses and use smart contracts to automate the trading process. The platforms of Ecochain and CarbonX play a significant role in helping companies track and reduce their carbon footprint, providing effective recommendations for CO_2 mitigation. TerraVerde is a blockchain-based platform that enables the creation, trading, and redemption of sustainable land use and forestry credits. The platform uses blockchain technology to ensure the integrity and transparency of credit transactions. In addition, ForesetCoin has been treated as a sustainable land use and forestry blockchain-based platform to ensure that companies create, trade, and redemption of sustainable forestry credits. The reported applications demonstrated the potential of technology to support efforts in reducing CO_2 emissions by providing transparency, accountability, and incentives for sustainable practices.

3.6.4. Challenges and limitations

Most developed frameworks lack an understanding of trading boundaries, unified global platforms, measurement authenticity, transfer methods, and initial data acquisition. To address these limitations, the framework was recently proposed by Al Sadawi et al. [123] based on the idea of a blockchain of things, as well as a fair-trading mechanism (Fig. 7b). The modernized framework is recommended for use with Ethereum, Polkadot, Hyperledger, Interledger, and other platforms. However, the scalability of the multi-level blockchain network is challenging due to carbon budget calculation open to manipulation, corruption, non-transparency, lack of integrity, the allocation process for carbon allowance is complex, lack of CO_2 emission recording, ununiform with other trading systems, high transaction cost leads to less participants and firms obviate negative impacts of unfair trading and buying credits. Therefore, a few innovative mechanisms are recommended to advance at the technical level, such as carbon removal credits, climate-resilience bonds, green bonds, carbon-neutral certificates, and sustainable development certificates. Researchers are encouraged to develop robust offsetting frameworks, integrate green banking and investment, and implement carbon pricing mechanisms, as well as develop strategies for achieving a carbon-neutral future. The following practical steps must support to the vision of integrating AI, IoT, and blockchain technologies into existing mitigation frameworks: (1) identifying cross-sectional opportunities, (2) assessing existing mitigation frameworks, (3) designing integrated solutions, (4) implementing integrated solutions, and (5) scaling up integrated solutions.

4. Challenging role of CO_2 in the transition to a circular economy

At the early stage of the century, companies prioritized reducing carbon taxes over actively utilizing CO_2. The end-of-pipe solution typically involves capturing CO_2 from a stationary point source and either sequestering or utilizing it. The action may be reduced or reasonably utilized to produce waste CO_2, resulting in a circular economy. Presently, there is a hasty growth of cost-effective technologies for CO_2 management and utilizing new and existing products, which contributes to increasing the deployment rate of CO_2 sequestration projects, positive trends in sustainable development, and an unavoidable role in the world economy. Table 4 depicts the potential markets for CO_2-based products, which determines the relevance of industry and investors in circular economic strategies. The reported strategies involved in the circular economy design for recyclability and reusability are sharing and collaborating, product-as-a-service, closed-loop production, biodegradable materials, upcycling and repurposing, and waste-to-resource [139]. Circular economic practices could cut down the CO_2 emissions via energy transition, resource efficiency, carbon geological storage, and other channels [140]. The suggested CO_2 reduction mechanism of the circular economy refers to urban-industrial symbiosis, energy from organic waste, and shifting to an intra-sector circular economy. Regarding the transition, it is essential to consider the economic value of the developed circular economy. Fig. 8 presents the conceptual version of the CO_2 transitional role in the circular economy. The factors involved in CCS and utilization are necessary for the sustainable, long-term development of any CO_2-based industry. Yet no reliable and comprehensive estimates of the factors mentioned are reported anywhere.

The transition from CO_2 to circular economy has increased economic value and project self-sufficiency. The explanations of each transition and each step, denoted by red and blue numbers, were provided for better understanding. In this context, carbon capture, utilization, and storage require self-sufficiency and long-term progress, independent of further government assistance. Projects related to CCS can enhance economic stability and are considered key conditions for large-scale advances. Circular economy, when integrated with waste management, relies on three key production stages that utilize waste as a resource: reduce, reuse, and recycle. When considering CO_2 as a resource, it is essential to incorporate recovery strategies, as recovered CO_2 can serve beneficial purposes by substituting for other waste-derived or conventional materials.

4.1. Contribution of circular economy to the CO_2 reduction potential

The concept of circular economy is closely related to other terms, including cradle-to-cradle, performance economy, material efficiency, resource efficiency, material footprint, and closed-loop supply chain. Similarly, CO_2 is known as carbon, a greenhouse gas and a contributor to climate change and global warming. Hence, CO_2 mitigation directly refers to climate change mitigation. Circular economic studies have been a significant component of a broad landscape of CO_2 mitigation across various sectors, including industry, energy, waste, building, transportation, and agriculture. Table 5 presents a summary of key studies on the circular economy in various sectors and their associated CO_2 mitigation prospects. Nearly 34% of the studies focused on reducing CO_2 via circular economic principles, including recycling, reducing, reusing, and cross-cutting in the industry sector. For example, 1.5 kg of CO_2eq emissions (66–70%) from the iron ore industry were reduced by using recyclable concrete [142]. Approximately 1 ton of marble-based geopolymer green cement production reduces CO_2 emissions by 54% compared to Portland cement [143]. On the other hand, using sawmill charcoal powder instead of coal in the cement industry reduces carbon emissions by 455–495 kg of CO_2eq MW h^{-1}, equivalent to an 83–91% decrease. Importantly, the closed-loop supply chains for automotive thermoplastic polymer waste recycling generate 73% less CO_2 than the forward supply chain using polyethylene terephtalate seats [145]. Utilizing biomass for fossil fuel and jet fuel could reduce CO_2eq emissions by 75% and 60%, respectively. A life cycle assessment (LCA) was conducted for wood pellets and baggase and identified a reduction in carbon emissions of 80–94% and 47% when using coal and fossil jet fuel, respectively [148,151].

The bioenergy LCA reports range from attributional to consequential LCA, and the key interest is the direct and indirect substantial land use consequences, which decrease the LCA-assessed mitigation savings. About one ton of seaweed cultivation and processing can reduce the net value of 34 tons of CO_2. The development of AD plants is a viable alternative for electricity producers, offering a reduction in carbon footprint of up to 1.07 kg CO_2eq kW h^{-1} and achieving a maximum GHG mitigation of 131% [152]. Like AD plants, the biogas digestate from pig farms suggests 152.5 thousand tons of CO_2eq have been achieved [183]. Recycling of wind turbine materials at the end of service life has advantages for a 60 MW wind park with a 7351 ton of CO_2 mitigation [184]. It was identified that circular economic interventions can offer energy reductions and thus contribute to achieving the goal of an 80% reduction in CO_2 emissions by 2050. Waste management strategies could mitigate 58% of CO_2 emissions, proved by a case study conducted in Ahmedabad, India [157]. Municipal solid waste treatment plants for urea production play a significant role in the CO_2 reduction of 0.8 tons of CO_2 per ton of urea produced [159]. The Ireland case study confirmed that biogas production from wastewater treatment plants (food) has the potential to reduce 4.5 Mt CO_2eq of global warming. The replacement of conventional materials into novel secondary materials for certain building products comes to the following carbon saving potential: (1) production of wood plastic composite reduces 0.95–1.42 kg CO_2eq, (2) production of aggregate enabled concrete reduces 0.008 kg CO_2eq, and (3) production of composite bricks reduces 0.025 kg CO_2eq [185].

The substitution of a high amount of fly ash for cement materials is a feasible option to enhance the environmental performance of the building concrete as well as a reduction of CO_2 emission. It was observed that rethinking building materials and substituting cement with recycled materials in a specified ratio advances a whole new array of mitigation options in CO_2 emission potentials. Rethinking concrete materials benefits small residents with large household sizes, fewer second homes, shared office spaces, and dual-use spaces, which could secure the buildings from climate change [170]. The retrofitting principle is an alternative for the Atlanta residential sector, where natural gas provides heating and reduces CO_2 emissions by 3%. Different circular economy strategies, including fuel alternatives, design modifications, recycling and reuse, ownership models, and car sharing in the transportation sector, were examined for CO_2 mitigation. For instance, the use of electric vehicles and hydrogen fuel power cells has relatively lower full life-cycle emissions of 269 and 235 g CO_2 km^{-1}, respectively [186]. The hull reuse design in ship design found an extraordinary reduction potential in CO_2 emissions from 222 to 158 tons. Additive manufacturing for lightweight metallic aircraft components could save 92–215 million metric tons of CO_2 and thousands of tons of aluminum, titanium, and nickel alloys by 2050. A limited number of studies have been published to address the circular economy for CO_2 mitigation in the agricultural sector. Principles such as closed-loop, waste-to-energy, recycling, and efficiency are employed to mitigate CO_2 emissions from the agricultural sector.

Life cycle assessment was conducted on fish canning, pork, and cassava starch production for the reduction of GHG emissions. Apart from this, the landfill plan offers the ultimate mitigation potential of 2.68 kg CO_2eq per operational unit. The reduction and recycling of national food waste resulted in a 55% and 64% reduction in CO_2eq, respectively. However, several investigations failed to report specific emissions savings, were not thoroughly studied within the wider scope, and had many unclear concepts related to circularity. Hence, the researcher summarized the findings of the reported literature on the linkage between the circular economy and CO_2 mitigation [17]. Fig. 9a outlines the evidence of circular economy potential for CO_2 mitigation by different sectors. Among the sectors, the industry sector investigations have sharp carbon savings for the recycling of iron and concrete by 60–90%. Secondly, the use of solid waste in cement production and biomass energy offers a 40–90% reduction in GHG emissions. Thus, by applying circular economic measures, maximum savings were achieved in the industry, energy, and transport sectors, mid-term savings in the waste and building sectors, and lower returns were reached in agriculture. However, the articles have not addressed quantification and its related issues, technologies, and sectors. It was observed that efficiency studies might be a minority group, and they have corresponding attention with modest overlaps, and rethink studies confirm the long-term growth trend. Further, refusing, rethinking, and reducing have the highest priority while recycling and recovering the present lower part from a linear economy to a circular economy, demonstrating an extensive crooked. Achieving a productive circular economy requires a broad implementation of strategies with reduce, reuse, and rethink approaches.

Several barriers have been identified that hinder the adoption of circular economic practices, including a lack of awareness and understanding, economic and financial constraints, regulatory and policy frameworks, technological and infrastructure limitations, social and behavioral barriers, supply chain and logistics complexity, and data information gaps across various sectors. By focusing on these barriers and complexities and implementing sector-specific strategies, circular economy practices can be adopted and scaled up to achieve significant reductions in CO_2 emissions. Reverting waste into the economy as recycled materials is a critical part of the circular economy. Out of the circular economic policies, approximately 50% of policies focus on waste-related issues. Nearly 148 circular economy-related actions were reported in 2023 by the European Environment Agency (EEA), which facilitates waste-to-energy recovery, biowaste to biogas for energy production, and carbon emission reduction [187]. Approximately, 3070 kt CO_2eq emissions will be reduced when associating the circular economy with policy and measures by 2030.

4.2. Challenges for linking circular economy and carbon emission mitigation policies

According to the published articles, carbon emissions in the waste sector stem from the treatment and disposal of solid and liquid waste. The historical and projected GHG emissions for the waste sector in the European Union were reported by EEA in 2024 [187]. In 1990, the historical waste carbon emission was approximately 185 Mt CO_2eq, with methane and landfills accounting for around 70% of waste sector emissions. In 2021, carbon emissions were reduced by 45% and reached 110 Mt CO_2eq, and European Union countries previously attained a 41% reduction in 2022. Carbon emissions are projected to decline by 58% by 2035 compared to 1990 levels, with a potential 68% reduction if additional policies are implemented. In many cases, CO_2 has been considered to be a new solvent medium to achieve efficient carbon capture [188,189].

Every country has unique and significant policy measures for the waste sector. Nevertheless, these policy measures alone are not a reliable indicator for national reporting. There are 218 single policy measures and 15 group policy measures linked to the policy measures related to the waste sector in 2023. Still, 15% of waste sector policy measures were quantified. Furthermore, the cross-sectional effects are rarely reflected in the registered policy measures across various sectors, except for the waste sector. Gaps in reported policies concern prevention schemes for non-food waste, the preparation of reuse measures, recycling programs for metals and other materials, quantification of waste and energy sector impacts, and technical landfill solutions, including mechanical biological treatment and enhanced coverage materials. Furthermore, carbon emissions generated from the fuel and energy required for the recycling process are included in the energy sector's calculations. Hence, there are certain challenges to linking circular economic actions and carbon emission mitigation.

Policymakers should take the following concrete steps to implement CO_2 mitigation strategies at both the national and global levels. The suggested concrete actions for policymakers to practice at the national level are developing and implementing national climate plans, establishing carbon pricing mechanisms, investing in clean energy technologies, implementing energy efficiency standards, and promoting sustainable land use practices. At global levels, strengthening international climate agreements, establishing global carbon pricing mechanisms, developing and deploying global clean energy technologies, implementing global energy efficiency standards, and promoting global sustainable land use practices. Fig. 9b outlines the current challenges for integrating the circular economy and carbon emission policies. It was observed that policy and regulatory frameworks such as waste management regulations, recycling targets, landfill bans, carbon pricing, and tax incentives for circular economy practices are recommended for resolving the integration policy challenges. In addition, circular economy business models, including product leasing, pay-per-use, sharing platforms, collaborative consumption, and closed-loop manufacturing, are anticipated to develop to enhance the circular economy efficiency for CO_2 mitigation. In addition, six essential steps provide guidelines for countries to initiate or enhance the integration of the circular economy's carbon emission potential into climate change mitigation efforts: raise awareness and eliminate silos; identify circular economy measures with significant GHG reduction potential; incorporate existing circular economy measures and quantify the resulting emission reduction targets in national climate reporting; assess whether additional legislative proposals are required; track progress and institutionalize processes; and further develop the method.

5. Significance of reducing carbon emissions within waste management

Reducing carbon footprint within waste management indicates minimizing the GHG or CO_2 emissions linked with waste generation, collection, transportation, treatment, and disposal. The major sources of CO_2 emissions in waste management include the decomposition of organic waste (CH_4 production), energy consumption for waste collection and transportation, incinerations and landfilling treatments, and production and transportation of waste management equipment. Enhancing waste management and refining waste segregation practices can significantly reduce carbon emissions and strengthen global sustainability efforts. Waste management practices towards a net-zero future and benefits to climate change mitigation, energy savings, resource conservation, water conservation, pollution reduction, cost savings, and improved public health. The best way to reduce our carbon footprint, as well as optimize waste management, is as follows: maximize container usage, reduce single-use plastics, introduce new waste streams, specific waste containment placement, and implement a reusable waste containment system. Within 12 months, the United Kingdom successfully eliminated the incineration of 900.8 tons of single-use plastic and the disposal of 132.5 tons of cardboard through the reusable system. In this context, the knowledge of LCA on converting from single-use to reusable sharp containers is crucial. Unscrupulous ways of mixing waste streams or poor waste segregation practices adversely affect the carbon footprint. Every waste stream has individual disposal and treatment characteristics; hence, safety practices drive sustainable outcomes. By considering all guidance for safe management, a new waste stream is recommended, which cuts down the amount of waste sent for alternative treatment and high-temperature incineration and diverts the waste to more sustainable outlets.

There are several strategies mentioned to reduce global CO_2 emissions in waste management, including waste minimization, recycling, waste-to-energy, composting, landfill gas capture and utilization, energy-efficient waste collection and transportation, biodegradable waste management, closed-loop production and consumption, and carbon offsetting and capture. In this context, a major key performance indicators (KPI) are waste diversion rate, recycling rate, composting rate, energy recovery rate, CO_2 reduction, GHG emission reduction, resource depletion index, and cost savings. Germany has the highest recycling rate (66.1%) in the world. However, less than 1% of household waste is sent to landfills in Sweden. Currently, 34 waste-to-energy plants are implemented in Sweden, supplying 1,445,000 and 780,000 households with heat and electricity, respectively. Some of the most impressive initiatives for waste management are Sweden's waste-to-energy program, San Francisco's recycling and composting program, Vancouver's zero waste strategy, Waste Management Carbon Reduction Program, and the European Union's circular economy package. Yet many countries lack participation in optimizing waste management to reduce their carbon footprint. Hence, instantaneous action is urged to achieve a sustainable and climate-resilient future.

6. Future research and development needs

Through a critical review of the current literature, this section outlines the future research and development needs for advanced tools used in CO_2 mitigation and discusses the requirements of the circular economy and waste management in reducing the carbon footprint. Developing economic activities and enduring unavoidable urbanization are crucial to increasing future CO_2 emissions. A variety of methods and models are being utilized to forecast CO_2 emissions, and both developed and developing countries are responding to these efforts. Based on the understanding of current study methodologies for CO_2 emission reduction, we outlined the recommended future research and development needs for advanced tools (Fig. 10a) and the circular economy (Fig. 10b). The proposed requirements are categorized into three distinct time frames: short-term, mid-term, and long-term. Individual tools have their own merits and limitations; further studies must perform more frequent combined applications of diverse econometric models to reduce modeling bias. Further, econometric models are integrated with AI to improve prediction accuracy. Recent pinch analysis studies have been conducted to reduce CO_2 emissions through waste management and CO_2 mitigation in the transportation sector. The application of pinch analysis may extend to cleaner production by considering the principal footprints of nitrogen, land, phosphorus, and biodiversity. Regarding P-graphs analysis, the related research accounted for uncertainties in energy and biorefinery network optimization; however, efforts are needed to maximize their economic viability. A knowledge gap exists in P-graph approaches to green ammonia and other renewable energy sources, highlighting potential research opportunities.

A computational fluid dynamic simulation studies frequently produce unreliable outcomes, potentially affecting policymakers. Hence, more inter-comparison model studies are warranted. Most importantly, advanced AI techniques such as Multi-agent and Monte Carlo are recommended to incorporate with uncertainty simulations to improve the capabilities of models. Furthermore, future research is necessary to investigate the model's input, parameters, structure, output, and guidelines for informed climate decision-making. Certainly, the continuous improvement of study data is equally important. Improved representation of CO_2 sinks and sources, incorporation of climate change feedback, and development of probabilistic CO_2 forecasting systems will help offer policymakers more robust recommendations. Changes in global production chains and increasing trade among developing countries impact CO_2 emissions in these regions. The timeline to mitigate CO_2 using advanced tools deserves more attention. As a result, direct research urged the development of advanced tools in cross-cutting research areas such as data science, modeling, observation, uncertainty, and decision support. Further, emerging technologies including IoT, edge computing, blockchain, AI, and quantum computing are surging for high-level research and development.

The datasets and metrics used to assess the CO_2 mitigation tools span a broad range. Hence, we need to ensure the quality and uniformity of the data sources by employing several strategies such as data quality assurance, addressing geographical and industry variability, data integration and fusion, and transparency and replicability. Further, a collaborative framework among engineers, environmental scientists, policymakers, and other stakeholders is required to develop sustainable and integrated solutions to mitigate CO_2 emissions and address the complex challenges of climate change due to the complex nature of CO_2 mitigation problems. Most researchers initially intended to study only energy and CO_2 mitigation strategies; however, they have been extended to include economics and profitability as key decision-making criteria. Implementing advanced PI tools and economic strategies requires a thorough economic feasibility analysis to ensure that the benefits outweigh the costs. The economic feasibility analysis should consider factors including capital expenditure, operating expenditure, benefits and savings, payback period, and return on investment. Several economic strategies can be applied to improve the economic feasibility of implementing advanced PI tools such as energy pricing and tariffs, carbon pricing and credits, tax incentives and Rebates, and public-private partnerships. Limited case studies have demonstrated economic feasibility analysis by implementing PI tools and economic strategies. For instance, a chemical plant resulted in a 15% and 20% reduction in energy consumption and GHG emissions, respectively. Furthermore, some specific tools involved in improving the economic feasibility of implementing PI strategies are real-time optimization tools, digital twins, and cloud-based PI platforms. Hence, the economically feasible strategies for implementing PI tools can reduce energy consumption and GHG emissions, while improving productivity and profitability.

The findings of LCA are extremely dependent on the system periphery. Even though the circular economy is the most agreed-upon analysis, it is occasionally streamlined due to the lack of data. Sharing economy platforms, business models, and advanced recycling technologies are needed for further research to reduce the carbon footprint. Many efforts are thus required for the energy, industry, and waste sectors to develop policies and regulations on the circular economy. In addition, further studies on industry-specific applications, including electronics and e-waste, food and agriculture, textiles and fashion, transportation and mobility, and construction and building materials, are demanded for formulating a linkage between CO_2 mitigation and circular economy policies. Integrating waste management and climate change mitigation will support energy and resource conservation rates that can ensure sustainable development.

7. Conclusion and outlook

In this work, we have reviewed and discussed the advancement of PI tools, including pinch analysis, P-graph, AI and ML, CASD, IoT, sensor, and hierarchical blockchain technologies. The summary of the key findings is as follows.

- Pinch analysis is an insight-based tool that offers efficient energy process systems in industrial applications and power sector planning. Its application is also gradually expanding into the waste management and transportation sectors to mitigate carbon emissions. Pinch analysis is a primarily used steady-state tool, which limits its ability to model dynamic processes.
- The benefits of P-graph in carbon mitigation include systematic and holistic carbon management, identification of optimal solutions for carbon reduction, integration of multiple carbon mitigation strategies, quantification of carbon emissions, and flexibility and adaptability to changing carbon regulations and prices. Yet, the application in the subsection of renewable energy streams, CCS, and NETs has not been explored comprehensively.
- Among AI and ML, ANN-based algorithms and extreme learning models effectively predict CO_2 emissions from energy consumption, forecasting CO_2 concentrations in the atmosphere, optimizing CO_2 strategies, and identifying CO_2 emission sources and sinks. However, the deployment of AI technologies also presents significant challenges, including high energy requirements for implementation and integration within existing systems, biases in training data, limited interpretability, and a lack of transparency. These limitations complicate the use of AI in informing carbon management policies. In response, we identify and propose solutions to the top 15 key challenges hindering the application of AI in sustainable and clean production.
- Computational fluid dynamics simulation was recognized for its remarkable contribution to carbon saving through an understanding of fluid (CO_2) dynamics behavior in real industrial configurations. Studies have shown that CASD offers a user-friendly interface for designers while also being cost-effective, with fast simulation and analysis. However, AI integrated with CASD could create more effective CO_2 reduction strategies since CASD requires updates and relies on predefined rules.
- The Internet of Things has reduced the carbon footprint in five different ways: smart energy grids, smart metering, green transportation, sustainable agriculture, and smart building management. More recently, integrated IoT–AI systems have been demonstrated to streamline the use of gas sensors for real-time carbon emission monitoring, offering end-to-end solutions for environmental data acquisition and analysis.
- The slow adaptation of blockchain resulted in a limited number of studies being conducted in the blockchain frameworks for the carbon emission trade market. However, the real-world application of this technology was emphasized by highlighting employed platforms. Researchers are encouraged to develop robust offsetting frameworks.
- The transition from CO_2 emission reduction to a circular economy has increased economic value and stability, which are the key criteria for large-scale developments. The integration of circular economic actions into CO_2 reduction efforts for waste is inadequate in national climate policies and measures due to their cross-sectoral nature and the challenge of assessing their effects.
- Yet, many countries lack effective waste management, which hinders their efforts to reduce their carbon footprint. Hence, immediate action is urged to achieve a sustainable and climate-resilient future.
- Several economic strategies can be applied to improve the economic feasibility of implementing advanced PI tools. These include energy pricing and tariffs, carbon pricing and credits, tax incentives and rebates, and public-private partnerships.
- Ultimately, achieving cleaner production across energy-intensive industries through the implementation of advanced PI tools can help secure a sustainable future for the planet and future generations.

CRediT authorship contribution statement

Divya Baskaran: Writing - Original Draft, Visualization, Methodology, Conceptualization, Writing - Review & Editing. **Hun-Soo Byun:** Writing - Review & Editing, Supervision, Project Administration, Methodology, Funding Acquisition, Validation.

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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