A Comprehensive Survey on 100% Renewable Energy Transition Roadmap for Global Decarbonization: A Story Told So Far

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Abstract:

To limit the impacts of climate change, the carbon dioxide CO_2 emissions (CE) correlated with the energy sector must be decreased. Reduction of CE will have a positive effect on the atmosphere by avoiding the adverse impact of global warming. To attain an eco-environment, the initial energy resource needs to move from traditional fossil fuels to unpolluted renewable energy (RE). Thus, enhancing the utilization of RE actively decreases air pollution and adds secure sustainable energy allocation to ensure future energy needs. Integrating sources of RE not only drops CE but also decreases fuel consumption, leading to significant economic savings. This paper presents the transition of global energy that will have a largely positive impact on the growth and future stability of economies with cost-effective and more sustainable all over the world. Significant reductions can be accomplished by using applicable policies and technologies. In the context of current discussions about climate change and the reduction of CE, this paper critically analyses some policies, technologies, and commonly discussed solutions. Technologies like digital twin (DT), transfer learning (TL), Edge Computing (EC), Distributed Computing (DC), and some other technologies with their work for the reduction of CE are discussed thoroughly in this paper. The given techniques in this survey paper present the best optimal solutions for CE reduction.

Keywords: CO_2 emissions; Renewable Energy Integration; Edge Computing; Transfer Learning; Distributed Computing.

Nomenclature:

CE	Carbon Emission
RES	Renewable Energy Supply
TTL	Task Transfer Learning
SDGs	Sustainable Development Goals

RMSE	Root Mean Square Error
GDP	Gross Domestic Product
LCOE	levelized Costs of Electricity
GHG	Green House Gas
IoT	Internet of Things
NREAPs	National Renewable Energy Action Plans
CCS	carbon capture and storage
OECD	Economic Cooperation and Development
NPC	Net Present Cost
EKC	Environmental Kuznets Curve
MFHC	Multi-Family Housing Complexes
ML	Machine Learning

I. Introduction:

A special article of the IPCC is presented on global warming of 1.5°C, expressing that climate change (CC) has a worse impact than projected [1], [2], [3]. Warming human-induced went higher than levels of pre-industrial at 1°C approximately, indicating severe effects of climate change [4]. The warmest years are recorded from the last two decades [5], [6], [7]. Weather incidents are becoming more extreme. In [8], [9], [10], [11], [12], the survey shows that the public is very disappointed about climate change as they face a challenge of intensity and enhancing the number of phenomena such as sea level increase or storms, fires, droughts, and floods. Climate change is assumed to be worse than many different types of diseases. It is human-caused, and the major reason is the fossil fuel enhancing combustion to cross the energy growth requirement [13], [14], [15], [16].

Several choices are present for the removal of CO_2. CO_2 emission (CE) can be acquired at point bases such as non-energetic regions like cement plants or traditional plants that eject flue gases. However, a few plants are ancient and cannot be retrofitted. Further, the removal system of CO_2 is present in some plants and does not capture the whole emissions just the average rate of 50-94% range [17], [18]. In contrast, directly acquiring the emission of CO_2 is not possible by marine transport and aviation of long-distance. A huge number of minor emitters, like transport regions, interpret 50% of emissions of global GHG, as just difficult to neutralize by traditional applications capture of CO_2 [17]. These proofs are undeniably required to find extra clarifications capable of acquiring CO_2 free from location and origin.

Another mitigation of the CC technique is acquiring CO_2 clearly from the air. Hitherto, some plants are naturally doing it. Nonetheless, they did not continue to enhance the emission of anthropogenic [19], [20], [21], [22]. Afforestation, bioenergy with acquisition of carbon and storage, and improved weathering were present to decrease the dilution of CO_2 in the atmosphere [23]. However, it limits their commercial feasibility, and all these calculations are linked to risks [24]. Climate change's recent development and enhanced emission of carbon dioxide (CO_2) worldwide reveals that, even though the renewable energy (RE) contribution to the main energy source is extending, all countries must enhance their struggles considerably to decarbonize the energy zones in the upcoming years [25].

Some significant literature on energy networks evaluates the justification of CC with a fall in the intensity of carbon emissions through all economic regions usually called “deep decarbonization”. Currently, literature also highlights the requirement for the ‘emission of net-negative’ or ‘net-zero’ energy network that decarbonizes the total economy, concealing energy demand and supply, with other emission sources comprising forestry, land use, agriculture, and industrial processes. The decarbonization level relies on the scientific group results that reduce unalterable destruction from CC, concentration of GHG would not be beaten, e.g., a goal of 450 parts per million (ppm) of CO_2 [26].

The decarbonization (DB) of energy zones has been the focus of research for many years, and just gained high attention. It is usually conceded that the maximum noticeable way to accomplish decarbonization is the RE use. Therefore, several countries previously used an unceasingly enhancing share of renewable resources, like hydro, geothermal, solar, or wind to produce electricity and several countries have now gained very huge contributions of RE for the generation of electricity due to hydropower, like Costa Rica (93%), Norway (97%), and Paraguay (99%) [16]. USA and China had the largest wind energy installation and capacity of solar photovoltaics worldwide in 2019 [27].

RE integration is still a challenging dare usually divided into social issues, economic, and technological. The supreme problem is to confirm that the selection of technology is accessible at a suitable cost and the required scale, especially for zones that are hard to decarbonize, such as transport or industry [28], [29], [30]. [31] reported that Sustainable Development Goals (SDGs) focus on risks created by the CC impact in reversing and eroding decades of development on SDGs, food protection, and inequality. In this framework, a global energy network change is of extreme significance as the use of energy is accountable for the majority of emissions of global greenhouse gas (GHG) [32]. Transition concerns the huge contribution of RE will abridge gaining a universal approach to affordable and clean energy, reducing water scarcity, and decreasing emission of GHG by excluding the usage of freshwater in thermal electricity plants [33]. This transition has previously happened with the availability of RE higher than 27% of the generation of global electricity in the last of 2019 [34], adding the production of RE technologies to almost 11%, mainly solar photovoltaics (PV) and wind turbines. Focused on the reduction of cost, RE is huge cost modest with traditional thermal electricity plants, in some RE zones budget is less than the running budget of existing nuclear and fossil power plants [35], and solar has appeared as the source of the least minimum cost of generation of electricity in mankind's history [36], [34].

The flow of this survey is given in Figure 1.

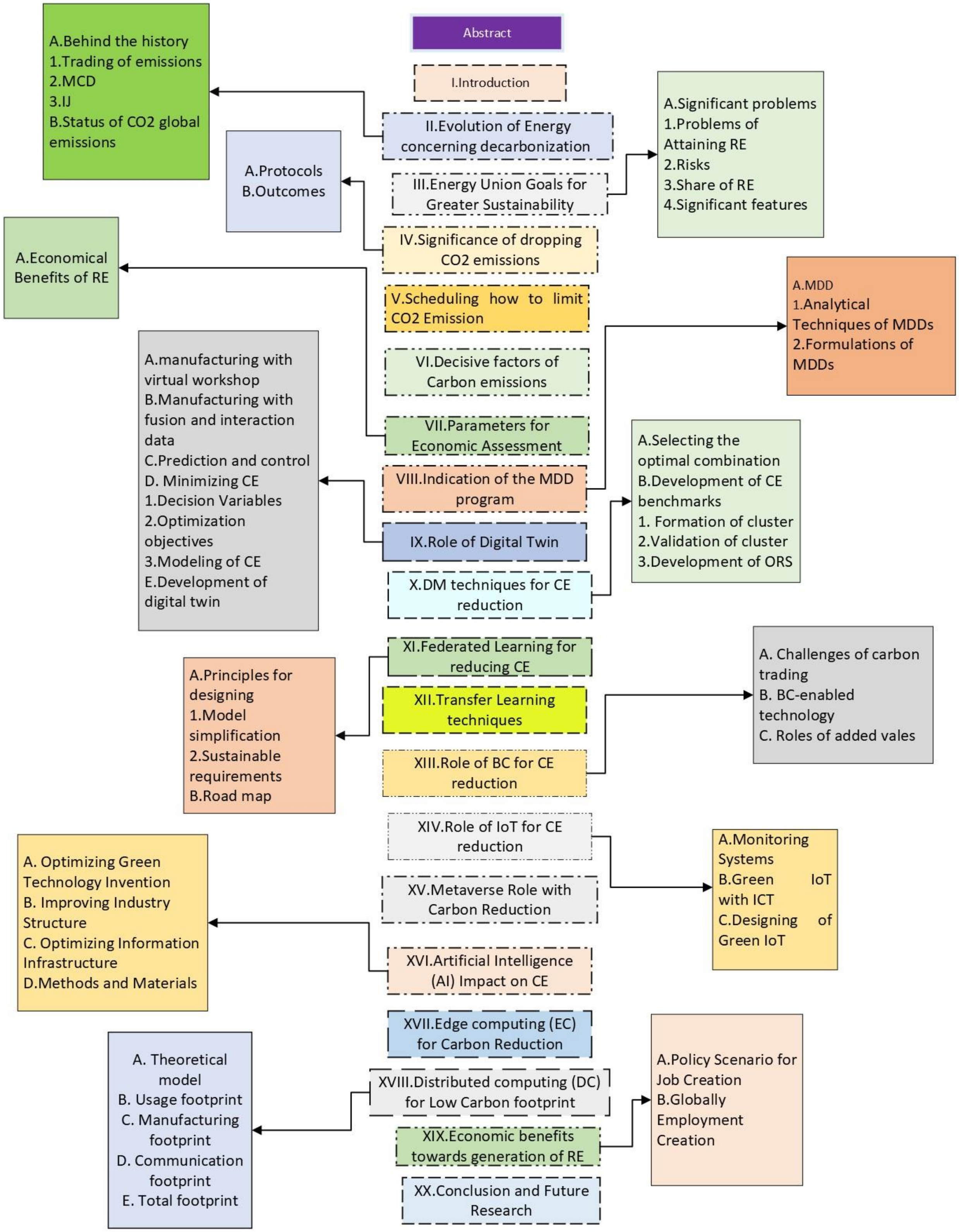


Figure 1. The flowchart of this survey paper.

A. Contributions:

A complete study of energy evolution regarding decarbonization with background history and CO_2 status has been explained in section II. The goals of energy unions for higher sustainability with significant issues and particular risks are described in section III. Section IV and Section V define the significance of CE reduction and precautions to take to limit CO_2. The environmental Kuznets Curve is explained in section VI with their benefit of carbon emission reduction. The economic benefits of using RE are given in section VII. Section IX explains the architecture of controlling Low-carbon by driven digital twin Job-shop manufacturing with decision and optimization variables. The optimal combination and the best technique of modeling data mining techniques with the formation and validation of MFHC clusters are described in section X. Principles for designing less carbon emission with computing and communication footprint by using federated learning are explained in section XI. Blockchain technology with challenges and solutions of carbon trading are described in section XIII. Monitoring systems of IoT and green IoT with ICT applications for decreasing CE and their drawbacks are given in section XIV. Metaverse Green efforts with different layers are explained in section XV. The roles of edge computing and distributed computing are explained in sections VII and VIII. Section VIX explains the economic benefits of the generation of RE with policy scenarios and the global creation of jobs. Conclusion and future research are given in section VX. Various technique's roles in the reduction of CE and their major contributions are given in Table 1.

Table 1. Main contributions of this paper.

Reference	**Year**	**Contribution**
[37]	2020	Discuss the decarbonization challenges in the energy sector.
[38]	2021	Evaluate the blockchain system for CE trading utilizing the smart contract and blockchain of things.
[39]	2022	Discuss directions and ongoing efforts of carbon neutrality meet with the metaverse.
[40]	2021	Discuss the optimization of reducing CE with cutting parameters by using digital twins.
[41]	2023	Evaluate the task transfer learning for the prediction of total hydrocarbon emissions.
[42]	2022	Evaluate the technique of new hybrid data mining to forecast the GHG.
[43]	2023	Discuss the reduction of carbon and energy footprint Analysis of Distributed and Federated Learning.
[44]	2019	Evaluate the Job creation towards 100% RE by 2050 during the global energy transition.
[45]	2020	Discussed the role of AI in attaining the goals of sustainable development.
[46]	2021	Evaluate the investigation of energy sustainability by using reliable RE to reduce CE in a high-potential area.
[47]	2014	Discuss the IoT and BOM-based life cycle assessment of CE decreases and energy-saving of products.

[48]	2024	Evaluate the algorithm of distributed computing for the electricity flow of CE and intensity of CE.
Our Survey	2024	Thoroughly analyze the different techniques and algorithms for reducing carbon emissions towards renewable energy.

II. Evolution of Energy concerning decarbonization (DB):

A. Behind the history:

The first casual effort worldwide to stabilize and control the deliberation of GHG in the environment occurred in 1992 in Rio De Janeiro at the Earth Summit, where several countries decided to the United Nations Framework Convention on Climate Change (UNFCCC) [49]. The crucial aim of this agreement is to "attain a concentration of greenhouse gas stabilization in the environment at a rank that would stop dangerous interference of anthropogenic with the climate network" [50]. This rank is attained within "a sufficient time frame to permit the ecosystem to familiarize itself naturally in the climate alteration, to confirm that production of food is not vulnerable and to permit the development of the economy to continue sustainably" [50].

The United Nations described three procedures that assist some countries with devotions under the procedure of Kyoto in extending their drop of target emissions cost-effectively [51], [52]:

1. Trading of emissions:

The organizations have limitations on emissions, which are stated as allowances of emissions. The allowances for emissions can be operated among organizations that are below or above their objectives.

2. Mechanisms of Clean Development (MCD):

Organizations can execute projects of emissions reduction in emerging countries and receive certified saleable credits for emission reduction (CER).

3. Implementations of Joint (IJ):

This method allows organizations to earn a reduction of emission units from the removal or reduction of emission units project with another organization.

The goal of Sustainable Development 7 has the scale to "confirm the universal way to modern, sustainable, reliable and affordable services of energy by 2030" [53]. Agreed success indicators are the portion of the population with primary and electricity reliance contact on technologies and fuels, the share of RE in the ending total use of energy, and the intensity of energy calculated about gross domestic product (GDP) and primary energy.

B. Status of CO_2 global emissions:

Plenty of certificates have been completed on friendly climate investments that are not economically attractive. The profit is built through schemes of emission dealing that are not devoted to research or technology of low carbon, which caused a deficiency of struggle to attain decarbonization. ETSs did not include the agriculture sector, buildings, or transport because extreme emissions exist in them. For IJ and MCD, there was no enticement for security caused by less emission-certified decreases. Overall, there was a reduction of monitor and no evaluation of sustainability in the state for each methodology, which made it tough to display the development.

Since 1990, the population of the world has been increasing steadily, almost reaching 8 billion in 2022. It is predicted in 2060 to touch 10 billion. However, the number of people without electricity retrieve has been reducing since 1990 and dropped by less than one billion in 2015 for the first time and we expect that this number will further decline. This growth indicates that the energy demand will further increase. In [54], [55] predict an enhancement in the providing efficiency and utilize the energy of 'end-use', which would respond to the demand enhancing from the rising population. To classify the maximum potential for reducing the emission of CO_2, the emissions from the end-use and secondary sectors of energy are inspected. The maximum emissions are linked with the generation of heat and electricity, and considering industry in all areas of the world, see Figure 2 [56]. The emission in the world per sector region presents that the emission of CO_2 in Asia from the generation of heat and electricity is huge. Emissions in Asia from the industry and building sectors are also very high compared to other sectors and transport did not add in international aviation and marine [57].

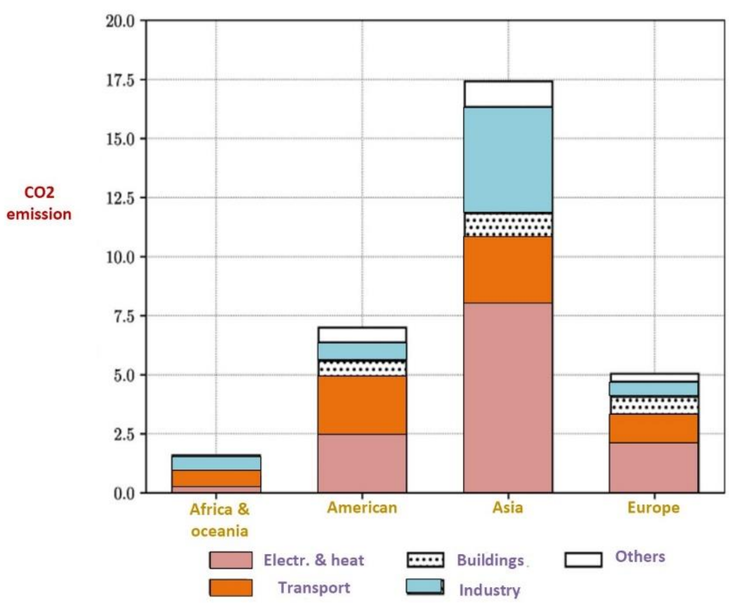


Figure 2. maximum emissions in all areas of the world.

III. Energy Union Goals for Greater Sustainability:

The European Commission (EU) has implemented a scheme of framework to determine an Energy Union with goals to contribute to alteration towards economic competitiveness, energy security, and higher sustainability [58]. The union's attention to forming cooperation between the Member States and higher solidarity to diversify and pool energy resources. It would add participation of energy markets and strengthen the interconnectedness of transmission where compulsory to 'build the EU number one in RE in the whole world and win the battle verses to the global warming' [58], [59].

A. Significant problems:

Energy union faces two significant problems that have appeared associated with governance. The first matter is the time frame and overall objective of the union. Specifically admonished that to accomplish the aim of the Paris Contact, a 'red line' of attaining GHG net-zero emissions by 2050 was required to prevent liabilities for the generation. Considering some state's members presented unwillingness to indicate specific data [60]. The second important concern is the interconnection level that would be required to attain such aims. Hanger and Lilliestam [61] define the conflicting opinions of the two associations that support 100% RE futures for DESERTEC [62], EUROSOLAR [63], and Europe. On the other side, EUROSOLAR supports energy decentralization and the disempowerment of the structures and actors that have generated an undemocratic and unsustainable energy organization [64].

If we consider DESERTEC, it imagines an extremely regulated and centralized network of export and import wind and solar systems throughout Europe [65]. Moreover, the third selection is possible. Battaglini et al. [66] support a methodology for Europe that merges the centralized super grid and decentralized smart grid to generate a vision of a super smart grid, contending that "the two ideas are matching and must be present to assure an evolution to a decarbonized economy". In ref [67], Adnan et al suggested optimal scheduling strategies for smart home energy networks.

1. Problems of Attaining Renewable energy:

The RE 100% transition required political aid. It also required novelty, not only policy strategies but also efficient governance, technological, and smart measures. Adnan et al. [68] proposed the super smart grid unleashing the energy-efficient integration of RE. To accomplish these goals, many countries have to reread their strategies for energy transition, governance, and procedures to add financial encouragement for the transition. Thanks to previous instruments and measures to stimulate RE, the RE cost has been substantially less market diffusion and technological learning, and improved scale of economics. There are united EU aims explained to enhance the RE share. The general policy needed the EU to achieve 20% at least of its consumption of whole energy from RE by 2020. Also, EU all countries must confirm that 10% of their fuels are required for the transportation of RE resources by 2020 in National Renewable Energy Action Plans (NREAPs).

From 2007 to 2017 time period, the RE capacity installed by Europe grew from 258 GW to 512 GW [69]. As shown in Figure 3, progress mainly comes from bioenergy (94% plus), onshore wind

(180% plus), offshore wind (1365% plus), and solar (1966% plus). RE capacities are growing mostly wind and solar have enhanced competitiveness and reduced the cost of RE based on levelized costs of electricity (LCOE) [70]. The technology of storage also gives similar results of cost reductions mainly in the batteries [69]. Therefore, joining storage and RE may suggest a power solution of low cost in the future [66].

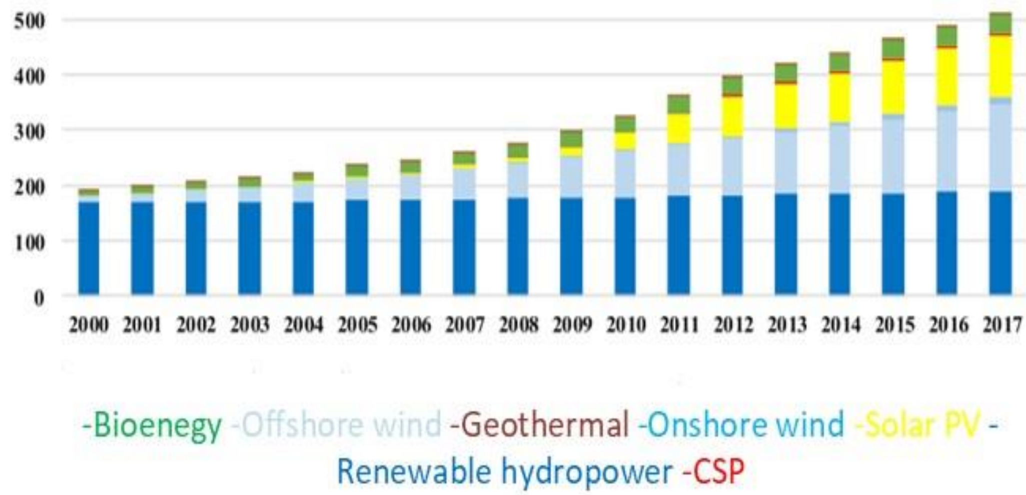


Figure 3. Installed RE capacity.

2. Particular risks for low-carbon energy:

The generation of nuclear power and the scheme of carbon capture and storage (CCS) is planned as a system of low-carbon energy for future solutions [70]. However, both contain such particular risks and huge costs that the comparative benefits to culture are progressively hard to see. Nuclear power has steadily enhanced over the previous decades in the LCOE position. This is caused by ever-huge expenditures of assets that look from enhancing the complexity of the system, overruns of construction time, huge budget, and a requirement to shelter the society from terrorism threats and accidents of nuclear danger. Further, indirect and direct subsidies of the public for nuclear are at a huge level. Notable of these adds the socialization of several risks linked with nuclear power.

There are many arguments why the fossil energy viability that relies on CCS is also doubtful. Ram et al. [71] review how CCS characterizes an option of high risk, and high cost on social grounds, environmental, and economic grounds. Firstly, it is not neutral of carbon, and future leakage risks will need efforts of vigilant management for a generation. Secondly, CCS-based fossil fuel complicates the point that CO_2 is not only a dangerous discharge linked with fossil fuels and does nothing to report such dangers to environmental health and humans as the emission of heavy metal, nitrogen oxide, and sulfur oxide. Third, RE is less costly than the CCS. Fourth, construction and budget assaults add to the technology with the poor economy that has yet to act the experience required to capture carbon at a large scale.

3. Share of RE:

For these arguments, the system of RE 100% has been suggested as economically viable and feasible clarification on a global scale [71], and there seems to be a rising organization of systematic literature to help this [72]. 100% RE with energy scenarios has also been recognized as compliant with the sustainability criteria in a wide range and regards are known universal boundaries [73]. Currently modeling work in Europe also launched the economic possibility and technical effectiveness of RE's extraordinary share, and the strong backup function of transmission interconnections is highlighted [74], [75], [76], [77], [78], [79], [80], [81]. Moreover, Child et al. [82] suggested that the technology of storage could help an evolution concerning a cost-optimal, system of 100% RE for Europe. Further, the majority of this work did not argue the role of transmission interconnections and flexible generation in feature, nor was the sufficient discussion to permit references from a document viewpoint [83].

4. Significant Features:

Features are vital tools for energy experts and policymakers. They can support policymakers in setting socio-political arrangements for concentrating energy and environmental problems like air pollution and global warming [84],[36]. Energy features are basic measures that support avoiding factors disturbing the environment (emission of CO_2, GHG) and increasing the population's life quality. The available energy and the environment are two difficult problems directly prompting the consumer demand for energy supply and GHG reduction rate. The features in Table 2 show an entry for energy experts and policymakers to come up with an altered practical technique to enhance conservation sustainability while completing energy requirement [84], [85]. Table 2 also gives information on the maximum difficult indicator that has the highest effect on the environment and energy.

Table 2. The most critical features for energy and environment.

Features	**Energy**	**Environment**
Municipal waste generation strength	×	√
Instruments used for environmental policy	×	√
Green space evolution	×	√
Energy Investment	√	×
Urban planning	√	√
Recent technology	√	√
Share electricity generation	√	√
Forest area	×	√
Energy efficiency	√	×
Yearly freshwater withdrawal	×	√

Policy	√	√
The strength of using fish resources	×	√
Energy equity and access	√	×
Quality of freshwater	×	√
The pattern of changing consumption	√	√
Treatment of wastewater	×	√
Share transport of renewable	√	√
Emission intensities	×	√
Final consumption	√	×
Reduction of GHG	×	√

IV. Significance of dropping CO_2 emissions:

Because of the rising alarms about universal CC, CF alleviation is formally a serious subject whereby in-depth investigation and wide research are being conducted to discover sustainable solutions as it is measured to be one of the focal points [86]. In this esteem, wide efforts are being made internationally to combat CC by dropping CO_2 emissions and utilizing low fossil fuels as the main energy source. Further, comparable universal environmental agreements such as the Tokyo and Paris Protocols highlight the reputation of dropping GHG releases to achieve the goal of a net-zero potential with sustainability [87], [88], [89].

A. Protocols for dropping GHG emissions:

The separation and capture of the CO_2 process from a plant's fossil fuel is an actual coordinated action and strategic planning process to attain a sustainable future [90]. The EU has effectively dropped GHG emissions from 1990-2012 by 17%. With suitable current strategies and planning in place, they are functioning towards dropping this value in 2020 by 20%. The EU's goal is to continue to employ the Tokyo Protocol to repeatedly drop GHG emissions [90].

The research disguises topics on effective policies, progress, and global prospects regarding the environmental impacts discussed in [89]. It also investigates methods to decrease environmental risks. Moreover, a useful investigation of the environmental influence has been approved by H.H. Khoo et al. [91], to compare and evaluate the traditional fossil fuel generation and CO_2 potential confiscation in Japan and Norway. The evaluation of the effective technologies' application, storage, and carbon capture environmental impacts was investigated in [92]. Different studies on the life cycle valuation were conducted with a concentration on storage, utilization, and carbon capture. It was established that storage and carbon capture can reduce the potential of global warming by 63%-82%, but it can increase some other effects of the life cycle [92].

B. Outcomes of capturing CO_2:

In [93], J. Koornneef et al. examined new environmental outcomes regarding the capture of CO_2 that is shaped by different regions such as transport and power. They measured projects linked with the production of natural gas, increased recovery of oil, storage of underground gas, and carbon capture. Important features of storage and control options and CO_2 capture were explored by D.Y.C Leung et al. with the reduction of carbon set objectives [94]. Table 3 displays the emissions by region. Table 1 displays that China produces the largest emissions.

Table 3. Emission by area (CO2 in millions of tons).

Region	**1995**	**2010**	**2010**
World	22,150	31,189	37,848
China	3051	5322	7081
Economic Development and Cooperation Organization	10,763	13,427	14,476
Economic Transition	3135	3852	4465
Rest of the world	4791	8034	11,163

V. Scheduling how to limit CO_2 Emission:

It takes a process that has three stages Process Outward Stage (POS), Process In Stage (PInS), and Process Inward Stage (PIS) shown in Figure 4 [95]. This process stage has an Energy and Matter (E&M) movement diagram that is shown in Figure 4. Various relevant research areas have been accepted for the mitigation of the emission of CO_2 which is linked to this classification given in the Table 4.

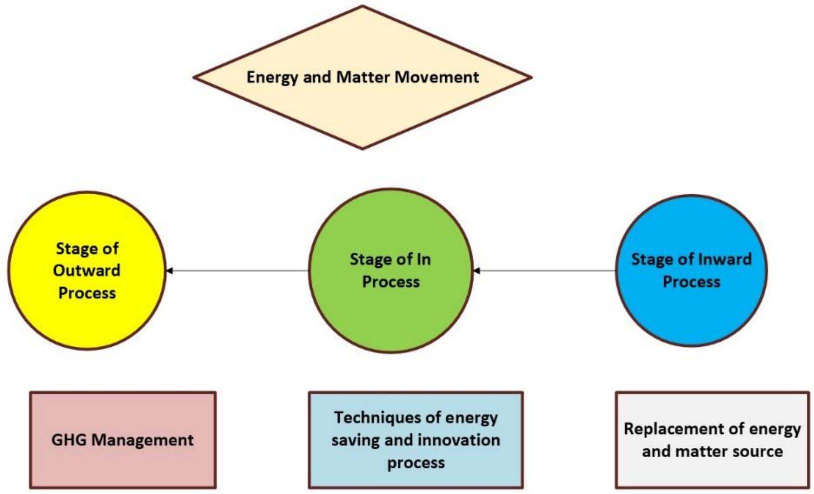


Figure 4. Three stages of the process.

a) POS: It is comprised of technology for limiting carbon emissions via storage and capture.

b) PInS: It comprises technology of energy-efficient and innovation that decreases carbon emissions in the process of production. This phase is very beneficial for industries of energy rigorous.

c) PIS: This stage comprises energy source technology replacement via flowing towards technology and cleaner fuels for substantial replacement via adjusting the assets and formulas of the material for receiving less material carbon. Several energy sources like hydrogen, bioenergy, biofuel, wind, and solar energy sources can be utilized for the production of better energy.

Table 4. Mitigation of CO2 in three process stages.

ref	Stages of the E&M movement	Research areas	Feasible technology
[96],[97]	POS	Use, capture, and separation of CO_2	Storage and capture of CO_2 emission
[98], [99]	PInS	Redesign the product, and improve the process	Process innovation
[100], [101]		Plant retrofitting and recovery of energy	The technology of energy-saving
[102], [103]	PIS	RE sources, Replacement with low-carbon fuels	Replacement of energy source
[104],[105]		Redesign the product and replace the raw material	Replacement of matter

A. Limit the CE from Industries:

It is a necessary job to limit the CE. Design is required to acquire a CO_2 discharge from industries that do not pass the emission limit. Xu and Zhang [106] examined the issue of multi-product generation restriction via planning and mechanism of carbon trading. Comparably, Costa et al. [107] studied approaches for capacity planning while restricting the production of CE. Hauschild et al. [108] suggest an evaluation of life cycle valuation for environmental, social, and economic improvements in the generation chain which targets to limit the CE for decreasing global warming. Further, Varbanov and Klemes [109] suggest several works for energy efficiency development in the process of production for decreasing CE. Comparably, Bhowmik et al. [110] present the optimal development of sustainable green energy.

Recently, Varbanov et al [111] suggested overall research trends and challenges for the reduction of pollution and energy saving by increasing effective training, integration of CO_2, energy conversion, and heat transfer. Pinch Analysis (PA) gives a graphical approach for reducing the operation of resources in the industry. Integration of heat total-site problem [112], energy reduction issue in the network of batch water [113], network synthesis heat exchange [114], and water conservation problem have been broadly explained by utilizing PA from the last decade. It can also be utilized for planning optimal production and a network of supply chains for reducing CE. Shenoy and Singhvi [115] reported the breakthrough in the supply and production chain by introducing the Aggregate Production Planning (APP) procedure. They defined:

a. A cascade design for inventory variations and production that relied on consumption (inventory declined) and production (inventory increased).
b. Production composite curve and demand composite curve in production vs. time rate plot.
c. Inventory axis vs. inventory composite time curve, like the heat integration curve of the grand composite [116].

VI. Decisive factors of Carbon emissions:

Kuzets [117] first proposed the decisive factors relationships with carbon emission and the proposal is the hypothesis of the Environmental Kuznets Curve (EKC). In this hypothesis, an inverted U-shaped curve between economic growth (usually represented by gross domestic generation, GDP) and the emission of CO_2 is shown in the Figure 5. After that, many researchers searched the economic growth effect on the emission of CO_2 and verified the EKC hypothesis validation via empirical studies in ref Selden and Song [118], Holtz-Eakin and Selden [119] and Dinda and Coondoo [120].

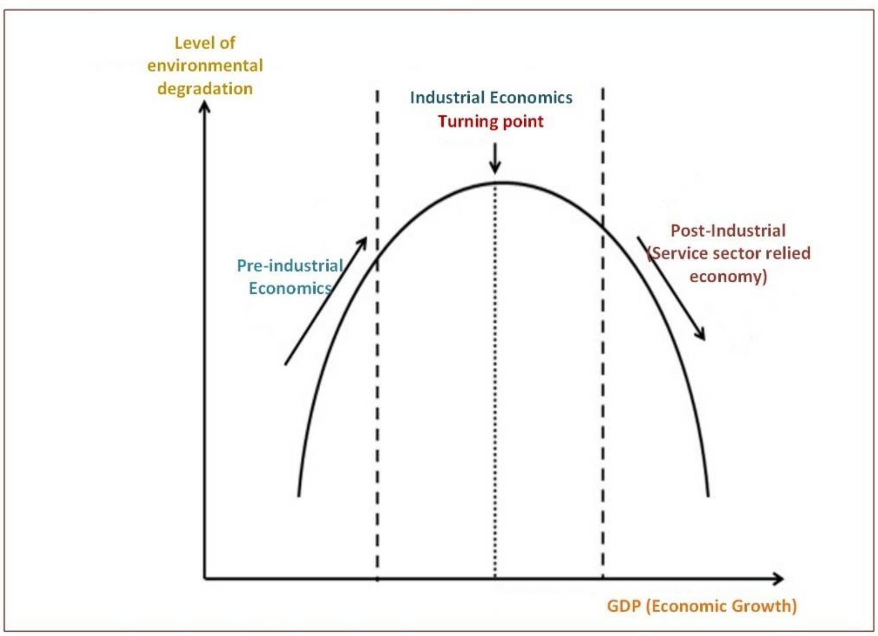


Figure 5. Environmental Kuznets Curve.

Various other basic features may impact carbon emissions. These features comprise urbanization [121], consumption of nuclear energy [122], investment in foreign direct [123], [124], trade openness [125], [126], transport service [125], energy consumption [126], [127], urbanization

[128], consumption of natural gas [129], [130], electricity consumption [129], [130], (Cowan et al., 2014), renewable energy consumption [131], [132], finance [132], agriculture [133], [134], and so on shown in Figure 6.

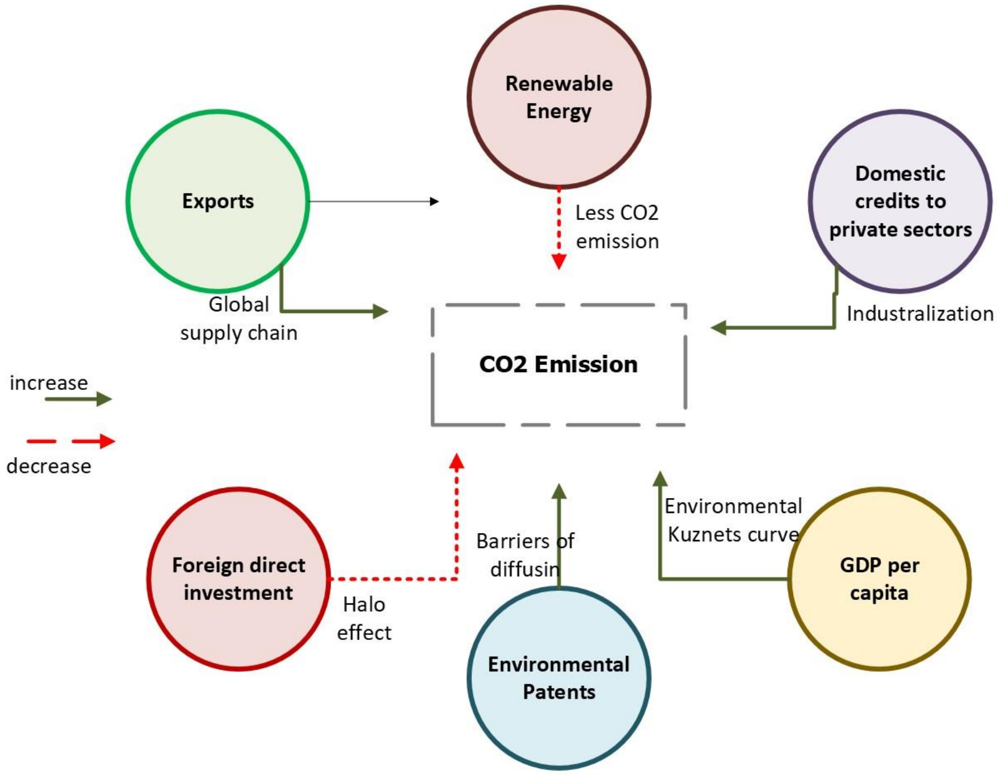


Figure 6. Basic features that impact CE.

Further, the expansion of environmental rights, which helps in the reduction of carbon emissions is mostly ignored in earlier studies. Some studies investigate the effects of environmental rights on the emission of CO_2 by relating econometric techniques. Voigt et al. [135] presented the technology enhancement impact on the intensity of energy reduction, but they used the decomposition technique of the index of Logarithmic mean Divisia. Noailly and Wurlod in ref [136] consider the involvement of environmental rights in reducing CE by guessing a cost function of translog, which relies on the function of industry assembly. Unlike them, a fixed-effect panel is applied with a quantile regression technique to estimate the effects of environmental rights for all countries.

A. Renewable Energy Supply Effects:

To examine the effects of RE supply, the CO_2 emissions variables, and environmental rights, the data is collected from the indicators of World Development [137], and the environmental database of the Organization of Economic Cooperation and Development (OECD). Seven different variables are utilized renewable energy supply (RES), exports of services and goods (EXP), expansion of environmental technologies (DET), CO_2 emission per capita (CEPC), GDP per capita, domestic credit for the private sector (DCP), and investment on foreign direct (IFD).

CEPC denotes the CO_2 emission units from the primary energy combustion (natural gas, crude oil, coal, and other fuels) separated by population. Figure 7 describes the CEPC time series of four countries Brazil, Russia, India, and China from 1998 to 2020. The Russian CEPC is the highest among all other BRIICS countries, on the other hand, India has the lowest CEPC. Figure 7 shows the CEPC distribution is diverse in different countries.

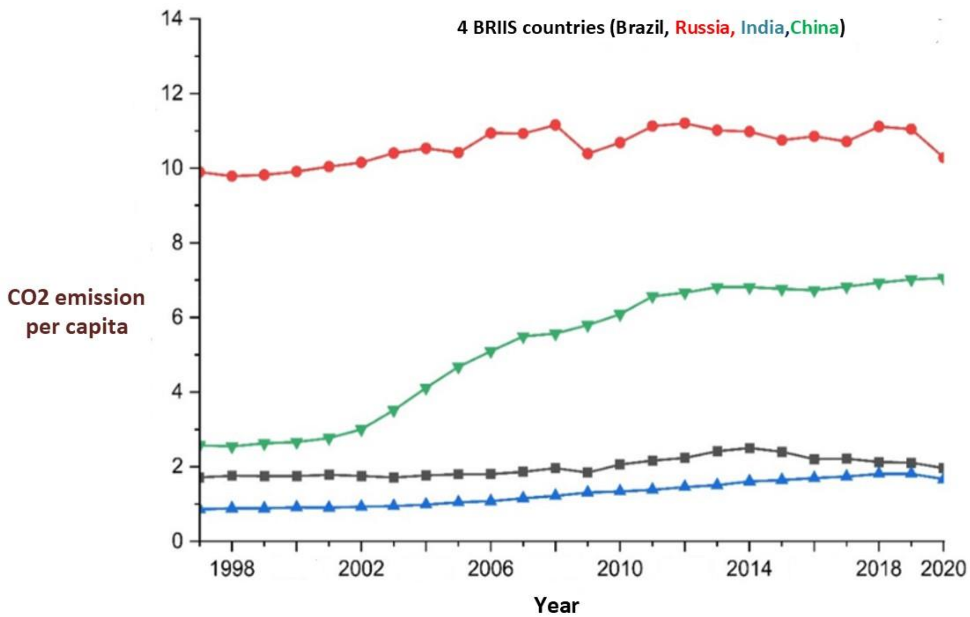


Figure 7. CEPC distribution in different countries.

The supply of RE is represented by the proportion of the RE supply to the combined main energy source. RE comprises wind, combustible renewables, solar energy, geothermal, etc. Fig exposes the RE time series for the BRIICS countries. Generally, India, Indonesia, and Brazil have the highest RE compared to South Africa, Russia, and China. According to the OECD database, the RE average fraction to the main energy supply in Brazil was about 42%, and India and Indonesia were 31.3% and 35.7%. Furthermore, South Africa, Russia, and China have less RE supply [138].

VII. Parameters for Economic Assessment:

The next equations are utilized to measure the parameters essential for the economic valuation of the hybrid network [139]. It calculates the net present cost (NPC) in $:

$$NPC = \frac{C_{t,yearly}}{CRF(h,m)} \tag{1}$$

$C_{t,yearly}$ is the complete yearly cost, the capital recovery factor is CRF, 'h' is the real yearly interest in % which can be measured based on the nominal discount and inflation rate, and 'm' is the time project period. The CRF can be measured using this formula:

$$CRF(h,m) = \frac{h(1+h)^m}{(1+h)^m - 1} \tag{2}$$

The levelized cost of energy (COE) is measured as follows:

$$COE = \frac{C_{t,yearly}}{E_m + E_g} \tag{3}$$

Where E_m is the generated electrical energy and E_g is the exported electricity from the microgrid [140].

Yearly cost saving is the return on investment (ROI) linked to the initial investment which is measured in the following equation 4:

$$ROI = \frac{\sum_{h=0}^{m} C_{h,f} - C_h}{n(C_p - C_{p,f})} \tag{4}$$

$C_{h,f}$ is the nominal reference cash flow of the network, C_h is the nominal annual current flow of the system, C_p and $C_{p,f}$ is the original cost of the current and reference network respectively.

Finally, this equation is used for the emission of CO_2:

$$A_{\mathrm{CO2}} = CEF_c F_q HV_v \times C_f \times 3{:}\,667 \tag{5}$$

Where A_{CO2} is the total amount of CO_2 emission, CEF_c is the factor of carbon emissions (TJ/ton carbon), F_q is the quantity of fuel (liter), HV_v is the value of fuel heating, and C_f is the fraction of oxidized carbon. Table 3 gives the different scenarios of different countries, and it shows that the combination of Bat/DG has an ideal supplementary design concerning economic networks. There are some environmental, economic, and technical results of using a hybrid network that is cost-effective and has less emission of CO_2.

A. Advantages of RE:

- Environmentally, the battery, Distributed Grid (DG), WT, and PV network with a renewable fraction of 72% returned to a yearly reduction of CO_2 > 2000kg in comparison to the pure grid (electricity).

- Economically, the diesel generator and battery combined with WT/PV directed to the best hybrid network formation with energy costs of almost 0.151 $/kWh. The addition of a hydrogen tank, electrolyze, and fuel cell unit to this network, increased the energy cost to 0.2301$/kWh, and the investment revenue dropped from 15.6% to 13.5%.
- Technically, combining a hydrogen tank, electrolyze, fuel cell, battery, and diesel generator with only 262 kWh/year of extra electricity generated the best outcomes for decreasing energy thrashing of the hybrid WT/PV network by removing the hydrogen unit. In contrast, the quantity of extra electricity will increase six times more.
- The outcomes of the sensitivity investigation present the highest reasonable variety of energy costs will be 0.120 to 0.240$/kWh, which signifies the suitable operation of this network in several environmental and economic situations. To accomplish a cost-effective result, in the areas with hybrid systems, the average radiation is 4.2kWh/day, and the average wind speed is greater than 5.3 m/s.

The review of investment techniques presents that choosing useful indicators such as unique policies for the execution of new technology, there are three vital advantages to renewable energy investment higher sustainable generation of electricity, reduction, and an economic explanation for stakeholders to put investment in renewable projects given in Table 5.

Table 5. Benefits of RE with load at different locations.

ref	location	RE	Non-RE	RF (%)	Load	COE	Year
[141]	Malaysia	PV/FC	battery	100	140	0.355	2017
[142]	Pakistan	WT/PV	Bat/DG	84	205	0.450	2016
[143]	Algeria	WT/PV	DG	63	22.5	0.210	2020
[144]	Iran	WT/PV	Bat/DG	67.3	242	0.197	2019
[145]	Turkey	WT/PV/FC	Bat/DG	95	165.6	0.282	2018
[146]	India	WT/PV/FC/Bio	Bat/DG	-	724.8	0.163-0.214	2020
[147]	Nigeria	WT/PV	Bat/DG	-	7.23	0.459-0.562	2019
[148]	Cameroon	WT/PV	Bat/DG	91.4	100	0.443	2019
[149]	Ethiopia	WT/PV/FC	Bat/DG	99	16000	0.179	2016
[150]	China	WT/PV/FC	Bat/DG	72.2	13.68	0.151	2020

VIII. Indication of the MDD program:

Commonly, two wide model groups are engaged to examine climate change mitigation. Top-down versions of models support macroeconomic interfaces, while bottom-up versions of models highlight the technological pragmatism of demand and supply. Furthermore, many hybrid techniques have been established by enhancing technological explanations to top-down versions of models or enhancing bottom-up models by macro-economic loop. For example, the Energy Department of the US utilizes the hybrid national energy modeling system (NEMS) to formulate its Annual Energy Outlook.

At the maximum aggregation level, integrated assessment models (IAMs) merge many economic and technical modules. Most of them arrange less expensive technologies in their imitation, e.g., IAMs support an aggregated depiction of climate change moderation impacts and costs by region and sector into an endogenous tradeoff and metric of single economic the reduced cost with mitigation cost of climate change. For a broad review of the classification and nomenclature of energy network models.

A. Models of Deep Decarbonization (MDDs):

This study is limited to models that discover energy pathways of deep decarbonization in the extended run by joining physical origins with economic deliberation by utilizing computational software. The deficiency of any typical network of classification and nomenclature recognizes MDDs as a subdivision of economic-engineering models, containing such hybrids that reduce the expenses of attaining an exogenously definite reduction in the emission of GHG over time. Ignoring the bodily models of climate change, MDDs estimate the mitigation costs to support many technological facts than nearly other techniques of modeling, like IAMs. Concentrating on electric power networks, MDDs reduce the current value of the associated generation and investment energy costs to fulfill exogenously set requirements of energy for individual main energy subsectors over the topic of modeling horizon to yearly emission restrictions. Relying on the research interest and policy objectives, MDDs frequently join dissimilar techniques of modeling at different temporal and spatial levels of resolutions.

The MDD mathematical formulation relies on a deterministic, simple structure.

$$minimize \sum_{k=1}^{K} [{}^{b(w)_k}/{}_{(1+\partial)^k}] \qquad 6$$

Such that

$$\begin{aligned} h_i(w) &= 0 \\ g_i(w) &\leq 0 \end{aligned} \qquad 7$$

Where ‘w’ is a changing decision vector, e.g., the plan, ‘K’ shows the yearly time, the cost function is the b(w) that is reduced with a discount rate ‘∂’, and g_i and h_i are inequality or equality functions constraints. It directly solves equation 6, suppose it present, denoted w_0, relies on the set ‘w’, b(w), $h_i(w)'$s, and $g_i(w)'s$. ‘b(w)’ is also the operating and capital cost, the latter adds the fuel, maintenance, operating, and fixed costs. This function also includes the cost of societal that is indicated in the market price for services and goods and may comprise externalities, societal, and non-market costs relied on the MDD.

1. Analytical Techniques of MDDs:

MDDs support esteemed visions on the energy network evolution of decarbonization to a group of low-carbon and help in supporting the policy suggestions of such long-term evolution from societal. Environmental and economic viewpoints theme to practical restriction and theoretical assumptions. Reviewing the studies of technology and science viewpoint, the framework of MDD is not only estimated to be precise in taking the physical certainty in an active sense but is also told as characteristic of the modeler's regulating sympathetic of the energy network. Modeling of energy networks has been evaluated for extreme mathematics use in potential policy issues and energy research. Waisman et al. recognize the main gap between country-specific and global models that should be talked about and the target of the Paris Agreement. Previous studies have also criticized modeling restrictions in taking heterogeneity in feedback, innovation of technology, and decision-making between the energy systems and macro-economy. The additional study highlights the requirement for deploying, demonstrating, developing, and researching zero-emission applicant technologies relying on their projected and current costs except for any modeling of formal quantitative. Experts have also recognized the requirement for the presence of energy efficiency, reporting the distributional controls in reflecting implementation and policy realities.

2. Formulations of MDDs:

The formulation of MDD assures the presence, but not essential uniqueness of a resolution, at a comparatively less cost linked to economic outcomes. It accepts for the best, not all bodily assets that are restricted. Some exclusions may be in the arrangement of restraints on the size and number of recent nuclear power plants that can be structured geographically or over time limitations on bioenergy, geothermal, and hydroelectric facilities. Suppose resources of wind and solar generation are expected to be infinite along with the capacity to generate electric vehicles. In that case, it also generates limited electricity for passenger vehicles, air-conditioning, heat, and lighting by utilizing non-carbon-releasing energy resources. It also did not enhance costs for these approaches, so it can always structure infinite sources at a moderately low cost linked to the economic output [151].

IX. The architecture of controlling Low-carbon by driven digital twin Job-shop manufacturing:

To apply the job-shop intelligent manufacturing for the production of low-carbon, the digital twin-obsessed architecture of controlling low-carbon is proposed as presented in Figure *8*. This architecture offers a guideline for controlling and evaluating job-shop manufacturing [152]. Based on the model of the digital twin and data of the digital twin, this architecture comprises three components, i.e., data fusion and interaction of the digital twin, job-shop manufacturing of low-carbon model with virtual workshop, and carbon control methods and emission predictions [153].

Author in ref [154] suggest the evolution of the smart grid by unleashing the power of digital twins, blockchain, etc. main contributions are given in Table 6.

A. Job-shop manufacturing of low-carbon model with virtual workshop:

It is a virtual design of the physical job shop, and all the carbon emission-related objects of the job shop must be formed shown in Figure 8. Here, it comprises four types of objects: the job shop's environment, cutting tools and machine tools, workpieces, warehousing equipment, and logistics [155]. For every object, dynamic, and static information must be considered. Software of 3D modeling is utilized for assembled job-shop statics models, cutting tools machine tools, etc. Further, the data of related dynamics is to be inserted into the static models. In the job shop, it comprises gases, electric energy, and water consumption, because it is linked with carbon emissions [156]. For a machine tool, the cutting fluid and power consumption required to be studied. For a cutting tool, the service life and carbon emission production are needed [157]. The warehouse and AGV power consumption are required to be studied, while the hour norm and machining processes of a workpiece are needed [158]. This data will organize the model of dynamic data of the virtual workshop, which will be reorganized to keep in step with the physical one [159].

B. Manufacturing of low carbon with fusion and interaction data of digital twin:

In the virtual workshop, it is just not utilized for creating with the physical world, but also be renewed synchronously [160]. To understand this purpose, the first stage is to develop a network of data sensors. For manufacturing low-carbon job shops, the network of harvesting sensor carbon emission means the network of gathering data for manufacturing of low-carbon, which comprises carbon emission data, state of the WIPs, and machine tools. Considering the processes of real production, the formation of the sensor network comprises two parts, the construction of a dynamic one and the static network formation. The network of dynamic sensors has a purpose at one or various certain tasks of production after the scheduling and planning of production, which means picking suitable sensors to build a sub-network to help with the logic formation task process [161], [162]. On the other hand, the formation of a static network is recognized after the shape of the manufacturing network, which is a part of the physical formation process of the manufacturing networks [163]. After the construction of the dynamic network, digital data needs to be garnered, and the usage efficiency of the sensors is also maximum. Further, the fusion and interaction data are also significant, which will utilize various technologies of data interface. For Enterprise Resource Planning (ERP) communication, the technology of WEB service will be used, and the languages of JSON and XML can be utilized. For the physical world control network, the OLE and Enterprise Service Bus (ESB) for process controlling can be utilized for solving real-time and business state data, respectively [164].

C. Prediction and control of low-carbon emission with a data-driven digital twin:

To understand the production of low-carbon emissions, the algorithm of artificial intelligence is utilized to develop the control model of low-carbon. This model input is data of digital twin production, and the output is control or prediction of carbon emission decision-making in Figure 9 [165], [166]. The whole process is shown in Figure 10.

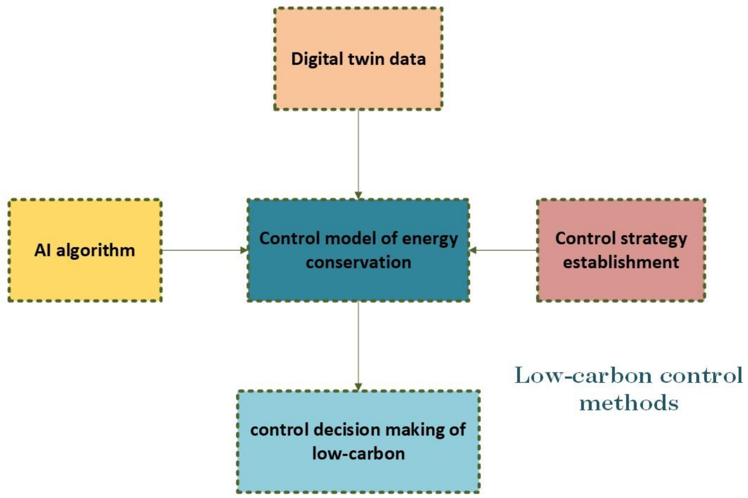


Figure 8. Method of Low-carbon control method.

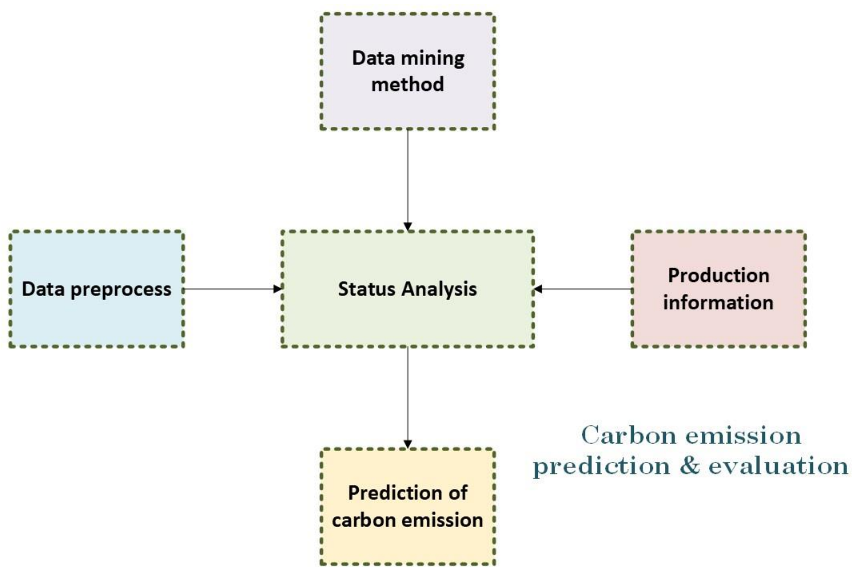


Figure 9. Prediction and Evaluation of CE.

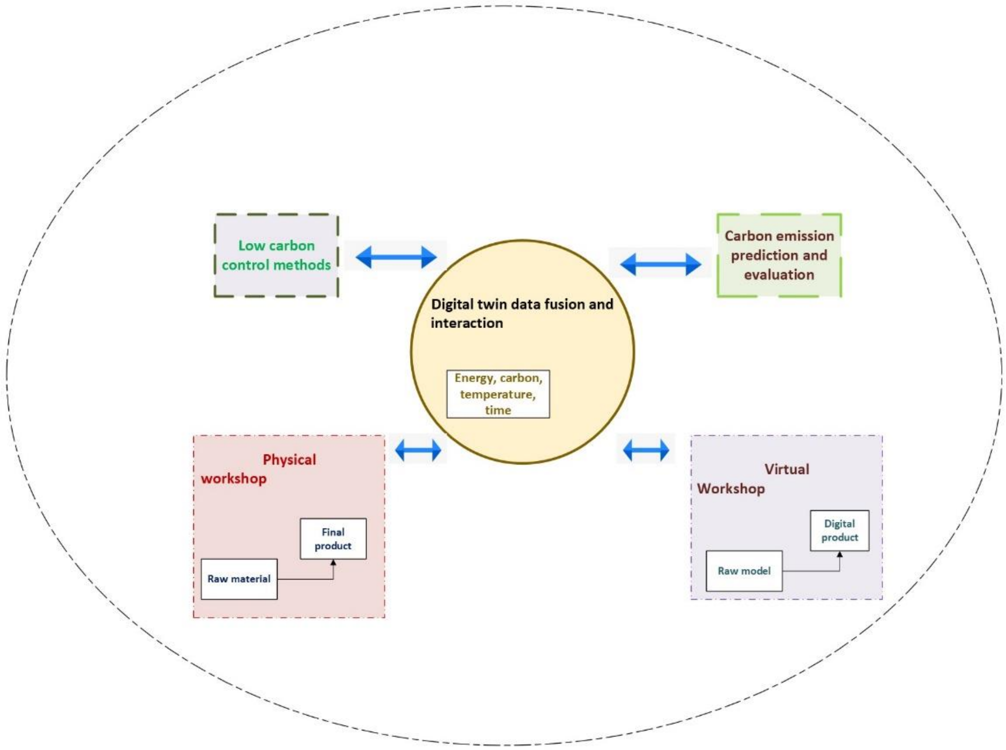


Figure 10. whole procedure of fusion and interaction of DT.

Digital twins as an advanced technology for smart manufacturing, supply a new methodology [155]. It is an active way to attain dynamic optimization of real objects by real-time links between the objects with the reliability of the models and helps the continuous development attained from physical machining [167]. The optimization method cutting parameter of the digital twin is suggested with optimized cutting features based on real machining conditions for decreasing carbon emission and enhancing machining efficiency [168].

D. Minimizing carbon emission with digital twin-cutting parameters:

We assume that machine circumstances are calculated during the machining process to obtain starting optimal cutting features. Carbon emission is minimized by establishing an optimization model of multi-objective and using an NSGA-II algorithm for solving [169], [170].

1. Decision Variables:

Spindle speed with decision variables, cutting width and depth, and federate are vital parameters of cutting for CNC machining [171]. Some parameters like cutting width and depth are dependent on the machine's accuracy and allowance, and they have no influence or little carbon emissions. Further, the decision variables are set as federate V_f (mm/min) and spindle speed n (r/min) [172].

2. Optimization objectives:

Carbon emissions are necessary for various planning objectives processes but from the view of economic benefits, time of processing is also essential [173]. Carbon emission objectives are considered in the result shown in equation 8.

$$F(n, W_f) = \min CE_o \tag{8}$$

3. Modeling of carbon emission:

CNC machining [174] is linked to many features of carbon emission, such as cutting fluid $CE_f(kgCO_2)$, cutting tools $CE_t(kgCO_2)$, consumption of raw materials $CE_m(kgCO_2)$, and electricity consumption $CE_e(kgCO_2)$.

In this part of the machining process, the material CE_m removal amount is almost similar for altered cutting parameters, so the entire carbon emission can be symbolized in equation 9:

$$CE_o = CE_f + CE_t + CE_e \tag{9}$$

The calculations of CE_f, CE_t, CE_e are described below in equation 10:

$$CE_f = \frac{PT_p}{P_{fluid}} \times CEF_{fluid} \times V_{fluid} \tag{10}$$

PT_p is the processing time, P_{fluid} is the change period of cutting fluid, CEF_{fluid} is the emission factor of cutting fluid and V_{fluid} is the volume of milling [175].

$$CE_t = \frac{PT_c \times CEF_{tool} \times X_{tool}}{60 \times T_{tool}} \tag{11}$$

PT_c is the material removal time, CEF_{tool} is the emission factor of cutting tool, X_{tool} is the weight of the tool [40].

E. Development of digital twin for carbon emission reduction in industries:

Initially, CO_2 emission data in the atmosphere are gathered from the world in real-time, through sensors. Then measures power production in real-time through a prosumer meter [176] from PV panels and wind turbines, in a specific period. Further, the machinery code QR [177] is needed in each process of manufacturing are then scanned for the energy needed from every device [178]. Simultaneously, carbon emission data from history are present in the atmosphere and are recalled from previous manufacturing processes from the server, where is stored [179]. The process is shown in Figure 11.

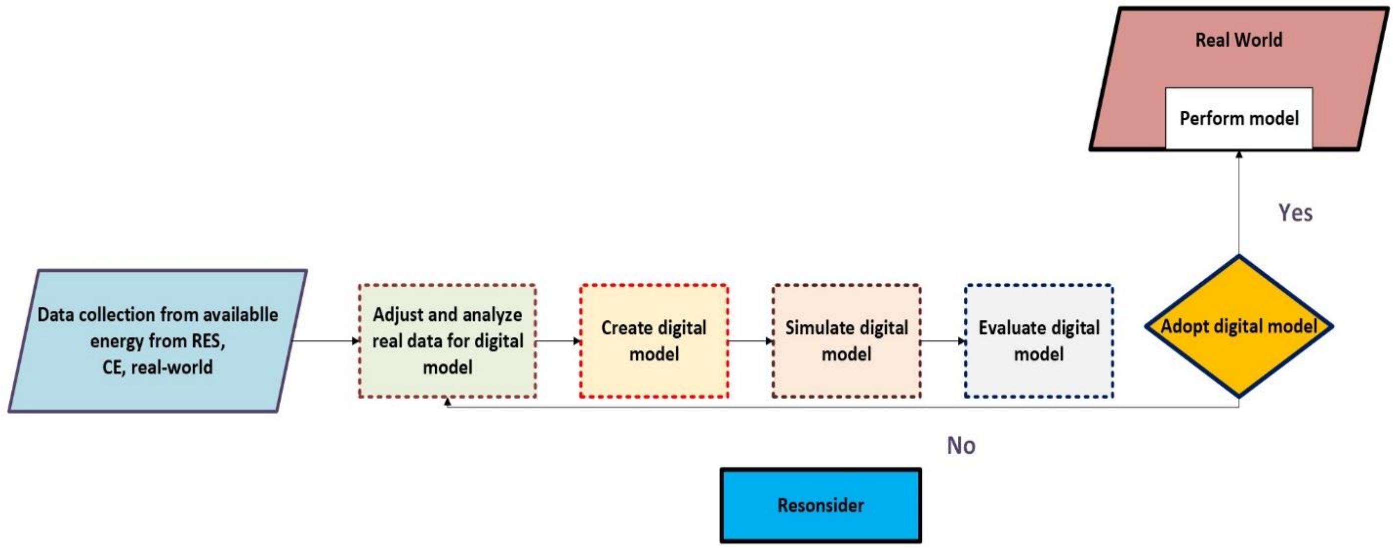


Figure 11. The process of DT development.

Table 6. The contributions of DT for reducing CE.

ref	year	contributions
[180]	2012	S.T. Newman used cutting parameters and reduced the CE by 6–40% in the manufacturing process.
[181]	2015	Yi et al. suggested the boundary model of CE, caused by the raw materials production and cutting process.
[182]	2016	Liu et al. established a CE model for the optimization of cutting parameters, using tools, but not raw materials.
[183]	2017	Li et al. proposed a multi-objective algorithm to solve the cutting parameter optimization.
[184]	2017	Li et al. investigated cutting parameters with DT and created a balance between cost and energy consumption.
[175]	2018	Jiang et al. improved a novel model combined with consumable and transferable CE, and the source is cutting fluids, raw materials, etc.
[166]	2019	Chaoyang Zhang proposed a DT-driven prediction of CE and controlling of low-carbon.
[185]	2019	Zhou et al. established the NG-NSGA-II algorithm to balance the objectives of CF.
[186]	2021	Qinglin Qi proposed DT as an enabling innovative technology for smart and new manufacturing.
Our Survey	2024	It includes all the aspects of Digital Twin for reducing CE.

X. Data mining (DM) techniques are used for the reduction of CE:

Data mining applies several data analyses, tools, and techniques to discover relationships and patterns concealed in massive databases [187]. Further, data mining has a vital part in controlling GHG emissions and recognizing their environmental impacts [188]. The amount of GHG emissions, which comprise CO2, is predicted, and data mining techniques are used greatly to recognize the best policies to avert adverse consequences. It attempts to identify a good combination of present features by joining techniques of data mining, as well as find the best technique to predict CE [189].

A new hybrid technique is utilized to predict CE to the applicable factors. The Root Mean Square Error (RMSE) is also utilized to analyze the model and compare the results with other various techniques of data mining. For modeling, the test named Kruskal-Wallis was utilized to inspect the variables whether year and country had a statistically notable effect on CE [190], [191]. Another hybrid method is also used, a combination of Discriminant Analysis, linear-AS, and K-means techniques. Select the best model by comparing the values of the RMSE index for every technique [192], [193]. Additionally, the variable's best combination is present for prediction is also simultaneously identified.

The process of the joined method is such that first the present existing data are classified into dissimilar groups by method of clustering and CE are then predicted for every group using forecasting techniques of data mining comprising LINEAR-AS, LINEAR, ANN, Regression, and KNN [194]. In ref [195], Wagstaff et al. Suggested an algorithm of K-means that is used for K categories cluster data automatically [196], [197]. The purpose of this method is to first choose the midpoint of the first clusters and then begin as follows:

- Each observation dj is allocated to its closest cluster.
- Each cluster center Cj is modernized to mean the observation of cluster.

A. Selecting the optimal combination and best technique of modeling of data mining techniques:

As the modeling of each technique is performed, variables in different combinations (at least 4) are examined. The variable's best combinations are that minimize the error of model prediction. Generally, the combinations of total numbers are feasible for a set of 8 in state n, in this study, a variable solo subset cannot be less than 4. Consequently, it obtains the subset by measuring the combinations of whole numbers shown in the equation 12:

$$2^n - \left(\frac{n!}{1!\,(n-1)!}\right) - \left(\frac{n!}{2!\,(n-2)!}\right) - \left(\frac{n!}{3!\,(n-3)!}\right) - 1 \qquad 12$$

Where n is the variable's total numbers equal to 8. When the value is placed in the above-given equation, it makes the different states equal to 163 which is checked by each technique. Data mining five different techniques with variables best combination is shown in Table 7, regarding with error index. The table shows that the best and optimal method is LINEAR-AS with the least error, including eight variables year, country, RE, nuclear, hydroelectric, coal, gas, and oil. The value of the RMSE index is 12.71 for this technique which is significantly less than the other techniques given in Table 7[198].

Table 7. RMSE values for present techniques.

Variable combination	**Technique**	**RMSE**
Country, coal consumption, renewable energy, gas usage, Hydropower, oil consumption, nuclear energy, year	KNN	6.23
Country, oil usage, Hydropower, coal consumption, gas consumption, nuclear energy consumption, year	ANN	7.79
Country, oil consumption, coal, nuclear energy consumption, gas, Hydropower consumption, renewable energy, year	LINEAR-AS	3.56
Country, gas consumption, Hydropower, oil consumption, nuclear energy, coal consumption, renewable energy, year	Regression	8.26
Country, gas consumption, oil, coal, nuclear energy consumption, Hydropower consumption	GLE	5.56

B. Development of CE benchmarks from DM techniques:

1. Formation of MFHC clusters by using the DT approach:

To evaluate the performance of multi-family housing complexes (MFHC) of CE, it should be calculated relying on gas consumption and electricity. MFHC clusters are compared with the same characteristics to provide prediction performance or better classification. Because characteristics of MFHC have negative or positive impacts on CO2 emission [199], [200], [201]. Clusters of MFHC are formed by using DT, DT is a famous ML sorting method. The method DT is mainly split into three sorts (sorting and regression trees, C4.5, and automatic detection of chi-squared interaction) and a satisfactory type is utilized that relies on the data types (e.g. scale, data size, etc.). In this study, automatic detection of chi-squared relations is used for the analysis of the following details.

First, for the statistics scale, the CE per area of the whole floor is a dependent factor on the continuous measure, and thus, automatic detection of the chi-squared interface is more appropriate in comparison to DT other types (C4.5, sorting, and regression trees). Second, for the data size, this study creates MFHCs of an entire 1,212 in the database (southern region: 425; central region:

787), and automatic detection of the chi-squared interface is commonly fitting for analyses of data of higher than 500 in finite tree constructions [199].

2. Clusters of MFHC validation relied on statistical methods:

Results of statistical analysis with reliability validation is a compulsory stage when creating MFHC clusters by utilizing methods of DT. In the end, a group of MFHC with significant differences is analyzed in this study. It used the statistical method for non-parametric techniques like test of Kruskal-Wallis or Mann-Whitney Whitney or parametric approaches like ANOVA or t-test can be examined, and an appropriate analysis technique can be committed relying on these given situations:

- First it satisfies and depends on MFHC clusters on assumptions of homoscedasticity, regularity, and independence, and considering the two methods (non-parametric or parametric) can be utilized to study the MFHC group significant differences. For example, if it satisfies these mentioned expectations, parametric techniques like the ANOVA and t-test should be utilized for significant alterations analysis by the MFHC cluster, if not then non-parametric techniques like tests Kruskal-Wallis and Mann-Whitney should be utilized.
- Second, the statistical techniques can be used to rely on the MFHC group numbers that analyzed the significant differences. For example, the Mann-Whitney or t-test two groups of MFHC should be utilized for inspection of significant differences, if there are more than three groups, the Kruskal-Wallis or ANOVA test should be utilized [202].

Further suitable statistical techniques can be used for analysis relying on these mentioned conditions. For example, if it does not satisfy these three assumptions (homoscedasticity, normality, and independence), the test Kruskal-Wallis is the best method for utilizing [203], [204].

3. Development of ORS by using CE benchmarks:

Performance of MFHC by CE evaluation, the rating system of CE is needed. Several countries use the operational rating system (ORS) like South Korea, the USA, and the UK. For the calculation of energy efficiency of the transport, and infrastructure, the Ministry of Land and Building of countries uses ORS for certification system of building energy usage. This structure split the operational rating (OR) into five levels (level A: <50%; level B: 50-75%; level C: 75-100%; level D: 100-125%; level E: >125%), or the OR value is formed by equation [199]. CE's closer value is level A, which is superior to its performance, and the grade E value is inferior to the performance of CE.

$$OR_{w,x} = \frac{yCE_{w,x}}{tAF_{w,x}} \times \frac{1}{yBCE_{W,X}} \times 100 \qquad 13$$

Where $OR_{w,x}$ is the operational rating of MFHC (w) to group (x), $yCE_{w,x}$ is the carbon emissions in a year for similar MFHC (tCO_2/y), $tAF_{w,x}$ is the overall floor region for similar MFHC (m^2), and $yBCE_{W,X}$is the benchmark of CE in a year for similar MFHC (tCO_2/y. m^2).

Moreover, the OR is determined by relying on the CE yearly by group benchmark. In ref [205], Liu et al. represent the median and mean value of every group by using a benchmark, which relied on the data distribution. If the group information has a common distribution, at the average level of mean value, if there is a large irregularity in the distribution, the value of median is also considered as the average position [206]. Normally, the value of the median in groups is mostly used for CE benchmarks [42]. The process of MFHC clusters in reducing CE is revealed in Figure 12.

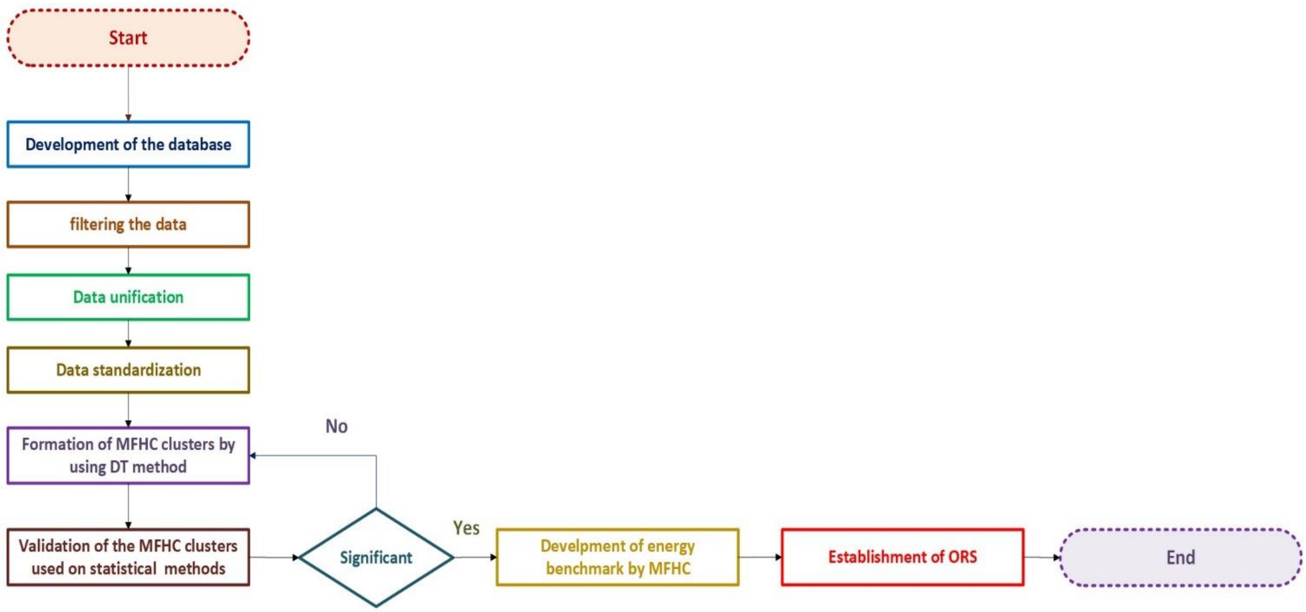


Figure 12. The process of MFHC clusters.

Table 8. main contributions of Data Mining.

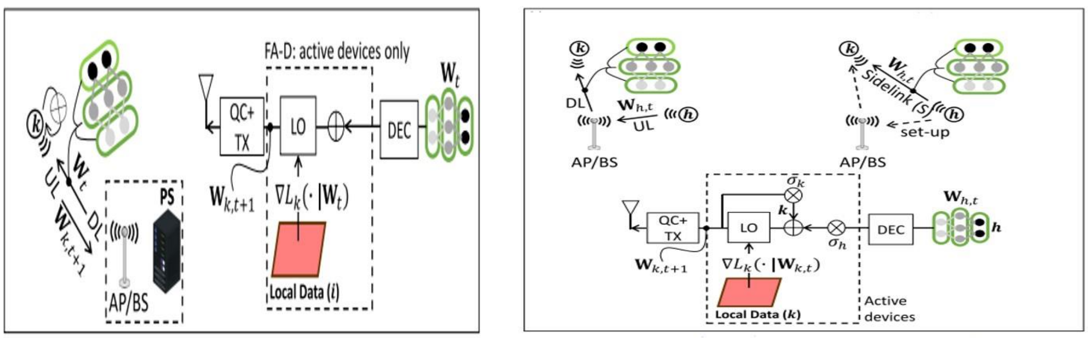
Ref	**Contributions**
[187]	DM applies several data analyses and techniques to discover patterns concealed in massive databases of CE.
[188]	DM plays a vital part in controlling GHG emissions and recognizing their environmental impacts.
[189]	DM technique identifies a good combination of present features to predict CE.
[190], [191]	This paper presents a hybrid technique to predict CE in the applicable factors.
[194]	By using DM techniques, it predicts every group clustering and prediction of CE.
[195]	Wagstaff et al. suggested an algorithm of K-means that is used for K categories cluster data automatically for CT.

[198]	DM uses several data analysis and techniques tools to discover relationships hidden in massive databases of CE.
	Our survey considers all these contributions.

XI. Federated learning for reducing CE:

A. Principles For Designing Less Carbon Emission:

First, we discuss the focal features that are estimated to drive the selection between paradigms of federated and centralized knowledge toward the design of sustainability [207]. Sustainability is used for corresponding GHG emissions calculation, stated as CF. The task is to recognize the functioning conditions that are required for strategies of federated learning (FL) that are Federated Averaging (FA), Consensus-Driven Federated Averaging (CFA), and FA-Deep sleep to produce low carbon than centralized learning (CL) is shown in Figure 13.



FA, FA-D

CFA(Sidelink transmission, D2D)

Figure 13. Procedure of FL.

FL advantages in comparison with CL are linked to computing and communication costs, as well as data $b(\varepsilon_l)$ and model $b(W)$ size. Energy models are considered and the carbon footprints for CL (C_{CL}) as well as for all the policies of FL (C_{CFA}, C_{FA}, and $C_{FA\text{-}D}$). Sections of sustainability focus essential conditions on computing and communication energy costs (efficiencies of computing and energy) as well as the ratio of carbon footprints $\frac{b(W)}{b(\varepsilon_l)}$.

1. Model Simplifications and Carbon Footprints:

The carbon footprints C_{CL}, C_{CFA}, $C_{FA\text{-}D}$, and C_{FA} are shortened in Table *9* for all the recommended procedures of CL as well as for FL. The models namely $E_{l,q}^{(T)}$and $E_l^{(C)}$, with carbon intensity CI_k of the generation of electricity. The terms CI_k relied on the definite geological areas where the symbols $k = 0, \dots \dots, K$ are mounted and are calculated in CO_2 emission corresponding to (kgCO_2-

eq/kWh): they compute how much CE is generated per kilowatt hour of nearby electricity produced [208].

Pointing common instructions for the evaluation of sustainability, the subsequent explanations are implemented to CF in Table 9. Starting with the costs of communication are computed on average, in expressions of the equivalent efficiencies of energy (EE), identified by ETSI (European Telecommunications Standards Institute) [209]. These are distinct as the fraction between transmissions of sidelink $EE_S = [E_{l,q}^{(T)}]^{-1}$or UL $EE_U = [E_{l,0}^{(T)}]^{-1}$, originated data volume DL $EE_D = [E_{l,0}^{(T)}]^{-1}$and the consumption of network energy spotted during the time needed to provide the same data [210].

Term of efficiency are calculated here in bit/Joule [bit/J] [211], [212] and we count special options of EE_S, EE_U, EE_D relied on the particular network performances. Moreover, when the interface of sidelink is not present, but uses the WWAN, it is $[EE_U]^{-1} + [EE_D]^{-1} \cong [EE_S]^{-1}$. Now considering the computing expenses, we describe the data center computing effectiveness (or PS) as $EE_C = [E_0^{(C)}]^{-1}$. It computes how much energy is consumed per discovering round and it is calculated in terms of round numbers per Joule [R/J]. In the end, the computing effectiveness of the machines k > 0 is defined here as $[E_l^{(C)}]^{-1} = \frac{EE_C}{\varphi l}$ with

$$\varphi l = \frac{E_l^{(C)}}{E_0^{(C)}} = \frac{P_l}{P_0} \times \frac{T_l}{T_0} \qquad 14$$

Devices with low power naturally experience a much higher time of local batch $T_l > T_0$ in comparison with information center T_0. On the opposite side, they utilize significantly shorter power $P_l \ll P_0$.

Table 9. Computing and communication footprints.

Computing $C^{(L)}$ footprint	**Communication $C^{(C)}$ footprint**
$C_{CFA}: C_{CFA}^{(L)} = n_{CFA}(\sum_{l=1}^{L_a} \frac{\varphi_l . CI_l}{EE_C})$	$C_{CFA}^{(C)} = n_{CFA^b}(w)(\sum_{l=1}^{L_a} \frac{N . CI_l}{EE_S})$
$C_{FA}: C_{FA}^{(L)} = n_{FA}(\sum_{l=1}^{L} \frac{\varphi_l . CI_l}{EE_C} + \gamma . \beta . \frac{CI_o}{EE_C})$	$C_{FA}^{(C)} = n_{FA^b}(w)(\sum_{l=1}^{L_a} \frac{CI_l}{EE_U} + \gamma . L . \frac{CI_o}{EE_D})$
$C_{FA-D}: C_{FA-D}^{(L)} = n_{FA-D}(\sum_{l=1}^{L_a} \frac{\varphi_l . CI_l}{EE_C} + \gamma . \beta . \frac{CI_o}{EE_C})$	$C_{FA-D}^{(C)} = n_{CFA^b}(w)(\sum_{l=1}^{L_a} \frac{CI_l}{EE_U} + \gamma . L_a . \frac{CI_o}{EE_D})$

$C_{CL}: C_{CL}^{(L)} = n_{CL}.\gamma.\frac{CI_o}{EE_C}$	$C_{CL}^{(C)} = \alpha.\sum_{l=1}^{L} b(\varepsilon_l)\frac{CI_l}{EE_U}$

2. Sustainable requirements and Regions for Carbon-Aware:

FL sustainability relied on the definite operating conditions (OC) regarding efficiency of computing (EE_S), and communication EE_S, EE_U, EE_D, as well as data $b(\varepsilon_l)$ and model $b(W)$ footprints. These operational points focus on necessary or practical necessities for green schemes. To make simpler the analysis, we study here $CI_k \approx CI$, as the broad outcomes with random values of carbon intensity CI_k. All the analyzed requirements and regions below are considered in Table 10.

- Computing efficiency
- Communications of direct mode (efficiency of side link)
- Model and data size
- Efficiencies of DL and UL in cellular communications

Table 10. Regions and requirements of carbon intensity.

Regions	**Requirements**
$\boldsymbol{R_{CI}}: \{\boldsymbol{CI_l}, \forall k: \frac{\boldsymbol{C_{CFA}^{(Z)}}}{\boldsymbol{n_{CFA}}} < \frac{\boldsymbol{C_{CL}^{(Z)}}}{\boldsymbol{n_{CL}}}\}$ $\{\boldsymbol{CI_l}, \forall k: \frac{\boldsymbol{C_{FA}^{(Z)}}}{\boldsymbol{n_{FA}}} < \frac{\boldsymbol{C_{CL}^{(Z)}}}{\boldsymbol{n_{CL}}}\}$ $\{\boldsymbol{CI_l}, \forall k: \frac{\boldsymbol{C_{FA-D}^{(Z)}}}{\boldsymbol{n_{FA-D}}} < \frac{\boldsymbol{C_{CL}^{(Z)}}}{\boldsymbol{n_{CL}}}\}$	$\sum_{l=1}^{L} \varphi_l CI_l < \gamma CI_o$ $\sum_{l=1}^{L} \frac{\varphi_l}{1-\beta} CI_l < \gamma CI_o$ $\sum_{l=1}^{L_a} \frac{\varphi_l}{1-\beta} CI_l < \gamma CI_o$
$\boldsymbol{R_{SU}}: \{\boldsymbol{EE_S}, \boldsymbol{EE_U}: \boldsymbol{C_{CFA}^{(C)}} < \boldsymbol{C_{CL}^{(C)}}\}$	$\frac{EE_S}{EE_U}.\frac{\alpha}{n.l_\alpha} > N.{}^{b(W)}\!/_{\sum_{l=1}^{L} b(\varepsilon_l)}$
$\boldsymbol{R_{b(W)}}: \{\boldsymbol{b(\varepsilon_l)}, \boldsymbol{b(W)}: \mathbf{max}\left[\boldsymbol{C_{FA-D}^{(C)}}, \boldsymbol{C_{FA}^{(C)}}\right] < \boldsymbol{C_{CL}^{(C)}}\}$ $\{\boldsymbol{b(\varepsilon_l)}, \boldsymbol{b(W)}: \mathbf{max}\left[\boldsymbol{C_{FA-D}^{(C)}}, \boldsymbol{C_{FA}^{(C)}}, \boldsymbol{C_{CFA}^{(C)}}\right] < \boldsymbol{C_{CL}^{(C)}}\}$	${}^{\alpha}\!/_{n} \times {}^{l}\!/_{l_a} > {}^{b(W)}\!/_{b(\varepsilon_l)}$ ${}^{\alpha}\!/_{n} \times {}^{l}\!/_{N.l_a} > {}^{b(W)}\!/_{b(\varepsilon_l)}$
$\boldsymbol{R_{DU}}: \{\boldsymbol{EE_U}, \boldsymbol{EE_D}: \boldsymbol{C_{CL}^{(C)}} > \boldsymbol{C_{FA}^{(C)}}\}$ $\{\boldsymbol{EE_U}, \boldsymbol{EE_D}: \boldsymbol{C_{CL}^{(C)}} > \boldsymbol{C_{FA-D}^{(C)}}\}$	$\frac{EE_D}{EE_U}\left(\frac{\sum_{l=1}^{L} b(\varepsilon_l)}{b(W)}.\frac{a}{n.l_a} - 1\right) > \gamma.{}^{l}\!/_{l_a}$ $\frac{EE_D}{EE_U}\left(\frac{\sum_{l=1}^{L} b(\varepsilon_l)}{b(W)}.\frac{a}{n.l_a} - 1\right) > \gamma$

B. Roadmap of FL:

FL is even a growing structure with a bunch to develop in a changed phase [213]. It focuses on the direction of future research and some challenges relied on our investigation [214]. Mainly, the footprint of carbon relies on the hardware's physical location, either in terms of communication or training, CE can be massively decreased by choosing consumers with connections to faster internet or from greener places. There will be applied firms in selecting clients in specific places more frequently e.g. greener location clients might not have adequate samples of data for directing or signify a twisted distribution of data [215].

However, it could indicate further investigation needed and demographic bias. Also, statistics of industries on the existing devices fleet are vital to enhance the CEs of FL. Certainly, in the real world, the effectiveness of hardware can change immensely from one client to another client. Further, in the physical places, we also like to select clients with equivalent computing capability, more competent hardware, and a range of encouraged potential biases. take the case centralized, tuning of hyper-parameter is of higher importance in decreasing period of training [216], [217].

In some experiments, it is decided only to adjust parameters of optimizer-connected (e.g. momentum, learning time) to increase performance at a sufficient level and fair comparison. The tuning is completed to simplify the FL training junction. Nevertheless, in FL, tuning of hyper-parameters becomes a highly difficult task as it theoretically adds hundreds of simulations (i.e. models, local clients), each assembled usage of a few datasets that are probably to monitor a very twisted distribution. In addition to tuning of client-side, the scheme of aggregation also suggest additional parameterization, that enhances the tuning process's complexity [218].

Therefore, innovative tuning algorithms of hyper-parameters should sensibly be planned to minimize CE by decreasing the released CE and mutually enhancing the accuracy.   The figure of local epochs is also a significant hyper-parameter that can affect the total CE. Settings of local epochs often carbon less than settings of 1 local epoch for non-IID, separated from the task of ImageNet. This is simply clarified by the cost of hidden interaction. certainly, a solo local epoch involves more rounds of communication and, therefore, energy to converge contrasted to five local epochs. Additionally, the communication rounds number needed for five local epochs is typically less than the communication rounds in five instances that are needed for one local epoch. In the framework of ImageNet, objects are mostly distinct as the training of local becomes needed high energy. Therefore, easily realizing the local epoch right number also distinctly appeared as a serious point in decreasing FLCEs [219]. In the end, CE also relied on aggregation policies [220]. With more strategies of superior aggregation, the number of communication rounds can be decreased, hence decreasing the overall CEs.

Table 11. Main contribution of federated learning.

Year	**Ref**	**Contribution**
2016	[221]	H. Brendan presented a practical technique for the FL of deep networks relying on an averaging iterative model.

2016	[222]	Jakub proposed the one-device intelligence distributed ML with federated learning to reduce CE.
2019	[223]	Deniz suggested federated machine learning with wireless fading channels
2020	[224]	Xinchi proposed the FL by raising environmental concerns and severe privacy for decreasing CE.
2020	[225]	L.U. Khan presents the open challenges, taxonomy, and recent advances in FL.
2021	[226]	Stefano suggests the FL opportunities for the cooperative connected system for controlling CF.
2021	[227]	Peter proposed the open problems and advances in FL
2021	[228]	Zhaohui presents the computation resource allocation and transmission with the efficiency of FL.
2024		Our survey includes all these aspects.

1. Communication and training energy:

Carbon footprint relied on the consumption of communication energy and training energy, which relied on the FL strategies, hyper-parameters training, hardware efficiency, and physical places of the hardware. We establish that the FL of carbon footprint is rigid to assess in comparison to centralized guidance without a framework, because of the essential difficulties in how FL is presently accomplished. The difficulties might include system heterogeneity, geographic distribution, client, and data collection. A comprehensive assessment was given in this portion for reducing CE with FL [229], [230].

XII. Transfer learning (TL) for CE reduction:

CE is determined to express the total emissions of GHG of activity or a particular substance, not captivating not only emissions of carbon dioxide (CO_2), but also other GHG, such as fluorinated gases, nitrous oxide (N2O), and methane (CH4). CE is utilized as a standardized piece of calculation to aggregate and compare the whole influence of different GHGs on climate modification and the environment. Metric tons, known as “t” or “MT” are mainly utilized as the CE measurement unit, where 1 metric ton is equal to 1000 kilograms [231].

Gitzel et al. [232] organized a study of factors investigation that involves the AI models with carbon footprint through all three phases of the machine learning (ML) method, involving model architecture inference, search, and training.

Walsh et al. [233] established an experiment on TL, where fine-tuned pre-trained are used for detailed tasks, headed to 14.8 times less than energy consumption at GPU that is compared to models training from scrape in a classification task of machine vision by utilizing the architecture of Xception model and the dataset of “cats_vs_dogs”. In ref [234] the author presents a method of transfer learning with an instance-based multisource by utilizing analysis of maximal correlation that removes the requirement for data of the source domain to practice a model of the target domain; as an alternative, it employs pre-trained models of the source domain to build a feature extraction distributed links for in the target area, by computation reduction during preparation [235].

The TL's main objective is to explain a target task by using the information found from source tasks in several connected fields, thereby removing the requirement to turn on from abandon with a huge data quantity. It can also be unraveled by utilizing pre-trained develops to report the same problems of deep learning [236], [237], [238]. By leveraging past developed source tasks knowledge, TL can decrease the computational resources and required period while increasing the efficiency of data [239], [240], [241], [242]. Therefore, it is compatible with the structure of friendly environmentally ML that needs usage of efficient data. Earlier defined transfer learning, let us reconsider the introduction of task and domain [243], [244]. Domain 'O' includes two elements: a marginal probability distribution 'XD' and feature space 'X', i.e., O = {XD, X} here X represents the instances set,

$$X = [x | x_l \in \chi, l = 1, \ldots \ldots \ldots, n] \quad 15$$

A task 'K' consists of a decision function 'f' and label space 's', that is, K = {f, s}. The decision operator is an implicit one, which is projected to be educated from the sample records. In training, a domain is normally seen through cases that have no label information. source task S_K related to source domain S_D is normally seen by utilizing their corresponding labels and instances pairs, which can be signified as:

$$S_D = [(x, y) | x_l \in \chi^S, y_l \in y^S, l = 1, \ldots \ldots \ldots, n)] \quad 16$$

In the target field, the statement normally comprises a kind of labeled case with a classified number and unlabeled cases. some source task(s) and domain(s) and a/some target task(s) and domain(s) is given, TL goes to employ the source tasks(s) and domain(s) knowledge to enhance the predictive operator 'f' of the target task(s) and domain(s) where $D_T \neq D_S$, or $T_T \neq T_S$.

Some researchers establish that transfer learning succeeds in decreasing the ML computational charges by reducing the required period for training. For instance, Liu et al. [245] utilize an autoencoder (AE) compression as a case survey and discovered that transfer learning substantially decreases the training period on data of high-performance computing (HPC) without performance compromises. Gayakwad et al. [246] discovered the training time reduction for models of deep learning using TL on an equivalent dataset. This idea relies on the resemblance of the characteristics in the same datasets and the layers category of deep neural nets are different.

Hence, as an alternative to the whole neural net training, just trained classification is responsible for the final layers, and the past weighted trained model is practical to the lasting layers, outcomes are time-saving substantial. As discussed, previously, TL is a popular approach used in few-short learning (FSL) for previous knowledge transferred from a source task to an FS target task [247], [248], [249], [250] to enhance accuracy, statistics efficiency, and learning speed. Here, transfer skills are attained by deep network pretraining on a huge training data amount that has been seen before in base classes, and then unseen in the new FS classes that are fine-tuned.

Moreover, using naive fine-tuning only rare examples leads to the performance of slow generalization and overfitting on the tasks of FS. In TL, the previous skills are removed from the source task by vanilla learning, without meta-objective usage. In meta-learning (ML), the subsequent prior by an external optimisation that estimates the prior benefit when learning the new task. Approaches of TL that frequently superior performance or demonstrate comparable on tasks of FSL when compared to the methods of intricate meta-learning that previously mentioned.

To enhance the knowledge growth of transfer-related inventions, researchers must talk about critical various problems. First, there is a requirement to discover transfer skills in a varied series of applications, covering their potential through several areas. Second, avoiding negative transfer or calculating transferability across domains is vital to ensuring the efficient transfer of knowledge. Additionally, TL interpretability research is vital to attain insights into the analysis behind transfer decision knowledge. The theoretical studies following the TL effectiveness will support a solid basis for its relevance. In the end, substantial reliance is given to transferring methods of knowledge on human experience and instruction, the comprehensive guidelines development is important. These recommendations will support determining practitioners what to allocate, how to transfer, and when to transfer skills successfully, making the process more practical and reliable.

A. Task Transfer Learning:

Task transfer learning (TTL) was proposed in this analysis to pay attention to single- and multi-task drawbacks. TTL was hardly useful for forecasting the facts of the core combustion engine (CE), although it is extensively explored in natural language and image processing ranges. TTL is a procedure in which a skilled model for a particular incident is predicted, that is, a pre-trained model, is changed into another fine-tuning phenomenon model for prediction [251], [252].

1. TTL method:

TL is organized by the task and domain relationships between the target and source given in Table 12 [253]. The task and domain relationships between the target and source are utilized to define the TL and traditional ML [254], [255].

Table 12. Applications of TTL.

	Learning settings	**Target & Source Task**	**Target & Source Domain**
	Traditional ML	same	same
Transfer Learning	Transductive TL	same	Different but related

Unsupervised Inductive TL	TL/	Different but related	Different but related

The inductive TL is defined as the function of target prediction learning is $f_p(.)$ in domain tasks by using source and task domain knowledge. The multi-task learning problem was projected for SVM [256], and it was adapted for inductive TL [253],[257]. In inductive TL,

$$z_s = v_s + z_0 \text{ and } z_T = v_T + z_0 \qquad 17$$

where z_s is the source task parameter, and z_T is the target task parameter. v_s and v_T are each source and target task parameters, correspondingly, while z_0 is a mutual constraint. The TL of SVM can be expressed as develops [253].

$$min_{z_0, v_T, \xi_{t_l}} \qquad 18$$

$$= \sum_{t \in S,T} \sum_{l=1}^{n_t} \xi_{t_l} + {}^{\lambda_1}/_{2} \sum_{t \in S,T} || \ v_T||^2 + \lambda_1 || \ z_0||^2 \qquad 19$$

$$s.t. \, \mathrm{y}_{t_l}(v_T + z_0). \ 1 - \xi_{t_l} \le \mathrm{x}_{t_l} \qquad 20$$

$$\xi_{t_l} \ge 0, l \in \{1,2, \dots, \dots., n_t\} \ and \ t \in \{S, T\} \qquad 21$$

Here, the parameters of positive regularization are $\lambda_1$and λ_2; slack variables ξ_{t_l} calculate the final model error z_0 builds on the data; cost function is the J(.). For the model of deep learning (DL), for the classification of images, TTL has been resulting from [41], [258], and can be changed for the regression applied. TTL was achieved as the schematic shown in Fig. The pre-trained model has hidden layers and the last two were again trained by utilizing the target information 'T' whereas, during training, the other hidden layer masses were frozen as shown in Figure 14 [41].

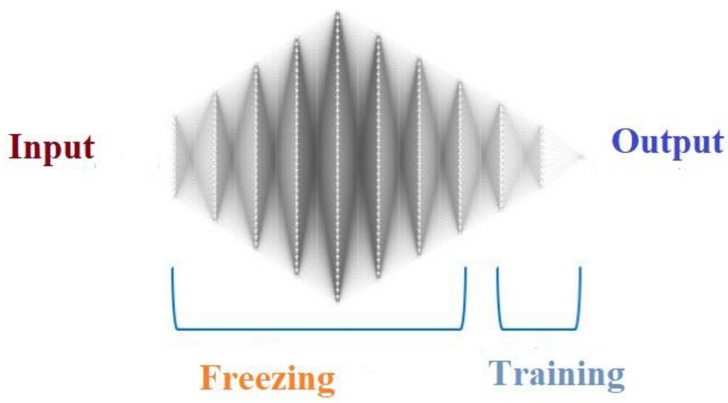


Figure 14. Layers of TTL.

XIII. Blockchain (BC) technology for CE reduction:

The technology of BC is described as a dispersed ledger that is immutable and cryptographically safe, in which data moving is extremely tough [259]. BC allows every transaction without the involvement of third parties needed. In ref [260], Laurence suggested the system of BC, where each made transaction is verified onto a ledger and then added into the block. Every block is linked with before a block and after it. When one block is linked within a chain, it converts immutable, and a solo cannot delete or alter the blocks. BC is a decentralization system that allows demanders and suppliers to sort transactions point-to-point. Every node of the enterprise will monitor a similar protocol.

In ref [261], Wang et al. suggested that BCs exist in two types, which are relied on mechanisms of access control. Public BC is the first type. In ref [262]Adnan et al. proposed the convergence of BC, AI, MV, etc. BC this type can be made without permission transactions and is anonymous. This type has the mechanism of incentivizing to inspire higher participants to link the association. The private BC is a second type. A member who is willing to link to the network is required to have system approval or be invited. Usually, a solo organization (private BC) has monitor access to a consortium of members [263], [264]. BC structure is given in Figure 15 [265].

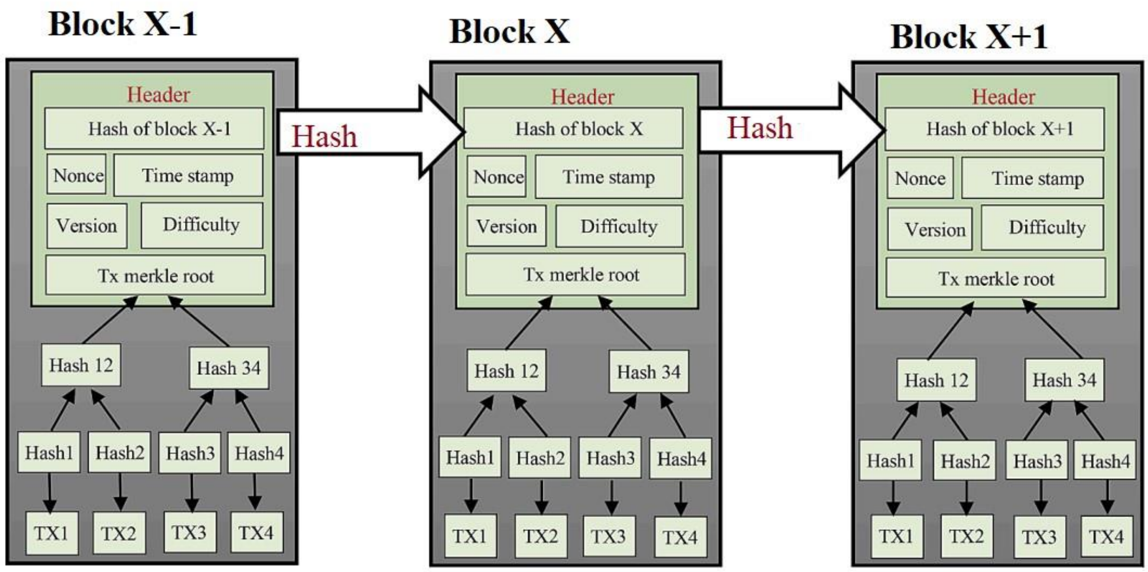


Figure 15. Structure of Blockchain.

A. Carbon Trading Challenges:

Carbon emission trading (CET) faces challenges and the procedures essential for executing a participated transparent system of carbon trading. Some challenges of CT are given:

- Carbon Stipends are Complex.
- The Procedure of Allocating Carbon Stipends is Complex [266].
- CT is considered by the absence of tracing calculations of CE.
- The calculations of the carbon budgets are open to abuse and manipulation [267].
- CT extends the capability to purchase high-carbon praises [268].
- The discrepancy in GHG emissions is ignored.
- The market of CT is described by non-transparency and corruption [269].
- The market of CT can be extremely complex and needs the charges of high transactions [270].
- There is no need for an Integrated market of Carbon Trading.

B. BC-enabled technology for the trading of carbon:

Carbon emissions (CEs) have developed a main interest, and production companies have gathered enhancing tension to bound the total of GHG of the whole generation. Khaqqi et al. [271] assumed that the technology of BC is utilized as an emissions trading proposal. An emissions trading scheme (ETS) is called a policy of tradable permits. In this situation, the total GHS numbers authorized are supplied to companies. At distinct times, contributors are needed to produce a statement on the total of generated emissions. Contributors can customize their GHG documents. A company that less GHG has generated than permitted can push its extra capability to others who have generated higher emissions than expected. An ETS supports producing companies in attaining a drop of CEs. The fidelity and transparency of the process of emission trading utilizing BC technology can enhance fidelity, transparency, and efficiency [272]. Trading of carbon using BC technology can confirm each transaction's safety. All operations will be recorded accurately in a joined record, and a timestamp proof will confirm that it traced back each operation. BC technology can transmit and record information flow in CE trading to prevent repeated transactions or lost quotas. Any unauthorized activity of trading will be noticed. All transactions of CE must obey the algorithm of the same consensus to build all processes consistent [273], [274].

1. Adoption of BC technology and environmental-technological-organizational:

The technological perspective discusses the technologies significant to a company. This comprises compatibility and technological competence. Technological ability signifies the arrangement of a company in the organization, as well as the knowledge level involved in such technology, and a company's cooperation to become concerned in the adaptation of such an action as well [275], [276], [277]

Recent technology adoption is frequently a strategic requirement to participate in the market [278], [279]. By adopting BC technology, companies can have more precise access to data in real-time and superior visibility of the market. These schemes can be transformed into the following premises Figure 16:

P1. Technology capability will have a positive and substantial connection to the BC technology adoption.

P2. Compatibility will have a positive and substantial link to the acceptance [280].

P3. Corporation size will have a positive and significant link to the approval of BC technology [281], [282], [283].

P4. Upper management helps have a positive and significant connection with the acceptance of BC technology.

P5. Economic compression will have a positive and significant connection to the BC technology approval.

2. Carbon performance and environmental-technological-organizational:

According to Gemunden and Ritter [284], technology competence allows an exploit technology internally, and organization to utilize. Further, technical competence helps in the planning of technology communications, adding the implementation of a necessary knowledge stage as it is linked to the existing techniques. Companies that are capable the technological acceptance will be able to work hard on the results of carbon (P6). In conditions of compatibility, adequately than physical data trace for CEs, the performance of the BC technique can support decreasing data loss, manipulation, and fraud. We discussed that companies adopting compatible technology for energy usage will indicate less carbon implementation (P7). The company's size is linked with the total assets of companies, which replicates a company's resources. The higher value of sustainability can be discovered in larger companies, and such companies manage to supply extra environmental indices in their yearly reports [285]. On the other side, without small-sized companies, government funding is typically opposed by inadequate budgets for obeying energy-related guidelines. Since BC technology has indicated carbon reduction and monitoring, the government will participate in initial funds for the adoption of technology. The small and large proportions of companies have the same prospects of attaining low performance of carbon (P8). Promotion of top management is a decisive feature in governments, which manages all methods, adding strategic planning and decision-making [286]. Companies will track their business well if the upper management helps the adoption of developing technology to attain a reduction of carbon (P9). In the end, companies are subject to competitive stress in decreasing the emissions of GHG in a population that is dedicated to reducing CEs. Stress for low implementation of carbon can be attained if the firm has noticed that participants have a better implementation of carbon than them (P10). It declarations can be transformed into the given premises:

P6. Technology expertise will have a positive and significant connection with the implementation of carbon.

P7. Compatibility has a positive and significant connection with the implementation of carbon.

P8. Company size will have a positive and substantial connection with the working of carbon.

P9. The support of upper management will have a positive and significant connection with the performance of carbon.

P10. Reasonable stress will have a positive and significant connection with the performance of carbon.

3. Carbon performance and adoption of BC technology:

A deficiency of the implementation of ecological agreements can no extended be overlooked [287]. Firms are required to participate in the technology to obey with assume responsibility and environmental principles for reducing CEs, and BC technique is a consistent platform to transmit the flow of information and records in CE trading. In ref [274], Pan et al. introduced BC technology that can be installed for corporate record carbon operations. Firms can imagine performance and evidence for the performance of carbon. The level of consumption will be established at indicated periods, and the CE reduction product will be gathered in the database [288], [289]. Thus, the BC technology adoption can support a firm in preventing fraudulent transaction traces with an exclusive cryptographic signature and a timestamp. The integrity and transparency of GHG help an organization to attain performance of low carbon [290].

P11. The acceptance of BC technology has a confident, positive, and significant relation to carbon implementation.

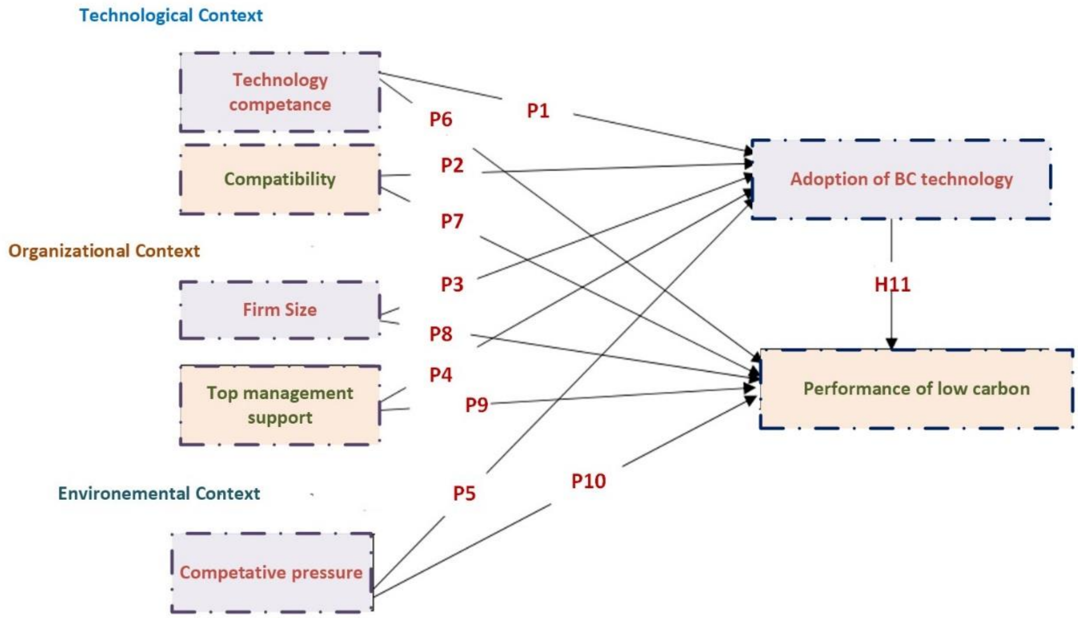


Figure 16. Premises of BC adoption.

C. Roles of value-added and Blockchain explanations in the carbon trading regions:

The technology of BC with its exclusive characteristics and detailed overhead can solve issues of carbon trading as well as progressing operation schemes and current practices. In the next explanation, BC's valuable position in the CT region is noted and given in Table 13:

1. Transparency:

Entities contributing to the market of CET have a full profile of the trading process of carbon stipends. Every node will be capable of specifying where and how trading of allowances occurred [291]. The absence of transparency is the greatest issue facing frameworks of CT for it opens for actions of manipulation. Therefore, the transparency of BC is a resource for the CT region that shall support it to attain the focus it was recognized for.

2. Security:

The structure of BC cryptography guarantees immutability and data security. Because of block dicing, with no circumstance to modify records in every block if the muddles of each block, with all sequential blocks, are rescheduled once again. It is an approximately impossible project. Further, the dispersed BC information traces do not grant any doubtful information validations since it is compulsory to find the agreement of most nodes before informing them [292]. Therefore, immutability and security are secured.

3. Eliminate central servers, intermediaries, and third parties:

BC as a dispersed system excludes the idea of dominant servers. In BC, information is saved in a dispersed approach where every association member would have a duplicate of all knowledge that is informed uninterrupted. Also, processes of data validation will be attained over the BC consent process without the requirement for central attendants to validate data. Data exploration could be accomplished with the help of smart agreements belonging to BC. Those benefits are enormously significant, specifically for a large platform of CT where new investors constantly bond with the group, hence, a structure dispersed is more accessible and does not tolerate from failure of a solo point [293].

4. Records of historical action:

Data related to CE trading, prices, budgets, allowances, and readings are immutably saved in capsulated and recorded inside blocks that could be discovered at the very initial reading or activity. This explains the arguments looking at the CT assists and sector in pursuing the advancement of the directed plans and schemes for coming improvements founded on past data [294].

5. Credible and Irreversible Transactions:

The formation of BC avoids double wasting which excludes fraudulent operations [295].

6. Built-in Consortium:

The structure of BC distributed and its implemented consensus method present consortium in CE values and reading since binding nodes assure that the information stays tamperproof. If all members have the means and the data to confirm that it has not been falsified or altered, then credibility could be attained [296].

7. Data Solitude:

The further section of the cryptographic blockchain organization relies on public/private pair keys, which confirms that the targeted or assigned group objects can access the information. This shall defend penetrating data associated with the processes of business approved by confident producers from receiving revealed while at a similar period sharing the essential CE allowances, analysis, and some created necessary KPIs to accomplish a beneficial and fair framework of carbon trading [297].

8. Automation:

Using smart agreements is a substantial appearance that adds competence to the operated support because of the sharp level of presented automation. A carbon share that is expected to be traded meets a particular situation, the smart agreement is prompted, and an evident significance will be transformed. Further, with the perfectly fixed requirements, integrity is guaranteed and established as properly. The bonds are stored and coded in BC are renovated in real-time and are capable of finishing CT themselves a result, the cost of high transactions is an alternative trial solved by smart bonds in adding to flexibility, integrity, and efficiency [298].

9. Consistency and Robustness:

All these aspects of BC confirm its consistency when assumed in frameworks of CT. Also, the consistency of BC, besides the extended record of its perfect implementation in numerous disciplines, confirms its extreme robustness [299].

It is sure from the description of BC's included estimates that incorporating this technique with a market of CET numerous facing tasks shall resolve it. The system of joint BC-CET will operate quick contracts in determining the carbon resources and calculating carbon adjustment spontaneously and lacking individual intervention. In the end, utilizing the BC of Belongings concept where sensors transfer utilizing BC shall support measurement tools, tracking, and vital monitoring, for the CO_2 released and supply the market of CET with secured and trusted data that is clear to all revelries. Viewing the problem of overlooking the collection of GHG releases faced in the promotion of CET, BC may give transparent and trusted data information that will help governments select the optimal approach to tackle this issue [300] [297].

Table 13. Aspects and contributions of Blockchain.

ref	**aspects**	**contributions**
[291]	Transparency	BC can specify where and how the trading of allowances occurred.
[292]	Security	BC guarantees immutability and data security.
[293]	Elimination	BC as a dispersed system excludes the idea of dominant servers.
[294]	Records	BC saves all the initial reading and activities of CT.
[295]	Irreversible Transactions	BC avoids double wasting which excludes fraudulent operations.
[296]	Built-in Consortium	BC distributed and its implemented consensus method present consortium in CE values and reading.
[297]	Data solitude	BC accomplishes a beneficial and fair framework of CT.
[298]	Automation	BC are renovated and are capable of finishing CT as a result, of the cost of high transactions.
[300]	Reliability	BC gives transparent and trusted data information to select the optimal approach to tackle the issues.

		Our survey considers all these aspects.

XIV. Internet of Things (IoT) for CE reduction:

A. Monitoring Techniques of IoT:

Monitoring techniques of IoT-based have a substantial ability to control CEs [301]. These structures allow individuals and organizations to trace their carbon footprints (CF) as given in Figure 17, recognize opportunities for emission decrease, and create notified assessments about the control of energy [302], [303].

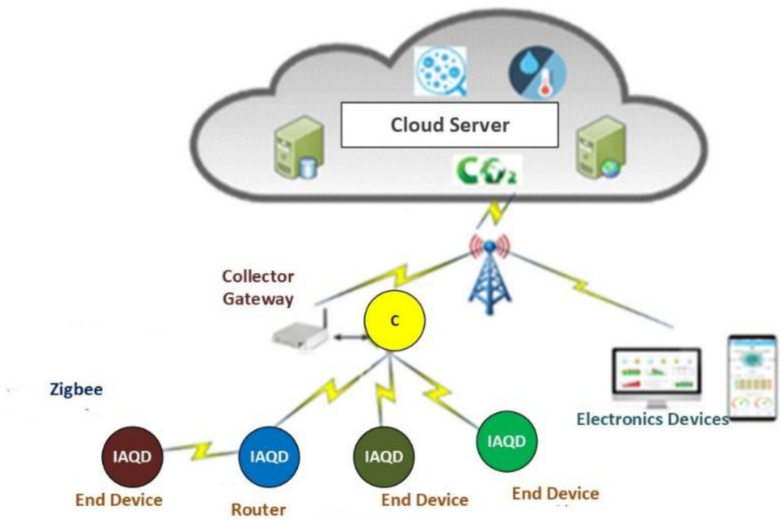


Figure 17. Monitoring IoT system.

Benammar et al. [304] designed a platform of IoT that examines indoor air conditioning in real time. This comprises criteria for several devices of smart mobile, wireless sensor networks (WSNs), and sensor technologies. Near access distributes and handles information around a web server to clients. The network utilizes Emoncms to save internal monitoring of air quality (IMAQ) data for long-term and immediate checking. This study helps the magnitude of several parameters of air quality, comprising ambient temperature, relative humidity, Cl_2, SO_2, O_3, NO_2, CO_2, and CO. The examine emphasizes the capability of monitoring systems of IoT-built control of CE, especially in indoor surroundings [304].

Ma and Wang [305] designed a model by utilizing DNT to balance reducing CE and extending resource economy and energy. To attain this, the authors established prediction of CE develops and integrated game premise to optimize the economy of resources. The conclusion of the simulation denoted that the popular model boosted the maximization of energy assets and lowered the CF cautiously. The researchers counsel that coming research on studies of frequent empirical to find out the inherent causes affecting the prediction of CE. The researchers explained the model's ability to reduce CEs while maximizing the economic resource.

The author in ref [306] employed an IoT-built network that controls and monitors releases of CO_2 from forest fires, industries, municipalities, and transport. The network senses levels of CO_2 in a town and discovers the most polluted zones. They accomplish that their network can support decreasing global warming by controlling and monitoring emissions of CO_2 in real-time. The advantage of monitoring methods of IoT-built is their capacity to deliver notified insights into patterns of energy consume [307].

By analyzing information from sensors and extra resources, organizations can recognize regions wherever they can present alterations to decrease CFs. Further, they also recognize specific processes or equipment that utilize additional energy than required. There are various challenges in employing monitoring methods of IoT-based for control of CE. These networks needed personnel investments, software, and significant hardware, to maintain and install [308], [309].

B. Green IoT with ICT for carbon reduction:

In [310], the author proposed the effect of information and communication technology (ICT) on CE and energy consumption in EC.

The researchers of [311] examined the usage of ICT applications and strategies to bring down EC and CE. The author of the ref [312], [313] suggest sustainable smart cities with data-driven technologies. In [314] the authors studied the principles and roles of IoT green and its capacity to improve the environment, economic progression, and life quality. They offer several advantages of decreasing the negative outcomes of recent technologies on individual health and the ecosystem. For ICT sustainability, solutions have absorbed the data center optimization through methods of sharing organization, which primes to a reduction in CE, enhances energy efficiency, and decreases e-waste appearing from disposals of material [315]. Furthermore, in [316] the authors summarized and discussed the qualifying techniques for green IoT which comprises green communication and internet networks, green data centers (GDC), green machine-to-machine (GM2M), computing of green cloud (CGC), green RFID (GRFID), green wireless sensor networks (NGWS) are shown in Figure 18.

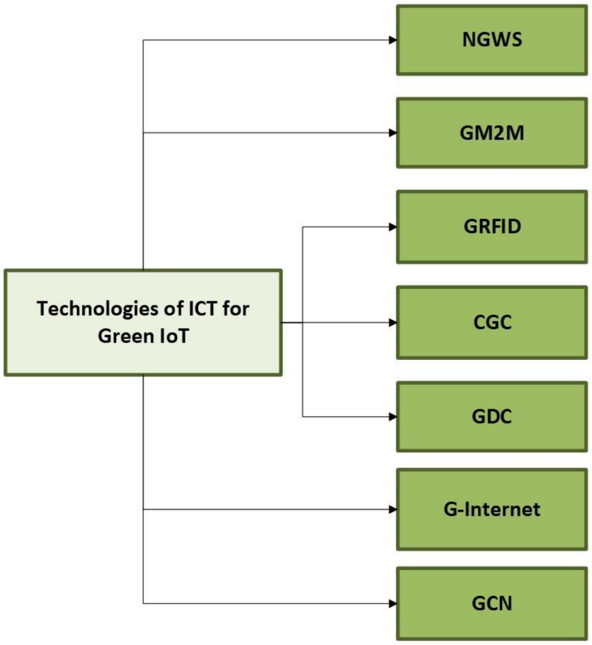


Figure 18. Technologies of green IoT.

The primary aim of greening IoT is to lessen pollution and CE, increase environmental conservation, and reduce power consumption and operational things costs [317], [318], [319].

Enabling technologies of ICT for green IoT, techniques of ICT play a fundamental part in estimating the effect of ICT on decreasing CE for applications of green IoT like smart building, smart transportation, and so on [310]. Green ICT contains several technologies such as cloud computing, telecommuting, IoT, virtualization, supercomputers, smart grids, and e-commerce, [311]. The researchers in [320] examined the green IoT and ICT relying on technologies of green communication, smart grid, and usages of computing technologies [321], [322].

1. Green M2M

Newly, technology is progressively becoming able and smarter to collect information without human interference. techniques of AI are the lead after the advancement of numerous modern technologies. Also, for recognizing the vision of a smart system of Machine-to-machine (M2M), communication of devices is required to be treated on a significant range. Chan et al. [323] explained patterns set for estimating the use-phase CE and power utilization for network services of wireless communication [324].

2. Green RFID

RFID is the mutual Identification (ID) and Radio Frequency (RF) term [325], [326], [327]. It is denoted as the networks of wireless communication utilized to allow IoT. Further, it does not require a scenario of operational Line of Sight (LoS) and draws the physical domain into the graphical domain very simply [328]. The application of RFID is given in Table 14.

3. Network of Green Wireless Sensors (NGWS):

The incorporation of wireless and interaction of sensing has directed to the Wireless Sensor Networks (WSNs) theory [329],[330]. It has certainly made the flourishing of IoT into a magnificent [331], [332]. The sensor is a sequence of massive, tiny low-cost and little-power electronic machines [333], [334], [335].

Hence, microprocessor leanings for WSNs contain decreasing EC, though enhancing the processor's speed. It is an arising thought in which the throughput performance and lifespan are extended while the CE is diminished. In ref [336], Mahapatra et al. examined three numerous ideas (viz. Error Control Coding (ECC), Wireless Energy Harvesting (WEH), and Wake-Up Radio (WUR)) to improve the implementation of green WSNs as decreasing the CE [337], [338].

4. Computing of Green Cloud Technology:

The technology of Cloud computing (CC) is a promising virtualization method utilized through the internet. It delivers almost all capabilities of unlimited computational, service delivery, and unlimited storage, via the internet as theoretically given in Table 14, the technology of CC is universal whereas IoT is extensive [339].

C. Green IoT Designing:

Acquiring appropriate procedures for increasing constraints of QoS (i.e., throughput, delay, and Bandwidth) will further efficiently and effectively to greening IoT. Extra research is required to extend the IoT device model, which supports energy usage reduction and CE. Energy saving and decreasing the CE are the most essential tasks for a green and smart environment [340], [341].

Table 14. Applications of CGC and RFID.

	Applications		**Applications**
CGC	Camera, Tablet, Monitor, Laptop, Mobile, Desktop, Cloud	**RFID**	RFID tag, RFID Antenna, RFID Station, RFID Reader,

D. Drawbacks

This underlines the complications tangled in adopting monitoring systems of IoT-based CE controlling. These hurdles incorporate substantial human resources, software, and hardware, needs for the upkeep and setup. Furthermore, a notable issue of privacy is connected to scrutiny and data gathering from entities and individuals. Overall, monitoring systems of IoT-based can be effective tools for CE controllers. As technology upgrades and decreases the costs, we expect to see more extensive adoption of these networks in the next years. Nonetheless, it is important to study these structures' challenges and potential advantages earlier than spending on them [342].

XV. Metaverse Role with Carbon Reduction:

In research by Emergen [343], the global market size of the metaverse has accomplished in 2021 is $63 billion and is projected to reach in 2030 is $1607 billion. With the fast metaverse evolvement, there will certainly be high CE at the same time. To undertake actual measures for the reduction of carbon emissions, we must first recognize the metaverse with the role of "carbon" by deliberating its CE in the following duration. Further, it is nontrivial to perform the estimation precisely as the metaverse is yet a constantly evolving and newly emerging concept that wraps up a wide scale of technologies. To decrease the estimation error, we consider the CE and energy consumption of the metaverse relying on the figures of energy specified by the following proper sources:

1. the market size of the metaverse and global IT: a report from a report from Research by Emergen [344] and The Business Research Company [345], respectively,
2. the energy consumption of networking, end devices, and data centers: articles on the energy of Information and Communications Technology (ICT) from Huawei Technologies [346], [347],
3. Blockchain energy consumption: research from the University of Cambridge for analyzing the Bitcoin energy [348], [349] and a paper from the Technical University of Munich for considering the overall cryptocurrency energy of [350].

The cryptocurrency energy consumption of the blockchain is taking since the blockchain is used for metaverse transactions. Since the cryptocurrency's energy numbers are only available before 2022, an exponential function is utilized to evaluate future energy consumption based on previous values [351], [352].

By multiplying the proportion of the market size metaverse to the market size global IT and energy numbers, we can assess the global metaverse energy consumption from the year 2022 to 2030 with every layer [351]. Figure 19 plots the growth trend and results. Based on the approximation, we obtain that the infrastructure energy consumption of the layer extends comparatively proportional to the metaverse total energy and captures about one-fifth of the total time. By dissimilarity, the consumed energy by the layer interaction remains constantly at a high level.

While a solo end-device mostly consumes only various Watts, growing demand and their huge quantity for transmission of data still lead to a share of high energy for interaction of supporting immersive. Temporarily, its energy share fell off in 2022 from about three quarters in 2030, it is less than half. The energy dropped share can be recognized in the economy layer fast growth, whose 8× increased the energy consumption in the eight years. This strong growth is expected, as the existing blockchain technology is mostly assumed to be unexpectedly energy-consuming for the demand to complete computations of useless hash and lots of terminated. To measure the CEs, it is kept in mind that energy consumption is not only determined but also linked with the electricity generation carbon intensity which gets reduced due in huge part to an improving clean energy share. Therefore, Figure 19 shows the carbon intensity energy numbers of electricity generation [353], we assess the corresponding CE of every layer from 2022 to 2030 as shown in Figure 20.

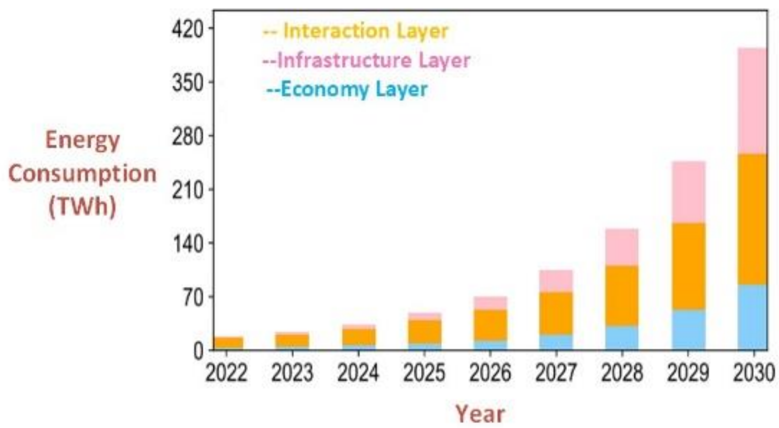


Figure 19. the growth and trend of energy consumption from 2022-2030.

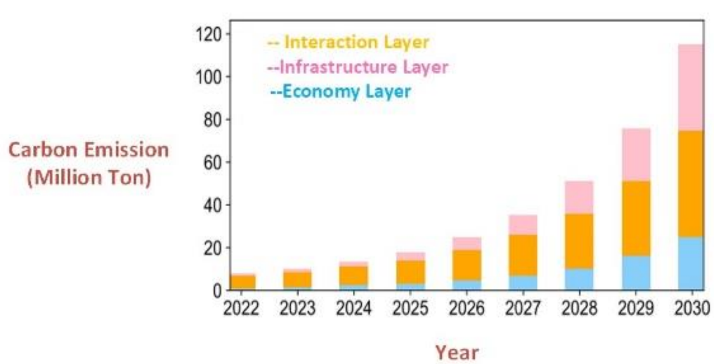


Figure 20. the growth and trend of carbon emissions from 2022-2030.

The metaverse CEs spread as high as 115.30 Mt by 2030 year. To contend with climate change and succeed in carbon neutrality as guaranteed, global CE should be lowered to 23.63 Gt by 2030 [354], [355], which conditions the accounts of metaverse for almost 0.5% of the global CE. We contend that it is gradually urgent to think of enough green phases when operating and building the metaverse and prepare several green techniques to address its carbon problems. The metaverse will justify as high as 0.5% of global CEs by 2030 unless we obtain an effective preventive process from now on. It should identify global considerations for its carbon problem and reassure collaborative attempts on green techniques [356], [357].

A. Metaverse Green Efforts:

In the IT sector to address the carbon problem, several green techniques have appeared. As given in Figure 2, these techniques will support reducing the carbon footprint in the metaverse three layers[274].

1. Adoption of BCques can be classified into the enhancement of the entire infrastructure, power system, cooling system, and IT system, as well as concerning all of them.
2. Interaction Layer: At the layer of interaction, given the whole interaction process with others, the techniques comprise the enhancement of networking, MR/VR/AR-based applications, and end devices.
3. Economy Layer: At the layer of economy, the techniques essentially refer to the enhancement of BC technology. However, these present techniques also establish limitations when splitting with workloads of the metaverse.

It will dive into these mentioned green techniques for the three layers of the metaverse by examining their limitations and applicability shown in Figure 21. If there presents a moderately prominent estimation error, in the examination of the metaverse's growing trend, the metaverse carbon footprint will still be great enough to underline the significance of the green effort.

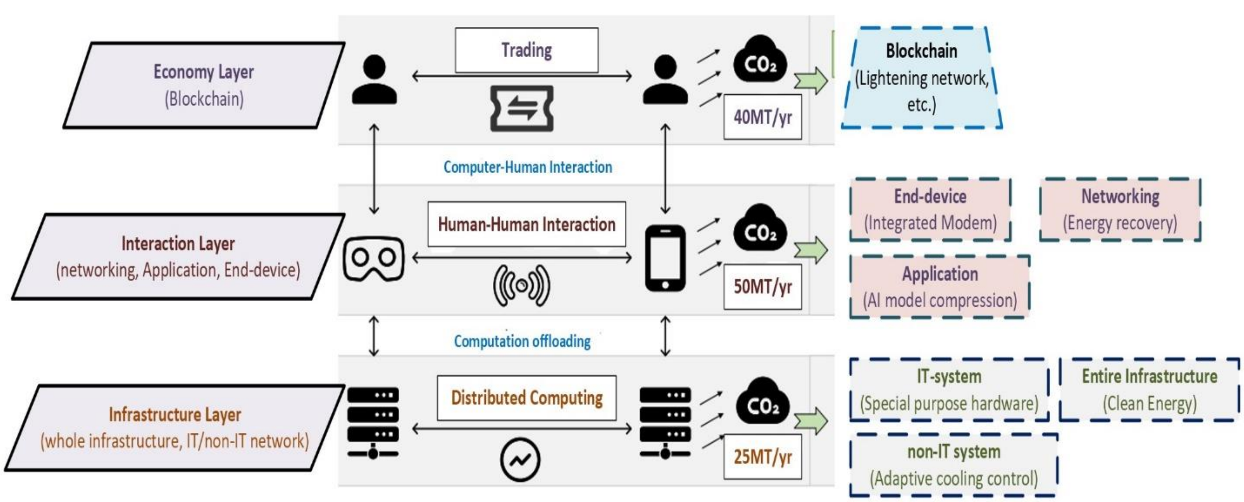


Figure 21. Three layers of the metaverse.

B. AI model compression with metaverse:

It is assumed that AI-based services play a substantial function in the metaverse. However, their enormous energy utilization justifies our special consideration as well. When huge AI model training includes 6 billion factors only to 13% of the entire process, the CE released by GPUs will be as high as home powering in America for 1 year [358], [359]. The technique of model compression has appeared as an applicable method to reduce CE of model inference and training, by reducing the model size and thus the time and resource overhead without notably modifying the accuracy.

With the fast metaverse evolvement, it is assumed that a user’s growing number will see the metaverse when it presents better QoE of trading, playing, working, etc., soon. However, we debate that this may come at the price of CE and large energy consumption, which will mainly delay the path to carbon neutrality[360], [361]. To enhance understanding of this carbon problem, we first divide the metaverse into three layers of carbon-intensive and approximate their carbon footprints from 2022 to 2030. The outcomes show that the metaverse CE in 2030 will reach close to 0.5% of the global CE if we cannot bring effective procedures [362], [363], [364]. Given this vital issue, we then describe a wide array of emerging and current green techniques to examine their limitations and reduce CE when realizing the metaverse workload's specific requirements. In the end, we propose future directions and various insights to assist in making every layer green [39].

XVI. Artificial Intelligence (AI) Impact on CE:

Studies on AI's impact on CE are mixed up. The well-known opinion remains that AI has an encouraging impact on the reduction of CE [365], [366]. First, technical advancement may promote the upgrading of industrial structure, adjustment of energy structure, and economic development, which can lower CE efficiency [367], [368], [369], [370]. The technology of AI may charge great information from various sources to resolve difficult problems, hence reducing CE and boosting productivity GDP per unit. Next, AI as a technology of cutting-edge generates information spillover and data and increases productivity, which permits technologies of carbon neutrality [345][274].

Adoption of BC technology and environmental-technological-organizational:

The technological perspective discusses the technologies significant to a company. This comprises compatibility and technological competence. Technological competency signifies the formulation of a company in the organization, with the knowledge level involved in such technology, and a company's cooperation to be.

However, other researchers contend that technical improvements carried out by AI not only decrease energy depletion but also outcome in lesser energy amounts and surplus, which may additionally inspire energy transition and use, thereby falling the projected energy reserves of the knowledge. This sensation is called the “rebound effect” [371], [372]. AI is comparatively energy-concentrated for industrial use, as industrial robotics and ML are considerably more energy-concentrated than workers. Recently, the computational intensity essential for general technologies of AI such as DeepMind’s AlphaZero Go cycle has roughly expanded every 3.4 months, three times between 2012 to 2018. AI that relies on deep learning is developing the major device of corporate development in information centers around the world, with CE and energy utilizing it produces not seriously controlled, it will begin a “butterfly effect” devastation. In the interim, the EU has proceeded with an alert that the GHG emissions in industries with AI could rise to 14% for the coming two decades. This article analytically implies that it is of main consequence to discover whether AI has a negative or positive outcome on CE [373], [374], [375].

A. AI Reduces CE by Optimizing Green Technology Invention:

Technical innovation and progress are referred to as vital portions of emission reduction and energy maintenance [376], [377]. Technology diffusion supports the stimulation of green technology and processes of cleaner manufacturing in environmentally stained areas, which has a promising effect on CE and energy execution [378].

B. AI Reduces CE by Improving Industry Structure:

Upgrading industrial structures is a main driving intensity for pollution reduction and energy maintenance. With upgrading the industrial configuration, factors steadily transfer from areas with less marginal effectiveness to areas with huge marginal effectiveness. The tools of resource provision with the AI economy can rearrange capital, labor, and other source features to encourage the industrial assembly to the industrial chain high termination, which is favorable to decreasing pollution emissions and increasing energy efficiency [379], [380], [381].

C. AI Reduces CE by Optimizing Information Infrastructure:

Information structure, which is naturally friendly with minimized CE, fewer destructive externalities, and economic activity promotes dematerialization [382], [383]. Further, information infrastructure urges businesses to devote themselves to information technology, which decreases the activities of CE. Also, it facilitates information structure improved communication, and articulation between downstream, midstream, and upstream, initiatives in the industry chain, with the propagation of data and information between the manufacturing industries and productive facility, thereby attaining the parting of the service link from the production connection and a cleaner and further operation model and efficient production [384].

D. Methods and Materials:

1. Identification Approaches:

This article examines the impact of AI on CE. The standard model is:

$$CET_{r,y} = \beta \ln AT_{r,y} + \alpha + \mu_t + \mu_r + \lambda W_{r,y} + \varepsilon_{r,y} \qquad 22$$

where $CET_{r,y}$ represents the CE intensity of; $AT_{r,y}$ calculates the AI growth level of region 'r' in year 'y'; $W_{r,y}$is a control variables set; $\varepsilon_{r,y}$ is the error term, and μ_t and μ_r indicate the fixed time effect and fixed area effect. The coefficient 'β', is the net effect of AI development level on the intensity of CE, is the key coefficient. A vital negative 'β' represents reduced CE intensity because of enhanced AI progress. Either an irrelevant or a positive β represents an insignificant effect of the enhancement of AI on CE.

2. Variables:
3. Basic Independent Variable (Development Level of AI):

In the period of the digital world, AI is widely utilized in several areas of society and the economy. Inspired by an applicable study, it uses a technique related to the "Bartik instrument" to build the exposure to the robot (ETR) for region 'r' in year 'y':

$$ETR_{r,y} = \sum_{l \in \emptyset} \gamma_{c,l} \,.\, APD_{l,y} \qquad 23$$

where $\gamma_{c,l}$ represent the employment proportion in industry 'l' in the manufacturing region, $APD_{l,y}$ represents the robot dispersion in year 'y' in industry 'l' at the country level, $\gamma_{c,l}$ and $APD_{l,y}$ are measured:

$$\gamma_{c,l} = {P_{r,l}}/{P_{r,}} \qquad 24$$

$$APD_{l,y} = {SR_{l,y}}/{P_{l,}} \qquad 25$$

where $P_{r,l}$ represents the industry-employed population in region 'r', $P_{r,}$ represents the manufacturing sector employed population in region 'r', $SR_{l,y}$ notes in year 'y' the stock of industrial robots in industry 'l' in countrywide.

4. Dependent Variable (Intensity of CE):

It worked on town industrial CE owing to the reality that products of AI are currently pitched regarding businesses. It also splits urban industrial CE into two classifications: straight emissions from the use of energy such as LPG and natural gas, and emissions comes from electricity in town industries [385],[386], [387], [388] the CE is calculated as follows:

$$CE = C_1 + C_2 + C_3 = \alpha_1 E_1 + \alpha_2 E_2 + \alpha_3(\eta E_1) \quad 26$$

$$CET = {}^{CE}/_{GDP} \quad 27$$

C1 and C2 represent the CE from LPG and natural gas, and C3 is the CE of the consumption of electricity of the whole union; E1, E2, and E3 denote the use of industrial electricity, LPG, and natural gas. α1, α2 denotes the factors of CE of LPG and natural gas, α3 is the GHG factor of the fuel chain of coal power, and η represents the share of generation of coal power to entire generation [389].

5. Instrumental Variables

Throughout the sample, like China, the industrial robot's growth in the US can indicate the tendency of technological growth, and its effect on China's CE contents the endogeneity hypothesis of instrumental variables. Changes in the industrial robot supply of the US do not associate with variables involving the carbon intensity of China during the same period, satisfying the homogeneity hypothesis of instrumental variables [390], [391].

6. Control Variables

This work control variables are investment with fixed asset (invest), represented as the proportion of the city's entire investment with secure benefit to regional GDP; financial expansion level (f in), urbanization ratio (urban), which is stated as the municipal district with population share; and government interference (expenditure), which is stated as the proportion of the city's overall public expenditure funds to the regional GDP [392], [393].

The effect of the improvement of AI on CE for the level of 270 prefectures using panel data cities in China 2011-2017 [394], [395]. Publicly available statistics from the China Research Data Service Platform (CNRDS), EPS Data Platform, Yearbook of Statistical China City, International Federation of Robotics (IFR), and Database of Enterprises of China Industry, are the primary bases of research data. The Table 15 includes the expressive statistical evaluation of the variables [396], [397].

Table 15. statistical evaluation of the variables.

Variables	**Symbols**	**Standard Deviation**	**Mean**	**Max.**	**Min.**	**50 percentiles**
CE Intensity	CET	1.020	0.0300	6.200	−1.450	−0.270
Population (%) in urban areas	Urban	0.0500	0.0800	1.270	0.0100	0.0700
Financial expansion	fin	0.290	0.790	2.200	2.200	0.760

Government interference	Expenditure	1.030	11.94	16.08	8.130	11.82
Exposure to robot	In ETR	0.870	2.380	5.370	−0.0700	2.380
Fixed asset investment	invest	0.240		1	0.0500	0.300

XVII. Edge computing (EC) for Carbon Reduction:

This section decisively examines the leading trends toward the EC for a green environment. Distant from offering insight into the algorithmic and architectural aspects, we accomplish an accurate estimation of the literature by several assessment constraints. These evaluation constraints are largely derivative from the literature on new advances in EC [398], [399], [400], [401], [402], [403], [404], [405], [406], [407]. Taking five altered assessment constraints, namely, sustainability, context responsiveness, security, caching, and scalability, for the estimation of the current developments are as follows and given in Table *16*.

A. Sustainability:

This contrasts with the use of RE sources and the energy-efficient design. Furthermore, sustainability discusses energy gathering, which receives energy from radiofrequency foundations and environmental sources and keeps it for additional usage. The main sustainability objective is to decrease CE. A major portion (>80%) of produced energy by utilizing brown supplies [408]. Hence, sustainability is an essential key feature measured in the structure of EC-permitted organizations. In addition, this measure suggests an enhancement in profit, hardware reliability, and reduced carbon footprint [409].

In the future, the densification of servers and devices is projected, which in alter will outcome in restrictions of energy. Thus, sustainable expansions are essential. Sustainability in EC can be done by utilizing sources of RE [405], energy harvesting [410], [411], [412], and design of energy-efficient [413]. Sources of RE include wind, geothermal, and biomass energy. The design of efficiency has three significant portions, software of energy-efficient, resource management of energy-efficient, and hardware of energy-efficient shown in Figure 22. Other than the design of energy efficiency and sources of RE, energy gathering contracts with the energy withdrawal from external resources for extra source in the small device’s operation, such as wearable tools and sensors [409], [414], [415], [416], [417].

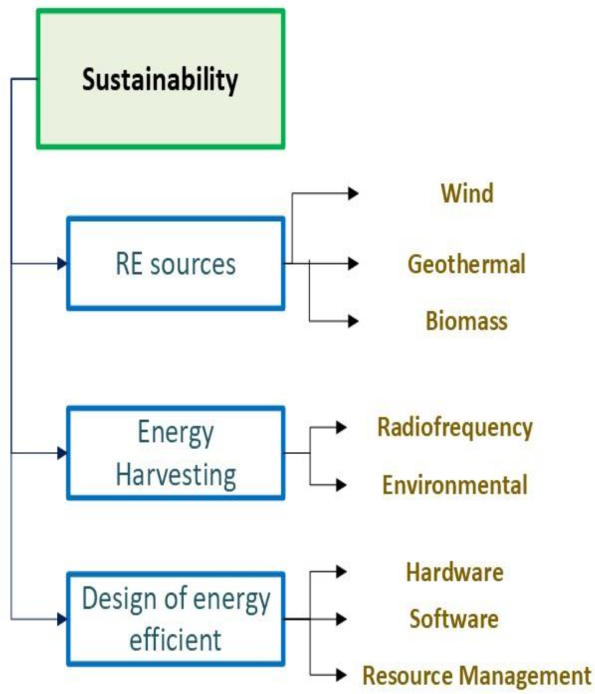


Figure 22. Three significant aspects of edge designing.

Energy is collected either from ecological resources, such as thermal, solar, and wind, or from foundations of radiofrequency. There are important distinctions in the gathered energy from cooperation sources of radiofrequency and natural sources [418]. Thus, it is authoritative to propose a hybrid network that utilizes mutual grid energy and harvested energy. A mixed network initially must completely utilize gathered energy and then advanced utilize grid energy in instances when the level of harvested energy becomes less than the required operation energy. Hybrid energy supplies are used to allow sustainable operation. Sources of hybrid energy make use of both grid energy and harvested energy on necessity. First, such a network applies accessible collected energy. Then grid energy is utilized only when the gathered energy level reduces below the application's essential energy level [419], [420], [421], [422], [423], [424].

Sustainability is an alternative important requirement when planning EC infrastructures for a green environment. The densification of EC servers and end-user machines is expected. Therefore, this adds major energy limitations to the whole green city design infrastructure. Therefore, tackling the task of huge energy intake without demeaning QoS is essential. The three major aspects are linked to sustainability of the EC-enabled green cities:

- harvesting energy [425], [426], [427];
- use of RE sources [428], [429], [430]; and
- design of energy-efficient [431], [432], [433].

The EC-enabled infrastructure of green cities is proposed to design energy consumption by engaging innovative communication technologies and architecture design. Various styles to enhance the energy effectiveness of the EC system model comprise caching with energy-efficient [434], sleeping [435], offloading of energy-forced and offloading with computation of energy-aware, and user suggestion [436]. Further, technologies of wireless networking of energy-efficient, such as ZigBee and IPv6 can be utilized to support the sustainable operation of network [437], [438], [439], [440]. In [441], Gai et al. suggested communication of cognitive wireless that applies EC and reinforcement knowledge to enable operation with efficiency. Other than the design of energy-efficient, an ecosystem with EC that utilizes energy from power generation plants will contribute to the CF. However, an EC infrastructure should use energy from RE sources, such as hydropower solar, and wind. On the other side, energy can be collected from environmental supplies, such as sun and wind [442] radio-frequency supplies, such as interference signals and transmitters [443]. Energy harvesting proposes substantial rewards but undergoes casual variations in both radiofrequency and environmental energy [444], [445], [446], [447]. Thus, it must utilize hybrid supplies that also use grid energy and harvest energy on request if the level of collected energy drops below the essential energy. The edge attendants are proposed for roles in several diverse applications to help a huge number of handlers. However, edge servers are also projected to assist and help with algorithms of computationally exclusive ML. Therefore, high-performance retention is used as one of the capable explanations for allowing sustainable EC-aided smart surroundings [448], [449].

1. Context Responsiveness:

The capability of the network to acquire knowledge about the surrounding environment and node's locations. Context awareness suggests various advantages, comprising the addition of more denotation to data of emergency management support, M2M communication assistance, smart IoT mechanism, and program implementation of smart town facilities, to assign a limited [450], [451].

2. Security:

This mentions a tool's cyber security and physical security. Further precisely, cyber security contracts with information from attacks, computing infrastructure, and network protection [452],[453].

3. Caching:

The transient storage of famous matter at unique positions in a complex allows contact with little dormancy. Caching also decreases network congestion by preventing the flow of frequent traffic. Caching contracts with the loading of famous matter and EC supplies computation funds, but these ideas can be leveraged instantaneously in smart cities to allow a variation of smart purposes [454].

4. Scalability:

The aptitude of a network to allow elastic facilities as per manipulator requirements without misplacing QoS results with the process of cost-efficient [413].

Table 16. Main aspects of edge computing.

ref	aspects	contributions
[450], [451]	Responsive facility	It has the capability of acquiring knowledge at different locations.
[453]	Privacy	It controls all the physical and cyber security.
[454]	Caching	It has the power of storage and decreases network congestion.
[413]	Scalability	It allows the process of cost-effective.

XVIII. Distributed computing (DC) for Low Carbon footprint:

the evaluation of the carbon footprint (CF) and latent reserves footprint of such a follow the wind/follow the sun (FTWFTS)-relied on a distributed information center. It will simplify the notion of RE and as a replacement for considering energy of high-footprint (HF) and energy of low-footprint (LF). As a measure for the CF, we will utilize carbon in grams, if otherwise suggested. The mathematical version is given for defining the CF and reserves of such an infrastructure of a distributed information focus which is fueled by a located mixture of HF and LF energy [455], [456], [457].

A. Theoretical model:

Develop and consider a model for appraising its complete CF. The several parameters quantification in our interpretation will be organized [458], [459], [460]. To present our theoretical model, we study the infrastructure of a distributed basic data point. It comprises of ‘p’ proportionately sized locations. Of these ‘p’ locations, on average ‘q’ locations are functioning. When a particular location becomes non-active, processing and data are moved to the alternative lively location, retaining the total of functioning information centers always to ‘n’ equal. At this fact, it is vital to point out that, while we practice the term information center, our model will be separate in the mass of the information center. An information-filling location is an energy-improved structure housing huge attendants, or it be as tiny as a solo attendant. It might be helpful to imagine an information center location as a computing connection of any feasible size [461], [462], [463].

Each location is operated by either HF or LF. The average accessibility of energy LF against HF is judged equal, for every location [464], [465]. This accessibility ratio ‘b’ may be the outcome of the average sequential accessibility of an exact RE source (for example, wind or solar power), or agreements of restricted service rank between the utility provider and the information center operator. To decrease the whole footprint, the LF use will be expanded by drifting the working of an information center operated by HF energy to an information focus where LF is present. When the energy of LF is absent, HF will be utilized to deliver guaranteed service. The whole carbon footprint ‘T’ of the beyond-designated infrastructure of the distributed information focus, averaged over an extended sufficient time, then add the footprint of communication ‘Tc’, usage ‘Tu’, and the manufacturing ‘Tm’:

$$T = T_c + T_u + T_m \qquad 28$$

The ‘Tm’ will be the emitted carbon through the fabrication of the apparatus (network apparatus, servers, etc.) internally and at the sites. The ‘Tu’ will be the outcome of the energy utilized through the use period. The ‘Tc’ is the emitted carbon by jobs and transferring data from location to location. All these footprints are extracted in g CO2-eq. Formerly we detail every footprint, it is beneficial to show the arising assumptions we will get for our theoretical template:

- Do not believe the remaining LF energy.
- Imagine each location in the allocated information core to be of identical size.
- Suppose immediate location resettlement. That is, we suppose that relocation requires no period and creates no further expenses not reported for in the ‘Tc’. If the migration frequency is comparatively low, this hypothesis will hold.
- Suppose a non-active information core location utilizes less energy. Although this is a confident hypothesis for significant information cores, this is possible for micro-scale information centers containing a few attendants (recall that the designated information focus, model is free of the information focus size). A non-active energy location could be decreased to (approximately) zero by hanging all attendants.

B. Footprint of Usage:

Let us consider ‘h’ the probability that a location is driven by the energy of LF. We consider ‘k’ the whole number of information place locations that are driven by LF and ‘hk’ the probability of this ‘k’ number. This change is specified by the function of likelihood mass of the binomial distribution:

$$h_k = \begin{matrix} s \\ k \end{matrix} h^k (1-h)^{s-k} \qquad 29$$

It is also known as natural development. The possibility for the same ‘k’ locations driven by LF is h^k. The probability for the (s‒k) lasting locations to be not driven by LF is $(1-h)^{s-k}$. The number of systems to select the ‘k’ location out of a whole of ‘s’ location is provided by the binomial factor $\begin{matrix} s \\ k \end{matrix}$ and can be estimated as:

$$\binom{s}{k} = \frac{s!}{k!(s-k)!} \quad 30$$

Assumed 'J' the CF of the whole usage part of a solo location when driven entirely by LF and 'G' the CF when driven entirely by the energy of HF. The whole footprint of usage 'Tu' for all locations is: If k ≥ n (if available energy of LF is sufficient or more locations than needed):

$$T_u = nJ \quad 31$$

$$Else:$$

$$T_u = (n-k)G + kJ \quad 32$$

Thus, utilizing the risks of 'k' remaining a specified term, the whole usage T_u becomes:

$$T_u = \sum_{k=n}^{s}[h_k nJ] + \sum_{k=0}^{n-1}[h_k(n-k)G + kJ] \quad 33$$

The 1st term defines the prejudiced footprint if sufficient locations are driven by the energy of LF, and the 2nd term is after this is not the issue. When swapping Eq. (30) in (34) we find the whole usage $T_u$of the infrastructure of distributed information cluster:

$$T_u = nJ\sum_{k=n}^{s}\left[\binom{s}{k} h^k(1-h)^{s-k}\right] + \sum_{k=0}^{n-1}\left[\binom{s}{k} h^k(1-h)^{s-k}(n-k)G + kJ\right] \quad 34$$

The footprint of usage outcomes entirely from the energy of electrical (EE). The intensity of emission from electricity illustrates the emissions of GHG in g CO2-eq/kWh. By using 'IJ' and 'IG' to represent the intensity of emission for electricity of LF and HF correspondingly. With Ed, the energy utilized by a solo location through the whole use level, J and G can thus be extracted as:

$$J = I_J E_d, G = I_G E_d \quad 35$$

C. Footprint of Manufacturing:

The whole footprint of manufacturing 'Tm' is a purpose of the CF cost 'O' for developing one information center location, and the number of information center locations 'm':

$$T_m = mO \tag{36}$$

it is appropriate to study the developing element ‘e’, which is the proportion of the footprint of carbon manufacturing ‘M’ of a solo location over the CF ‘G’ of a solo location:

$$e = \frac{M}{G} \tag{37}$$

Apparatus where it releases a smaller amount of GHG than the distinctive GHG released through its use stage will have an element e < 1. Now, we can modify eq:

$$T_m = meG = meI_G E_d \tag{38}$$

We learned the apparatus to be generated with HF energy, by stating ‘M’ as a role of ‘G’ in its place of ‘J’.

D. Footprint of Communication:

Drifting data or jobs through information centers suffers an additional CE amount. This will primarily be owed to the energy utilized for

- duration and preparation of the migration,
- the transport over an optical system, and
- transferring the information core to the non-active condition or contrariwise.

It is established that the operating cost of the beyond three circumstances is insignificant with esteem to the carbon released in the use and manufacturing period and can thus be overlooked for now. Information clusters are normally linked by optical systems [466].

E. Total footprint

Combining Equations from carbon manufacturing and usage, the total footprint is fixed by:

$$\begin{aligned} T = \; & meI_G E_d + nJ \sum_{k=n}^{s} \left[\begin{matrix} s \\ k \end{matrix} h^k (1-h)^{s-k} \right] \\ & + \sum_{k=0}^{n-1} \left[\begin{matrix} s \\ k \end{matrix} h^k (1-h)^{s-k} (n-k)G + kJ \right] \end{aligned} \tag{39}$$

It relies on the ‘Ed’ value, the single usage energy position. It alters altering on the information core type and size and the data and processes the jobs. We can remove this factor if we standardize the whole footprint over the solo position of usage energy ‘Ed’. Now, we can appropriately definite this whole standardized footprint T_{norm} as a task of the LF intensity of energy emission ‘IL’, the HF intensity IH energy emission, and the element e:

$$T_{norm} = \frac{T}{E_d} \quad (40)$$

$$= meI_G + nI_J \sum_{k=n}^{s} \left[\begin{matrix} s \\ k \end{matrix} h^k (1-h)^{s-k} \right] + \sum_{k=0}^{n-1} \left[\begin{matrix} s \\ k \end{matrix} h^k (1-h)^{s-k} \, (n-k) I_G + kI_J \right] \quad (41)$$

Now have a CF metric separate from the information foundation type and size, and with unit, (g CO2-eq/kWh).

XIX. Economic Benefits Towards Generation of Renewable Energy (RE):

In a few years, the potential of job creation in technologies of RE in the situation of energy evolution has expected consideration from a few stakeholders comprising civil society, the private sector, government agencies, and academia [467]. The author [468] suggests the RE integration with multi-microgrid. Adnan et al. [469] proposed the transient stability and load flow balancing with the integration of RE [470]. The International Renewable Energy Agency (IRENA) has valued jobs related to RE to grow in 2030 by about 16.7 million [471] and their yearly analysis of employment globally linked to RE displays that a population of 10.3 million were hired in 2017 [472]. Jacobson et al. projected jobs formed and jobs missing for an infrastructure of long-term of sustainable energy that delivers 100% renewable energy in entirely regions (industry, cooling/heating, transportation, electricity) from solar, water, wind power (except nuclear, biofuels, and fossil fuels power) for the California state and obtained that it will generate a 40-years 220,000 net in operation plus construction jobs (190,600 new operation jobs for 40-years and 442,200 new construction jobs for 40-years, some 413,000 jobs missing in recent California of nuclear-based and fossil-fuels industries).

Further, in ref [473] Jacobson et al. evaluate their focal situation by 2050 (generation of electricity with 100% solar power, water, and wind with entirely energy regions) would generate a permanent net of 24.3 million, 139 countries in the world have full-time jobs. This assessment comprises 52 million creations of new enduring jobs for RE of 100% and supply of transmission for huge, electrified energy regions (comprising transport, heat, and power) up to 2050, and jobs are about 27.7 million are missing in the recent industries of nuclear, biofuel, and fossil fuel [474].

Trends of employment expressively differ across the altered technologies of energy generation. Many recognizable approaches have been utilized to compute the impacts of employment in the changing energy regions and have been well familiar in [475], [476], [477]. Further, the several approaches applied can be considered top-down and bottom-up techniques, or more precisely utilize the models of input-output or analytical [478]. Moreover, [479],[480] focus on a life cycle and value-chain technique respectively, for guessing job formation mostly from RE development. Additionally, several studies reflect different kinds of jobs linked with energy production, the mutually approved arrangement is induced, indirect, and direct jobs. In ref [481], IRENA explains an operational and clear definition of these relations, with their clarification across studies. In [482] recognize that analytical training by utilizing wide surveys is established to be further suitable for provincial education, while output/input techniques are more suitable for international and national studies.

In [483], [484], Jacobson et al. evaluate the standard jobs in the main situation of per unit energy relying on jobs of the National Renewable Energy Laboratory (NREL) and models with Impacts of Economic Development. These are output/input economic models with various uncertainties and assumptions. On the other side, [471], [485] assume approaches of easier analytical impacts of estimating jobs that also have a huge transparency level. This involves using of job employment factor (EF) and intensities, explained as the quantity of jobs oriented from specific energy sources capacity investment or addition. The EF approach used for job creation estimation with the scenario of Greenpeace energy potential is acknowledged by [486], and an updated version is given in [487], [488].

A. Policy Scenario for Job Creation:

A scenario for the best policy involves the generation of 100% electricity from several options of storage and resources of RE through the different areas of the world, focusing on the Agreement of Paris. The expansion of power regions is organized by dynamic electricity growing demand obsessed by emerging and developing countries and enhances the share of RE in the whole mixture of supply. The outcomes indicate an expanding trend of RE that will recompense for the phasing out of the repeatedly decreasing fossil fuels numbers with the generation of nuclear power. From the output, the installed RE capacity will touch in 2030 by almost 14,000 GW and greater than in 2050 is 28,000 GW. A supply of 100% electricity from RE leads to almost 23,600 GW of capacities of installed geothermal power, bioenergy, hydropower, wind energy, and solar PV generation by 2050 as given in [489], [490]. The segment of RE in the whole electricity will reach 99.65% worldwide in 2050. Generation of RE, mainly wind energy and solar PV, is estimated to provide around 87% of the whole generation of electricity in 2050, of which 95% is delivered by batteries. The installed generation is governed by the storage of gas, while the whole generation of battery storage is governed. The LCOE for the global power network decreases from 70 €/MWh in 2015 and it will decline in 2050 to 52 €/MWh. Furthermore, outcomes of the regional energy transition in the world [489], [490].

B. Globally Employment Creation:

With the quick ramp-up of inducted generation capacities, developing RE technologies share are noted [491]. This tough growth in the RE region will lead to an enhancement of more than 70% in 2030 direct jobs of power, and the generally created jobs will be 1.5 times increase in 2050, rivaled to 2015. Created jobs resume to increase to reach about 34 million jobs by 2030. They decrease to about a range of 30 million and next progressively enhance to about 35 million jobs by 2050 as displayed in Figure 23.

This is usually due to huge capacities staying reinvested and replaced in, as their decommissioning provides lifetimes of 2% of overall jobs by 2050. In 2050, jobs in wind energy will be 1.4 million, batteries 4,5 million, and solar PV 22.2 million are the main technologies jobs through the period 2015-2050. Jobs of nearly 7.3 million in wind energy are provided from 2020 to 2030, and solar energy is cost-effective they push the bulk of the installation before 2050 and stabilize the wind sector jobs. In 2050 jobs created in bioenergy are 2.3 million and 1.9 million hydropower and stable share in the whole period. Solar power is perceived to swap coal and it is the major energy resource creation, as compared to 10% jobs in 2015 and 64% jobs in 2050. Moreover, it is well-accompanied creating jobs of about 13% by battery storage in 2050. On the other side, sectors of nuclear power, gas, and coal jobs are perceived to decrease rapidly as shown in Figure 23.

Classification of jobs in categories transmission, decommissioning, fuel supply, maintenance, operation, installation, construction, and manufacturing shaped through the energy period 2015-2050 is displayed in Figure 23. Jobs in the sector of fuel are decided to reduce from 44% in 2015 of the combined jobs to reach 2% in 2050, as nuclear power and fossil fuels power capacities decrease. On the opposite side, it can be noted that jobs in maintenance and operation have the most important enhancement in the total jobs that were generated in 2015 is 15% to 50% in 2050. This specifies that the evolution towards a 100% RE network permits the generation of more steady jobs, which can donate to the economic steady development of countries focused on the emerging areas of the circle and support unemployment by youth tackling [492]. In many regions of the world, this may be a reagent to progress in political stability with social well-being [493]. Additionally, Figure 24 also explains the electricity development in definite jobs, that stay quite steady around the whole period.

In 2015 897 jobs/TWh_{el} and then in 2030 increased to 1091 jobs/TWh_{el} due to huge assets during this time, ahead of 2030 it decreased in 2050 continuously to around 715 jobs/TWh_{el} [44].

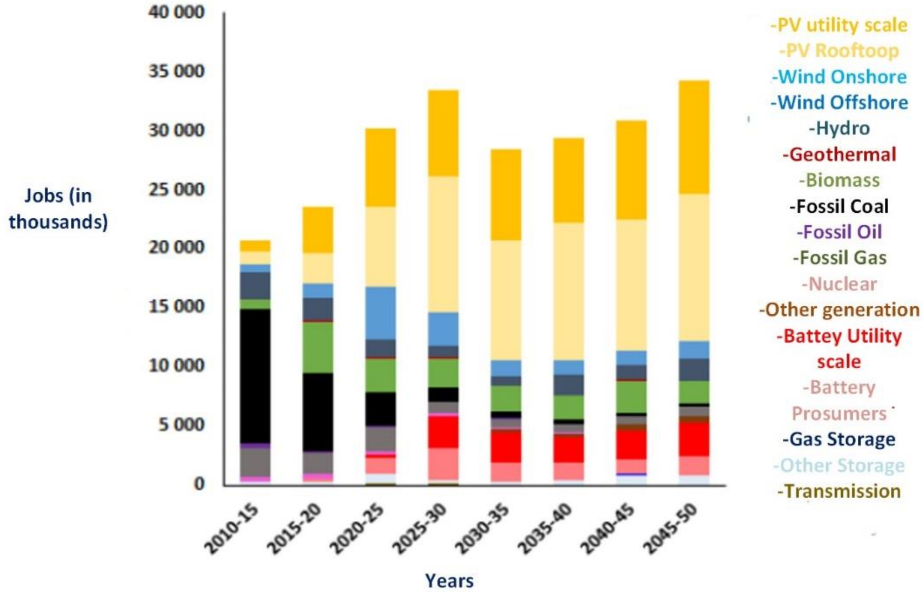


Figure 23. Jobs are generated by the several technologies of storage and power generation.

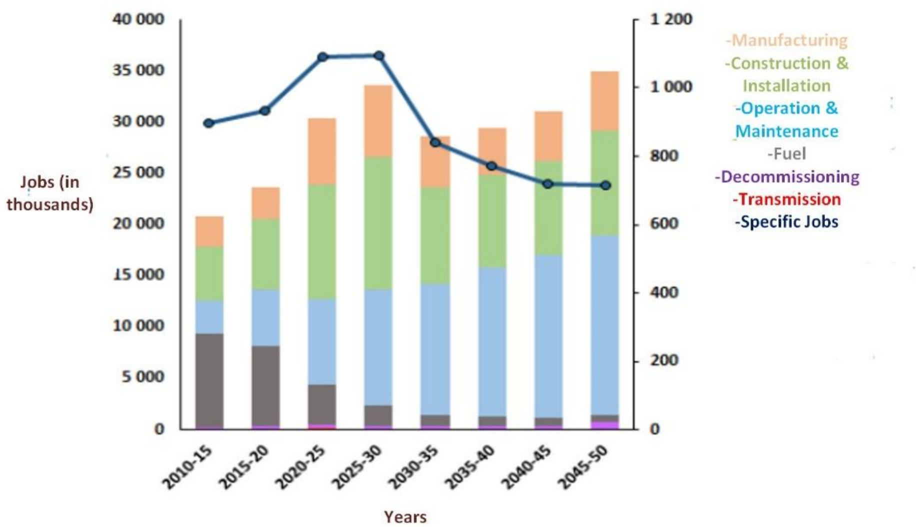


Figure 24. jobs created relied on distinct categories with specific job development during the global energy transition 2015-2050.

The evaluation of correlated reviews and the novelty of our effort are given in the Table *17* along with their advantages and limitations. This review paper is broadly distinct due to the functioning of CE reduction techniques, policies, and their complete types.

Table 17. evaluation of related reviews and the novelty of our work. Note: CE- Carbon Emission, MDD- Models of Deep Decarbonization, RE- Renewable Energy, EKC- Environmental Kuznets Curve, E&M- Energy and Movement Process, DT- Digital Twin, DM- Data Mining, FL- Federated

Learning, TL- Transfer Learning, MV- Metaverse, BC- Blockchain, IoT- Internet of Things, EC- Edge Computing, AI- Artificial Intelligence, DC- Distributed Computing.

Ref	**Duration**	**CE**	**MDD**	**RE**	**EKC**	**E&M**	**DT**	**DM**	**FL**	**TL**	**MV**	**BC**	**IoT**	**EC**	**AI**	**DC**
[231]	2009-2019	√	×	√	√	×	×	×	×	×	×	×	×	×	×	×
[494]	2010-2020	√	×	√	×	×	×	×	√	√	×	√	√	√	√	×
[495]	1993-2023	√	√	√	×	×	×	×	×	×	×	×	×	×	×	×
[496]	2008-2019	√	×	√	×	√	×	×	×	×	×	×	×	×	×	×
[497]	2007-2017	√	×	√	×	×	×	×	×	×	×	×	×	×	×	√
[498]	2014-2024	√	×	×	×	×	×	×	√	√	×	×	√	√	√	×
[499]	2012-2022	√	×	√	×	×	×	×	×	×	×	√	√	×	×	×
[500]	2013-2023	√	×	√	√	×	×	×	×	×	×	√	√	×	×	×
[501]	2012-2022	√	×	√	×	×	√	×	×	×	√	√	×	×	√	×
[502]	2010-2020	√	×	×	×	×	×	√	×	×	×	×	×	×	×	×
[37]	2008-2019	√	×	√	√	×	×	×	×	×	×	×	×	×	×	×
Our work	Up to 2022	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√

XX. Conclusion and Future Research:

This paper's energy transition roadmap for global decarbonization highlights the crucial position that reducing CE shows in contending climate change (CC). The evolution to a fully RE system is not purely a strategic essential but necessary for attaining meaningful reductions in GHG emissions. This survey approves that RES such as hydropower, wind, and solar, are decisive in significantly decreasing carbon footprints (CF), thereby supporting global objectives for carbon neutrality.

This review specifies a specified roadmap for transitioning to RE, outlining vital strategies and steps for successful implementation. It focuses on the requirement for a diverse combination of renewable technologies to guarantee a continuous and stable energy supply. This review indicates that the energy decarbonization sector is a complex problem where several political, social, technical, economic, and environmental aspects must be instantaneously considered. The current condition concerning the sector's energy decarbonization is far from acceptable. Supporting both "affordable and clean" energy for entirety makes us unite social justice and environmental sustainability while remaining inside the planetary social boundaries.

The economic evaluation depicted in the survey further emphasizes the benefits of RE in the context of CE reduction. While the primary capital investment in RE infrastructure and technologies can be noteworthy, the environmental benefits and long-term savings are substantial. Reduced dependence on fossil fuels translates into lower carbon emissions and decreased pollution, aligning economic incentives with environmental goals. The survey emphasizes that investing in RE is not just an environmental obligation but also a sound decision economically that can raise job creation and sustainable growth.

Policy regulatory support and frameworks are vital sections of the transition roadmap. This research has been categorized into three of the E&M movement phases. Innovative technology applications at every process phase result in a reduction in CE with the RE integration with the current sources of energy and advancement in the efficiency of E&M. Different techniques like DT, DM, FL, AL, and many others are discussed briefly in this survey for reducing CE and attaining green environment.

Finally, this review underlines that a 100% RE will be achieved in the future and significant CE reductions need collective action at all stages of society. individual commitment, corporate responsibility, and public awareness are key to lashing the forward transition. By fostering a supporting RE initiatives and sustainability culture, stakeholders can participate in a global effort to decrease CE and mitigate climate change. This survey serves as both a guide and a demand for action, demonstrating that with innovative strategies and unified effort, a low-carbon and sustainable future is within reach.

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