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Blockchain-Based Carbon Accounting for Green Grid Infrastructure: A Decision-Making Approach Integrating Life Cycle Assessment and Multi-Agent Simulation

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ABSTRACT

To support the achievement of carbon neutrality, a transparent mechanism for monitoring carbon emissions throughout the entire lifecycle of energy infrastructure, including UHV power grids and electricity transmission networks, is required. This study introduces a blockchain-enabled framework that integrates electricity, heating, gas, and cooling demands to facilitate comprehensive carbon emission tracing. The proposed framework enables carbon emission records to be stored securely in an immutable and transparent manner through blockchain technology. Moreover, it expands carbon accounting to encompass every stage of the energy lifecycle, beginning with energy production and continuing through system decommissioning. To capture uncertainties associated with energy consumption and blockchain operations, Monte Carlo Simulation (MCS) is applied. Critical system variables, including energy utilisation, emission indicators, and transaction duration, are modelled under varying operational conditions to examine the framework's reliability. Furthermore, the framework incorporates Life Cycle Assessment (LCA) alongside multi-agent simulation to investigate the long-term environmental impacts of energy infrastructure. A case study undertaken in Hengqin, China, indicates that carbon emissions increased to 480 tonnes in June owing to greater cooling demand, while emissions reached 490 tonnes in January because of heating requirements. The capability of the power transmission network to accommodate these seasonal fluctuations contributed to lower emission levels during off-peak periods. The findings confirm that blockchain provides a secure, transparent, and decentralised solution for carbon accounting in integrated energy systems by removing intermediary involvement and lowering operational expenditure. Additionally, the framework offers stakeholders greater authority over energy pricing and distribution processes. Overall, the proposed approach establishes a comprehensive carbon accounting framework for green grid infrastructure, enhancing security, operational efficiency, and system flexibility across the entire energy lifecycle.

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1. Introduction

Climate change mitigation and the pursuit of carbon neutrality have become major global priorities for governments and industries. Consequently, greater attention has been directed towards reducing emissions from the energy sector, which remains one of the largest contributors to greenhouse gas emissions and therefore plays a decisive role in achieving these environmental objectives. Within this sector, green grid infrastructure, particularly Ultra-High Voltage (UHV) power transmission systems, is essential for transmitting renewable energy over long distances [1]. Although these systems facilitate the large-scale integration of clean energy, carbon emissions are generated throughout their entire lifecycle, including raw material extraction, construction, operation, maintenance, and eventual decommissioning.

Therefore, developing an accurate approach for quantifying emissions across every lifecycle stage has become increasingly important. However, fragmented data sources, inconsistent information, the absence of real-time verification, and non-uniform reporting practices continue to hinder the establishment of reliable emission baselines and effective regulatory compliance [2]. As energy systems become increasingly interconnected and complex, implementing a transparent and reliable carbon tracking mechanism is indispensable. Such a mechanism provides complete visibility of emissions, preserves data integrity, and supports informed decision-making throughout the lifecycle of energy infrastructure [3].

Recent advances in digital technologies have provided practical alternatives to overcome the limitations associated with conventional carbon accounting approaches. Among these technologies, blockchain has emerged as a decentralised, immutable, and tamper-resistant ledger capable of improving the credibility of carbon accounting systems [4]. Within energy applications, blockchain enables carbon emission records to be securely stored and traced, preventing unauthorised modification once the information has been recorded [5]. This capability enhances data reliability while reducing dependence on third-party verification services by streamlining the reporting process [6]. Likewise, LCA offers a recognised methodology for quantifying carbon emissions throughout every stage of an energy project's lifecycle [7]. It further identifies emission-intensive processes, thereby supporting resource optimisation and environmentally sustainable decision-making [8].

In addition, MCS is employed to represent uncertainties associated with energy consumption, emission intensity, and operational conditions [9]. Through probabilistic modelling, MCS evaluates system performance across numerous possible scenarios. MAS further complements this analysis by representing interactions among various stakeholders, including energy producers, consumers, regulators, and service providers. Collectively, these techniques establish a comprehensive framework for monitoring, analysing, and mitigating carbon emissions within modern energy systems. To overcome the shortcomings of existing carbon accounting practices, this study proposes a comprehensive blockchain-based framework for green grid infrastructure. The proposed architecture combines blockchain technology with LCA, MCS, and MAS to support end-to-end carbon emission tracking across integrated energy systems comprising electricity, gas, heating, and cooling. Blockchain enables secure sharing and transparent management of emission information among stakeholders, thereby strengthening accountability while improving operational efficiency.

To ensure reliable system performance under varying operational conditions, uncertainties in energy consumption and emission indicators are addressed using MCS. Furthermore, LCA facilitates detailed assessment of environmental impacts throughout the infrastructure lifecycle, whereas MAS captures the dynamic interactions among stakeholders and their influence on emission outcomes. To demonstrate its practical applicability, the proposed framework is evaluated through a case study conducted in Hengqin, China. The analysis examines seasonal emission variations together with the contribution of the power transmission system to overall carbon emissions. The findings confirm that the proposed framework provides secure, transparent, and cost-effective carbon accounting. By reducing intermediary involvement, enhancing stakeholder control over energy distribution and pricing, and supporting scalable implementation, the proposed framework offers an effective solution for promoting sustainable energy development and advancing carbon neutrality. Overall, it presents an integrated blockchain-based approach for carbon accounting across green grid infrastructure.

2. Related Works

Consequently, the existing body of literature is comprehensively reviewed to illustrate the increasing sophistication of digital technologies, including blockchain, simulation techniques, and lifecycle assessment tools, for carbon emission monitoring within energy systems. Numerous studies have developed frameworks and models that employ blockchain to strengthen data security, utilise LCA to assess environmental impacts, and adopt simulation approaches, such as MCS and MAS, to address uncertainty and stakeholder behaviour. Although these studies demonstrate that such technologies improve traceability, transparency, and decision-making, they continue to encounter several common challenges, including substantial computational requirements, interoperability constraints, and limited scalability in practical implementations. Table 1 summarises the principal findings of previous studies by highlighting the methodologies adopted, their key strengths, and the corresponding limitations associated with carbon accounting and sustainable energy infrastructure.

The development of IT, especially artificial intelligence, is progressing at a high rate, consuming a significant part of the internal auditing fields of the accounting profession. AI presents almost limitless opportunities to improve audit activities by boosting efficiency, accuracy, and risk management.

Table 1

Problem Formulation

Author(s)	Techniques Involved	Advantages	Disadvantages
Kumar et al. [10]	Control & Computational Strategies	Suitable for developing regions	Lacks lifecycle carbon tracking
Liu et al. [11]	Multi-Agent Nash Equilibrium	Optimizes large-scale renewable integration	High computational demand
El Maghraoui et al. [12]	Smart Grid Reliability Framework	Enhances grid fault resilience	No focus on emission analysis
Kilthau et al. [13]	P2P Trading with SSI	Enables decentralized control	No integrated carbon accounting
Khalid [14]	AI-Enabled Digital Systems	Supports predictive and sustainable grid ops	High cost and digital dependency

A study focusing on the Indian and African energy markets [10] investigated control and computational strategies for integrating green energy into socio-technical power infrastructures. The proposed approaches addressed challenges specific to emerging economies and demonstrated how these could be incorporated into effective renewable energy integration strategies. However, the study did not incorporate lifecycle carbon tracking, thereby limiting the comprehensiveness of its sustainability assessment. A Multi-Agent Nash Equilibrium approach was adopted in [11] to optimise gain scheduling for large-scale integration of wind and photovoltaic power generation. The proposed model enhanced coordination among distributed energy resources and improved resource allocation within renewable energy networks. Nevertheless, its considerable computational complexity restricts its suitability for real-time applications and large-scale energy systems.

A comprehensive framework for improving smart grid reliability was presented in [12], emphasising power system stability and resilience. By integrating advanced digital technologies, the framework enhanced fault detection, system monitoring, and operational reliability. Despite these advantages, lifecycle carbon assessment and emission accounting were not incorporated into the proposed methodology. An energy dispatch framework combining peer-to-peer (P2P) energy trading with Self-Sovereign Identity (SSI) technology was introduced in [13]. The framework strengthened consumer privacy, increased user control over energy transactions, and supported congestion management within distributed energy networks. However, it did not include mechanisms for carbon emission monitoring or accounting, thereby limiting its contribution to environmental sustainability. Under the Energy 4.0 paradigm, the study reported in [14] explored the role of artificial intelligence in accelerating digital transformation within sustainable power systems. The proposed approach improved predictive analytics, operational monitoring, maintenance planning, and overall grid efficiency. Despite these operational benefits, implementation requires substantial investment in digital infrastructure, while carbon accounting capabilities remain absent.

The reviewed studies collectively reveal several persistent limitations in existing approaches to carbon accounting and green grid infrastructure. Although many proposed frameworks enhance energy system optimisation, they generally overlook lifecycle carbon tracking, which is essential for comprehensive sustainability assessment. Similarly, while improvements in grid reliability, decentralisation, and operational efficiency have been widely reported, carbon emission monitoring and environmental impact assessment remain inadequately addressed. Furthermore, although artificial intelligence-based approaches enhance predictive system performance, they involve significant implementation costs and depend heavily on advanced digital infrastructure without integrating carbon accounting capabilities. These limitations highlight the need for a comprehensive framework capable of combining secure, transparent, and immutable carbon emission tracking throughout the lifecycle of energy infrastructure. To overcome these shortcomings, this study proposes a blockchain-based framework integrating multi-energy flow management, LCA, and MCS to account for uncertainties throughout the energy generation, consumption, and decommissioning stages.

3. Integrated Framework for Carbon Emission Accounting in UHV Power Grids and Transmission Systems

The proposed framework provides comprehensive carbon accounting across the entire lifecycle of UHV power grids by integrating advanced technologies and analytical methodologies. Initially, real-time multi-energy data are collected from key UHV grid components, including information on energy consumption, transmission losses, and carbon emissions through IoT-enabled sensors and smart meters. These data are subsequently utilised to quantify lifecycle carbon emissions by estimating carbon equivalents based on energy inputs and corresponding emission factors during the construction, operational, and decommissioning phases. Blockchain technology, supported by automated smart contract validation, ensures that emission records remain secure, transparent, and immutable.

Furthermore, MCS is employed to capture uncertainties associated with energy demand, grid efficiency, and emission factors, producing probabilistic emission estimates and identifying critical risk areas. LCA is applied to quantify cumulative carbon emissions and evaluate their long-term environmental impacts, whereas MAS simulates stakeholder interactions under different carbon pricing mechanisms and policy scenarios. By integrating these techniques, the proposed framework delivers a comprehensive data-driven approach for optimising the carbon footprint of UHV power grids while supporting informed decision-making towards carbon neutrality and sustainable energy development. The overall architecture of the proposed framework is illustrated in Figure 1.

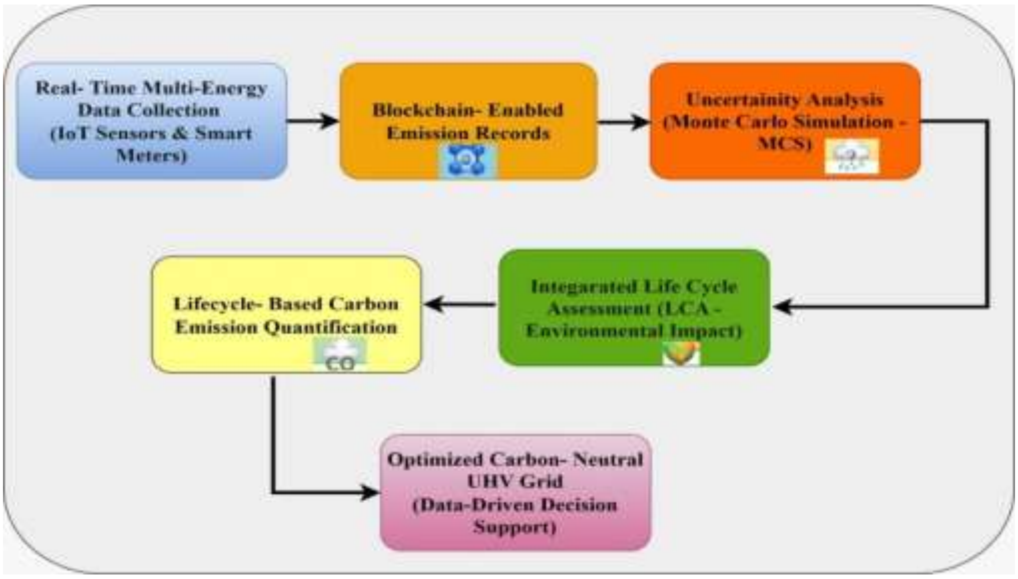

Fig.1: Proposed Architecture

3.1. Real-Time Multi-Energy Data Collection Across the UHV Grid Lifecycle

The implementation of real-time multi-energy data acquisition across the entire lifecycle of UHV power grids and their associated transmission networks establishes a reliable and transparent framework for carbon emission accounting. Owing to the extensive geographical coverage and high-power operation of UHV grids exceeding 800 kV, continuous monitoring is essential to effectively manage their large-scale transmission infrastructure [15]. To achieve this, digital control technologies, together with IoT-enabled sensors, smart meters, and phasor measurement units (PMUs), are installed at substations, converter stations, transmission corridors, and load centres to capture accurate information on the interactions between electricity transmission, heating networks, gas systems, and industrial cooling demands within the UHV infrastructure [16]. These monitoring devices continuously acquire high-frequency time-series measurements, including current (I), voltage (V), frequency (f), power factor (PF), ambient temperature (T), and reactive power (Q), enabling real-time assessment of transmission losses and power quality. The resistive power loss in UHV transmission lines is determined using the following equation:

$$P_{loss} = I^2 . R \quad (1)$$

The parameter (R) denotes the resistance of UHV conductors, which varies with conductor material, operating temperature, and transmission distance. Owing to the high operating currents and long transmission distances associated with UHV networks, transmission losses constitute a significant factor that must be accurately evaluated for reliable carbon emission accounting [17]. To ensure comprehensive emission monitoring, the proposed data acquisition framework encompasses every stage of the UHV grid lifecycle, beginning with system design and extending through the production of concrete, steel, and high-voltage equipment, operational transmission losses, substation cooling processes, maintenance-related energy consumption, and finally decommissioning or infrastructure repurposing. Emission records generated throughout these lifecycle stages are automatically assigned time stamps and synchronised with Geographic Information System (GIS) data to associate UHV transmission line locations with time-specific emission assessments [18]. The total energy consumption for the integrated multi-energy system is calculated using the following equation:

$$E_{total} = E_{elec} + E_{heat} + E_{gas} + E_{cool} \qquad (2)$$

A comprehensive evaluation of energy consumption enables accurate estimation of carbon footprints through the application of emission conversion factors [19]. During Step 2, the blockchain infrastructure preserves the collected information by maintaining secure, immutable records of carbon emission data across all nodes throughout every stage of the UHV grid lifecycle. This integrated data management framework establishes a reliable foundation for intelligent lifecycle carbon accounting within green energy infrastructure systems [20].

3. 2. Lifecycle-Based Carbon Emission Quantification

The proposed methodology begins by quantifying carbon emissions generated throughout the complete lifecycle of the UHV power grid and its transmission network, covering the construction, operational, and decommissioning stages [21]. Carbon emissions associated with individual UHV transmission components, including substations, transformers, transmission lines, and distribution units, are estimated by considering material consumption, energy utilisation, and lifecycle activities [22]. The objective is to evaluate the carbon footprint of each lifecycle phase in accordance with the requirements of ISO 14064 and the GHG Protocol. These internationally recognised standards facilitate consistent and accurate quantification of carbon emissions across all stages of energy production, material processing, and transportation [23]. Carbon emissions at each lifecycle stage are determined using the following equation:

$$CO_{2-eq} = \sum(E_I \times EF_I) \qquad (3)$$

The formula measures energy usage through item i using E_I as a standard unit. It quantifies the overall energy demand associated with manufacturing materials, transporting them to the required locations, and operating electricity distribution systems [24]. The 〖EF〗_I stands as the emission factor that shows how much CO2 comes out when using specific energy for process I. Project-specific carbon emissions are influenced by two primary factors: the energy sources utilised throughout construction and the selection of materials incorporated into the infrastructure [25].

During the construction phase, emissions associated with steel tower fabrication are evaluated separately from those produced through concrete utilisation in substation development. Construction processes are highly energy-intensive, and their emission factors are typically greater than those of many other industrial activities, particularly in steel production [26]. In the operational phase, most emissions arise from transmission losses within the UHV network. Most operational carbon output is therefore linked to electrical energy dissipated as heat along transmission lines. These losses are quantified by relating to dissipated electrical power due to the emission intensity of the supplying power generation sources. Consequently, emission levels during operation are influenced by transmission distance, grid performance efficiency, and the composition of energy sources, including hydropower and other generation types [27].

Emissions during the decommissioning stage are derived from the energy required for system dismantling, material processing, and disposal or recycling of infrastructure components. Certain recycling processes are themselves energy-intensive and may generate significant emissions. For instance, dismantling transmission towers for steel recovery involves cutting, transportation, and processing activities that contribute additional emissions. The proposed framework evaluates the UHV transmission system across all stages, from development through operation to end-of-life dismantling, to determine total lifecycle carbon impact [28]. Emissions from all phases are consolidated into a single lifecycle-based measurement, enabling systematic assessment of environmental impacts across the entire system lifespan. This comprehensive approach allows stakeholders to clearly identify emission hotspots within each stage of the UHV lifecycle, supporting optimisation of system performance and reduction of emissions. It further enables improved decision-making aimed at minimising carbon output throughout the full lifecycle of the UHV grid and transmission infrastructure [29].

3.3. Blockchain-Enabled Emission Recording and Smart Validation

The system records emission information from the UHV power grid and transmission infrastructure through carbon transaction blocks. Each block securely stores key grid-related attributes, including geographical location, time stamp, lifecycle stage, and emission category. Once the emission datasets are aggregated, analytical methods are applied to compute the corresponding emission values using established calculation models.

$$CO_2 - eq = \sum(E_I \times EF_I) \quad (4)$$

The energy consumption verification uses the E_I and 〖EF〗_I process data inputs and checks these values against emission standards in smart contracts which then confirm them [30]. The carbon emission accounting framework verifies recorded data against predefined benchmarks through smart contracts, which ensure compliance with ISO 14064 and GHG Protocol requirements. When the input data satisfies these validation conditions, the corresponding transaction block is appended to a permissioned blockchain. This controlled-access blockchain architecture permits authorised stakeholders to retrieve information while preventing unauthorised access and prohibiting any modification of finalised records [31]. The integration of blockchain infrastructure with smart contract mechanisms enhances emission reporting by ensuring data immutability alongside automated verification processes. Consequently, the system supports reliable and cost-efficient monitoring and validation of carbon emission data across all UHV grid lifecycle stages, thereby contributing to the fulfilment of established sustainability standards [32].

3.4. Uncertainty Analysis through Monte Carlo Simulation (MCS)

A simulation model of the UHV power grid system is developed using MCS to capture stochastic behaviour within power system operations. Variability in input parameters introduces inherent uncertainty into system measurements. In this framework, MCS treats key variables such as energy demand (E), transmission efficiency (η), and emission factors (EF) as probabilistic inputs defined by their respective statistical distributions [33]. Transmission efficiency is modelled using a normal distribution, whereas energy consumption is represented through a log-normal distribution to reflect its asymmetric variation patterns. Each input variable is assigned an appropriate probability distribution, after which multiple simulation iterations are executed using randomly sampled values. This process generates a wide range of emission outcomes, producing a probabilistic emission profile that defines expected carbon emission ranges. The resulting emissions are computed using the following equation.

$$CO_2 - eq = \sum(E_I \times EF_I \times \eta_I) \qquad (5)$$

The algorithm measures total energy use E_I and emission factor 〖EF〗_Itogether with transmission efficiency ηi for each simulation i. The test system identifies the dominant factors contributing to variations in carbon emissions, particularly changes in transmission efficiency and fluctuations in energy consumption. By applying MCS, the framework isolates inefficiencies that lead to elevated emission levels and evaluates how operational adjustments can improve overall system performance. The analysis of probabilistic outcomes provides decision-makers with a clearer understanding of potential risks and system responses under different operating conditions, thereby supporting more informed management decisions [34].

3.5. Integrated Life Cycle Assessment and Multi-Agent Decision Simulation

The UHV grid research phase evaluates total carbon emissions across all development stages using LCA, spanning from initial design through operation and maintenance to final dismantling. This lifecycle-based methodology quantifies all greenhouse gas emissions generated from system inception to decommissioning, including the operational period. Within the MAS framework, agents representing energy producers, grid operators, and regulatory authorities interact to manage carbon pricing mechanisms across different jurisdictional levels [35]. The simulation environment enables assessment of how varying carbon pricing strategies and regulatory policies influence grid operations and environmental outcomes. Through MAS-based dynamic modelling, operational control of the grid is continuously adjusted, while stakeholder behaviour is adapted to align system performance with carbon governance objectives. The integration of LCA and MAS provides a data-driven approach for evaluating UHV grid emissions, enabling reliable emission tracking and supporting the achievement of sustainability targets.

4. Performance Evaluation

This section evaluates the implementation outcomes and performance of the integrated carbon emission accounting system developed for UHV power grids. Following deployment of the proposed framework, emission quantification accuracy improved due to the incorporation of real-time data integration, in contrast to conventional static models. IoT-enabled sensors facilitated lifecycle-based emission tracking through high-resolution monitoring, while blockchain ensured data security, immutability, and auditability, thereby outperforming traditional database systems in terms of transparency and integrity. The reliability of system forecasting was also enhanced, as MCS effectively managed uncertainties associated with power transmission variability and fluctuating energy demand.

Furthermore, the integration of LCA with MAS enabled stakeholders to conduct adaptive policy simulations and construct interaction-based models that are not supported by conventional frameworks. Overall, the proposed system demonstrates improved precision in emission monitoring, greater resilience to operational disruptions, and enhanced policy adaptability, making it a robust solution for carbon neutrality in high-voltage infrastructure. The energy infrastructure project records CO_2 emissions in tonnes across four lifecycle stages, namely transportation and material production, installation, construction activities, and operation, as illustrated in Figure 2.

During the design stage, total emissions are approximately 100 tonnes, with transportation contributing the largest share at around 50 tonnes. Emissions increase significantly during procurement and construction phases, reaching about 230 tonnes, primarily driven by infrastructure production and onsite construction activities. The operational stage exhibits the highest emissions, totalling roughly 290 tonnes, with major contributions originating from transportation processes and material-related production activities. In contrast, the decommissioning stage shows a substantial reduction in emissions to approximately 50 tonnes, reflecting the gradual decline in project-related activities across all categories. These results highlight the necessity of implementing effective emission reduction strategies, particularly targeting construction and operational phases where most emissions are concentrated.

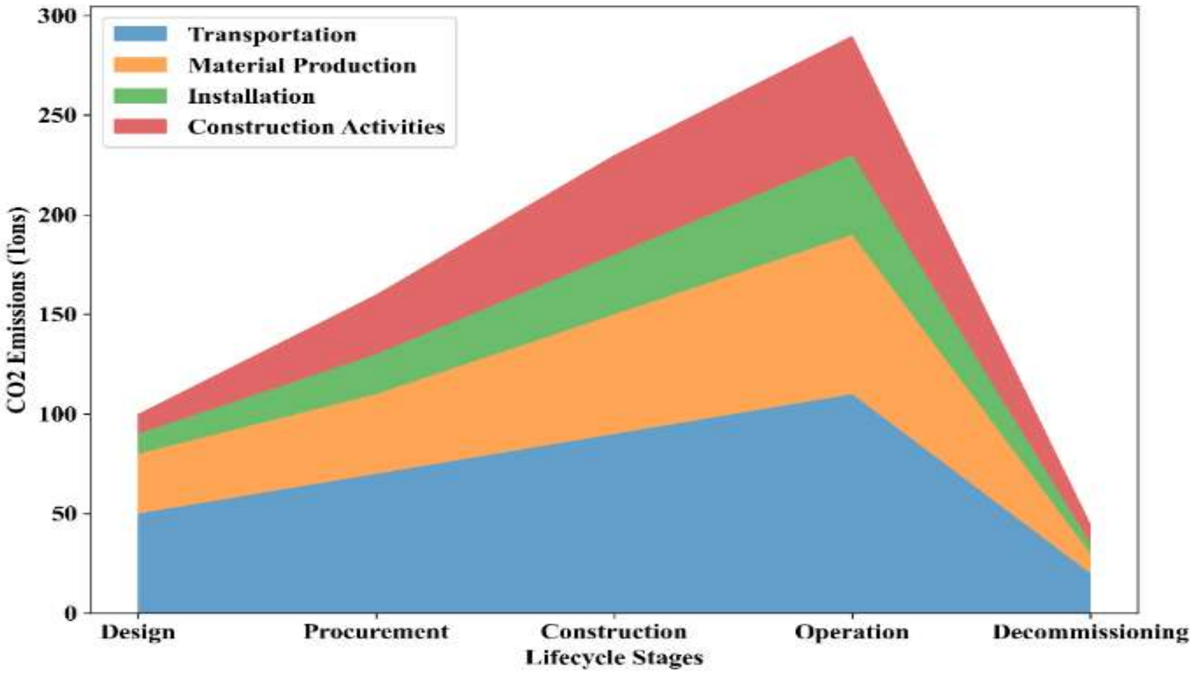

Fig.2: Co2 Emission

Figure 3 illustrates monthly fluctuations in carbon emissions (in tonnes) over a 12-month period. The data show substantial variability, with emissions increasing from approximately 270 tonnes in January to a peak of around 480 tonnes in June. February records comparatively elevated emissions at about 410 tonnes, followed by a declining trend from March through April. Lower emission levels observed in May contribute to a sharp reduction that continues into August, when the annual minimum of approximately 140 tonnes is reached. Emissions then rise again, reaching about 420 tonnes in October before declining towards the end of the year, falling to nearly 110 tonnes in December. These variations indicate a strong seasonal influence on emission patterns, driven by changes in energy demand, environmental conditions, and operational activity across different months.

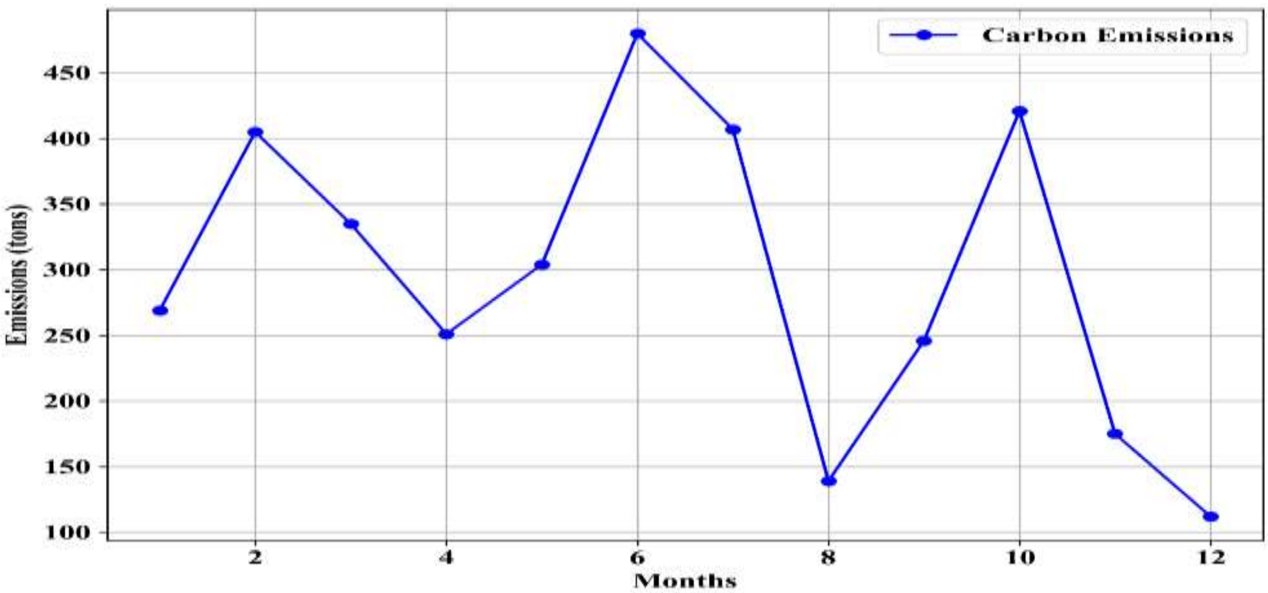

Fig.3: Emission

Lifecycle-stage CO_2 emission analysis for three UHV projects (A, B, and C) is presented in Figure 4. For Project A, total emissions are approximately 345 tonnes, distributed across operation (120 tonnes), construction (100 tonnes), procurement (70 tonnes), design (50 tonnes), and decommissioning (10 tonnes). Project B records total emissions of about 310 tonnes, with the highest contribution arising from the operational phase (110 tonnes), followed by construction (90 tonnes), procurement (60 tonnes), design (40 tonnes), and decommissioning (10 tonnes). In Project C, overall emissions reach roughly 390 tonnes, comprising operation (130 tonnes), construction (100 tonnes), procurement (80 tonnes), design (60 tonnes), and decommissioning (10 tonnes). The results indicate that the operation and construction stages are the primary contributors to carbon emissions across all three projects, whereas the decommissioning phase consistently contributes minimally to the overall environmental impact.

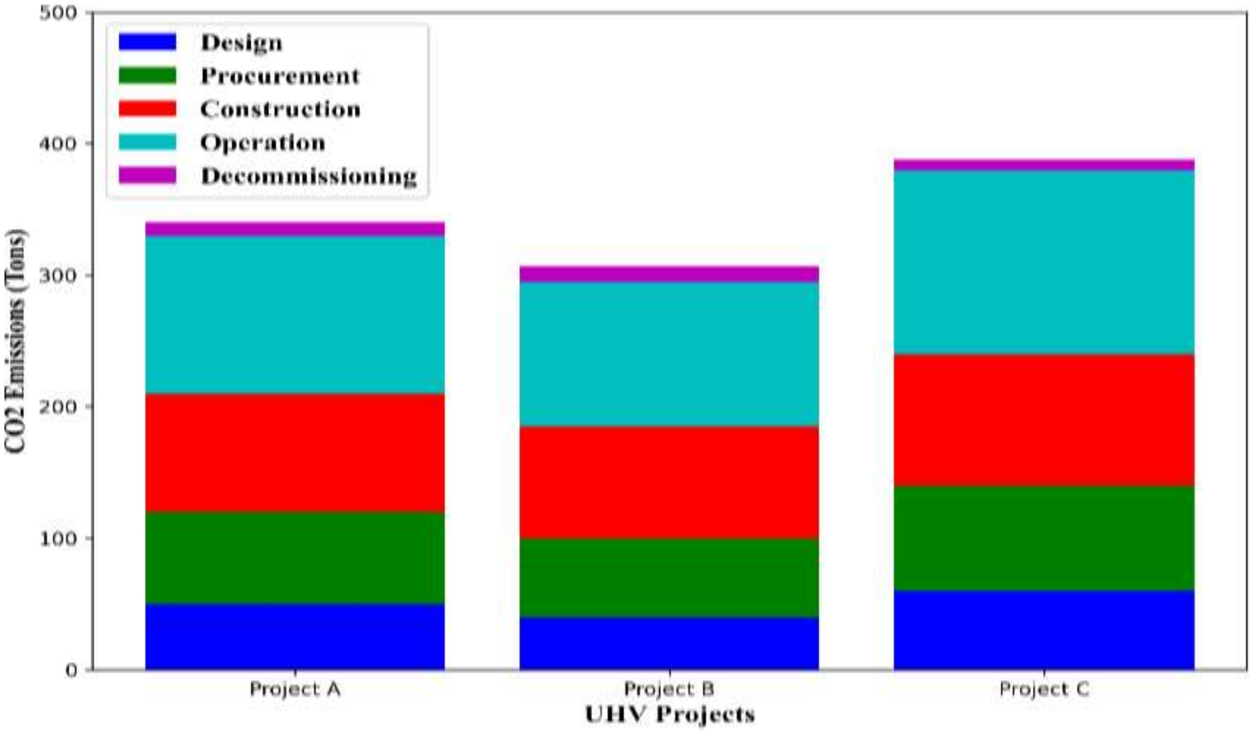

Fig.4: Co2 Emission UHV Projects

Figure 5 compares carbon emission monitoring results between a traditional system and a blockchain-based system. The traditional approach records approximately 4000 tonnes of emissions, whereas the blockchain-enabled system tracks around 2500 tonnes. This reduction of roughly 1500 tonnes indicates improved accuracy and operational efficiency in carbon footprint monitoring when using blockchain-based frameworks. The blockchain system enhances carbon accounting by preventing data duplication, ensuring immutability, and providing full transparency of recorded transactions, thereby enabling more reliable and optimised emission reporting. The lower emission values observed in the blockchain system are attributed to improved transparency, which reduces instances of unreported or undocumented emissions during infrastructure development processes. Overall, the results support the assertion that blockchain technology strengthens transparency and empowers stakeholders in carbon emission management by eliminating intermediaries and reducing operational costs.

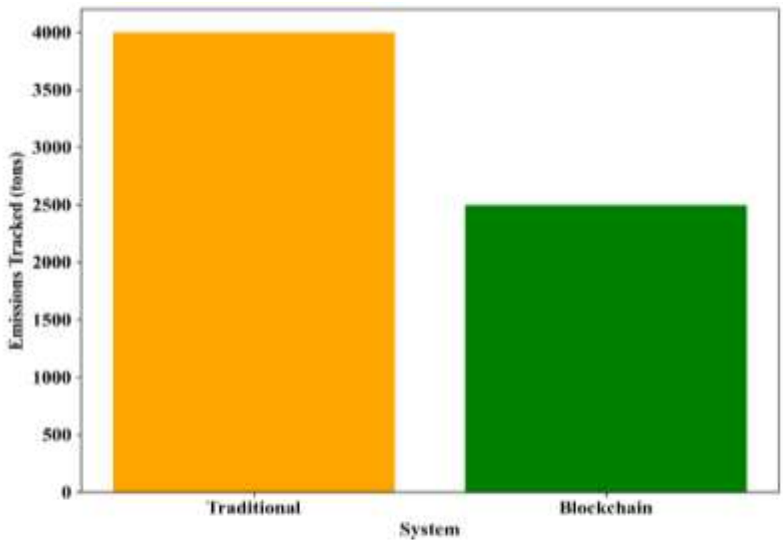

Fig.5: Emission Tracked

Figure 6 presents the distribution of carbon emissions across the three principal lifecycle stages of a project, spanning production, operation, and decommissioning. The results indicate that the operational phase contributes the largest share of emissions at 50.0%, primarily due to continuous system operation and maintenance activities that significantly increase overall environmental impact. The production stage accounts for 33.3% of total emissions, mainly driven by raw material extraction, equipment manufacturing, and construction processes. In comparison, the decommissioning phase contributes 16.7%, representing the lowest proportion, although dismantling and waste processing still require considerable energy and resources. This lifecycle-based emission distribution reinforces the importance of prioritising emission reduction strategies during the operational stage, while also promoting sustainable practices in production and decommissioning activities. The integration of blockchain-based carbon accounting further enables real-time monitoring across all lifecycle stages, ensuring accurate and transparent data support for sustainable decision-making in energy infrastructure development.

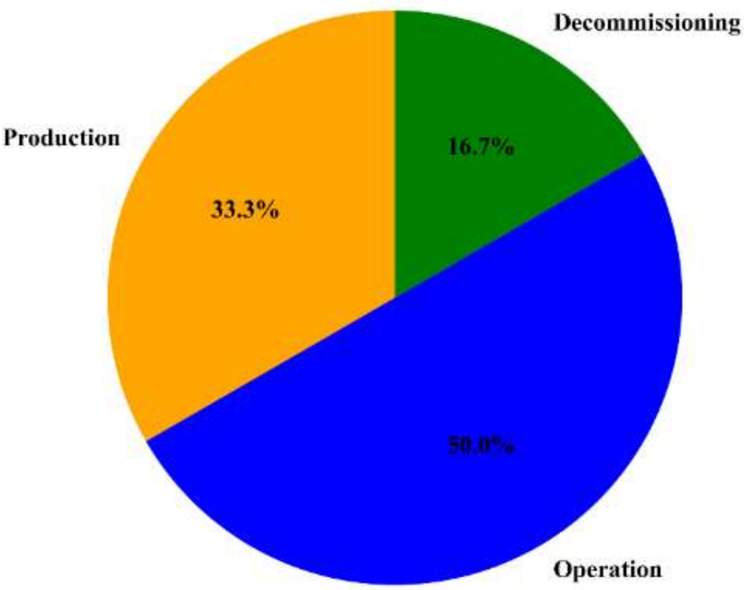

Fig.6: Lifecycle Emissions

Figure 7 illustrates monthly carbon emission variations over a 12-month period, revealing clear seasonal patterns measured in tonnes. The data indicates that emission levels are strongly influenced by seasonal energy demand fluctuations. The highest emissions occur in January, reaching approximately 490 tonnes, primarily due to increased heating requirements during winter. A marked decline is observed by March, where emissions drop to around 100 tonnes as seasonal energy demand decreases. In May, emissions fall further to approximately 125 tonnes following the higher levels recorded in April. During the summer period, emissions rose significantly, particularly in June and July, reaching about 470 and 430 tonnes respectively, driven by increased cooling demand. Elevated emission levels are also observed in September and October, at approximately 470 and 460 tonnes, before decreasing to around 270 tonnes in November. In December, emissions rise again to roughly 330 tonnes due to the early activation of heating systems during winter onset. These fluctuations demonstrate the importance of incorporating seasonal variability into carbon accounting frameworks. Real-time emission tracking supported by blockchain systems enables dynamic adjustment of energy-related carbon outputs monthly, allowing stakeholders to implement targeted emission reduction strategies during high-impact periods.

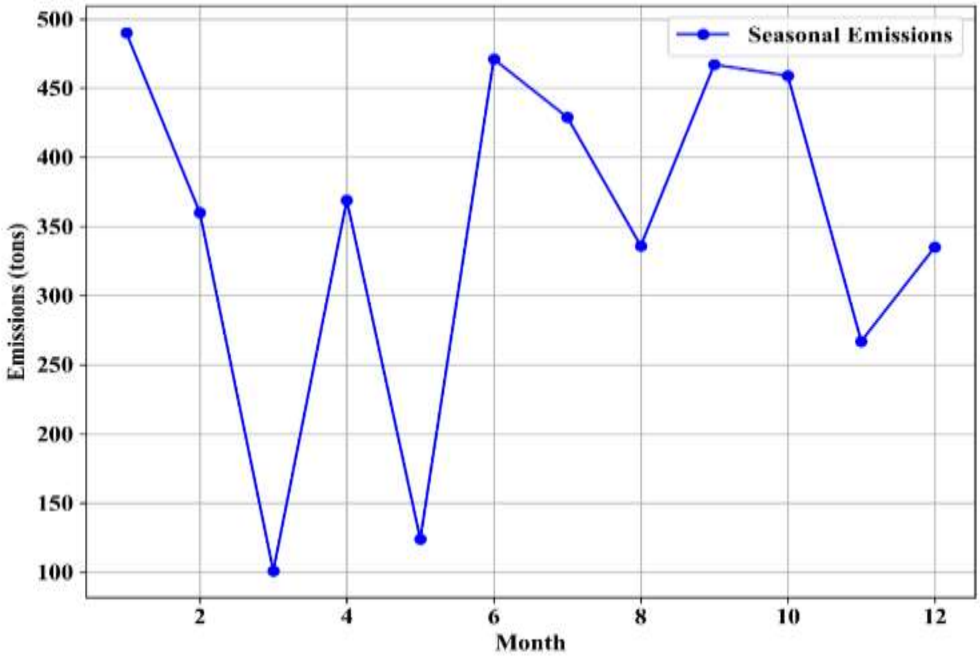

Fig.7: Emission Validation

Figure 8 presents a statistical distribution illustrating the frequency of carbon emission levels across defined tonne intervals. The distribution exhibits an approximately normal pattern, with the highest frequency observed in the 200–250 tonne range, reaching about 85 occurrences. This mid-range interval represents the dominant emission band, indicating a typical or baseline emission behaviour across the monitored energy systems. In contrast, emission values outside this central range, particularly between 100 and 300 tonnes, occur less frequently, with each category generally recording fewer than 20 observations. The histogram demonstrates an overall symmetrical shape, as emission values are distributed around the mean with comparable frequencies on both the lower and higher ends of the distribution. This pattern is useful for representing emission variability and uncertainty, making it particularly suitable for MCS applications. When integrated within blockchain-based carbon accounting frameworks, this distribution supports improved emission forecasting, enhanced risk assessment, and more informed decision-making for sustainable energy project planning.

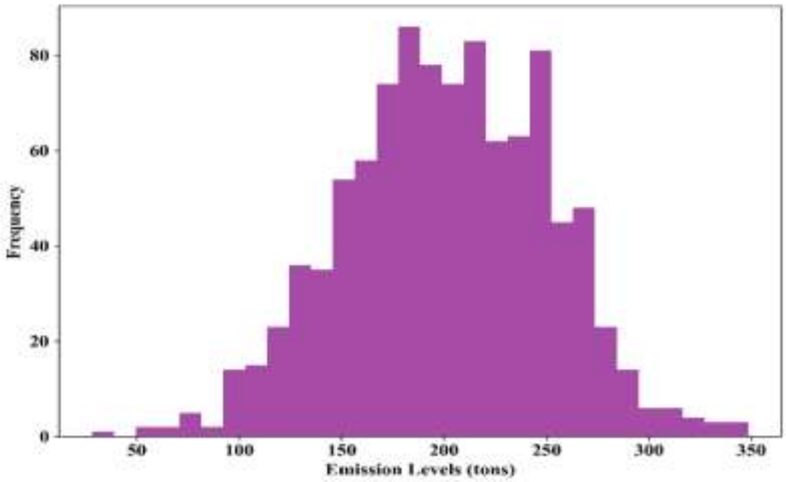

Fig.8: Monte Carlo Simulation

Figure 9 presents a comparative analysis of energy consumption and corresponding carbon emissions between Hengqin and Shanghai, China. In Hengqin, an electricity usage level of 1,000 kWh results in carbon emissions of approximately 250 kg. In contrast, Shanghai exhibits significantly higher energy consumption at around 2,000 kWh, producing about 400 kg of carbon emissions. Although Shanghai consumes roughly twice the energy of Hengqin, its emissions are only about 1.6 times higher. This indicates a non-linear relationship between energy usage and carbon emissions, suggesting differences in energy efficiency or variations in energy source composition. The results highlight the importance of location-specific energy strategies, demonstrating how regional consumption patterns directly influence total urban carbon emissions.

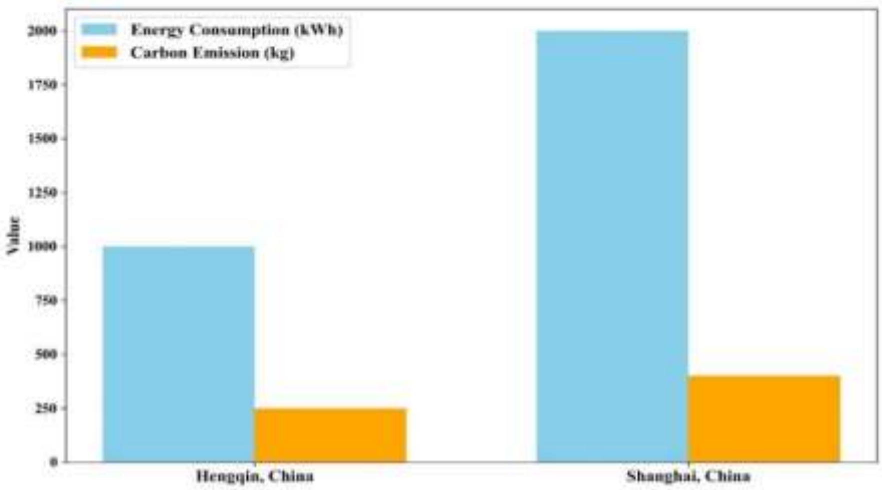

Fig.9: Energy Consumption and Carbon Emission

The comparison presented in Figure 10 indicates that the proposed blockchain-based framework outperforms traditional Life Cycle Assessment (LCA) across key dimensions of carbon accounting. In terms of transparency, traditional LCA is rated low due to limited traceability of emission data, whereas the proposed framework achieves a very high rating by enabling secure, immutable, and blockchain-based tracking of emissions. Regarding lifecycle coverage, conventional LCA demonstrates only a medium level of capability as it typically evaluates isolated stages of energy infrastructure projects. In contrast, the proposed framework provides a comprehensive assessment across the entire lifecycle, from material production and manufacturing through to operation and end-of-life retirement, resulting in a very high rating. For energy type coverage, traditional LCA remains limited at a low level, while the proposed framework achieves a very high rating by incorporating multiple energy vectors, including electricity, gas, heating, and cooling systems. Overall, the proposed framework demonstrates superior performance in delivering detailed, transparent, and integrated carbon accounting for complex multi-energy systems across their full lifecycle.

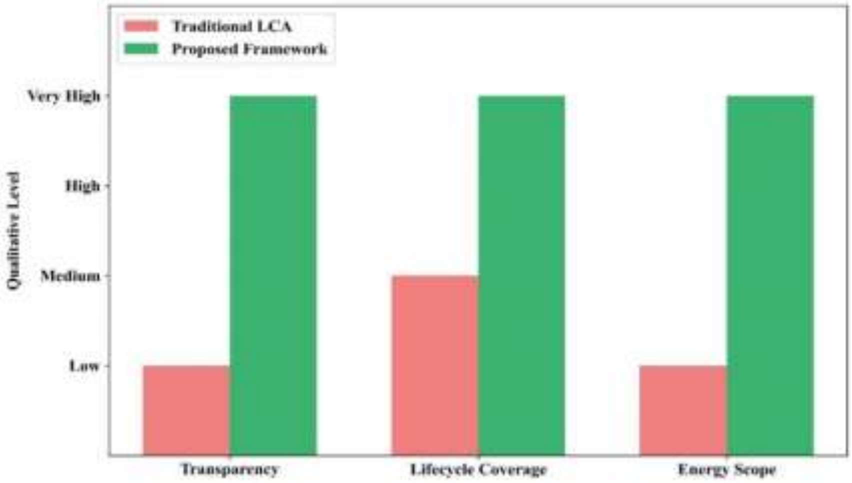

Fig.10: Qualitative Level

Figure 11 provides a comparative assessment of monthly carbon emissions across three stakeholder categories: utility companies, regulators, and consumers. The results show that consumers consistently contribute the highest emission levels throughout the year, reaching a peak of over 410 tonnes in August. Utility companies exhibit comparatively stable emission patterns, generally fluctuating within the 250–300 tonne range. In contrast, regulators record the lowest emissions overall, with levels declining to below 100 tonnes by December. The observed monthly variations, particularly the pronounced peaks in consumer emissions and the lower values associated with regulatory entities, indicate significant disparities in emission contributions across stakeholder groups. These findings highlight the need for targeted mitigation strategies, with particular emphasis on managing consumer behaviour and addressing seasonal demand variations to achieve effective reductions in overall urban carbon emissions.

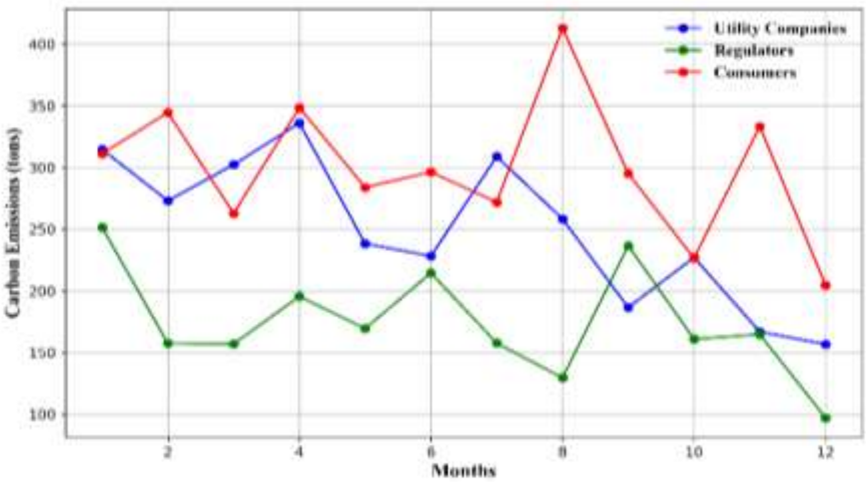

Fig.11: Carbon Emissions

4.1. Discussion

The integrated carbon emission accounting framework for UHV power grids demonstrates superior performance compared to conventional systems by enabling more accurate and transparent emission measurement. Through the integration of IoT sensors and blockchain technology, the framework supports real-time lifecycle monitoring with enhanced auditability, overcoming the limitations of non-integrated traditional approaches. Across the UHV lifecycle, the construction and operational phases represent the highest emission contributors, recording approximately 290 tonnes and 230 tonnes respectively, while the decommissioning stage contributes around 50 tonnes.

Monthly emission analysis reveals clear seasonal variation, with peak values observed in January (490 tonnes) and June (480 tonnes), and minimum levels recorded in March (100 tonnes) and August (140 tonnes), reflecting fluctuations in heating and cooling-driven energy demand. At the project level, emissions are dominated by the operational phase across Projects A, B, and C, with values of 345 tonnes, 310 tonnes, and 390 tonnes respectively. Comparative system analysis shows that blockchain-based monitoring records approximately 2,500 tonnes of emissions, whereas traditional systems track around 4,000 tonnes, indicating improved precision and reduced redundancy in data reporting. In terms of lifecycle distribution, operation contributes the largest share of total emissions at 50%, followed by production at 33.3%, and decommissioning at 16.7%. MCS results indicate that emission values predominantly cluster within the 200–250 tonne range, with a peak frequency of 85, confirming system stability under uncertainty. Regional comparison further shows that Shanghai consumes 2,000 kWh of energy compared to 1,000 kWh in Hengqin, resulting in emissions of 400 kg and 250 kg respectively, suggesting relatively higher efficiency in Shanghai’s energy utilization patterns.

Overall, the blockchain-based framework achieves very high performance in transparency, lifecycle coverage, and energy scope assessment, whereas traditional LCA systems remain limited to low-to-medium performance levels. The incorporation of MAS further enhances the framework by modelling stakeholder interactions and enabling localized emission analytics, thereby improving forecasting accuracy and supporting adaptive, data-driven energy management strategies within sustainable energy systems.

5. Conclusion

The proposed blockchain-based system enables full lifecycle carbon tracking across energy infrastructure projects covering electricity, heating, gas, and cooling systems through secure, transparent, and tamper-resistant mechanisms. It integrates blockchain with MCS, LCA, and MAS to capture uncertainties in energy consumption, emission variability, and transaction times. Compared with traditional systems reporting about 4,000 tonnes of emissions, the blockchain framework records approximately 2,500 tonnes, reflecting improved transparency and around 37.5% higher data accuracy. Across lifecycle stages, emissions are dominated by the operational phase (50%), followed by production (33.3%) and decommissioning (16.7%), all requiring continuous monitoring. Data from Hengqin, China, shows clear seasonal variation, highlighting the importance of temporal tracking as emissions rise during peak summer and winter demand. The framework remains robust under varying operational and environmental conditions. MCS-based results show an approximately normal emission distribution centred in the 200–250 tonne range, indicating stable performance across scenarios. In addition, the framework reduces operational costs and improves stakeholder control over pricing and energy distribution by removing intermediaries and automating carbon accounting. Overall, the proposed system provides a scalable, efficient, and sustainable solution for carbon tracking in multi-energy systems, supporting long-term carbon neutrality goals in green power grid development.

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