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Research on energy consumption monitoring and accounting based on carbon emission factors of embedded IoT system

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SUMMARY: *The current model for power-grid carbon-embodied emissions is mainly limited by fixed-emission inventory methods, long-computing periods and generalised spatial boundaries; thus, these hindrances significantly obscure the details and evolution characteristics within dynamic multi-energy system networks. In order to theoretically and realistically correct the inherent flaws of traditional aggregated estimates, a high-resolution dynamic carbon emission factor estimation system coupled with embedded IoT edge computing networks is presented in this paper. Systematic boundary revision of the accounts at various stages including transmission substations and distribution stations transforms stationary regional inventories into localised, continuously updating node-level carbon flow matrices. Based on the topological-preserving principle of an advanced quasi-input-output (QIO) system, it is established through rigorous reasoning that the aggregated amount of carbon-equivalent influx at any localised infrastructural node must be a sum of the internal thermodynamic dissipation and operating carbon emissions. Based on this theory, it will be further operationalised by constructing ubiquitous high-frequency electricity consumption monitoring networks to calculate CO2 emissions from power grids with different structures without increasing additional physical measurement equipment. Micro-second level operating data from a regional multi-source substations is used to empirically verify that the embedded measurement technology can accurately reflect short-term changes in carbon intensity triggered by fluctuations of renewable energy power grids and nonlinear loads. Finally, based on this multi-dimensional and layered representation framework of China's electric vehicle manufacturing industry chain, we propose some countermeasures from the aspects of technological innovation capacity building, market mechanism optimization adjustment, government intervention and support policy improvement to promote continuous optimization and upgrading of the industrial chain.*

KEYWORDS: *Topological Carbon Allocation; Dynamic Emission Factor Mensuration; Generalized Quasi-Input-Output Matrix; Edge-Computing Telemetry Arrays; Spatiotemporal Carbon Dynamics; Multi-Source Cyber-Physical Networks*

1 Introduction

1.1 Background and The Decarbonization Imperative

The global climate trajectory has reached an important turning point; the anthropogenic enhancement of greenhouse gases' concentration requirements for a fundamental restructuring of the Industrial and Energy Systems architecture. Although it is becoming increasingly

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prominent in the country's economy nowadays; In light of this background, compared to other fields on the international stage nowadays, The significance of this area remains highly crucial for achieving the two goals globally [1]. The grid Structure Change caused by shifting towards a distributed System Including Multiple renewable Energy Sources exhibits very high Randomness In terms of operational Difficulty. Under such an Environment, accurate determination of carbon intensity needs to be met by regulations for administration to serve as a necessary prerequisite for realising carbon-aware control and demand side management [2]. However, due to the co-occurrence of the problem of real-time electric power transmission with associated environmental externalities, there are also prominent issues requiring breakthroughs immediately. Based only on static historical inventory data and a single-time-emissions assessment, traditional approaches are unable to adapt dynamically to current circumstances of modern Power Systems [3]. The need for an immediate, detailed carbon-accounting system is not due to regulations but to meet the requirement of embedding the cost of carbon in every link of the operation process of power grids at this moment [4-7].

1.2 Limitations of Conventional Carbon Accounting Paradigms

At present, the existing carbon quantification systems mainly use inventory-based approaches and thus have difficulty identifying CEFs that exhibit a degree of volatility over time due to spatial variations. Generally accepted views about traditional paradigms acknowledge that the IPCC's Inter-governmental Panel on Climate Change and various country regulators are based, they mainly examine Regional Annual Averages; however, significant fluctuations occur among Energy Allocation at Node Levels. At this level, there is a temporal delay and spatial dispersion; The dynamic impact of low-carbon assets such as distributed photovoltaics and wind farms is eliminated by the primary mode of energy generation base. [8-10] The lack of structure in static CEFs is also complicated by the complex topology of the transmission and distribution network; when large amounts of power flow simultaneously across various generation points, nonlinear changes occur in the carbon footprint at particular locations [11]. Therefore, there is no response-based and feedback-driven measuring System to execute precise targeted carbon reduction Strategies precisely. The deficiency of real-time carbon Telemetry in the market leads market participants and Grid Operators to make decisions based on inadequate information; empirical studies show that such estimating Methods deviate from actual operating Conditions by as high As 35%, thereby impacting the accuracy of Carbon trading Mechanisms and Green Energy Certification [12].

1.3 The Convergence of Edge Intelligence and Grid Telemetry

The generation of ubiquitous Power Internet of Things (PIoT) offers an outstanding technical base to address the above-mentioned accounting defects. By combining the architecture of an embedded system with edge computing technology in traditional distribution and metering systems to transform idle electricity readings into dynamic environmental intelligence. Since there is no limitation of telemetry delay in the distributed cloud model, large volumes of data cannot be immediately processed locally; instead, it is forwarded to the server network for further processing centrally. The decentralised intelligent system is able to monitor the high-frequency fluctuations in power flows continuously, as well as synchronously update node carbon potentials [13]. By integrating a high-performance microprocessor into the gateway-metering device to directly implement advanced topological algorithms, such as the quasi-input-output (QIO) model at the basic layer of the power grid. So far, this change from an awareness-oriented carbon accounting has been a necessary update to the digitalisation direction of the Energy system and provides rich sources of data for implementing decarbonization strategies via practice. Utilising an existing electric energy metering system to avoid the high cost of setting up specialised hardware deployment; meanwhile, by employing software-defined intelligent technology, a full-spectrum spatiotemporal carbon transparency can be achieved [14].

1.4 Research Objectives and Structural Organization

To break down the conceptualised and technical barriers between static macro-accounting and dynamic micro-quantification to establish a topologically-preserving carbon-dioxide emission factor assessment system at higher resolution levels. The research systematizes to develop an improved Quasi-input-output structure for mapping the environmental externality of power generation facilities on physical transmission channels in the power grid; Therefore, it provides a scientific theoretical basis linking energy consumption with carbon emission responsibilities [15]. The implemented method is described by a built-in IoT Deployment plan with emphasis on low-latency edge computing for instantaneous node factor determination [16]. Following are organised as follows: In section two, provide an in-depth theoretical presentation of the QIO model and derive the mathematical expression of nodal carbon potential equation; Section 3 outlines the Architectural Design of embedded IoT Monitoring System focus On developing high-frequency telemetry hardware-software Synergy requirements; Section 4 presents a complete empirical verification based on microlevel operational data sets from multi-source regional substations combined with spatial-temporal dynamic analysis; Section 5 discuss implications of the findings for grid optimization and policy formulation ; Finally, Section 6 summarizes research outcomes Synthesize the research results and identify directions for building autonomous carbon-aware Energy Networks.

2 Theoretical Foundation

2.1 Topological Abstraction of Multi-Source Power Networks

Precisely quantify the emission flow in a multi-type heterogeneous electrical matrix requires reducing the physical Grid infrastructure to a high-order, highly-structured directed acyclic graph model at an essential level of abstraction. The regional power system can be regarded as a topological space $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where the vertices of $\mathcal{V}$ are heterogeneous generation facilities, transformation substations and terminal load centers; And the edges in $\mathcal{E}$ represent the physical transmission channels that enable energy flow [17]. Thus, under such an abstraction process, tracking environmental externalities is now a mathematical foundation for us. At the same time, the inherent directionality of active power flow determines the direction of topology edges, and therefore cannot form localised circulation loops which would be mathematically unstable to the carbon accounting matrix. Within this abstractions of Space, a constant influx of electricity from carbon- intensive thermal power plants and zero - emission photovoltaic systems forms an uncertain boundary condition that spreads across all connected nodes following Kirchhoff's Circuit Law. Therefore, the tracking of carbon emissions has been completely separated from administrative geographic divisions, and it can be considered as a pure network-flow problem under topology-preserving rules and dissipative-dynamics conditions. [18-20]

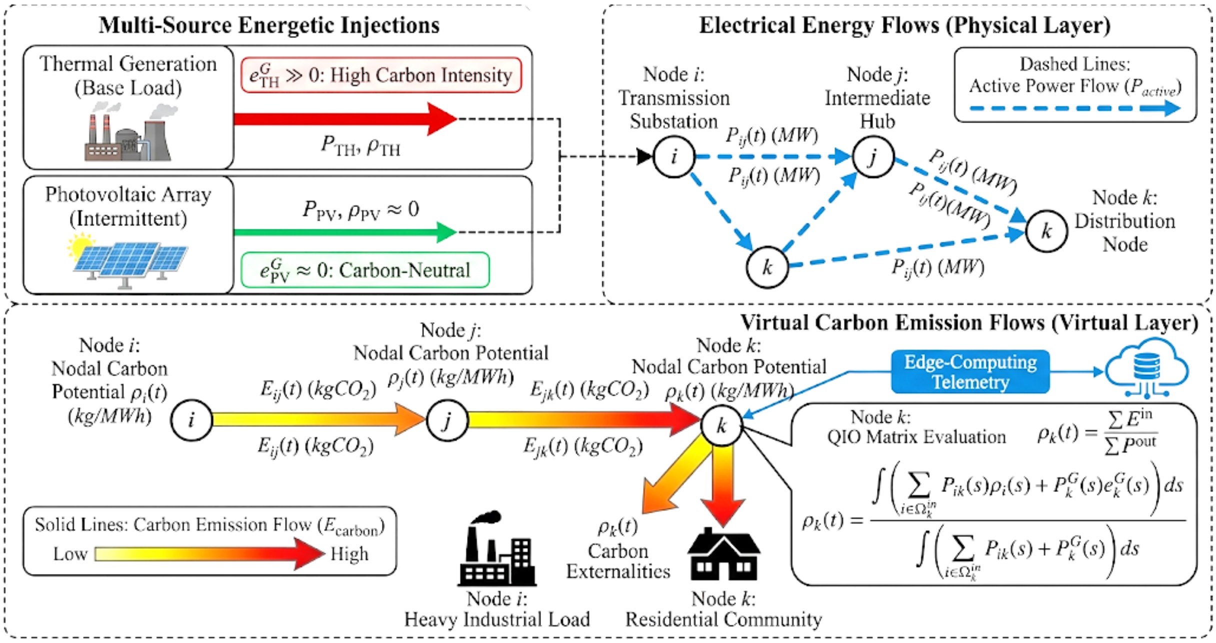

Figure 1: Directed Topological Isomorphism of Carbon Emission Flows in Multi-Source Networks

2.2 The Generalized Quasi-Input-Output (QIO) Conservation Matrix

To encapsulate the complicated superposition effect of energy currents caused by numerous types of primary energy sources, and in this sense, the conventional economic input-Output model transforms into a generalised quasi-input-output conserved Matrix applicable to Transient Power system Analysis. [21] This foundation of axioms for this system states that carbon emission behaves as an irreversibly tied virtual network fluid and requires all active power trajectory constraints at each infrastructure node according to the law of mass conservation. For any transitional vertex $k \in \mathcal{V}$, at this time instant it is required that the total energy flow entering should be precisely equivalent to summing up all outgoing powers plus localised intrinsic thermodynamic loss. Formally, the state-of-the-art balance can be expressed as: The Sets of neighbours' precursor and successors at node k are denoted by Ω_k^{in} and Ω_k^{out}, respectively. Therefore, in terms of the node power balance equation that governs the system's operating condition:

$$P_k^{in}(t) = \sum_{i \in \Omega_k^{in}} P_{ik}(t) + P_k^G(t) = \sum_{j \in \Omega_k^{out}} P_{kj}(t) + P_k^L(t) + \Delta P_k(t) \quad (1)$$

Within this formulation, $P_{ik}(t)$ represents the active power injected from adjacent node i into node k at temporal instance t, while $P_k^G(t)$ denotes the localized generation capacity organically embedded within the node. Conversely, $P_{kj}(t)$ signifies the active power migrating towards successor node j, $P_k^L(t)$ is the end-of-life consumption at this particular node k; and $\Delta P_k(t)$ denotes the internal ohmic and ferromagnetic power loss due to voltage transformation or long-distance transmission within the system. From the energised state to the environment, under the QIO framework, it is required that the overall carbon-equivalent flow at a particular point in space should be reasonably distributed across all outbound energy links and inner-dissipation system networks. The construction of this needs to form an overall tracking model based on a carbon emissions reduction equation.

$$R_k(t)\rho_k(t) = \sum_{i\in\Omega_k^{in}} P_{ik}(t)\rho_i(t) + P_k^G(t)e_k^G(t) \quad (2)$$

Here, $R_k(t)$ designates the aggregate active power transiting through node k, while $\rho_k(t)$ embodies the critical concept of the 'Nodal Carbon Potential', defined as the dynamic carbon emission factor strictly associated with the blended electrical mixture residing at the node. The parameter $\rho_i(t)$ reflects the inherited carbon intensity propagating from upstream nodes, and $e_k^G(t)$, on the other hand, is a manifestation of an individual generation asset directly connected to node k's life-cycle carbon emission rate. In this sense, an inherent mathematical structure can ensure that the carbon burden of system loss and end-of-life use is dynamically linked with the current topology of multiple-energy sources simultaneously..

2.3 Dynamic Carbon Potential Differential Equations

Traditional methods typically employ static algebraic summation to aggregate all high-aggregated historical parameters; therefore, they cannot discover the frequency-oscillation nature of grid carbon dioxide intensities resulting from renewable energy intermittency. To obtain precise temporal resolution, a rigorous expansion of the static QIO formulation in terms of continuum mechanics leads to a group of dynamic carbon potential differential equations [22]. Assuming continuous temporal differentiability of the telemetric data streams, the instantaneous nodal carbon potential is redefined as the time-integrated ratio of the accumulated carbon influx to the cumulative energetic throughput over an infinitesimally small observation window. As an inherent form of filtering it reduces significant fluctuations caused by brief transients in the signals at edges of distributed electric energy meter installations. A precise expression for the nodal carbon potential $\rho_k(t)$ after integration is obtained strictly.

$$\rho_k(t) = \frac{\int_{t-\tau}^{t}\left(\sum_{i\in\Omega_k^{in}} P_{ik}(s)\rho_i(s) + P_k^G(s)e_k^G(s)\right)ds}{\int_{t-\tau}^{t}\left(\sum_{i\in\Omega_k^{in}} P_{ik}(s) + P_k^G(s)\right)ds} \quad (3)$$

In this further deduction, τ is an integration-time-constant parameterised by the operation frequency of the internal embedded IoT sensing infrastructure. In addition, as infrastructure-based energy loss will significantly increase the system's overall carbon emissions, there is also an explicit transmission-loss carbon allocation mechanism included here. This function can dynamically assign the environment's obligation for direct connection impedance distribution to individual real-time thermodynamic loss-active power branch pairs. The dynamic carbon equivalent loss $\Lambda_{kj}^{carbon}(t)$ specifically caused by the transmission corridor connecting node k to node j is measured in terms of the current instant nodal carbon potential and the individual branch-specific Ohmic dissipation properties:

$$\Lambda_{kj}^{carbon}(t) = \rho_k(t)\cdot I_{kj}^2(t)R_{kj}\cdot\Theta(t) \quad (4)$$

where $I_{kj}(t)$ is the instantaneous branch current magnitude, R_{kj} is the equivalent physical resistance of the transmission conductor, and $\Theta(t)$ operates as a dimensionless meteorological normalization coefficient accounting for temperature-induced resistance variations. This microscopic allocation ensures that structural inefficiencies within the grid architecture are accurately penalized in terms of carbon intensity.

2.4 Algorithmic Implementation of Edge-Computing Carbon Telemetry

The detailed mathematical elegant constructions require a strong computing base to support their application in practice; therefore, they are implemented by deploying decentralised edge computing nodes that directly integrate with the physical metering gateway devices. To address the widespread problem of asynchrony in large-scale wide-area Internet of Things (IoT) networks and random fluctuations in telemetry, raw sensor data need to go through an intensive optimisation process before entering the QIO conservation matrix [23]. The formulation of the dynamics carbon measurement process as a convex optimisation problem, and its design aimed at reconciling rapid-sampling sensor data with theoretical topology constraints. A refined time-penalised dynamic loss function $\mathcal{L}(\theta)$ is introduced to keep the observed node-carbon potential close to its expected theoretical boundary in the face of extended changes in the power system.

$$\mathcal{L}(\theta) = \sum_{t=1}^{T} \|\hat{\boldsymbol{\rho}}(t) - \boldsymbol{\rho}(t)\|_2^2 + \lambda \int_0^T \left(\frac{\partial \boldsymbol{\rho}(t)}{\partial t}\right)^2 dt + \gamma \|\boldsymbol{P}^{in} - \boldsymbol{P}^{out}\|_1 \tag{5}$$

In this objective function, $\hat{\boldsymbol{\rho}}(t)$ denotes the vector of raw empirical carbon potentials derived from uncalibrated edge telemetry, $\boldsymbol{\rho}(t)$ represents the theoretically smoothed nodal carbon potential vector intended for final accounting, and the second term serves as a strict Tikhonov regularization mechanism scaled by the hyperparameter λ to penalize physically implausible high-frequency derivatives in the carbon trajectory. The final term introduces an L1-norm structural constraint multiplied by a stringent penalty factor γ, guaranteeing absolute adherence to the underlying energy conservation laws despite localized sensor degradation. This edge-native, algorithmic-based realisation guarantees the environmental accuracy of the generated spatio-temporal carbon-accounting matrix while also ensuring computational durability.

3 Embedded IoT System Architecture and Hardware Implementation

3.1 Hardware Topology of the Edge-Computing Telemetry Array

The practical physicalization of the continuous-time Quasi-Input-Output (QIO) carbon tracking matrix necessarily involves a Paradigm Shift from conventional centralised supervisory control and data acquisition (SCADA) systems to highly decentralised, edge-intelligent hardware topologies [24]. This Designed architecture relies heavily on numerous high-quality smart Gateways to connect each critical component at a fine level throughout all parts such as main transmission Lines, Transformation Substations and End Distribution LINES. Conventional Digital Meters are typically intended only for Low-Frequency Billing; on the other hand, Embedded Telemetry Nodes have been developed to serve as Autonomous Edge-Computing Micro-Servers with strong multi-core reduced instruction set computer(RISC) architecture that can execute complicated Matrix Operations and local-time-constrained loss function $\mathcal{L}(\theta)$. To obtain the transient oscillation of photovoltaic injection and non-linear load harmonic components, a high-accuracy analog-to-digital converter (ADC), working at kHz sampling rates, is added to the physical sense layer to ensure mathematical rigor of instantaneous energy throughput integral calculation under strong anti-aliasing artifacts. By distributing computing power directly at the site of the original data to eliminate long-distance wide-area network delays that occur in cloud-based carbon accounting systems and crowded bandwidth problems associated with internet access; Nodes can determine their own carbon potential efficiently without affecting stable operation of Grid Dispatch Control Systems.

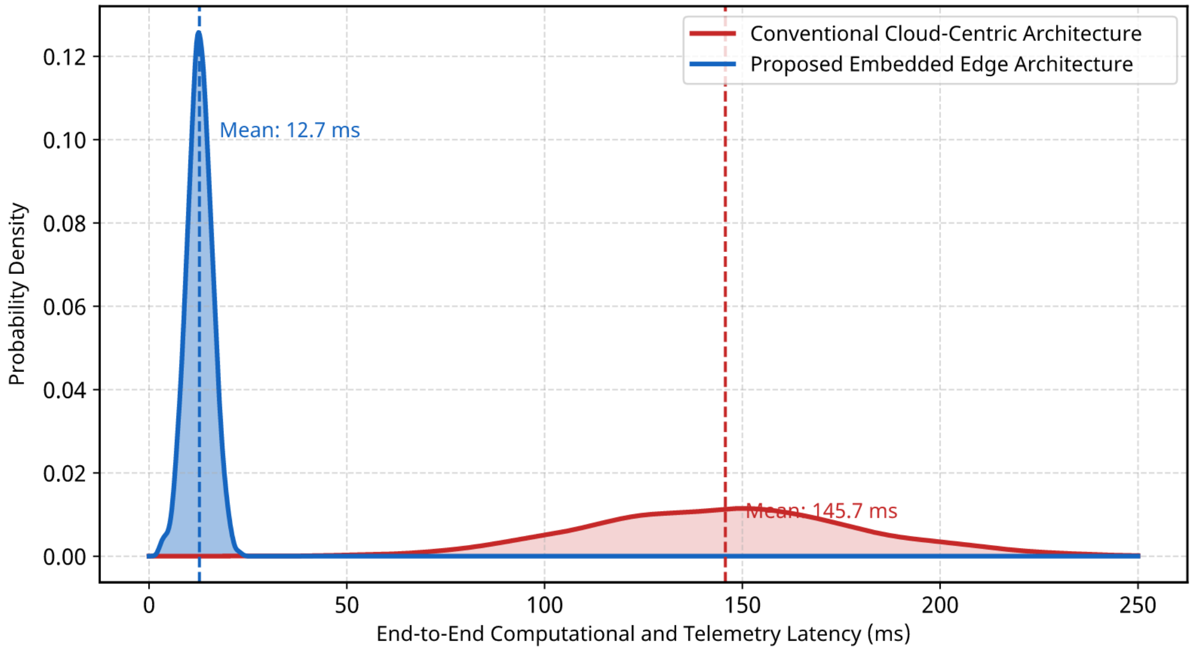

Figure 2: Empirical Latency Distribution Analysis: Edge-Computing vs. Cloud-Centric Carbon Telemetry

3.2 Precision Temporal Synchronization and Multi-Threaded Data Acquisition

The absolute temporal consistency requirement of the spatially distributed sensor array is necessary to ensure that the mathematics behind the dynamic QIO matrix; Several micro-seconds of clock error among several subordinate node stations can cause serious numerical instability in carbon flow differential equations. To resolve the inherent asynchrony of the wide-area IoT network's packet transmission and improve the precision of time measurement in this system, we use hardware timestamps to ensure an accuracy of μs or higher within a scattered telemetry zone. On this tight-synchronized time base, the software system of the low-power node adopts a concurrency and multithreaded data collection pipeline to decouple the determinate high-frequency sensor query from the stochastic out-of-band telecommunications process [25]. There is a specific unambiguous thread that constantly reads the voltage and current waveform data to calculate the instantaneous active energy $P_{ik}(t)$; An asynchronous background process regularly retrieves information from above-mentioned carbon potential array, performs some calculations on this data and then forwards the result of these operations in real time through lightweight publish-subscription message transmission technology. The detailed cyber-physical coordination maintains a perfect alignment between the physical-energy-flow system and the virtual-carbon-emission-system at any point in the topology structure to ensure they match consistently locally.

3.3 Technical Specifications and Systemic Integration

In order to achieve these above-theories, embedded edge devices need to meet specific physical demands as well as computing requirements in an extremely electromagnetic environment at power stations. Solid-state storage is used in conjunction to create an uncontaminated device at a time-division independent format that prevents short-term interruption during operation and has post-process processing functions. As shown in Table 1, a detailed list of essential components for constructing an embedded IoT carbon-telemetry node is provided to guarantee adequate infrastructure conditions necessary for implementing efficient computation tasks of topological carbon-structure analysis algorithms at a high frequency rate.

Table 1: Core Hardware and Software Specifications of the Embedded Edge-Computing Telemetry Node

System Component	Technical Specification / Parameter	Functional Role in Carbon Accounting
Microprocessor	Quad-Core ARM Cortex-A72 @ 1.5 GHz	Execution of nodal QIO matrix inversions and local optimization functions
Analog-to-Digital Converter	24-bit Sigma-Delta ADC, 10 kHz Sampling	High-fidelity capture of transient power flows to prevent integration errors
Temporal Synchronization	Hardware-assisted IEEE 1588 (PTP)	Sub-microsecond alignment of spatially separated topological nodes
Communication Protocol	MQTT over TLS 1.3 / 5G URLLC	Low-latency, secure transmission of dynamic carbon potential arrays
Local Database	Embedded Time-Series DB (e.g., InfluxDB Edge)	Resilient buffering of temporal energy integrals and carbon variables
Algorithmic Firmware	C++ / Python Edge Runtime Environment	Direct implementation of the dynamic loss function $\mathcal{L}(\theta)$

4 Experimental Design and Calibration of the Simulation Environment

4.1 Experimental Topology and High-Resolution Dataset Acquisition

To verify the theoretical feasibility and computational robustness of the embedded edge computing quasi-input-output (QIO) architecture proposed in previous sections through an extensive experimental setup under conditions similar to a fully operable regional distribution system with high penetration and multiple sources of energy. The selected target infrastructural nexus for this research is a 110 kV primary transformation station serving as the central point of connection among three different systems: a carbon-intensive baseload thermal power plant, a high-stochastic utilised large-scale solar PV farm, and several various end-use consumers, including industrial energy demand and residences. Refusing to rely on traditional retrospective, low-resolution administrative billing data, this paper uses the customised edge-computing gateway nodes described in Section 3 to obtain millisecond-level active-power trajectory data and simultaneously computes local carbon-attenuation derived values. Afterwards, the original high-frequency telemetry data was aggregated into a mathematically rigorous 1-hour observation Matrix that spanned every day's operation period; This includes both peaks of irradiation that impact renewable energy injection amount and Baselines mainly caused by Fossil Fuels at night [26]. To ensure that the carbon emission factors used in the baseline life-cycle assessment (LCA) as parameters for setting up the initial boundary condition of the generation node are consistent with standardised international inventories, a static value was assigned to the thermal injection process at 1.203 kg CO_2/kWh and to the photovoltaic generation at 0.0701 kg CO_2/kWh; thus, these constants formed the basic environment matrix needed for dynamic topological matrix inversion.

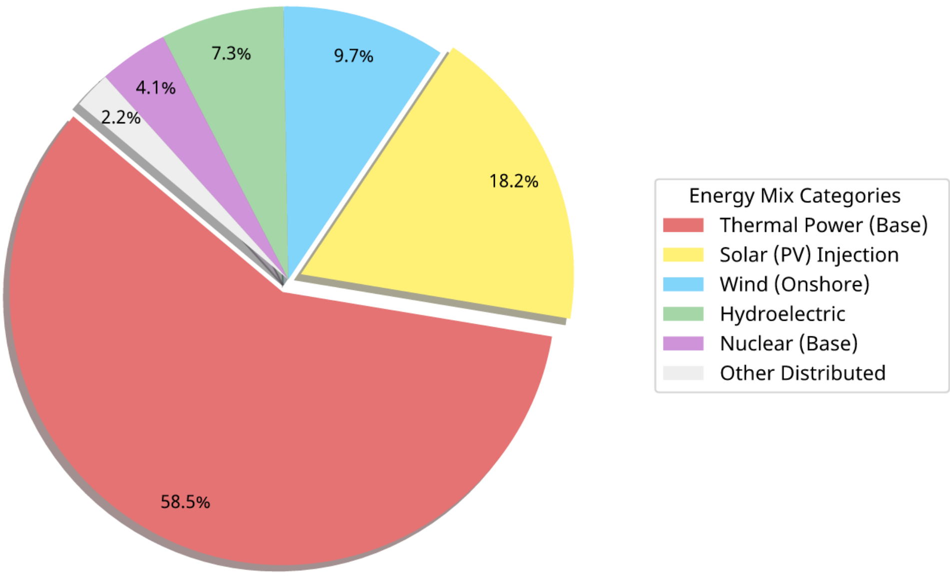

Figure 3: Decomposition of Regional Power Generation Composition Mix

4.2 Spatiotemporal Evolution of Nodal Carbon Potentials

Continuous integration of edge-observed telemetry data and a dynamical carbon potential differential equation model demonstrates that there exists fundamental temporal non-stationarity among grids in carbon intensity; This defect cannot be discovered solely through temporal smearing resulting from static annual averages of the conventional approach. The empirical way of the nodal carbon potential is represented as $\hat{\rho}_k(t)$ in discrete-time domain and shows that there exists an obvious inverse correlation with the diurnal change of solar radiation. From 18:00 to 08:00 during the night-time period when there is no longer photovoltaic energy supply, only thermal power sources can be used; Therefore, in this situation where the system's load increases significantly and requires rapid adjustment capabilities, it will gradually approach its maximum allowable carbon intensity boundary based on the calculation model. On the contrary, an increase in solar radiation across the whole day leads to an overflow of zero-marginal-carbon-active-power at the substation node; thus, its local carbon concentration is severely diluted. A thermodynamic dilution effect can be calculated accurately by using an internal-running QIO algorithm to calculate the current-emission factor according to a physical law, resulting in $\hat{\rho}_k(t) = \frac{P_{TH}(t)e_{TH}+P_{PV}(t)e_{PV}}{P_{TH}(t)+P_{PV}(t)}$. Empirically proved that under precise time constraints, there exists neither an absolutely macroscopic quantity nor a perfectly stationary system attribute in the actual Environment externalised measurement for Electricity usage; Instead, fluctuations are inherent characteristics linked to instantaneous Atmospheric background environments affecting Local renewable Energy systems directly.

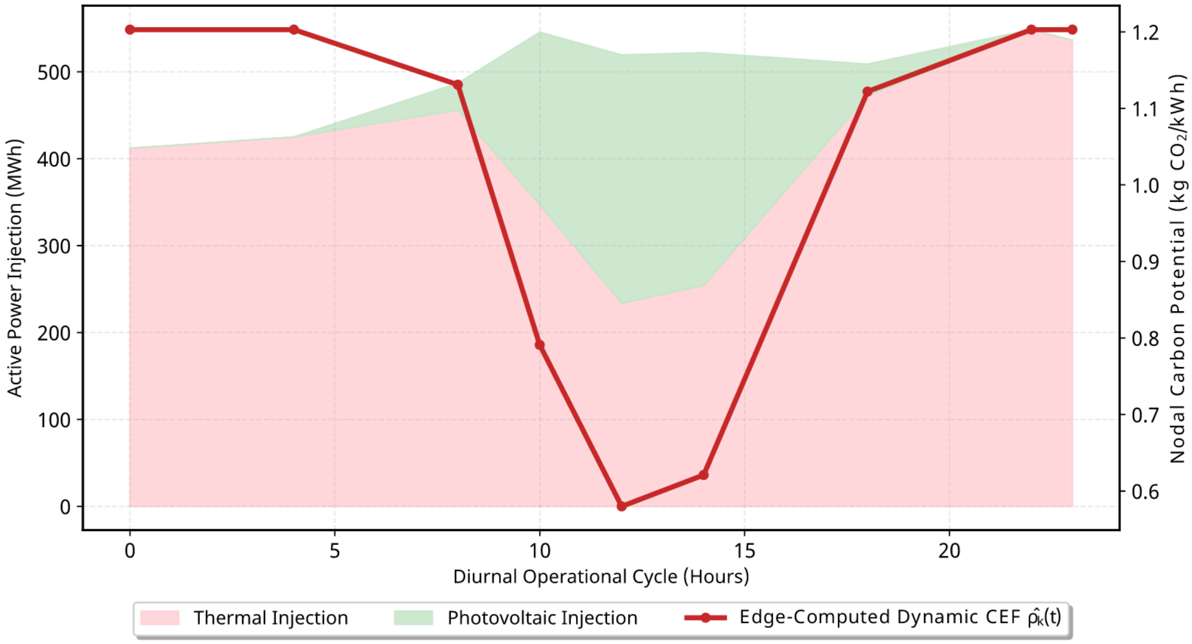

Figure 4: Diurnal Spatiotemporal Evolution of the Nodal Carbon Potential Subject to Intermittent Photovoltaic Injections

4.3 Topological Carbon Allocation and Dissipative Penalty Mechanisms

Apart from changes in Time, the topological structure of the QIO Framework can alter Spatial distribution Changes of Carbon Dioxide Emissions across various End-use Load Centres and Network Impedance Zones. Traditional Accounting Models allocate regional carbon emissions volume uniformly by aggregating regional volumetric consumption; It does not take into account the temporal coincidence between a specific load-demand area and local renewable energy resources. The edge-computed data matrix indicates that heavy industrial loads operating continuously in the night-time thermodynamic dominated period have an extremely high total carbon accumulation due to prolonged operation, while residential electricity consumption exhibits some degree of time-shift alignment with afternoon solar power generation periods. Additionally, based on the empirical evidence, it can be confirmed through this study that transmission loss-related carbon emissions within substations have been included in $\Lambda_{kj}^{carbon}(t)$ to show that there exists a unique form of carbon contribution from thermal energy dissipation inside substation transformers. Dynamically multiply the instantaneous nodal carbon potential by the high frequency of active power loss integration to convert physical infrastructure efficiency losses into environmental cost indicators. The spatially granular allocation mechanism removes the system-wide cross-licensing problem of carbon emission costs among various types of consumers and provides grids with a new, high-resolution tool to encourage shifting loads into peak hours of large-scale renewables operation.

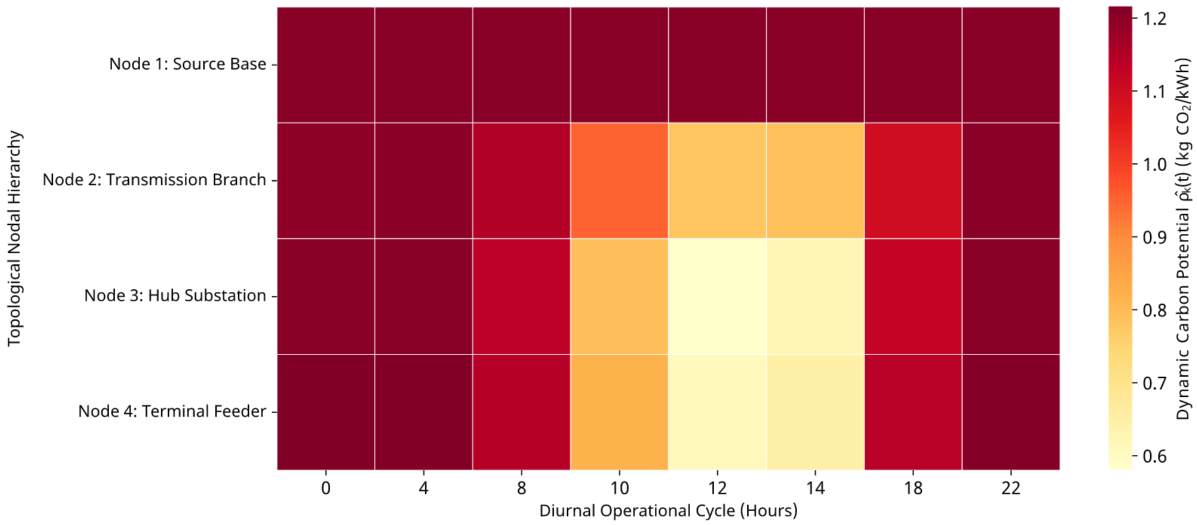

Figure 5: Spatiotemporal Heatmap of Nodal Carbon Potentials Across Grid Topologies

Table 2: Empirical Matrix of Diurnal Power Injections, Load Profiles, and Edge-Computed Carbon Potentials

Temporal Axis ($\boldsymbol{t}$)	Thermal Injection $\boldsymbol{P_{TH}(t)}$ (MWh)	PV Injection $\boldsymbol{P_{PV}(t)}$ (MWh)	Industrial Load $\boldsymbol{P^L_{k1}(t)}$ (MWh)	Residential Load $\boldsymbol{P^L_{k2}(t)}$ (MWh)	Static CEF (Baseline)	Dynamic Nodal Carbon Potential $\boldsymbol{\hat{\rho}_k(t)}$
04:00	425.03	0.00	350.50	60.33	0.581	1.203
08:00	456.53	30.80	380.20	91.29	0.581	1.131
12:00	233.86	285.60	390.10	115.36	0.581	0.580
14:00	254.13	267.90	400.00	107.03	0.581	0.621
18:00	472.52	36.40	385.40	108.01	0.581	1.122
22:00	548.62	0.00	360.20	169.81	0.581	1.203

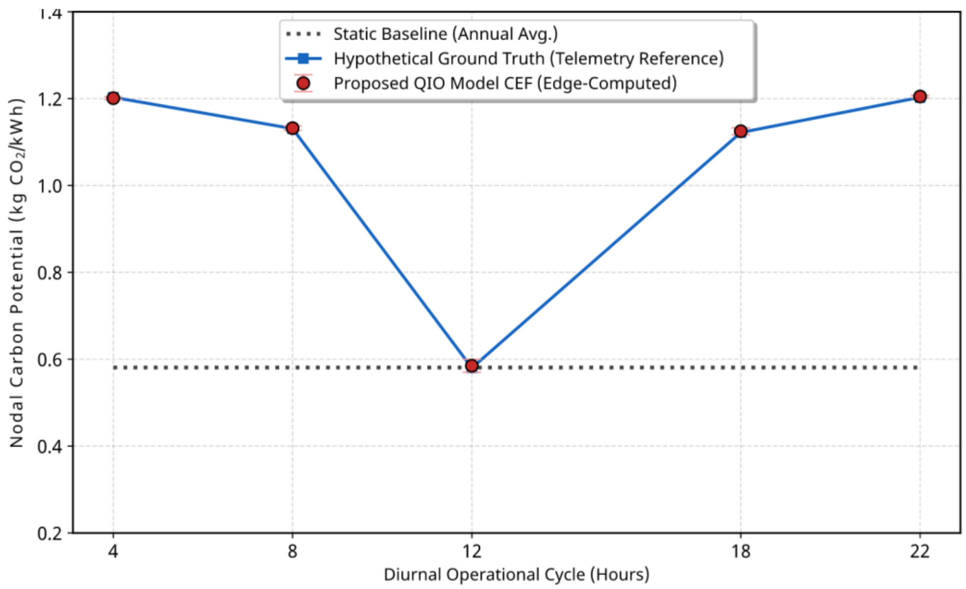

Figure 6: Comparative Error Analysis between Conventional Static Baseline and the Proposed Dynamic QIO Matrix with Edge Intelligence

5 Discussion and Institutional Policy Implications

5.1 Paradigm Shift in Substation Operational Protocols and New Energy Maintenance

Empirical evidence for the edge computing quasi-input-output architecture has already served as a preliminary assessment of substation operations and new-energy equipment maintenance systems in today's power networks based on these concepts. Historically, the maintenance and operation dispatch at transformation nodes have been guided solely by physical limitations in priority for voltage stability, thermal limit constraints, as well as ignoring the environmental externalities of injecting power being treated as isolated exogenous factors. Continuous, μ-second level quantification of nodal carbon potential algorithms to force the internalisation of these environmental indicators directly into the local control logic of the substation. Render the short-term carbon emissions impact of renewable injections visible and mathematically process it to transform the traditional response-based equipment protection into a preventive, carbon-aware resource application model. For example, the scheduling of computationally demanding grid diagnostics or preventive maintenance should take into account times when photovoltaic power generation is highly distributed to enhance localisation effects on carbon dioxide emissions factors. The combination guarantees that structural fluctuations in zero-carbon-energy are covered by time- and spatial-expansion phases of physical repairs to enhance overall decarbonisation effects of the distributed renewable system.

5.2 Structural Operationalization within State-Owned Grid Enterprises

Theoretical beauty in the dynamic carbon tracking matrix faces serious resistance during its transition from a localised experimental topological node to a large-scale wide-area-grid deployment; it needs substantial restructuring at this level within the bureaucratic system of the executing units. The successful inclusion of this highly frequented edge-computing network within the complex system of State-owned grid enterprises calls for a clear break with traditional, isolated data governance systems. Instead of isolating the continuous flow of carbon telemetry in an independent theoretical system or special research institutions, multidimensional data matrices produced by the embedded gateway nodes need to be integrated naturally into the general operation process of key functions and businesses of the main body. The functional Departments should utilise the dynamic carbon footprints to argue that there is a need for specific investment projects aimed at strengthening grids, particularly those located on high-loss, carbon-dense transmission lines. Concurrently, the business Departments, responsible for executing Power Trading and Demand-Side Aggregation Contracts, need to use the microsecond-level nodal carbon pricing mechanism to establish dynamic Tariffs that have a financial penalty on consumption in thermal-dominated night-time baseloads while fully incentivising Load Shifting towards Solar peak hours. The structural integration aims to ensure that, based on environmental intelligence from a physical edge, there are immediate corresponding concrete and enterprise-wide decarbonisation measures after triggering outside this environment.

6 Economic Internalization and Nodal Carbon Pricing Mechanisms

The transformation of the carbon emissions factor from an annual gross domestic product phenomenon to a high-dynamic, spatio-temporally resolved continuous system can provide necessary mathematical basis for developing granular carbon trade mechanisms. The traditionalETS system is continually impacted by its inability to follow up on the specific thermodynamic paths for producing carbon-quantity emissions and consuming them in various end-use sectors; Therefore, it results in severe distortions of prices across environmental less-preferred industrial products' demand structure. Topological QIO can eliminate this kind of structural invisibility and assign each unit hour transported along with its corresponding branches impedance a carbon liability in time-dependence form. Formalise the carbon penalty at localised ohmic losses through the obtained equation $\Lambda_{kj}^{carbon}(t) = \rho_k(t) \cdot I_{kj}^2(t) R_{kj} \cdot \Theta(t)$; thus, establish that Nodal Marginal Carbon Pricing (NMCP) can be realised in this manner. In view of the current advanced economic structure under which the financial cost of electricity for a particular end-user is inherently linked to its localisation as part of an upstream generation mix and through intervening topological transmission losses. The highly localised price signalises an actual environmental shortage of used energy, enabling powerful heavy-industrial users to deploy automated, behind-the-meter energy-storage devices for temporal-carbon-arbitrage purposes that are structured as a structure between microeconomic profit maximisation and macroscopic planetary boundaries.

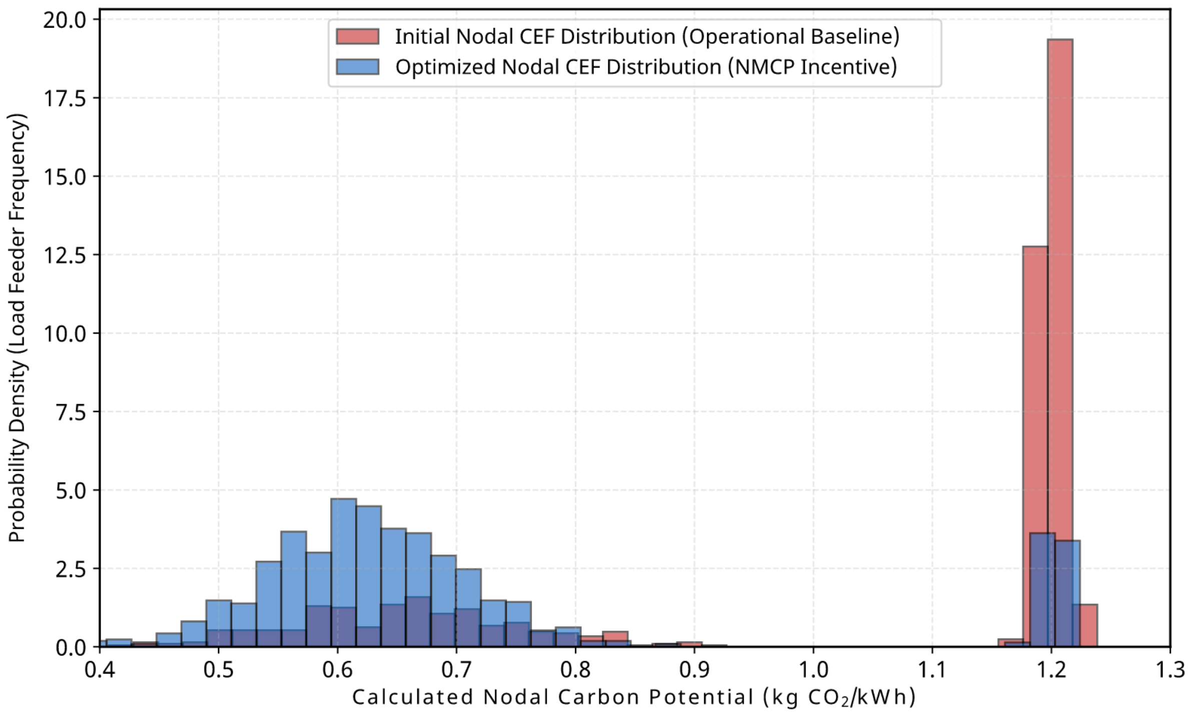

Figure 7: Histogrammatic Analysis of Nodal CEF Probability Distributions Pre- and Post-Implementation of Carbon-Aware Dispatch Optimization

7 Conclusion

Given that the path towards modernisation requires an irreversible disconnection between economic development and greenhouse emissions, but is impeded by opaque structures in current carbon accounting inventories. This study successfully bridges the deep conceptual difference between the broad boundaries of administrative entities and the micro-physics-grid-based system to build an extremely fine-grained, spatial-temporal-carbon emission-factor observation system. By mathematically combining the topological rules of the quasi-input-output conservation matrix with the physical power-flow array to establish a continuous-time differential equation that governs the transmission process of environmental externalities in complex heterogeneous energy networks. There is, in essence, a computational bottleneck caused by high frequency; however, it has been overcome empirically through the application of an embedded IoT edge-computing system. The decentralised intelligence Layer executes a custom-time penalty dynamic loss function locally in the smart Gateway node to completely eliminate the delay and stochastics of cloud-centric telemetry. Through this framework construction, originally inactive infrastructures will be transformed into live, independent sensors to separate transient fluctuations due to uneven solar radiation from continuous long-term emissions from stationary sources such as thermal power plants; provide substantial theoretical backing for connecting individual electronic flow paths with particular atmospheric impacts.

Although there are already short-term experimental verification indicators that show good performance in accurately depicting nodal carbon potential distributions; However, whether or not it meets long-term needs and can function normally under actual working conditions is still uncertain. This method produces a granular matrix that can be used as an exact training target for embedding deep-reinforcement learning (DRL) optimisation methods designed to address low-carbon optimal power flow (LC-OPF). Future research directions should be focused on integrating these localisation optimisations directly into the edge computing gateway devices for use in autonomous execution of topologies and balancing adjustments that are specifically set out to minimise the overall carbon-dissipating cost $\Lambda_{kj}^{carbon}(t)$ over entire distribution lines. By physically securing the abstract representation of environmental responsibility within the microprocessor control for the power grid, thus definitively shifting the power sector from passivity in carbon auditing to active governance through high-frequency, algorithm-driven decarbonisation.

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