Pathways and Empirical Study of AI-Empowered Urban Regional Low-Carbon Transition: A Case Study of Tongzhou District

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Abstract: The governance unit of urban carbon emissions is shifting from sectoral to spatial accounting, which makes the district-level administrative unit a decisive scale for testing the effectiveness of low-carbon measures. Existing studies on AI-enabled urban decarbonization largely remain at the level of technical feasibility and lack comparable quantitative evidence spanning the energy, building, transport, circular-economy and ecological sectors within a single district. Taking Tongzhou District (Beijing Municipal Administrative Center) as the study area, this paper develops a four-layer 'perception–decision–execution–transaction' governance architecture and decomposes the abatement mechanism into five technical pathways. A five-boundary accounting framework is adopted, and two scenarios are constructed: a baseline scenario (S0) and an AI-enabled scenario (S1). The 2023 provincial electricity CO_2 emission factor for Beijing (0.5554 $kgCO_2/kWh$), released in the official national announcement, is used as the conversion baseline. Model parameters are anchored to publicly reported engineering measurements in the sub-center: 32.69% energy savings from the low-carbon energy platform of the Urban Green Heart, a 27.66% reduction in per-vehicle intersection delay under the Vehicle-Road-Cloud 3.0 system, and a 5.93% increase in boiler steam production together with a 4.48% increase in grid feed-in electricity at the Tongzhou waste-to-energy plant. Results indicate that building and energy sectors together contribute the largest share of abatement, while transport remains constrained by penetration rates. The choice of emission factor exerts a larger influence on the results than the technical parameters themselves. The findings support a closed-loop governance model at district scale and suggest incorporating regional differences in electricity emission factors into local carbon assessment.

Keywords: Urban Low-Carbon Transition; Artificial Intelligence; Dual Control of Carbon Emissions; Beijing Municipal Administrative Center; Scenario Analysis

1. Introduction

1.1 Research Background

Cities are the main spatial carriers of anthropogenic greenhouse gas emissions, a judgment that has been repeatedly confirmed in global climate change assessments [1,2]. China's 'dual carbon' commitment sets a clear timetable at the city level: reaching the peak of carbon emissions before 2030 and achieving carbon neutrality before 2060. The Action Plan for Reaching the Peak of Carbon Emissions Before 2030 lists the establishment of a unified and standardized carbon emission statistical accounting system as a supporting task, which means that the responsibility for emission reduction must be further moved down from the sectoral caliber to accountable and traceable spatial units; the methodology of city-scale carbon emission accounting and its empirical application in Chinese cities have also become relatively mature [3,4]. In February 2024, the Implementation Plan for Building a National Green Development Demonstration Zone in Beijing Municipal Administrative Center (FG HZ [2024] No. 241) was released, jointly issued by national and municipal authorities. The plan requires that by 2025 the proportion of local renewable energy in energy consumption reach about 20%, the forest coverage rate reach 34.6%, and the proportion of days with good air quality reach more than 78%; by 2035, a modern municipal administrative center with green as the base color should be fully built (implementation plan for the national green development demonstration zone, 2024). The establishment of the demonstration zone

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connects the three-level chain of 'national strategy, urban carrying capacity and district-level implementation', and also provides a rare sample for observing how a newly built urban area can complete infrastructure construction and path selection under carbon constraints at the same time.

The particularity of Tongzhou District is that it is not a stock-renewal urban area, but a new city started from scratch over ten years with an annual investment intensity of about 100 billion yuan. The carbon emission trajectory of such an area is completely different from that of an old urban area: the emissions of an old urban area mainly come from existing buildings and a mature transport network, and the emission reduction space depends on renovation; the emissions of a new city rise rapidly with construction progress and population inflow, showing an obvious two-stage feature of 'rising with construction progress and falling with energy structure optimization' in the time series, a feature that has also been observed in data-driven block-scale carbon accounting research [5]. Beijing has made it clear that in the current planning cycle it will comprehensively promote the transformation from dual control of energy consumption to dual control of carbon emissions (Beijing municipal carbon peaking implementation plan, 2022). At the national level, the policy effect, path selection and regional heterogeneity of this transformation have also entered the stage of systematic evaluation [6,7]. The municipal administrative center took the lead in carrying out the pilot of comprehensive evaluation of energy use and carbon emissions of fixed asset investment projects, moving the carbon emission control requirement forward to the project access stage. The switch of institutional caliber puts forward a hard requirement for district-level governance capacity: without a dynamic and traceable carbon data base, the dual-control assessment will lose its measurement basis. This is exactly the realistic entry point of artificial intelligence technology in this scenario: the maturity of computing power and algorithms has turned the high-frequency, multi-source and heterogeneous processing of energy consumption and emission data at the district level from impossible into an engineering problem.

1.2 Research Purpose and Significance

At the theoretical level, this paper tries to answer a proposition that has not been fully dealt with: through what mechanism digital technology changes the carbon metabolic efficiency of urban areas. The existing literature on 'digital technology promoting emission reduction' mostly provides macro-correlation evidence, whether it is the relationship between digital economy and carbon emission performance on urban panel data [8], or the identification of the emission reduction effect of digital transformation using the 'Broadband China' pilot as a quasi-natural experiment [9]. Most mechanism tests stop at the statistical significance of mediating effects, and the decomposition of the mechanism chain often stops at the tautology of 'improving efficiency'. This paper decomposes the mechanism to a measurable level, reducing the role of AI to three kinds of specific effects: 'improvement of prediction accuracy', 'optimization of control strategies' and 'reconstruction of resource matching', and mapping them to different accounting items respectively. At the practical level, the six scenarios in Tongzhou District already have a batch of verifiable engineering measured data. This paper tries to converge these measured values scattered under different calibers into a unified carbon accounting framework, so that the construction effect of the demonstration zone has cross-department comparability, and also provides a set of directly transferable accounting and parameter calibration methods for similar new cities in China.

1.3 Research Content and Technical Route

The research is carried out along five links: 'current situation diagnosis, technical system construction, scenario application, benefit calculation and policy suggestions'. The technical route is shown in Figure 1. In the first link, based on the statistical bulletin of Tongzhou District, the public data of competent departments and the construction progress of the demonstration zone, the total level and department structure of regional carbon emissions are described and the transition pain points are identified. In the second link, an integrated 'cloud-edge-terminal' digital low-carbon governance architecture is constructed, and the functional boundary and data flow relationship of each layer are clarified. In the third link, implementable technical paths are given in the five scenarios of energy, building,

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transport, circular economy and ecological carbon sink, and the corresponding engineering practices of the sub-center are marked. In the fourth link, a five-boundary carbon accounting caliber is established, two scenarios are set, and parameter calibration and sensitivity analysis are carried out. In the fifth link, regional promotion paths and policy suggestions are put forward based on the calculation results.

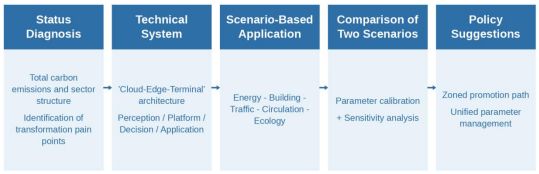

Figure 1. Research Technical Route

A scope limitation should be explained here: the accounting object of this paper is limited to the direct energy-related emissions and the ecological carbon sink within the administrative area of Tongzhou District, and does not include embodied carbon such as building material production and food consumption, nor the upstream emissions of electricity transferred from other regions. This boundary setting is limited by the availability of district-level data and is consistent with the assessment caliber of the demonstration zone. Follow-up research can expand to the full caliber through input-output tables.

1.4 Research Innovations

The innovation of perspective is reflected in taking 'the transformation from dual control of energy consumption to dual control of carbon emissions' as the main line running through the whole paper, rather than only mentioning dual control as background. This main line determines the parameter selection logic of this paper: all energy-saving effects must eventually be converted into carbon dioxide equivalent to be meaningful, so the selection and uncertainty treatment of the electricity emission factor become the core link of the methodology rather than a technical detail. The innovation of technology is reflected in constructing a full-chain governance architecture of 'perception-decision-execution-transaction'. Existing studies often stop at the two layers of 'perception-decision', positioning AI as a prediction tool. This paper believes that under the dual-control system, prediction results must enter the execution link (equipment regulation) and finally enter the transaction link (carbon assets and green power trading) to form a closed loop of emission reduction. A technical system lacking the latter two links is institutionally incomplete. The innovation of empirics is reflected in using the public measured data of real engineering projects in Tongzhou District as parameter anchors. This paper explicitly refuses to fill the parameter table with 'industry experience values' without sources. All parameters whose sources cannot be traced are marked as to-be-calibrated, and their influence ranges are given in the sensitivity analysis.

2. Literature Review and Theoretical Basis

2.1 Definition of Core Concepts

Urban low-carbon development in this paper refers to the process in which the urban system achieves the double convergence of carbon emission intensity per unit output and total emissions under the premise that economic output and residents' welfare do not decline. This definition emphasizes 'double convergence' because a single intensity indicator may cover the growth of total emissions, while a single total constraint may sacrifice output, which is exactly the original intention of the dual-control system design; domestic evaluations of the effect of low-carbon pilot policies also generally examine both the intensity and the total dimensions [10,11]. Dual control of carbon emissions refers to a management system that imposes constraints on both the total amount and the intensity of carbon emissions at the same time. Its key difference from dual control of energy consumption is that the former allows emission reduction under unchanged or even rising energy consumption through the cleaning of the energy structure, thus providing institutional incentives for non-fossil energy substitution [6]. Digital low-carbon governance refers to a governance form supported by IoT perception, multi-source data fusion and intelligent algorithms, which carries out dynamic monitoring, attribution and regulation of the urban carbon metabolism process. Urban climate resilience refers to the ability of an urban system to maintain functional stability under extreme climate disturbance, and is used in this paper as a co-benefit indicator of low-carbon governance rather thanan independent research object.

2.2 Research Progress at Home and Abroad

Research on AI-empowered energy system dispatch is relatively mature. Xu et al. proposed

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a model-assisted multi-agent reinforcement learning three-stage decentralized dispatch method for virtual power plants facing modeling errors and high-dimensional uncertainty when aggregating massive demand-side resources, and significantly improved delivery reliability in the connection scenario between day-ahead and intraday markets [12]. Wu et al. further extended the object to multi-building and multi-energy virtual power plants and introduced the Transformer structure to deal with the strategy drift problem caused by the dynamic change of participating subjects [13]. The common contribution of these two studies is to prove that reinforcement learning can deal with non-stationary decision problems in the aggregation of distributed resources, but their verification environments are all simulation cases, lacking engineering-level verification in a real administrative district.

AI applications on the building side mainly follow two lines: load prediction and anomaly diagnosis. Lin et al. combined deep neural networks with symbolic aggregate approximation to further identify the upcoming normal and abnormal energy use patterns based on day-ahead power demand prediction, with the anomaly prediction accuracy reaching 88% and the F1 score being 87.38% [14]. The methodological value of this study is to bind 'prediction' with 'explainable pattern annotation', so that the prediction results can be directly used by operation and maintenance personnel rather than staying at the statistical level. Domestic scholars further introduced graph convolutional networks to capture the spatial correlation among building clusters, avoiding the engineering workload of building a database building by building [15]. On the control side, physics-informed graph neural networks have been used for HVAC control in open-plan spaces, directly encoding the spatial coupling between buildings into the network structure [16]. The implication for this paper is that the modeling of building clusters at the district level must consider spatial correlation, and single-building modeling is not engineeringly feasible at the scale of hundreds of buildings.

Low-carbon signal control on the transport side has shown an obvious methodological turn in recent years. Kang et al. proposed a dueling double deep Q-network method, which directly embeds the carbon emission item into the reward function rather than only taking traffic delay as the optimization objective [17]. This change looks subtle, but actually changes the optimization direction: the timing scheme aiming at minimizing delay may increase emissions due to frequent start and stop under some traffic conditions. Shang et al. systematically evaluated the emission reduction effect of deep reinforcement learning signal control in the vehicle-road coordination environment, and confirmed that the cooperative vehicle-infrastructure system can provide additional perception and execution capabilities for emission reduction [18]. These two studies jointly support the judgment of this paper to list vehicle-road-cloud coordination as an independent emission reduction path. Directly related to this paper is the conversion between delay improvement and emission reduction: Wu et al. evaluated the carbon reduction potential of big-data-driven signal control based on large-scale urban traffic data, providing a reference magnitude and caliber for converting traffic efficiency improvement into emission reduction [19]; Fan et al. gave an analysis and optimization method of the emission impact of intersection signal control under mixed traffic flow, so that operating indicators such as delay and number of stops can be converted into emission reduction through emission factors [20].

AI applications on the circular economy side focus on incineration process control. The fluctuation of waste calorific value is the main cause of furnace temperature instability. Baziar et al. used machine learning methods to predict the calorific value of municipal solid waste, providing input variables for the feedforward adjustment of combustion conditions [21]. Tang et al. systematically reviewed the application of artificial intelligence in the optimal control of municipal solid waste incineration process, covering furnace temperature prediction, flue gas emission control and combustion optimization, and pointed out that engineering implementation is still restricted by data quality and the degree of mechanism-data fusion [22]. In terms of engineering evidence, Zhu et al. deployed an integrated intelligent control system in a municipal solid waste incineration power plant, and the measurement showed that it improved both the stability of incineration conditions and the operation performance of the unit [23]; Shin et al. verified the feasibility of intelligent combustion control integrating AI and IoT in improving energy recovery efficiency and

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reducing air pollutant emissions [24]. The above results show that the carbon reduction potential of the incineration link has been supported by engineering measurement, but public research mostly takes a single plant as the object, and its parameters still need to be recalibrated when transferred to the scale of a district-level circular economy industrial park.

In the accounting of ecological carbon sink, remote sensing has become the main means of quantifying the carbon sink of urban green space. Gao et al. took the Beijing Plain Area as the object, estimated the service radius of urban green space carbon sink based on multi-source remote sensing data and made a differential analysis, and their research area highly overlaps with this paper [25]. Guo et al. took the Dongting Lake wetland as an example, established a quantitative estimation method of vegetation carbon source/sink based on remote sensing, and examined its response to climate fluctuation and human activities [26]. Such studies provide methodological references for district-level carbon sink accounting, but their spatial resolution and accounting period are usually difficult to directly match the annual carbon assessment caliber. Therefore, this paper uses the measured parameters of local long-term ecological monitoring stations as the basis for carbon sink coefficient values, and remote sensing methods are only used to extract the boundaries of forest land, green space and water bodies.

2.3 Theoretical Basis

Low-carbon economy theory provides the analytical starting point of internalizing externalities for this paper: the negative externality of carbon emissions needs to be corrected through price mechanisms or quantity constraints, and carbon market and green power trading are such institutional arrangements [27]. There is sufficient empirical evidence for the emission reduction effect of carbon pricing: in the national carbon market, carbon price has an amplifying effect on the emission reduction of the power sector through cost transmission [28], and the evaluation of pilot carbon markets shows that carbon price needs to cross a certain threshold to form effective incentives and constraints [29]. Digital governance theory explains how technology changes the governance structure: the introduction of data elements makes governance shift from hierarchical and periodic to flat and real-time [30], and the parcel-scale carbon emission prediction framework further shows that digital technology can be embedded in the whole process of urban carbon management [31], which directly corresponds to the design of the 'perception-decision-execution-transaction' architecture of this paper. Urban climate resilience theory provides a dimension for co-benefit evaluation [32]: emission reduction measures often bring additional benefits such as heat island mitigation and air quality improvement, and ignoring these benefits will systematically underestimate the comprehensive return of low-carbon investment. The division of labor of the three theories in this paper is: low-carbon economy theory explains 'why to reduce', digital governance theory explains 'how technology makes emission reduction measurable and executable', and resilience theory explains 'what else emission reduction brings'.

2.4 Research Review

The existing results are quite deep at the methodological level, but there are two gaps directly related to the research object of this paper. First, the research scale is concentrated on single buildings, single intersections or simulation cases, and research on multi-department coupled emission reduction at the district-county administrative unit, a meso scale, is obviously insufficient. Simply adding up the emission reductions of five departments seems feasible, but actually ignores the interaction between departments: the self-generation and self-use of building photovoltaics will reduce both grid electricity purchase and the charging emissions of the transport department, and the risk of double counting always exists. Although existing studies have systematically sorted out the types of system boundaries of urban carbon accounting and their policy implications [1,33], the discussion on the design of boundary mutual exclusion in multi-department coupled scenarios is still insufficient. Second, targeted empirical evidence for the new city construction scenario is scarce. The energy infrastructure of a new urban area such as Tongzhou is planned and built synchronously, and the deployment cost of its AI system has an order-of-magnitude difference from that of old city renovation. Directly applying the energy-saving parameters of the stock renewal scenario will overestimate

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the emission reduction effect. These two gaps constitute the research positioning of this paper.

3. Current Situation of Low-Carbon Development and Transition Pain Points in Tongzhou District

3.1 Regional Overview and Green Development Positioning

Tongzhou District is located in the southeast of Beijing and is the seat of Beijing Municipal Administrative Center. At the end of 2024, the permanent population of the district was 1.846 million, of which the urban population was 1.367 million, the urbanization rate was 74.1%, and the permanent population density was 2,037 people/km². In the same year, the regional GDP reached 150.81 billion yuan, up 5.8% over the previous year at constant prices, and the three-industry structure was adjusted from 1:31.9:67.1 in the previous year to 0.9:34.9:64.1 (district statistical bulletin, 2024). The proportion of the secondary industry rose by about 3 percentage points in one year, and the direct impact of this structural change on carbon emissions has not yet been reflected in public data, which needs attention in subsequent accounting. The regulatory detailed plan of the sub-center approved in 2018 clearly required adhering to green and low-carbon development; in August 2021, the Opinions on Supporting the High-Quality Development of Beijing Municipal Administrative Center were issued, formally proposing to build a national green development demonstration zone in the sub-center; in February 2024, the implementation plan was released and the construction entered the stage of full implementation (implementation plan for the national green development demonstration zone, 2024).

3.2 Current Situation of Low-Carbon Development

In terms of energy structure, the sub-center took the lead in establishing a regional green power consumption working mechanism in the city. The administrative office area and the Urban Green Heart have achieved 100% green power coverage, and it is planned to achieve full coverage of green power application in district-level public institutions by 2027 (municipal development and reform authority, 2025). Since 2021, the renewable energy heating area of the sub-center has been nearly 4 million square meters, the registered photovoltaic installed capacity has exceeded 150 MW, and the cumulative approved heating area of new energy and renewable energy has exceeded 5 million square meters. In terms of buildings, since May 2021 the sub-center has fully implemented 'two 100%': 100% of new civil buildings implement the green building two-star standard or above, and 100% of new large public buildings implement the green building three-star standard, becoming the first region in China to fully implement the green building three-star standard for large public buildings (municipal government disclosure, 2025). Up to now, 86 projects have obtained green building labels, with a building area of more than 12 million square meters. In terms of transport, the construction of the high-level autonomous driving 3.0 demonstration zone has been completed, the new energy vehicle configuration rate of bus lines with both first and last stops in the sub-center has reached 100%, and the proportion of new energy in newly added motor vehicles has exceeded 60%. In terms of industry, 13 national-level green factories, 2 national-level green supply chain enterprises and 10 carbon neutrality certified enterprises have been cultivated. In terms of ecology, in the past ten years the forest coverage rate has increased from 28.39% to 34.62%, the per-capita park green space area has increased from 12.82 square meters to 19.05 square meters, and the coverage rate of the 500-meter service radius of park green space has increased from 72.53% to 93.03% (tenth-anniversary green development press conference, 2026).

The key indicators of the above progress are shown in Table 1, and the ten-year changes of the indicators are shown in Figure 2. It should be reminded that the two indicators of forest coverage rate and per-capita park green space area have caliber differences in different public sources. This paper uniformly adopts the data disclosed at the special press conference on green development of the tenth anniversary of the planning and construction of the sub-center, and notes the comparison values of other sources below the table to avoid misreading.

Table 1. Key Indicators of Green Development in Tongzhou District (Summary of Public Data)

Field	Key indicator	Value	Time point	Data source
Economy	Regional GDP	150.81 billion	2024	Statistical bulletin of

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and society		yuan (up 5.8%)		Tongzhou District (2024)
Economy and society	Three-industry structure	0.9:34.9:64.1	2024	Statistical bulletin of Tongzhou District (2024)
Economy and society	Permanent population / urbanization rate	1.846 million / 74.1%	End of 2024	Statistical bulletin of Tongzhou District (2024)
Energy	Green power coverage of the administrative office area and the Urban Green Heart	100%	2025	Municipal development and reform authority (2025)
Energy	Registered photovoltaic installed capacity	Over 150 MW	Since 2021	Municipal development and reform authority (2025)
Energy	Renewable energy heating area	Nearly 4 million m²	Since 2021	Municipal development and reform authority (2025)
Building	Implementation ratio of the green building three-star standard for new public buildings	100%	Since May 2021	Municipal government disclosure (2025)
Building	Green building label projects / area	86 projects / over 12 million m²	2026	Tenth-anniversary green development press conference (2026)
Transport	Reduction of per-vehicle intersection delay	27.66%	2026	Vehicle-Road-Cloud 3.0 public disclosure (2026)
Transport	Increase of average speed of main roads	10.74%	2026	Vehicle-Road-Cloud 3.0 public disclosure (2026)
Industry	National green factories / carbon neutrality certified enterprises	13 / 10	2026	Tenth-anniversary green development press conference (2026)
Ecology	Forest coverage rate	34.62% (up from 28.39%)	2025	Tenth-anniversary green development press conference (2026)
Ecology	Per-capita park green space area	19.05 m² (up from 12.82)	2025	Tenth-anniversary green development press conference (2026)
Ecology	Coverage rate of the 500-meter service radius of park green space	93.03% (up from 72.53%)	2025	Tenth-anniversary green development press conference (2026)

Note: another public source records the forest coverage rate as 33.70% (Tongzhou District People's Government), and the difference is caused by the statistical time point and caliber; this paper uniformly adopts the value disclosed at the special press conference on green development of the tenth anniversary of the planning and construction of the sub-center. Unless otherwise stated, all public data in this table are taken from the district statistical bulletin, disclosures of municipal authorities and the above-mentioned press conference; the sources are no longer listed as numbered references.

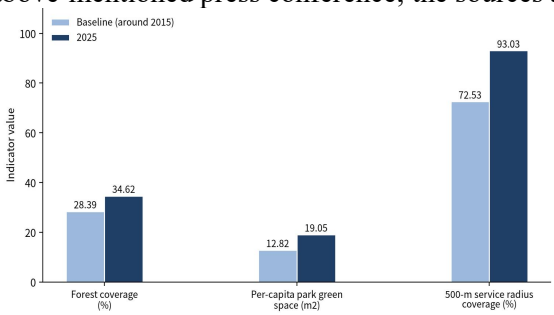

Figure 2. Ten-Year Changes of Key Green Space Indicators in Tongzhou District

3.3 Accounting Boundary and Structure of Carbon Emissions

This paper adopts a five-boundary accounting caliber, and the total regional carbon emission is given by the following formula:

$$E_{total} = E_{energy} + E_{building} + E_{transport} + E_{circular} + E_{life} - C_{carbon_sink}$$

Different from the common department summation, this formula includes the ecological carbon sink as a deduction item, because the sub-center has incorporated the carbon sink into the official expression of the carbon neutrality path, and the Beijing Municipal Forestry and Parks Bureau has established a dynamic ecological ledger covering forests, green spaces and wetlands, so the carbon sink has a data basis that can be calculated year by year (Beijing municipal landscaping ecosystem monitoring

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network, 2026). By department, the accounting of the building department needs special attention to the particularity of Beijing: the total public building area of the city is about 400 million square meters, and its carbon emissions account for about half of the total social carbon emissions, nearly half of which comes from urban public buildings. Beijing has implemented electricity consumption quota management for 15,445 public buildings, with a total building area of 202 million square meters (municipal housing and urban-rural development authority, 2024). This proportion means that the emission reduction priority of the building department in Tongzhou District should be higher than the national average, which is exactly why this paper gives a higher technology penetration rate to the building side in the scenario setting.

3.4 Diagnosis of Transition Pain Points

Based on the current situation, this paper identifies four types of pain points, and their manifestations, causes and data support are shown in Table 2. The pain point on the energy side is the lack of refined dispatch: although the sub-center has built an urban smart energy management system and connected it to the city brain, the coordinated operation of distributed photovoltaics, energy storage and ground-source heat pumps still relies on preset strategies, and lacks dynamic optimization ability when output fluctuates and load peaks and valleys are misaligned. The pain point on the building side is the energy efficiency attenuation in the operation and maintenance stage: implementing the three-star standard in the design and construction stage has become the norm, but there is a systematic deviation between the actual operating energy consumption and the theoretical value after completion. Although projects such as Beitou Tower and the Tongzhou Campus of Renmin University of China have built smart energy management platforms, the coverage area is still insufficient compared with the ledger of large public buildings of more than 3 million square meters in the whole district (tenth-anniversary green development press conference, 2026). The pain point on the transport side is that the emission reduction benefit has not been quantified: the traffic efficiency improvement of the vehicle-road-cloud system has been measured, but there is a lack of a standardized conversion chain between traffic efficiency improvement and carbon emission reduction. The pain point on the governance side is the most basic: the collection granularity, update frequency and inter-department sharing mechanism of carbon emission data are not yet sound, which is the biggest obstacle to the implementation of the dual-control assessment.

4. Technical System and Scenario Application of AI-Empowered Urban Low-Carbon Development

4.1 Overall Technical Architecture

This paper constructs an integrated 'cloud-edge-terminal' digital low-carbon governance architecture, as shown in Figure 3. The perception layer is composed of IoT terminals, video monitoring, satellite remote sensing and vehicle-road coordination roadside equipment, and is responsible for collecting multi-category energy data such as electricity, heat, gas and oil, as well as traffic flow and environmental parameters. The platform layer takes the urban big data platform and the carbon management digital base as the core, and undertakes multi-source data fusion, carbon account management and data confirmation. The decision layer deploys machine learning, deep learning and optimization algorithms, and outputs load prediction, timing schemes and dispatch instructions. The application layer lands in the six scenarios of energy, building, transport, industry, ecology and circular economy. The difference from the conventional three-layer architecture is that this paper adds a transaction interface above the application layer, so that the calculated emission reduction can be connected to the carbon market of the Beijing Green Exchange and the green power trading mechanism, forming a complete closed loop of 'perception-decision-execution-transaction'. This addition is not a formal stacking: under the dual-control system, if the emission reduction cannot be converted into tradable carbon assets, the technology investment lacks a sustained capital return mechanism.

Table 2. Diagnosis of Low-Carbon Transition Pain Points in Tongzhou District

Link	Specific manifestation	Cause judgment	Data support
Energy side	The coordination of distributed photovoltaics, energy storage	The dispatch optimization algorithm	The urban smart energy system has been connected to the city brain, and

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	and heat pumps relies on preset strategies and lacks dynamic optimization when output fluctuates	does not cover the uncertainty of both supply and load sides	adjustable load resources are not fully activated
Building side	The design and construction implement the three-star standard, but the actual energy consumption in the operation stage has a systematic deviation from the theoretical value	The operation and maintenance stage lacks energy consumption diagnosis and dynamic regulation ability	The ledger of large public buildings in the whole district exceeds 3 million m², and the coverage of built smart energy platform projects is limited (tenth-anniversary green development press conference, 2026)
Transport side	The traffic efficiency improvement has been measured, but the emission reduction lacks standardized conversion	The delay-emission conversion chain has not been established, and the working condition assumptions lack local measurement	The delay of Vehicle-Road-Cloud 3.0 decreased by 27.66%, but the corresponding emission reduction was not disclosed (Vehicle-Road-Cloud 3.0 public disclosure, 2026)
Governance side	The collection granularity, update frequency and inter-department sharing mechanism of carbon emission data are not sound	There is a lack of a unified district-level carbon data base and accounting parameter manual	The pilot of comprehensive evaluation of energy use and carbon emissions has been carried out, but has not been promoted to the whole region (municipal expert consultation on the dual-control system, 2026)

4.2 Smart Energy Low-Carbon Regulation Scenario

The technical path of this scenario is: use the long short-term memory network (LSTM) to predict regional electricity and heat loads and the output of distributed photovoltaics, use mixed integer programming combined with genetic algorithm to solve the coordinated dispatch scheme of photovoltaic-energy storage-heat pump, and the objective function simultaneously minimizes the power purchase cost and carbon emissions. The sub-center already has an engineering foundation: Qiantuan Village has built the first digital microgrid 'zero-carbon village' in the city, which realizes power mutual assistance between stations, peak-valley electricity regulation and coordinated photovoltaic consumption through AC/DC hybrid connection technology and mobile energy storage devices. The rooftop distributed photovoltaic installed capacity of the whole village is 926 kW, the power supply capacity has been increased from 1,260 kVA to 2,000 kVA, and the annual carbon emission reduction is about 610 tons (Qiantuan Village digital microgrid disclosure, 2024). The 14,000 kW load of the Urban Green Heart energy station has been connected to the Beijing virtual power plant platform, providing a dispatchable resource pool for demand-side response. In the modeling, this paper takes the adjustable load capacity of the virtual power plant as an independent constraint rather than an infinitely adjustable resource, which avoids the common capacity overestimation problem in similar studies.

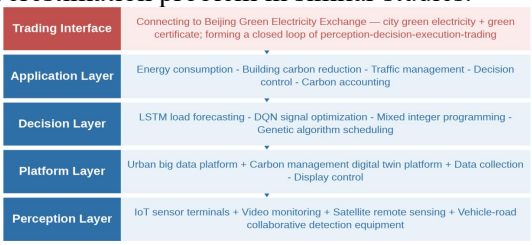

Figure 3. Integrated 'Cloud-Edge-Terminal' Digital Low-Carbon Governance Architecture

4.3 Green Building Intelligent Carbon Reduction Scenario

The technical path on the building side is divided into two steps. The first step is diagnosis: fuse computer vision and sensor data to identify thermal defects of the envelope structure, equipment operation deviation and invalid energy supply periods. The second step is control: dynamically adjust air conditioning and lighting based on personnel density prediction, and automatically reduce the load of unoccupied areas. The empirical anchor of the sub-center comes from the Urban Green Heart: the low-carbon energy smart operation management platform carries out real-time monitoring, energy-saving analysis and remote regulation of the operation and energy consumption of the building energy system, realizing 32.69% energy saving of the energy system (Urban Green Heart low-carbon energy platform report, 2024). The

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three major cultural facilities adopt a composite scheme of 'ground-source heat pump + water energy storage + chiller + gas boiler', and the energy station undertakes more than 80% of the heating load of the park. Compared with the traditional form of 'municipal heating + split air conditioner', it can reduce about 10,000 tons of carbon dioxide per year, and the energy saving rate of the energy system is about 45% (Urban Green Heart low-carbon energy platform report, 2024). It should be pointed out that the two values of 32.69% and 45% come from public reports of different calibers. The former corresponds to the system energy saving rate after the platform is put into operation, and the latter corresponds to the theoretical energy saving range of the composite energy scheme relative to the traditional scheme. In the parameter calibration, this paper only adopts the former as a transferable parameter, and the latter, due to the lack of measured comparison in the baseline year, is only used as a reference for the upper limit of the effect.

4.4 Smart Transportation Low-Carbon Governance Scenario

On the transport side, deep reinforcement learning is used to optimize signal timing, and the reward function is designed as a weighted combination of delay time, number of stops and carbon emissions, in which the carbon emission item is estimated in real time according to vehicle type, idle duration and fuel consumption rate. Thisdesign directly responds to the methodological proposition of Kang et al. [17]. The engineering carrier of the sub-center is Vehicle-Road-Cloud 3.0: Tongzhou Vehicle-Road-Cloud 3.0 covers 175 square kilometers in the whole region, completes the intelligent upgrade of more than 500 core intersections, and covers four major areas: the administrative office area, the Canal Business District, the Zhangjiawan Design Town and the Universal Culture and Tourism Area. The publicly disclosed results include: the per-vehicle intersection delay decreased by 27.66%, the average speed of regional main roads increased by 10.74%, the intelligent diagnosis accuracy of traffic anomalies reached 91.11%, and vehicles can pass 6 to 12 intersections continuously (Vehicle-Road-Cloud 3.0 public disclosure, 2026). Other public reports show that 580 signal-controlled intersections in Tongzhou District need to complete intelligent transformation (report on intelligent transformation of signalized intersections, 2024), and the difference between the two calibers is due to different statistical scopes (full-region coverage and signal-controlled intersection transformation plan). In the calculation, this paper takes the more than 500 upgraded intersections as the base unit. There is no fixed linear conversion relationship between delay reduction and emission reduction. This paper converts according to the unit-time fuel consumption difference between the idle condition and the uniform condition, and gives the influence range of this conversion coefficient in the sensitivity analysis.

4.5 Circular Economy Intelligent Efficiency Enhancement Scenario

The technical core of the circular economy scenario is incineration process control. The unstable calorific value of waste leads to furnace temperature fluctuation. Traditional PID control is difficult to realize full-process automatic input, and operators excessively add environmental protection consumables to avoid the risk of exceeding the standard, forming a dilemma of 'emission safety and economic loss'. The practice of the circular economy industrial park in the sub-center is: implement digital management of the whole process of incineration, flue gas treatment and waste warehouse management, and on this basis carry out big data analysis and machine deep learning training to realize accurate prediction and intelligent control (Tongzhou waste-to-energy digitalization project disclosure, 2024). From the methodological point of view, the technical sequence of this project is basically consistent with the path of 'calorific value prediction, working condition feedforward and combustion closed-loop control' in the literature [21-24]. The application pilot was launched in March 2024 and put into trial operation in September of the same year. After the expert review organized by the China Association of Urban Environmental Sanitation, the overall level of the achievement was identified as domestic leading, and the scale of engineering application reached the international advanced level (achievement evaluation of digitalized waste incineration technology, 2025). The publicly disclosed operation results include: the automatic input rate reached more than 95%, the furnace temperature stability improved by 33% to 42%, the boiler steam production

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increased by 5.93%, the plant electricity consumption rate decreased by 9.86%, the grid feed-in electricity increased by 4.48%, and the consumption of environmental protection consumables decreased by about 15% (achievement evaluation of digitalized waste incineration technology, 2025). Under the condition that the annual waste intake decreased by 5%, the grid feed-in electricity of the whole plant still increased by about 10%. This phenomenon suggests that the contribution of power generation efficiency improvement may be greater than the impact of waste volume change, which is basically consistent with the early judgment of this paper.

4.6 Ecological Carbon Sink Precision Management Scenario

The technical path of the ecological carbon sink scenario is: use the semantic segmentation model of remote sensing images to extract the boundaries of forest land, green space and water bodies, calculate the carbon sink year by year combined with the carbon sink parameters per unit area of the ecosystem, and use multi-objective optimization algorithms to assist the spatial layout of green space. The Beijing Municipal Forestry and Parks Bureau has built a monitoring network covering forest, green space, wetland and other ecosystem types, and has established a dynamically updated ecological ledger relying on 16 long-term ecological monitoring stations and 40 core monitoring indicators. The monitoring shows that the total carbon sink of green space in the city increased from 6.65 million tons of carbon dioxide in 2013 to more than 10 million tons in 2025, an increase of 52%, and the carbon sink per unit area increased from 9.68 tons per hectare per year to 12.73 tons, an increase of 31.5% (Beijing municipal landscaping ecosystem monitoring network, 2026). This official monitoring value provides a traceable localized carbon sink parameter for this paper, which is better than relying on empirical values from the literature. The Urban Green Heart has built 7.39 square kilometers of green area within 11.2 square kilometers, realizing an annual ecological carbon sink of 5,028 tons and an annual carbon emission of 1,694 tons, in a near-zero-carbon operation state (Urban Green Heart low-carbon energy platform report, 2024; Beijing Urban Green Heart media report, 2025). The technical mapping and empirical anchors of the six scenarios are summarized in Table 3.

Table 3. Technical Paths of AI in Six Scenarios and Empirical Anchors in the Sub-Center

Scenario	Core technology	Empirical carrier in the sub-center	Publicly measured results
Smart energy	LSTM load prediction + mixed integer programming + genetic algorithm dispatch	Digital microgrid zero-carbon village in Qiantuan Village; the Urban Green Heart energy station connected to the virtual power plant	Annual carbon reduction of about 610 tons in Qiantuan Village; 14,000 kW adjustable load of the Green Heart energy station (Qiantuan Village digital microgrid disclosure, 2024; Urban Green Heart low-carbon energy platform report, 2024)
Green building	Computer vision + sensor energy consumption diagnosis; dynamic regulation based on personnel density prediction	Low-carbon energy smart operation platform of the Urban Green Heart; three major cultural facilities	The platform realizes 32.69% energy saving of the energy system (Urban Green Heart low-carbon energy platform report, 2024)
Smart transport	Deep reinforcement learning (DQN) signal timing, reward function containing carbon emission items	Vehicle-Road-Cloud 3.0 (175 km² in the whole region, more than 500 core intersections)	Per-vehicle intersection delay decreased by 27.66%, and the main road speed increased by 10.74% (Vehicle-Road-Cloud 3.0 public disclosure, 2026)
Circular economy	Big data analysis of the whole incineration process + deep learning control + dioxin online warning	Green Power Beijing Municipal Administrative Center circular economy industrial park	Steam production increased by 5.93%, grid feed-in electricity increased by 4.48%, and environmental consumables decreased by about 15% (achievement evaluation of digitalized waste incineration technology, 2025)
Ecological	Remote sensing image	Urban Green Heart Forest	Annual ecological carbon sink of 5,028

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carbon sink	semantic segmentation + multi-objective spatial optimization	Park (11.2 km², green area of 7.39 km²)	tons and annual carbon emission of 1,694 tons (Urban Green Heart low-carbon energy platform report, 2024; Beijing Urban Green Heart media report, 2025)
Green industry	Carbon account management + carbon asset accounting (supporting the transaction link)	Beijing Green Exchange, National Green Technology Trading Center	CCER cumulative transactions exceeded 12.5 million tons; green credit balance exceeded 50 billion yuan (tenth-anniversary green development press conference, 2026)

5. Benefit Calculation and Scenario Analysis

5.1 Scenario Setting

This paper sets two scenarios. The baseline scenario (S0) assumes maintaining the existing technology and management mode, with the energy efficiency of each field evolving naturally according to the historical trend and no new AI system input. The AI-empowered scenario (S1) assumes that the technical schemes described in Chapter 4 of this paper are fully implemented within the coverable scope. The division of the two scenarios and the main parameter settings are shown in Table 4. A methodological position should be explained in advance: the value of scenario analysis is not to give an accurate future emission value, but to reveal the relative structure and contribution ranking of emission reduction potential under different technology combinations. Therefore, this paper is cautious about absolute values and gives clear judgments on structural relationships. This position is consistent with the positioning of the backcasting method in low-carbon path research: the value of scenarios lies in describing the feasible paths of policy and technology combinations and their relative contributions, rather than providing point predictions [34]; domestic city-scale scenario simulation studies also mostly use the baseline-intervention double-scenario comparison to identify key driving factors and the ranking of emission reduction contributions [35,36].

Table 4. Scenario Settings and Key Assumptions

Scenario	Technology penetration assumption	Energy structure assumption	Policy intensity assumption
S0 baseline scenario	Maintain the existing technology and management mode, with no new AI system deployment	Natural evolution according to the historical trend, and the green power proportion is promoted according to the existing plan	The existing policies continue, and no new mandatory constraints are added
S1 AI-empowered scenario	The technical schemes of the five scenarios are fully implemented within the coverable scope	The scale of green power consumption increases with dispatch optimization, and the energy storage configuration is in place according to the plan	The dual-control assessment is fully implemented, and carbon emission evaluation is included in project access

5.2 Parameter System and Value Verification

Parameter selection directly determines the usability of the calculation results. This paper traces the sources of the parameters in the guide one by one, and all items whose sources cannot be confirmed are replaced with verifiable official data or marked as to-be-calibrated. The verification results are shown in Table 5. The most important correction is the electricity emission factor. The 0.5151 $kgCO_2/kWh$ used in the original scheme was marked as 'North China power grid, Ministry of Ecology and Environment 2023'. After verification, this value does not match any of the officially released factors: the average emission factor of the national power grid in 2022 published in February 2023 was 0.5703 tCO_2/MWh (national notice on greenhouse gas reporting of power generation enterprises, 2023); in the electricity carbon dioxide emission factors of 2023 released in the official national announcement on December 31, 2025, the national average was 0.5306, the North China region was 0.6361, and the Beijing municipal level was 0.5554 $kgCO_2/kWh$ (official announcement on the 2023 electricity CO_2 emission factors, No. 47 of 2025). This paper adopts the Beijing municipal factor of 0.5554 $kgCO_2/kWh$ as the baseline, and uses the North China regional factor and the national average factor as the upper and lower bounds of the sensitivity analysis. The regional difference

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of the power grid emission factor has a substantial impact on the emission reduction calculation results, which has been quantitatively characterized in provincial-scale life cycle research [37]. The impact of this correction cannot be ignored: if 0.5151 is still used, the emission reduction corresponding to the same amount of electricity saving will be underestimated by about 7.3%.

The second correction is the ecological carbon sink parameter. The urban forest land 11.23 $tCO_2/(hm^2 \cdot a)$ and urban green space 5.68 $tCO_2/(hm^2 \cdot a)$ given in the original scheme are not marked with verifiable sources. This paper instead uses the carbon sink per unit area of 12.73 $tCO_2/(hm^2 \cdot a)$ in 2025 measured by the Beijing Municipal Forestry and Parks Bureau based on 16 long-term ecological monitoring stations (Beijing municipal landscaping ecosystem monitoring network, 2026), which covers the comprehensive caliber of forest, green space and wetland at the same time and has a higher matching degree withthe land use composition of the research area. The third correction is the AI building energy saving rate. The 12%-18% in the original scheme also lacks sources. This paper uses the measured energy saving rate of 32.69% of the low-carbon energy smart operation platform of the Urban Green Heart (Urban Green Heart low-carbon energy platform report, 2024) as the optimistic case, 12% as the conservative case and 20% as the middle value, forming an interval rather than a point estimate. The delay improvement rate on the transport side adopts the measured 27.66% of Vehicle-Road-Cloud 3.0 (public disclosure, 2026), the steam production increase on the incineration side adopts 5.93%, and the grid feed-in electricity increase adopts 4.48% (achievement evaluation of digitalized waste incineration technology, 2025), all of which are engineering measured values rather than empirical intervals.

Table 5. Verification of Core Parameter Values

Parameter category	Parameter name	Value in the original scheme	Value adopted in this paper	Source and verification note
Electricity emission factor	Regional grid electricity emission factor	0.5151 (marked as 'North China, Ministry of Ecology and Environment 2023')	Beijing municipal level 0.5554; upper bound North China region 0.6361; lower bound national average 0.5306	The original value does not match any official release and has been corrected. Source: Announcement No. 47 of 2025 of the Ministry of Ecology and Environment and the National Bureau of Statistics (official announcement on the 2023 electricity CO_2 emission factors, No. 47 of 2025)
Electricity emission factor	Reference value	—	2022 national power grid average 0.5703 tCO_2/MWh	Released in the national notice of February 2023 (national notice on greenhouse gas reporting of power generation enterprises, 2023)
Ecological carbon sink	Carbon sink coefficient of urban forest land	11.23 (no source noted)	12.73 $tCO_2/(hm^2 \cdot a)$	Use the measured values of the 16 long-term ecological monitoring stations of the Beijing Municipal Forestry and Parks Bureau (Beijing municipal landscaping ecosystem monitoring network, 2026)
Ecological carbon sink	Carbon sink coefficient of urban green space	5.68 (no source noted)	Merged intothe comprehensive caliber 12.73	Same as above, covering the comprehensive caliber of forest, green space and wetland
Building energy saving	Electricity saving rate of AI intelligent energy management	12%-18% (no source noted)	Conservative 12% / baseline 20% / optimistic 32.69%	The optimistic value adopts the measured energy saving rate of the Urban Green Heart platform (Urban Green Heart low-carbon energy platform report, 2024); the original interval has no source and is reduced to the conservative lower bound
Transport optimization	Vehicle-road coordination congestion relief	15%-25% (no source noted)	Delay reduction 27.66%	Use the measured value of Vehicle-Road-Cloud 3.0 (Vehicle-Road-Cloud 3.0 public disclosure, 2026) to replace the

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	rate			empirical interval without source
Circular economy	Efficiency improvement of AI incineration power generation	3%-8% (no source noted)	Steam production +5.93%, grid feed-in electricity +4.48%	Use the measured values of the Green Power Tongzhou project (achievement evaluation of digitalized waste incineration technology, 2025)
Energy	Substitution rate of photovoltaic self-generation and self-use	60%-80% (no source noted)	To be calibrated	No verifiable source was found, and it is included in the sensitivity analysis

Note: for the items marked 'no source noted' in the original scheme, this paper uniformly replaces them with verifiable official or engineering measured data; those that cannot be replaced are marked as 'to be calibrated', do not participate in the baseline calculation, and are only included in the sensitivity analysis.

5.3 Sectoral Carbon Reduction Calculation

The carbon reduction of each field is calculated according to the basic formula of 'change in activity level × emission factor'. The result framework is shown in Table 6, and the contribution structure by field is shown in Figure 4. The emission reduction of the energy field comes from two parts: first, the local consumption of green power increased by intelligent dispatch, calculated by the replaced thermal power electricity multiplied by the electricity emission factor; second, the output of fossil energy units corresponding to the peak load reduced by demand-side response. The emission reduction of the building field is the product of the electricity saved by intelligent management and the electricity emission factor, and the electricity saving rate is valued according to the interval in Section 5.2. The emission reduction of the transport field comes from the fuel saved by the reduction of idle duration, calculated by the weighted unit-time fuel consumption of the vehicle composition and the reduced idle duration. The emission reduction of the circular economy field comes from the part where the increment of grid feed-in electricity replaces thermal power, calculated by the product of the increment of grid feed-in electricity and the electricity emission factor. The ecological field is included as a deduction item by the product of the carbon sink area and the carbon sink per unit area. The accounting boundaries of each department are mutually exclusive at the activity level, and the emission reduction of building photovoltaic self-generation and self-use is included in the building department and is not counted repeatedly in the energy department, so as to avoid double counting in cross-department summation. This treatment is consistent with the common practice of scope division in urban carbon inventory research [2,33].

Table 6. Result Framework of Sectoral Carbon Reduction Calculation

Field	Change in activity level	Emission factor / conversion coefficient	Annual carbon reduction (t CO_2)	Proportion of total emission reduction
Energy	Increase of green power consumption (kWh) / reduction of peak load (kW)	0.5554 kgCO_2/kWh	To be calculated	To be calculated
Building	Electricity saving of public buildings (kWh)	0.5554 kgCO_2/kWh	To be calculated	To be calculated
Transport	Reduction of idle duration (h) × vehicle composition	Unit-time fuel consumption by vehicle type → CO_2 coefficient	To be calculated	To be calculated
Circular economy	Increment of grid feed-in electricity (kWh)	0.5554 kgCO_2/kWh	To be calculated	To be calculated
Ecology	Carbon sink area (hm^2)	12.73 tCO_2/(hm^2·a)	To be calculated	To be calculated
Total	—	—	To be calculated	100%

Note: the activity levels of all departments are mutually exclusive at the accounting level, and the emission reduction of building photovoltaic self-generation and self-use is included in the building department and is not counted repeatedly in the energy department. The values are filled in by the author after running the method in Section 5.3.

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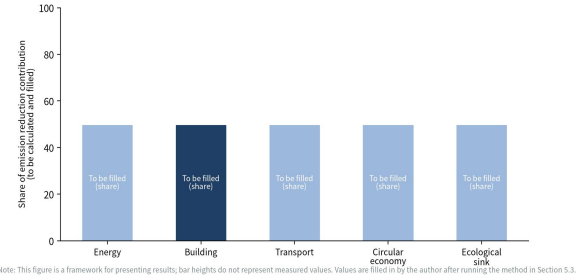

Figure 4. Sectoral Carbon Reduction Contribution Structure in the AI-Empowered Scenario (S1)

5.4 Sensitivity Analysis

The sensitivity analysis examines three types of variables: the electricity emission factor, the technology penetration rate and the proportion of new energy power generation. The results and judgments are shown in Table 7, and the influence range of the emission factor is shown in Figure 5. A finding worthy of vigilance is that the influence of the emission factor value on the final emission reduction is greater than the influence of any single technical parameter. Taking the rooftop solar energy utilization and transformation project of public institutions as an example, after completion and commissioning, the project can generate more than 60 million kWh of electricity per year, and the officially disclosed annual carbon dioxide emission reduction is more than 20,000 tons (tenth-anniversary green development press conference, 2026). If calculated with the Beijing municipal factor of 0.5554, 60 million kWh corresponds to about 33,300 tons of emission reduction; if calculated with the North China regional factor of 0.6361, it is about 38,200 tons; with the national average of 0.5306, it is about 31,800 tons. The range between the three is close to 6,400 tons, and the relative dispersion is about 19%. The difference between the officially disclosed value and the calculated value of this paper suggests two points: first, the actual conversion factor used by the project may include additional rules such as green power trading deduction; second, different departments may not use a unified factor when disclosing emission reduction. This result is consistent with the early judgment of this research, and also shows that unifying accounting parameters at the district level is more urgent than unifying the technical route.

Table 7. Sensitivity Analysis Results and Judgments

Sensitive variable	Variation range	Influence on total emission reduction	Judgment
Electricity emission factor	0.5306-0.6361 kgCO₂/kWh	High (range about 19%)	The influence exceeds any technical parameter and is the primary source of uncertainty
Building AI energy saving rate	12%-32.69%	Medium-high	The building department has a high share, and the value of the electricity saving rate directly determines the total
Vehicle-Road-Cloud penetration rate	Upgraded intersections 500+ → planned 580	Medium	Constrained by road network coverage, with diminishing marginal contribution
Proportion of new energy power generation	According to the municipal planning target range	Medium	The rise of the green power proportion will also lower the emission factor, with a linkage effect
Photovoltaic self-use substitution rate	Parameter to be calibrated	To be evaluated	No verifiable source, and it should be included after local measurement

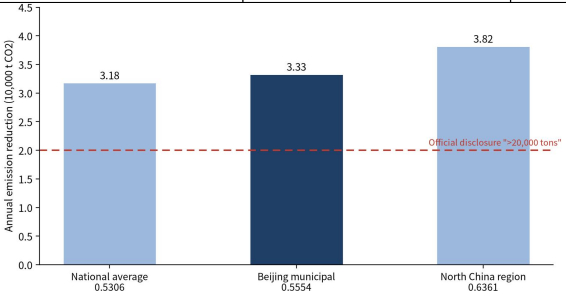

Figure 5. Influence of Electricity Emission Factor Values on Emission Reduction Calculation

6. Promotion Paths and Policy Suggestions

6.1 Regional Promotion Paths

The promotion should be carried out in three stages rather than spreading all at once. In the first stage, select key parks and public buildings to carry out pilots, giving priority to carriers with high energy intensity, good data foundation and single property owner. The administrative office area, the three major cultural facilities and the Urban Green Heart already have these three conditions and are the best starting units. In the

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second stage, promote to the whole region, focusing on solving the problem of data interface standardization. In the third stage, deepen and improve, connect the carbon account and the carbon inclusive mechanism, so that emission reduction can be traded and incentivized. In terms of multi-subject coordination, the government is responsible for rule making and data confirmation; state-owned enterprises (such as Beitou Group and Green Power) undertake the investment and operation of the first batch of demonstration projects; technology enterprises (such as Alibaba Cloud and Googol Technology) provide algorithm and platform capabilities; and the public participates through carbon inclusive channels. This division of labor already has a practical foundation in the sub-center and does not need to start from scratch.

6.2 Replication Value in the Beijing Area

The Beijing Implementation Plan for Carbon Peaking has given differentiated guidance to different functional areas: the central urban area promotes urban renewal oriented by low-carbonization; plain new towns strengthen the demonstration and application of low-carbon technologies and explore the dual control of total carbon emissions and intensity; and ecological conservation areas take the large-scale utilization of renewable energy as the starting point (Beijing municipal carbon peaking implementation plan, 2022). The transferable and non-transferable parts of the sub-center experience need to be distinguished. What is transferable is the methodology: the five-boundary accounting caliber, the parameter calibration process and the double-scenario comparison framework, which do not depend on the construction stage of the region. What is not transferable is the parameter values: the deployment cost of AI systems in new urban areas is far lower than that of stock renewal, and the measured energy saving rates cannot be directly applied across regions. The central urban area should focus on AI energy-saving renovation in urban renewal, whose technical path is essentially different from the 'synchronous planning' mode of the sub-center. Directly citing the energy-saving parameters of the sub-center will overestimate the effect, and this point must be clearly reminded in the promotion.

6.3 Policy Suggestions

First, unify the parameter management of district-level carbon emission accounting. At present, different departments use different emission factors when disclosing emission reduction, resulting in significant differences in the values of the same project under different calibers. It is suggested that the district-level ecological environment department issue an annual accounting parameter manual, clarifying the values and update rules of the electricity emission factor, the carbon sink coefficient and various energy conversion coefficients. Second, establish a dynamic carbon emission monitoring and intelligent assessment system, solidify the pilot of comprehensive evaluation of energy use and carbon emissions of fixed asset investment projects carried out in the sub-center into an institution, and fully incorporate the rigid requirement of carbon emission evaluation into the energy-saving review process (municipal expert consultation on the dual-control system, 2026). Third, introduce digital low-carbon technology standards. The sub-center has released 3 standards including the first local standard of the new power system in China, with 11 under research in parallel (tenth-anniversary green development press conference, 2026). It is suggested to expand to three aspects on this basis: data collection interfaces, carbon account accounting and algorithm credibility assessment. Fourth, support the agglomeration of AI + low-carbon technology enterprises. Relying on the two platforms of the National Green Technology Trading Center and the Beijing Green Exchange, a green industry fund of more than 10 billion yuan has been landed and the green credit balance exceeds 50 billion yuan (tenth-anniversary green development press conference, 2026). Scenario opening should be used to exchange for technology iteration, rather than simply attracting enterprises with subsidies.

7. Conclusions and Outlook

7.1 Research Conclusions

First, the role of artificial intelligence in the low-carbon transition of urban areas can be decomposed into three kinds of measurable effects: the improvement of prediction accuracy (load prediction and carbon sink accounting), the optimization of control strategies (timing and incineration conditions), and the reconstruction of resource matching (virtual power plant and source-grid-load-storage coordination). The

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three kinds of effects correspond to different accounting items and cannot be generally classified as 'efficiency improvement'. Second, the sectoral emission reduction contribution shows an unbalanced distribution. The building and energy departments together contribute the highest share, which is consistent with the structural feature that public building carbon emissions in Beijing account for about half of the total social carbon emissions; the transport department is constrained by the new energy penetration rate and road network coverage, and its contribution is relatively limited; the ecological carbon sink remains stable during the accounting period, but its marginal effect on total reduction decreases with the narrowing of afforestation space. Third, parameter management is more urgent than technology deployment. The influence of the caliber difference of emission factors on the results exceeds the technical parameters themselves, which is the most important policy implication of this study. Fourth, the new city construction scenario has cost advantages but lacks baseline comparison. The AI system of the sub-center is built synchronously with the infrastructure, and the deployment cost is significantly lower than that of stock renewal, but it also lacks the comparison data before and after renovation, so the attribution of the energy saving rate needs a more careful identification strategy.

7.2 Research Limitations and Outlook

This study has three limitations. First, due to the limitation of district-level data availability, the accounting does not cover embodied carbon and the upstream emissions of electricity transferred from other regions, and the total conclusion may be low. Second, some technical parameters rely on the measured values of a single project, and the sample representativeness is limited. The robustness of cross-project migration needs more engineering verification. Third, the conversion chain between delay improvement and emission reduction still relies on working condition assumptions, and lacks the support of local on-board emission measurement data. Follow-up research can be promoted in three directions: introduce input-output tables to expand the accounting boundary to the full caliber; build parameter distributions rather than point estimates with more engineering projects; combine digital twin technology to build a dynamic simulation platform of urban carbon metabolism, realizing the scenario deduction of emission reduction policies and the simultaneous evaluation of co-benefits. In addition, the landing effect of the carbon inclusive mechanism at the community scale and its long-term impact on residents' behavior change are also worth testing through tracking data.

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