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An integrated framework for reducing construction carbon emissions using real-time monitoring and econometrics

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The construction sector accounts for nearly 39% of global energy- and process-related CO_2 emissions, yet its decarbonisation is hampered by the lack of real-time, verifiable data during construction. To close this gap, we developed and validated an integrated, data-driven framework through a case study. The framework employs a Cyber-Physical System (CPS) with calibrated wireless sensors to stream high-resolution operational data from construction machinery. These data were used to train a Long Short-Term Memory (LSTM) model that predicted equipment-level emissions with a root-mean-square error of 0.0196 t CO_2 and a mean absolute error of 0.015 t CO_2. A fixed-effects panel econometric model further showed that each one-unit rise in a regional Green Finance Index lowered construction carbon intensity by $\beta = -0.082$ ($p < 0.01$). By converting granular site data into actionable insights, the framework links operational efficiency to financial reward, establishing a performance-based paradigm for carbon management. This pathway enables policy-makers to embed real-time tracking into green-finance instruments and allows practitioners to align project decisions with verified emission reductions, thereby accelerating progress toward global carbon-neutrality goals.

Keywords Carbon neutrality, Construction management, Cyber-physical systems (CPS), Deep learning, Green finance, Time-series forecasting

In the wake of international climate accords (e.g., the Paris Agreement) and mounting global initiatives to mitigate climate change, the construction sector has come under intensifying scrutiny for its considerable carbon footprint. As a principal contributor to global CO_2 emissions—responsible for roughly 39% of energy and processrelated discharges[1]—decarbonizing this sector is essential for achieving worldwide carbonneutrality targets. Focusing on the rapidly expanding construction industry in China, the present study seeks to bridge the gap between realtime carbon performance on construction sites and overarching climate objectives. The imperative to mitigate climate change demands concerted action from highemission sectors, with the construction industry representing a pivotal focal point[2]. In turn, its vast upstream demand for energy and materials significantly amplifies environmental burdens across regional supply chains and economies. Such emissions originate from a diverse building stock, broadly categorized into industrial, public, and residential structures, each exhibiting distinct carbon profiles and mitigation challenges (Fig. 1). They encompass both operational carbon, released during building use, and embodied carbon, derived from material manufacturing, transportation, and the construction process itself within the national context[3].

Although significant advances were made in reducing operational carbon through the implementation of energy-efficient designs, the complex challenge of managing embodied carbon from the construction phase remains a prominent and undermanaged frontier[4]. This challenge is particularly acute given that the bulk of future construction activity is projected to occur in emerging economies. Unlike most advanced economies that reached their peak CO_2 emissions decades ago (Table 1), many of these nations remain on an upward emissions trajectory, magnifying the global carbon impact of their construction choices[5]. In China, the context for this study, residential buildings constitute the largest share of construction activity, accounting for over 60% of the total completed area by construction enterprises (Fig. 2). To manage this growth sustainably,

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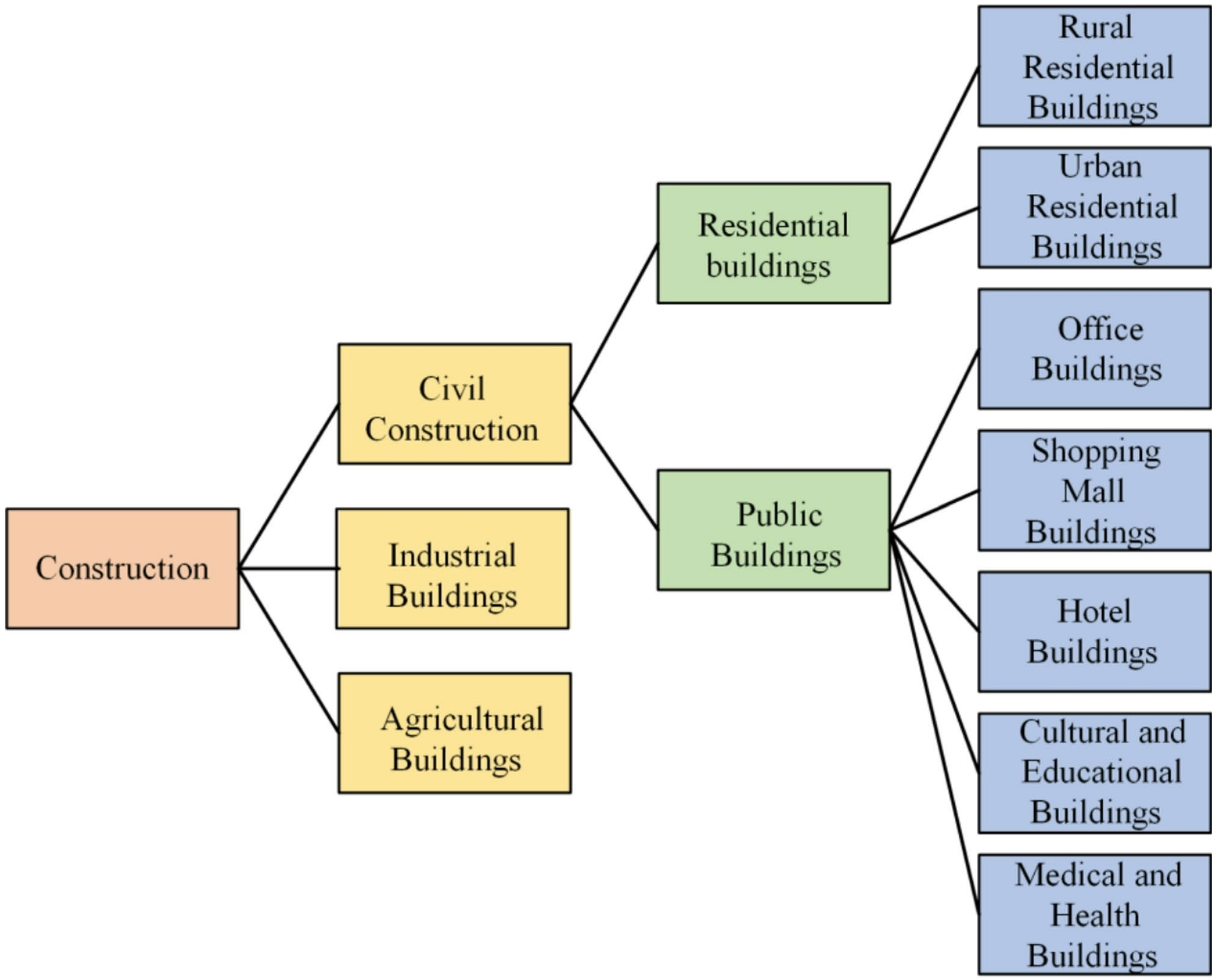

Fig. 1. Classification of building types by use, forming the basis for carbon-neutrality assessment.

Country	Time of peak total energy consumption	Time of peak total CO_2 emissions	Time of peak CO_2 emissions per capita	Peak level of CO_2 emissions per capita (t/person)
United States	2007	2007	1973	22.2
EU (15 countries)	2005	1980	1973	9.4
United Kingdom	2001	1975	1973	11.7
Germany	1985	1980	1980	13.4
Japan	2004	2007	2005	9.5

Table 1. Carbon dioxide emissions in developed countries.

building industrialization has emerged as a key strategy. The typical industrial chain process for this approach is illustrated in Fig. 3. This study, however, does not analyze the entire chain; instead, it focuses on the critical phases of component production and on-site assembly. The precise analytical boundaries adopted in this paper are defined in Fig. 4[6,7].

Nevertheless, effectively managing the carbon footprint within these defined boundaries is impeded by several intrinsic deficiencies. The most significant of these issues is a fundamental deficiency in data latency and granularity. A primary deficiency is the lack of timely and granular data. Conventional carbon accounting paradigms relied on static, life-cycle assessment (LCA) methodologies, with emissions estimated post-hoc using aggregated, industry-average data. The absence of real-time project-specific data hinders the implementation

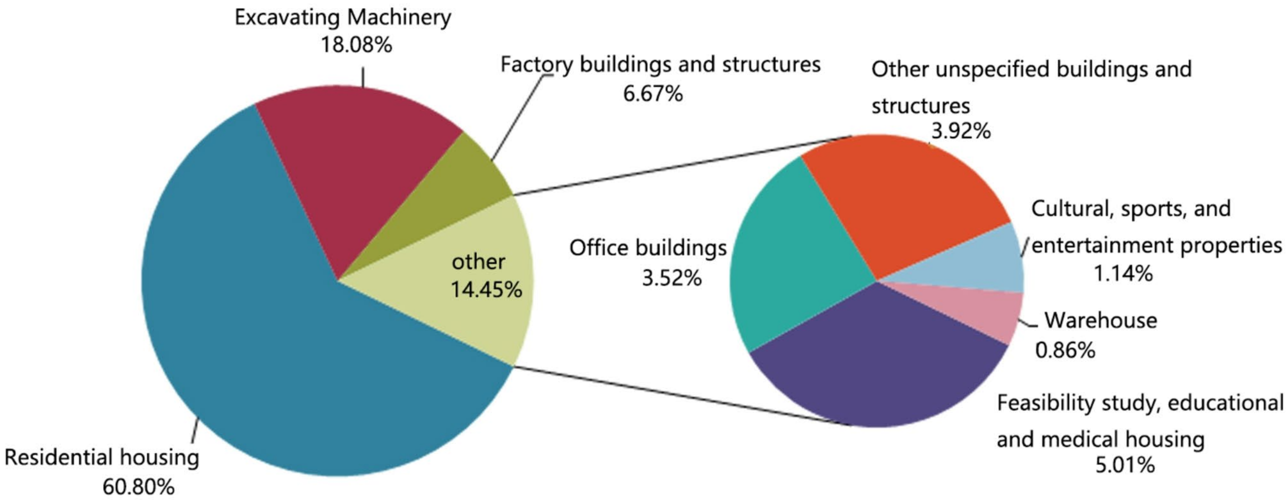

Fig. 2. Composition of completed housing area by construction enterprises in China, highlighting the dominance of residential buildings.

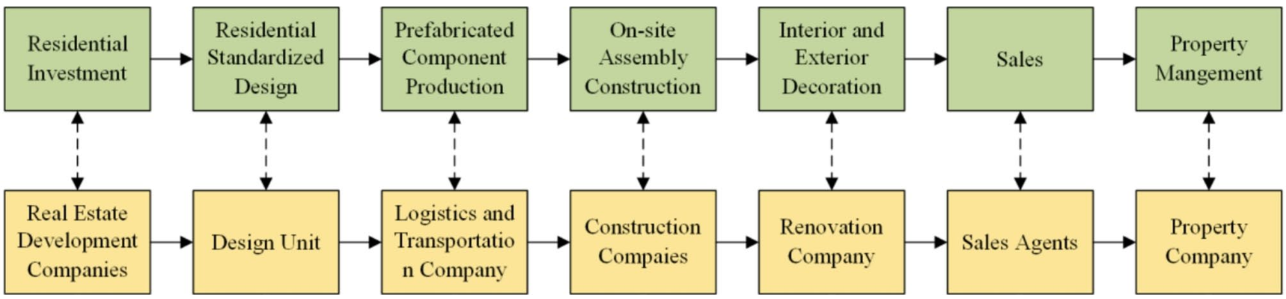

Fig. 3. The general process flow of the industrialized building chain.

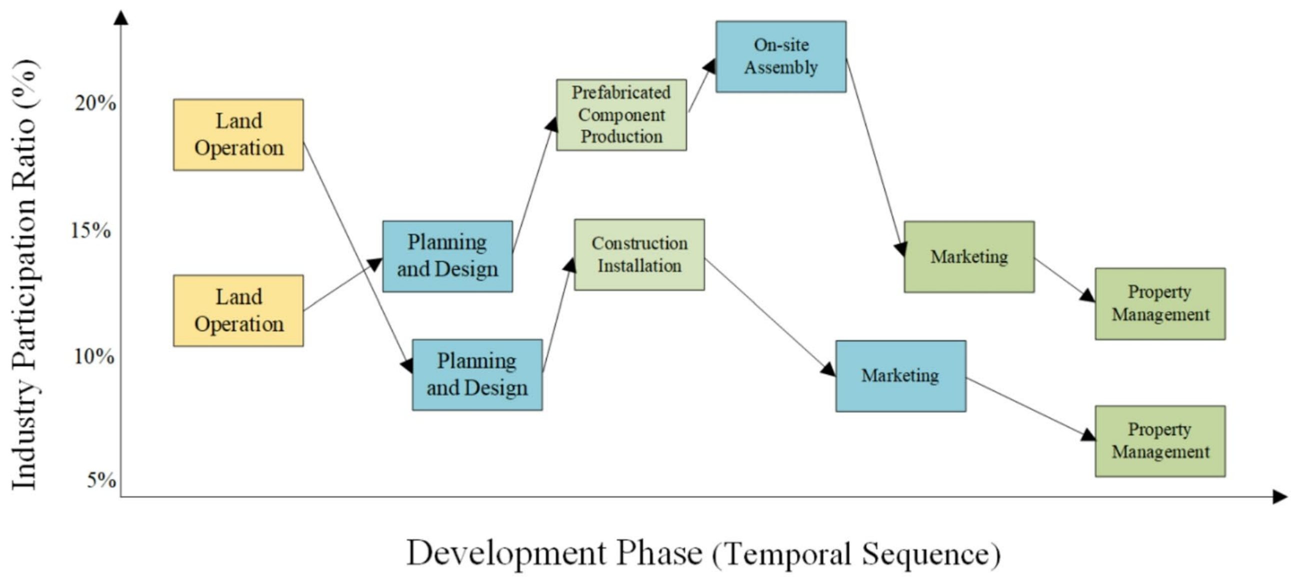

Fig. 4. The analytical boundaries of the industry chain adopted in this study.

of dynamic operational control, thereby impeding proactive intervention by project managers and the accurate verification of carbon performance against established goals by stakeholders[8–11].

This issue is further compounded by a substantial integration gap between on-site performance and macro-level financial incentives[12]. The prevailing green finance instruments, such as green bonds and credits, are typically benchmarked against design-phase certifications like LEED, rather than empirically verified, on-site operational performance[13,14]. Consequently, a robust mechanism to financially incentivize superior, measured carbon management remains underdeveloped. This phenomenon, extensively documented in academic literature, is known as the "performance gap." The gap refers to the discrepancy between the anticipated environmental benefits of green finance, as predicted by theoretical models, and the actual real-world impact observed in practice[15,16].

A corresponding analytical gap is also evident in the application of modern monitoring technologies. Although real-time monitoring systems such as CPS and IoT have demonstrated considerable potential in previous studies, their implementation has been largely restricted to basic data acquisition and visualization[17]. There is a critical need for the application of advanced analytics, such as predictive modelling, to translate high-volume data streams into the actionable intelligence required for proactive optimization. This intelligence can be used to identify sources of inefficiency or to forecast future emission trends[18].

Collectively, these issues highlight an overarching synergy gap in prior research. The conventional approach to scholarly inquiry into construction technology, carbon accounting, and green finance was characterized by a fragmentation of research across discrete disciplinary silos. This fragmented approach impeded the development of integrated solutions in which technological advancements could directly inform financial models and policy. Consequently, the synergistic potential of a holistic system that connects these domains was not systematically investigated or empirically validated.

For example, recent empirical work highlighted how green finance can enhance the carbon reduction efficiency of construction industries but often isolated this effect from concurrent technological and policy innovations[19]. Similarly, research examining green finance governance demonstrated its potential to reduce CO_2 emissions through capital allocation reform, yet it did not link this with advancements in construction technologies or integrated accounting frameworks[20]. Another study exploring green building finance systematically reviewed investment drivers and challenges but called for deeper cross-disciplinary modeling between finance and environmental technology domains[21]. Moreover, investigations into synergistic carbon mitigation effects from combined green and digital financial reforms suggested significant potential, yet these effects remain underexamined in construction-specific contexts[22].

In response to these multifaceted challenges, the present study develops and validates an integrated framework that, for the first time, bridges the gap between real-time data acquisition, predictive analytics, and financial decision-making in the construction sector. The novelty of this research resides not in any single technique, but in the holistic synthesis of previously siloed approaches—enabling a seamless closed-loop system that aligns site-level performance with financial incentives and policy objectives. The investigation is guided by the following primary objectives: (i) to design and validate a Cyber-Physical System (CPS) capable of continuous, automated collection of high-fidelity emissions data directly from construction machinery; (ii) to integrate advanced data-driven forecasting methods, such as time-series prediction algorithms, in order to enable proactive operational optimization; and (iii) to establish a robust quantitative pathway that links empirically measured emissions data with performance-based financial mechanisms, supported by rigorous econometric analysis of green finance impacts.

The resultant framework fundamentally redefines the role of real-time operational data, transforming it from a static reporting metric into a dynamic driver of financial and managerial decision-making. By seamlessly integrating monitoring, analytics, and policy evaluation, this approach provides a robust and scalable model for accelerating meaningful decarbonization in the construction industry, forging a direct and quantifiable connection between project-level outcomes and macro-level sustainability targets.

Methods

In order to address the critical, disconnect between on-site construction performance and macro-level financial incentives, this study develops and validates a novel integrated framework. The framework has been designed to function as a seamless data-to-decision pipeline, thereby creating a closed loop that translates granular operational data into actionable insights for both project managers and policymakers. The methodology is predicated on three distinct stages, which progress sequentially from micro-level data capture to macro-level policy analysis. The overall architecture of this integrated system is illustrated in Fig. 5.

Data acquisition and emission calculation

The foundation of the proposed framework is the ability to acquire accurate, high-fidelity data directly from the construction site. The core of the data acquisition system is constituted by a custom-designed wireless sensor module attached to key construction equipment (see Fig. 6). In order to ensure data accuracy, the CPS measurements were validated against traditional methods.

Once the operational data is collected, it is converted into quantified carbon emissions. The scope of the emission sources considered is defined in Table 2.

The general procedure for estimating carbon emissions is presented as Eq. (1), where C represents the total carbon emissions, E_i is the consumption of the i-th energy type, and δ_i is the corresponding carbon emission factor. A simplified version for machinery is shown in Eq. (2), where C is again the total emissions E is the total energy consumed (determined by power P multiplied by operational time T), and f is the specific carbon emission factor.

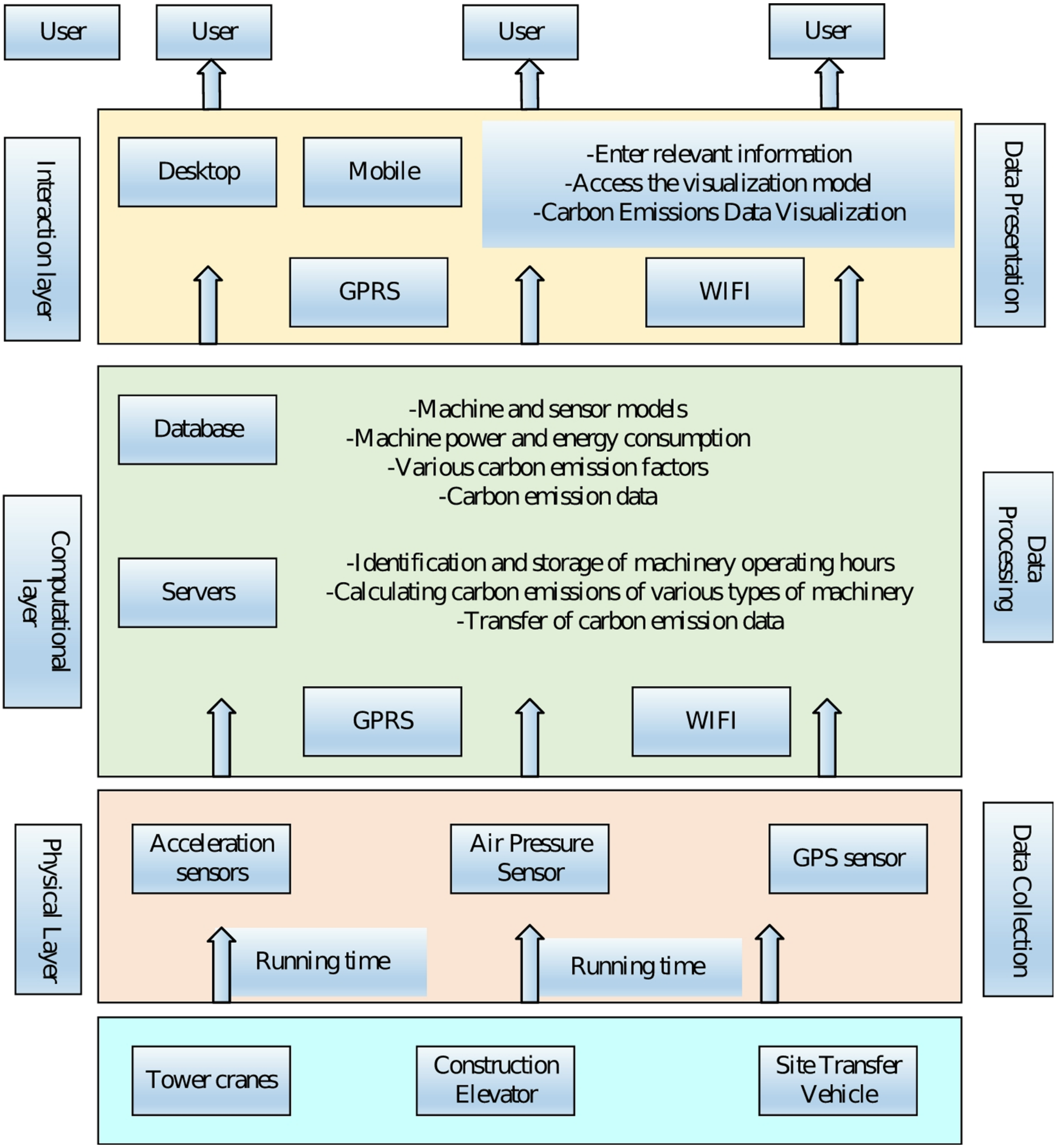

Fig. 5. The general framework of the Cyber-Physical System (CPS) for carbon monitoring and optimization.

$$C = \sum\nolimits_{i=1}^{j} E_i \times \delta_i \tag{1}$$

$$C = E \times f \tag{2}$$

The calculation principle of building carbon emissions was shown in Fig. 7.

The aggregate monitoring for different categories of equipment is further detailed in Eqs. (3) and (4). These formulas calculate the total emissions for a specific time period t (C_t) or equipment category v (C_v) by summing the product of parameters such as power ($P_{t,i}$), time ($T_{t,i}$), and energy usage rate ($EU_{v,i}$) with their respective emission factors (f_e, f_i).

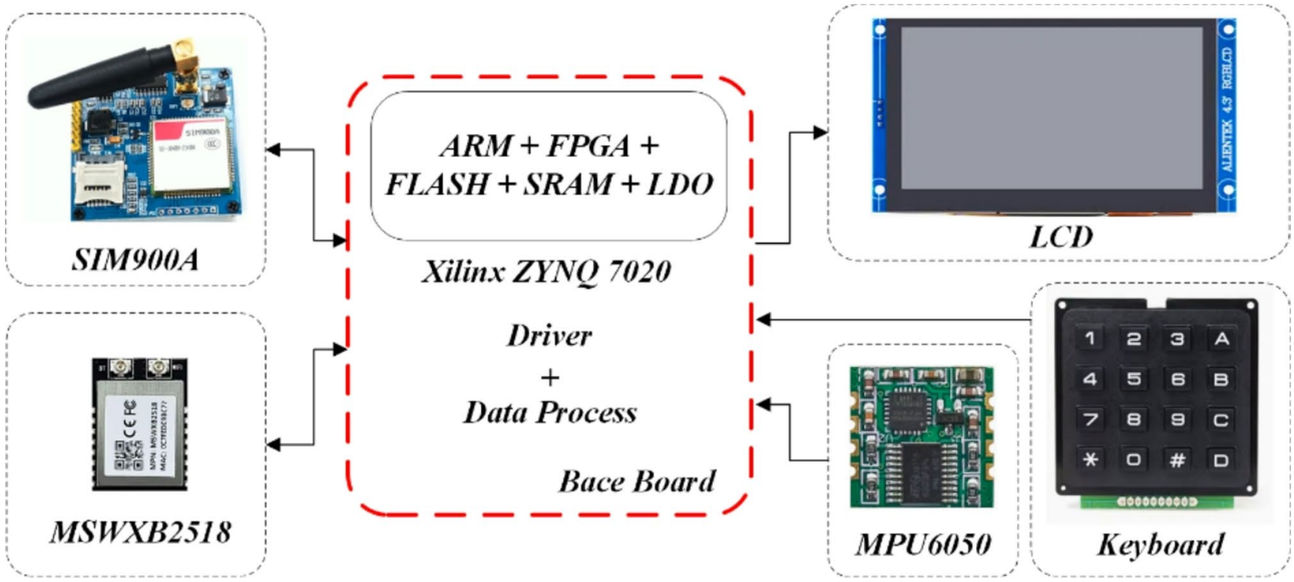

Fig. 6. Schematic of the CPS hardware module.

Serial number	Processes	Labor	Material	Energy consumption
1	Pre-construction inspection	Artificial respiration	Concrete	Electricity, gasoline, water
2	Stair components fixed	Artificial respiration	-	Electricity, gasoline
3	Lifting and transportation	Artificial respiration	-	Electricity
4	Stair components in place	Artificial respiration	-	Electricity
5	Installation error check and adjustment	Artificial respiration	-	-
6	Seam sealing and binning	Artificial respiration	Cement, sand	Electricity, water
7	Grouting material production	Artificial respiration	Grout	Electricity, diesel, water
8	Grouting operation	Artificial respiration	-	Electricity, diesel
9	Work surface cleaning	Artificial respiration	-	Water
10	Node protection after grouting	Artificial respiration	-	-
11	Temporary support removal	Artificial respiration	-	Electricity
12	Component installation joint construction	Artificial respiration	Concrete	Electricity, water
13	On-site repair	Artificial respiration	Cement, sand	Electricity, diesel, water
14	Surface treatment	Artificial respiration	-	Water

Table 2. Carbon emission sources identified in the process of component installation.

$$\mathrm{C_t} = \sum_{\mathrm{i}=1}^{\mathrm{k_t}} \mathrm{P_{t,i}} \times \mathrm{T_{t,i}} \times \mathrm{f_e} \tag{3}$$

$$C_v = \sum_{i=1}^{k_v} T_{v,i} \times EU_{v,i} \times f_i \tag{4}$$

The specific carbon emission factors used in these calculations are summarized in Table 3.

Project-level modeling and optimization

With emissions data reliably quantified, a Long Short-Term Memory (LSTM) network was employed to provide short-term emission forecasts. Following this, a multi-objective optimization model was constructed to formally address the trade-offs between speed, cost, and environmental impact. The objective function, shown in Eq. (5), seeks to minimize a total weighted value Z. This is achieved by summing the total project duration ($\sum t_{i,p}$), the total project cost ($\sum \gamma_i \theta_i \alpha_i$), and the total project emissions ($\sum \delta \alpha_i$), each multiplied by their respective normalized weights for time (ω_T), cost (ω_C), and emissions (ω_E).

$$\mathrm{minZ} = \omega_{\mathrm{T}} \cdot \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{t_{i,p}} + \omega_{\mathrm{C}} \cdot \sum_{\mathrm{i}=1}^{\mathrm{n}} \gamma_{\mathrm{i}} \theta_{\mathrm{i}} \alpha_{\mathrm{i}} + \omega_{\mathrm{E}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \delta \alpha_{\mathrm{i}} \tag{5}$$

The key parameters used in this optimization model, such as the specific values for the weights, are detailed in Table 4.

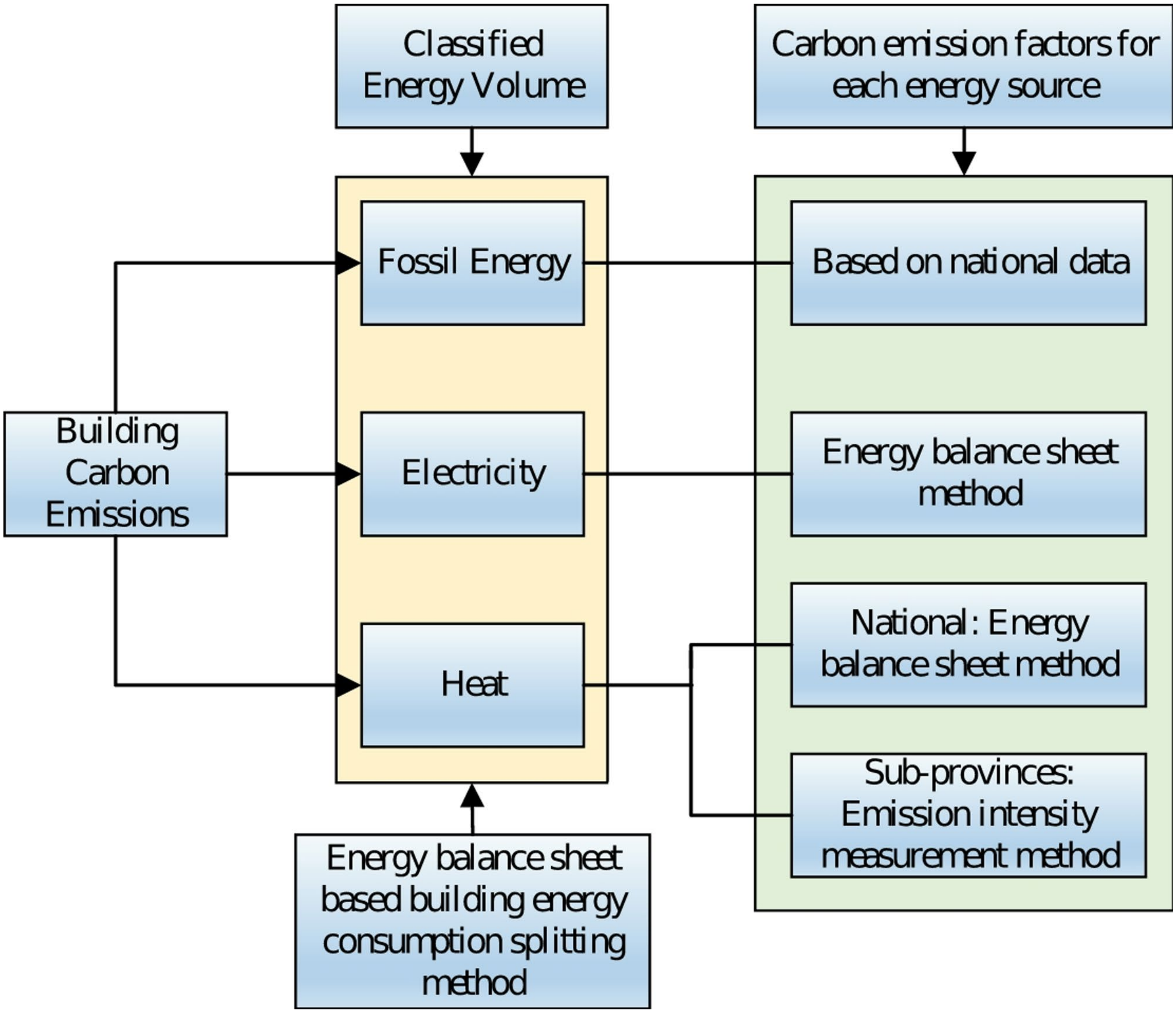

Fig. 7. Computational schematics.

Carbon Source	Carbon emission factor
Workers breathing	1.75kgCO2-c/person*workday
Water	0.86kgCO2-c/t
Concrete (C30)	342.85 kgCO2-c/m3
.Cement	740.62 kgCO2-c/t.
Sand	2.81 kgCO2-c/t
Electricity	0.9514 kgCO2-c/kWh
Gasoline	3.52 kgCO2-c/kg
Diesel	3.69 kgCO2-c/kg
Grout	512.62 kgCO2-c/m3

Table 3. Collated carbon emission factors for materials and energy sources.

The project-level optimization was guided by a data-driven framework, the workflow of which is detailed in Fig. 8. This framework illustrates the end-to-end process of transforming raw physical and simulated data into a solvable optimization problem through data integration, stochastic matrix modeling, and machine learning. The core optimization problem defined by this framework was then solved using a hybrid Ant Colony Optimization (ACO) algorithm, whose iterative process for finding Pareto-optimal solutions is shown in Fig. 9.

Curve coding	St_i	$\tau_{i,o}$	γ_i		α_i	δ	μ_i
S_{11}, S_{12}, S_{13}	10	10	0.15	0.5	0.2	0	0.2
S_{21}, S_{22}, S_{23}	10	10	0.15	0.5	0.3	0.2	−0.2
S_{31}, S_{32}, S_{33}	10	10	0.15	0.5	0.4	0.5	0.5
S_{41}, S_{42}, S_{43}	10	10	0.15	0.5	0.5	0.8	1
S_{51}, S_{52}, S_{53}	10	10	0.15	0.5	0.6	1.1	1.3

Table 4. Parameter settings for the multi-objective optimization model.

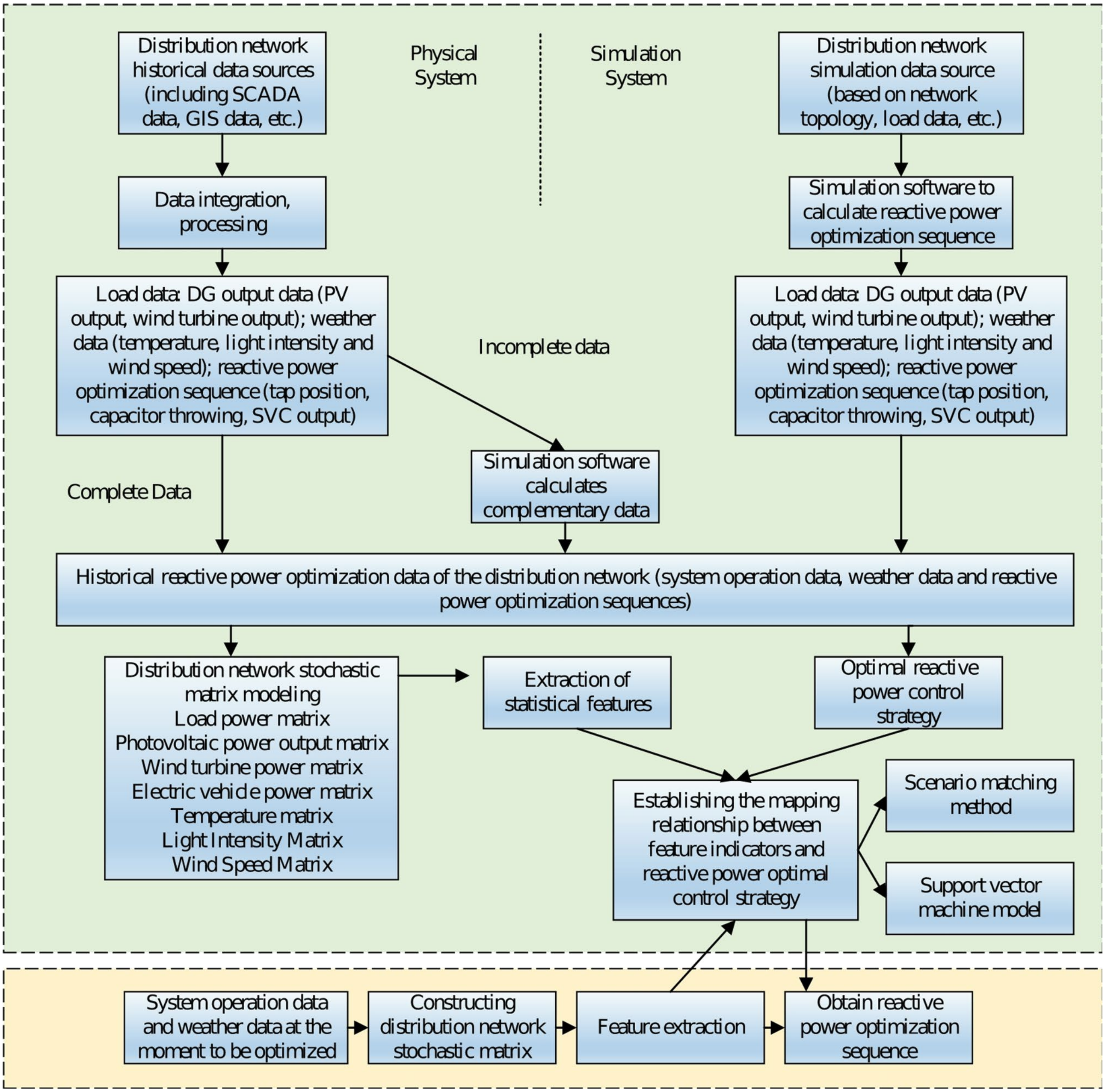

Fig. 8. Detailed workflow of the data-driven optimization framework, illustrating the process from data integration and feature extraction to machine learning-based strategy mapping.

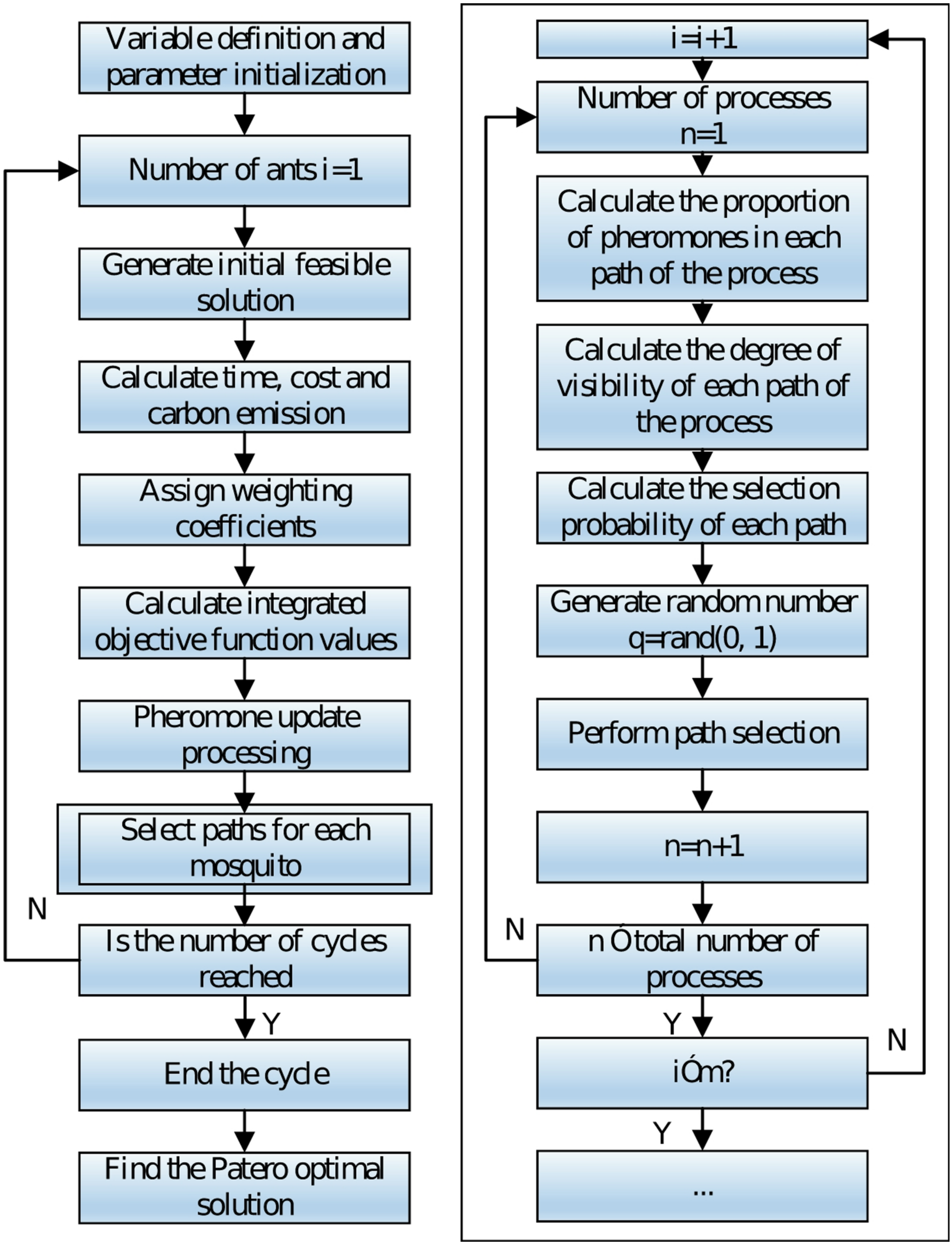

Fig. 9. Flowchart of the multi-objective optimization algorithm.

Macro-level econometric analysis

To connect our project-level analysis to the macroeconomic context, an econometric study was designed to measure the impact of green finance on carbon intensity at a regional level. The key independent variable, the Green Finance Index (GFI), was constructed based on the indicator system shown in Table 5.

A series of panel data models were specified. A baseline fixed-effects model was first established (Eq. 6) to assess the impact of the Green Finance Index ($GFI_{i,t}$) on Carbon Intensity ($CI_{i,t}$), while controlling for Foreign Direct Investment (FDI), Trade Openness ($TRAD$), Urbanization Rate (URB), and R&D investment (RD).

Target layer	Primary index	Characterization index	Indicator attribute	Indicator description
Green Finance	Green credit	Proportion of interest expenditure of high energy consuming industries	-	Interest expenditure of six high energy consuming industries/total interest expenditure of industrial industries
	Green securities	Proportion of market value of high energy consuming industries	-	A-share market value of six high energy consuming enterprises/total A-share market value of Listed Enterprises
	Green insurance	Depth of agricultural insurance	+	Agricultural insurance premium income/total agricultural output value
	Green investment	Proportion of investment in environmental pollution control in GDP	+	Investment in environmental pollution control/GDP

Table 5. The indicator system for constructing the green finance development level index.

The model includes province-specific fixed effects, μ_i, and time-fixed effects, ν_t, to account for unobserved heterogeneity.

$$C_{i,t} = \alpha_1 GF_{i,t} + \alpha_2 FDI_{i,t} + \alpha_3 TRAD_{i,t} + \alpha_4 URB_{i,t} + \alpha_5 RD_{i,t} + \mu_i + \nu_i + \varepsilon_{i,t} \quad (6)$$

To further explore causal pathways, a difference-in-differences (DiD) approach combined with a mediation model was employed (Eqs. 7–9). In this framework, we analyze the total effect of a policy intervention (represented by the interaction term $\mathrm{Treat} \cdot \mathrm{T}$) on the outcome variable $\mathrm{Y}_{i,t}$, as well as its effect on a mediating variable, $\mathrm{Mech}_{i,t}$, while including a vector of other controls.

$$Y_{i,t} = \alpha_1 \cdot \mathrm{Treat} \cdot T + \sum \beta_j \cdot \mathrm{Control} + \mu_i + \nu_t + \epsilon_{i,t} \quad (7)$$

$$\mathrm{Mech}_{i,t} = \alpha_2 \cdot \mathrm{Treat} \cdot T + \sum \beta_k \cdot \mathrm{Control} + \mu_i + \nu_t + \epsilon_{i,t} \quad (8)$$

$$Y_{i,t} = \alpha_3 \cdot \mathrm{Treat} \cdot T + \alpha_4 \cdot \mathrm{Mech}_{i,t} + \sum \beta_l \cdot \mathrm{Control} + \mu_i + \nu_t + \epsilon_{i,t} \quad (9)$$

Results

Real-time emission-forecasting performance

A cyber-physical monitoring system equipped with wireless sensors and a time-series forecasting module recorded data at a rate of one sample per second from tower cranes, construction hoists, and other equipment. Coupling the system with a long short-term memory (LSTM) learner — without revealing the network's detailed architecture — lowered the RMSE to 0.0196 t CO_2 and the MAE to 0.015 t CO_2 at a temporal resolution of 10 s per sample. Figure 10. shows the measured and predicted curves, which exhibited twin peaks at 08:00 and 12:00.

Table 6. compares the errors of stopwatch timing, conventional power meters and the CPS approach.

C_{t1}, C_{t2} and C_{t3} denote carbon-emission estimates obtained by stopwatch timing, power-meter logging and the CPS-based method, respectively. Values refer to a SYT80 (T6510-8) tower crane operating at 30 kW for 137 s.

Lifecycle emission distribution

Our analysis of the prefabricated staircase installation workflow revealed a clear distribution of carbon emissions across the lifecycle. The inventory showed that total emissions were partitioned primarily into energy (55% ± 4%), materials (37% ± 3%), and labor (8% ± 1%). Figure 11. provides a conceptual visualization of these emission sources across the key life-cycle stages.

To further investigate the impact of project scheduling on these emissions, a scenario analysis was conducted. The detailed results, presented in Table 7, quantify the trade-off between schedule acceleration and environmental impact. The analysis demonstrates that the Rush schedule (E_1) emitted on average 18% more CO_2 than the Normal schedule (E_2) and 37% more than the resource-Saving schedule (E_3). This increase was driven primarily by higher energy consumption, particularly from overtime electricity use and additional diesel-powered hoisting, whereas material-related emissions varied by a smaller margin.

These findings quantitatively establish that operational energy management and work pacing are the most critical factors in managing the carbon footprint of prefabricated component installation, providing an empirical baseline for the optimization analysis in the subsequent section.

Optimization & finance impacts

(a) Multi-objective optimization: The random-matrix ant-colony framework generated 98 non-dominated solutions that balanced project duration, cost and carbon intensity. Small-sized networks converged within 30 iterations, whereas large networks exhibited wider oscillations before stabilizing. Figure 12. plots the resulting Pareto frontier: cost premiums ranged from 0 to 5%, while carbon reductions spanned 17–23%, displaying a strong linear trade-off ($r = 0.99$). Table 8 lists five representative schemes; for example, shortening the schedule by 12% required a 3% cost premium but raised emissions by only 1%, whereas the lowest-carbon scheme achieved a 23% reduction at a 5% cost penalty.

(b) Scenario comparison Five optimization modules were benchmarked—Balanced, Duration-prioritised, Low-carbon, Cost-prioritized and Policy-driven. Descriptive statistics (Table 9) and Kolmogorov–Smirnov

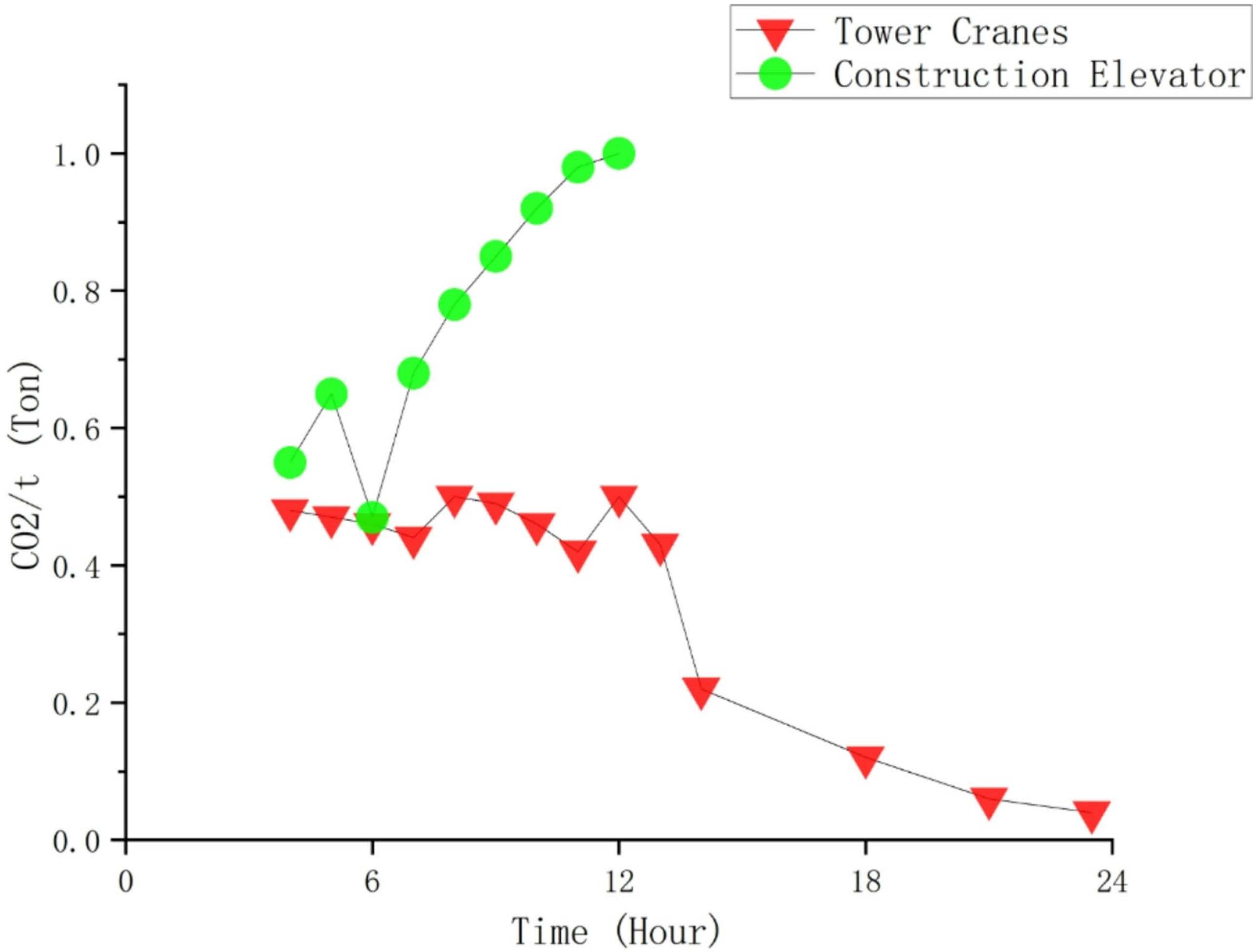

Fig. 10. Real-time carbon-emission trajectories of tower-cranes and construction hoists.

Mechanical model	Mechanical power(kW)	Stopwatch timing(s)	C_{t1} (kg)	C_{t2} (kg)	C_{t3}
SYT80(T6510-8)	30.0	137	1.11	1.08	1.16

Table 6. Comparison of carbon-emission measurement methods for prefabricated-stair installation.

tests (Table 10) showed that only the Low-carbon module (C) combined the lowest mean emission value with the highest dispersion ($p < 0.05$). The extra spread stemmed mainly from electricity- and diesel-intensive tasks, indicating that aggressive abatement strategies amplify sensitivity to site-specific energy profiles.

(c) Green-finance effect Panel fixed-effects regression (Table 11) indicated that a one-unit rise in the regional Green Finance Index significantly lowered construction carbon intensity by $\beta = -0.082$ ($p < 0.01$). Urbanization rate ($\beta = -0.049$, $p = 0.001$) and trade openness ($\beta = -0.018$, $p = 0.026$) also exhibited significant negative effects. In contrast, foreign direct investment was not significant ($p = 0.684$). Robustness checks using a one-period lag and heteroskedasticity-robust standard errors yielded coefficients of comparable magnitude and significance.

Stakeholder-cooperation network

Figure 13. visualizes the scale-free collaboration networks of five stakeholder groups in the low-carbon construction ecosystem. Designers & contractors form the most centralized cluster, exhibiting high degree-centrality hubs that coordinate information and resource flows. Suppliers and builders/consumers appear markedly sparser, while financial-technical institutions occupy an intermediary role that links cost control with technological diffusion. The government-regulator network shows a dual-core pattern, emphasizing both policy enforcement and guideline dissemination. Together, the topology indicates that emission-reduction initiatives are most leverageable through core contractors and governmental bodies, whereas supplier-side engagement remains the weakest link and should be prioritized in future policy design.

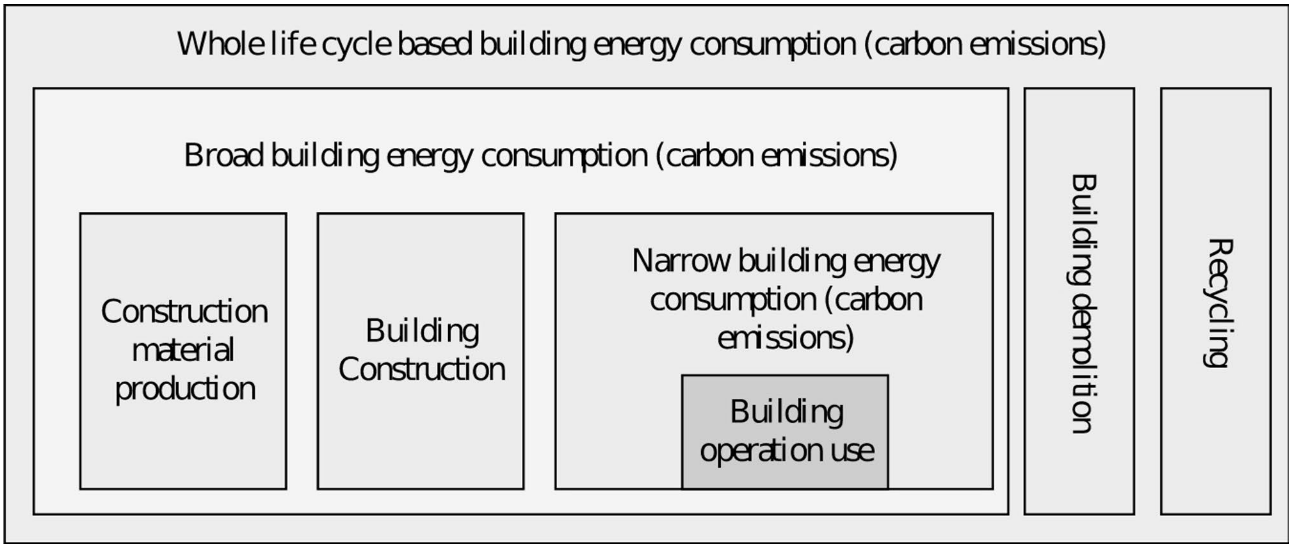

Fig. 11. Lifecycle distribution of carbon emissions across labor, material and energy stages.

Serial number		1	2	3	4	5	6
Rush work $E_1/kgCO_2$	Labor	0.01	0.05	0.02	-	-	0.23
	Material	0.42	-	-	-	6.6	14.5
	Energy consumption	1.7	1.1	1.4	-	-	0.8
	Total	2.13	1.15	1.42	-	6.6	15.53
Normal $E_2/kgCO_2$	Labor	0.03	0.06	0.03	0.12	0.01	0.05
	Material	0.36	-	-	-	5.85	0.32
	Energy consumption	1.5	1.8	-	4.6	0.05	0.6
	Total	1.89	1.86	0.03	4.72	5.91	0.37
Saving $E_3/kgCO_2$	Labor	0.02	0.08	-	0.25	0.01	0.02
	Material	0.33	-	-	1.2	-	0.88
	Energy consumption	1.2	0.8	-	4	-	0.01
	Total	1.55	0.88	-	5.45	0.01	0.91

Table 7. Carbon emission calculation results.

Discussion

The present study developed and validated an integrated framework to bridge the critical gap between real-time operational carbon performance in construction and macro-level green finance mechanisms. The analysis yielded three tiers of findings. Firstly, at the operational level, the results obtained demonstrate that a CPS-based system can accurately monitor and forecast emissions (RMSE = 0.0196 t CO_2). Secondly, at the project management level, the multi-objective optimization yielded a clear, quantifiable trade-off between cost, schedule, and carbon abatement. Finally, at the macroeconomic level, our econometric analysis established a significant negative correlation between green finance development and carbon intensity ($\beta = -0.082$, $p < 0.01$). In this section, the findings are interpreted, situated within the existing literature, and their implications discussed.

A primary contribution of this research is its direct response to the data latency and performance gaps that have long hindered the sector's decarbonization. The finding that the CPS-LSTM system can achieve high predictive accuracy is a key technical result. This finding indicates a substantial theoretical contribution, namely that the utilization of static design-phase certifications can now be superseded by verifiable, performance-based metrics. For instance, while prior studies effectively documented the existence of this gap by comparing design-phase energy models with post-occupancy utility bills[23,24], our work provides a novel, real-time mechanism to mitigate it during the construction phase itself. This shift in focus from post-mortem analysis to dynamic, on-site management is a significant development. Moreover, this study addresses the so-called 'analytical gap' by moving beyond the scope of simple monitoring. While the finding itself is the quantitative trade-off on the Pareto frontier – for instance, that a 23% emission reduction is achievable at a 5% cost premium – the broader contribution is the creation of a strategic decision-making tool. This represents a marked departure from earlier LCA-based approaches, which were limited to static, pre-construction options[25,26]. By contrast, the dynamic optimization framework utilized in this project enables continuous, data-driven adjustments throughout the project lifecycle. The work presented herein addresses the overarching synergy gap by demonstrating a closed-

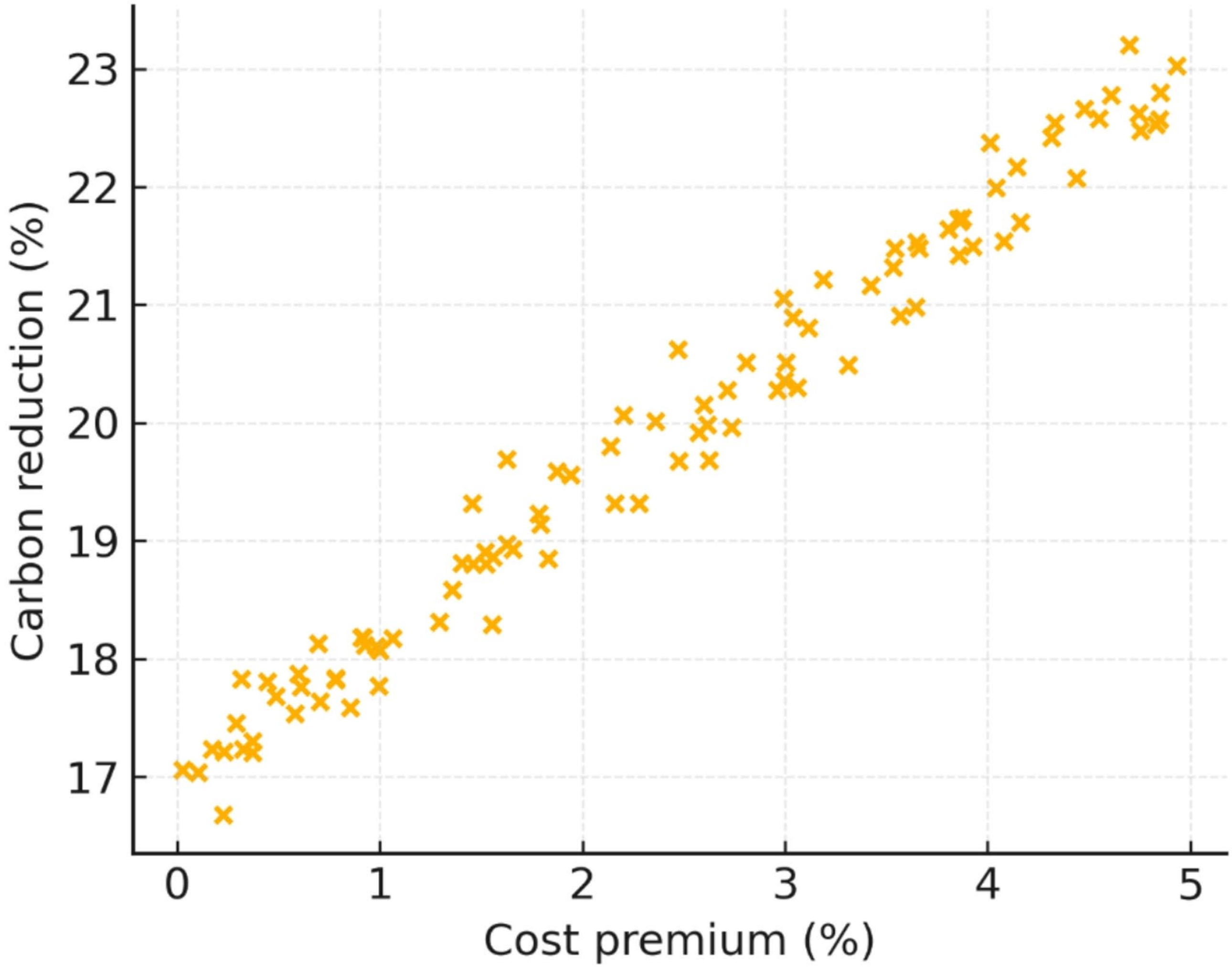

Fig. 12. Pareto frontier of the time–cost–carbon optimization ($n = 98$).

Scheme (ID)	Main objective	Cost premium (%)	Carbon reduction (%)	Schedule change (%)	Notes
A Balanced	Simultaneous time-cost-carbon	2.0	19.0	−5	Non-dominated midpoint solution
B Duration-prioritised	Minimize project duration	3.0	18.5	−12	Fastest schedule on frontier
C Low-carbon	Maximize carbon abatement	5.0	23.0	0	Lowest-emission point
D Cost-prioritized	Minimize extra cost	0.5	17.5	+ 3	Cheapest still Pareto-optimal
E Policy-driven	Align with local targets	1.5	20.0	−4	Meets regional 20% target

Table 8. Representative Pareto-optimal schemes balancing cost, carbon and schedule.

Type	Variable	Sample size	Mean value	Standard deviation
Module A(Balanced scenario)	0.500	0.073	0.566	0.060
Module B(Duration-prioritized scenario)	0.030	0.062	0.388	0.100
Module C(Low-carbon prioritized scenario)	1.000	0.100	0.267	0.283
Module D(Cost-prioritized scenario)	1.293	0.298	0.784	0.437
Module E(Policy-driven scenario)	1.304	0.865	0.367	0.111

Table 9. Descriptive statistics for five optimization modules.

Inspection method	K value	*P* value	Mean value	Result
Module A(Balanced scenario)	21.87	0.0010	0.65	Y
Module B(Duration-prioritized scenario)	20.37	0.0029	0.37	Y
Module C(Low-carbon prioritized scenario)	27.65	0.0011	0.28	N
Module D(Cost-prioritized scenario)	20.00	0.0012	0.11	Y
Module E(Policy-driven scenario)	19.78	0.0014	0.37	Y

Table 10. Kolmogorov–Smirnov test results for optimization modules.

Variable	Coefficient (β)	Robust SE	t-value	*p*-value	Sig.
Green Finance Index (GFI)	−0.082	0.021	−3.90	0.000	***
Foreign Direct Investment (FDI)	0.005	0.012	0.41	0.684	
Trade Openness (TO)	−0.018	0.008	−2.25	0.026	**
Urbanization Rate (UR)	−0.049	0.015	−3.27	0.001	***
Constant	1.216	0.087	13.95	0.000	***
N (panel-years)	265				
R^2 (within)	0.287				

Table 11. Panel fixed-effects regression of carbon intensity on green-finance and openness indicators.

loop system where each component informs the next, thereby providing an empirical validation for the "holistic synthesis" approach.

Beyond its theoretical contributions, the framework offers profound practical and policy implications, best understood through the collaborative ecosystem it enables (Fig. 14). This data-driven platform redefines the roles and interactions of at least four key stakeholder groups: For constructors, it transforms carbon management from a compliance burden into an optimization tool; for financial institutions, it provides a mechanism to underwrite "performance-based" green financial products; for design units, it creates a high-fidelity data feedback loop for evidence-based design; and for government and regulators, the platform offers a transparent and efficient tool for supervision. The importance of this governmental role is echoed in broader carbon reduction research; for example, recent research[27] identified a 'government-led environmental regulation' pathway as a key configuration for cities to achieve high carbon reduction performance. Instead of relying solely on prescriptive building codes, authorities could implement performance-based carbon taxes or cap-and-trade schemes, using the verifiable data from such CPS platforms as the official accounting record. This approach would foster innovation by allowing firms to choose the most cost-effective methods to meet emission targets[28–30]. Crucially, the framework allows for the quantification of financial incentive structures. Our optimization results revealed that a project achieving a 23% emission reduction at a 5% cost premium could receive a significantly larger financial discount that offsets the additional cost. This would establish a significant market-driven incentive for developers to adopt and scale these monitoring technologies[31]. This overall approach makes decarbonization not only environmentally desirable but also financially viable, directly operationalizing the negative correlation ($\beta = -0.082$) that our econometric model confirmed.

Limitations and future research

Notwithstanding the encouraging implications of this study, it is essential to acknowledge its limitations. Firstly, with regard to generalizability, the case study focused on a specific process within a single national context. The specific cost-abatement trade-offs identified on our Pareto frontier may vary significantly in different labour markets or with different material supply chains, which warrants caution in extrapolating our quantitative findings. Secondly, regarding the scope of the model, the primary focus of our analysis is emissions from heavy machinery (which constitute 55% of the total in our case). By centring on industrial machinery, we have successfully identified a substantial on-site emissions source. However, this approach fails to consider the significant embodied carbon emissions resulting from material transportation and the carbon footprint associated with worker commutes. These elements should be incorporated into future research endeavors. Thirdly, in terms of causal inference, while the econometric model demonstrates a strong correlation, it is unable to completely rule out the possibility of confounding variables, such as a concurrent rise in regional environmental awareness that could independently drive both green finance adoption and lower carbon intensity[32].

Consequently, future research should endeavor to address these limitations whilst concomitantly exploring new technological and financial frontiers. Specifically, three key directions are proposed: (i) the integration of this framework with Building Information Modeling (BIM) to create a full lifecycle digital twin; (ii) the application of more advanced machine learning techniques, such as reinforcement learning, for autonomous optimization; and (iii) the piloting of the novel performance-based financial instruments discussed, in collaboration with financial institutions and regulatory bodies.

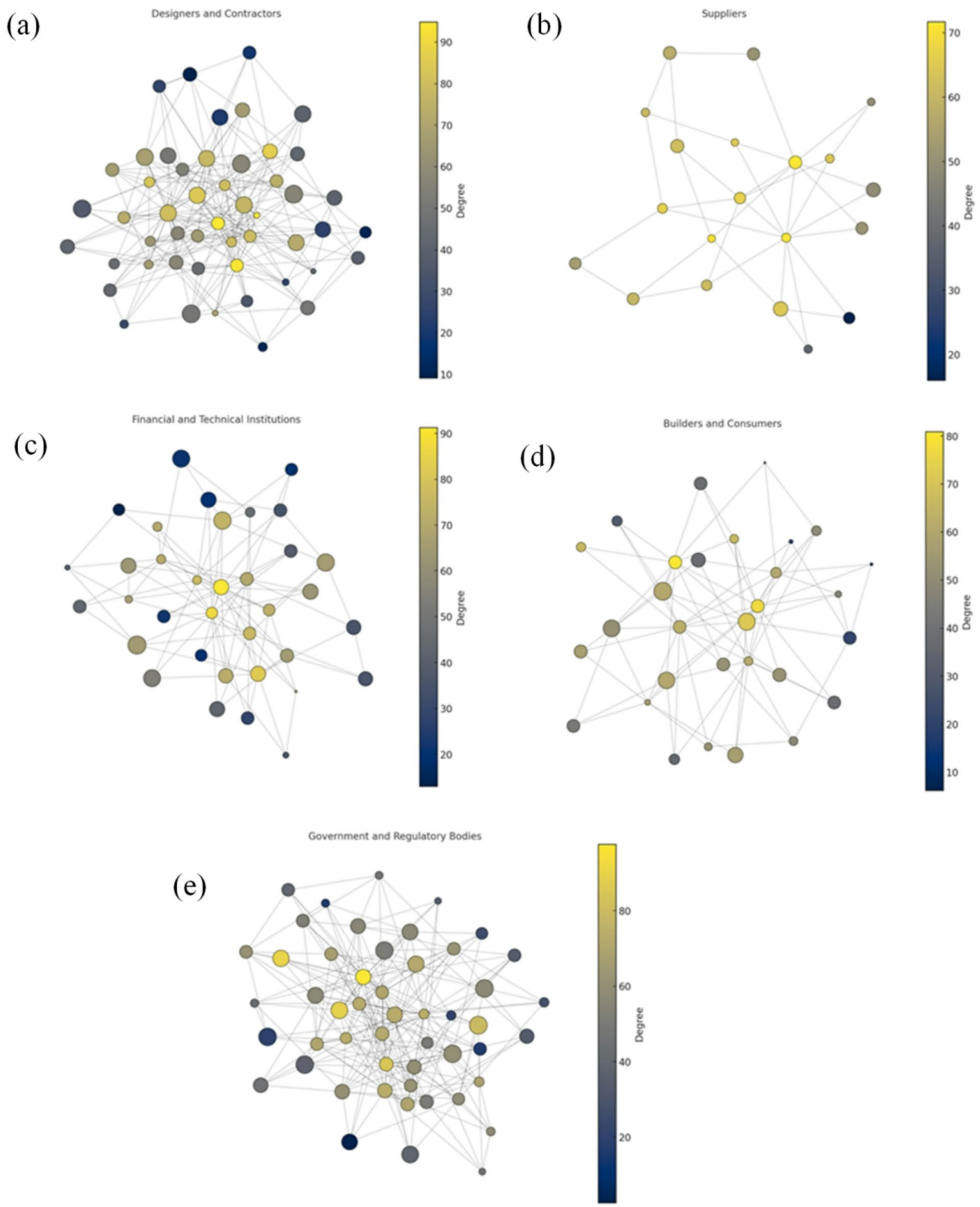

Fig. 13. Scale-free collaboration networks for five stakeholder groups; node size denotes entity count and color encodes degree centrality (light = high, dark = low). Subplots: (**a**) designers/contractors, (**b**) suppliers, (**c**) finance/tech, (**d**) builders/consumers, (**e**) government/regulators.

Conclusion

The present study addressed the critical disconnect between on-site carbon performance and financial incentives in the construction industry by developing and validating an integrated, data-driven framework. The research demonstrated the technical feasibility of using a Cyber-Physical System to accurately monitor and forecast emissions in real-time; revealed the quantifiable trade-offs between project cost and carbon abatement through

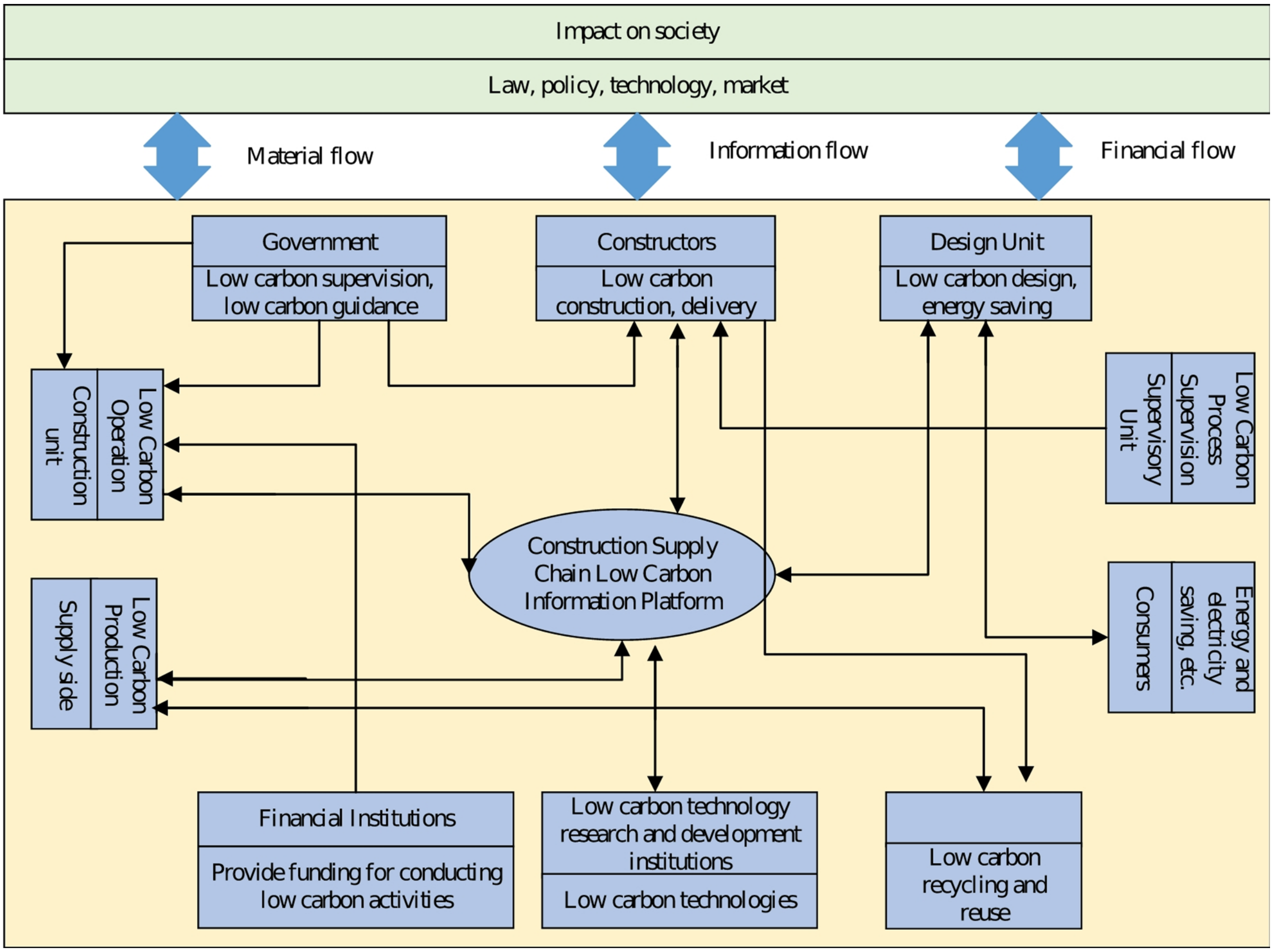

Fig. 14. A collaborative ecosystem framework for the low-carbon construction supply chain.

multi-objective optimization; and empirically confirmed the significant link between regional green finance policies and reduced carbon intensity. The primary contribution of this work is the establishment of a new, performance-based paradigm for carbon management. The proposed framework establishes a direct, evidence-based pathway from operational efficiency to financial reward, thus offering a robust and scalable model to accelerate the global construction sector's transition toward genuine, verifiable carbon neutrality. The findings of this research carry important practical and policy implications for the construction industry's decarbonization efforts. By enabling real-time monitoring and linking emissions performance to financial incentives, the proposed framework provides a viable pathway for stakeholders to operationalize carbon reduction goals. For instance, policy-makers could incorporate our real-time carbon tracking approach into green financing mechanisms or carbon trading schemes, ensuring that construction projects are rewarded for actual emissions reductions rather than just design-stage estimates. Industry practitioners (contractors and developers) can use the framework to make informed decisions in day-to-day project management, aligning economic incentives with carbon efficiency. In essence, our study's integrated approach bridges the gap between high-level climate policy and on-site construction practices, illustrating a practical route by which global carbon neutrality targets can be advanced at the project level."

Data availability

The data and materials used in this study are available from the corresponding author, Jia Liang, upon reasonable request. Please contact Jia Liang at jliang67@jh.edu.

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Author contributions

Conceptualization, F.B. and Q.C.; Methodology, F.B, Q.C. and X.Z.; Software, Z.L., X.Z., W.W., and J.L.; Validation, W.W., F.B, and X.Z.; Formal Analysis, F.B.,Q.C.,X.Z. and J.L.; Investigation, Q.C.,W.W., Z.L., X.Z., and J.L.; Resources, F.B.,Q.C.,Data Curation, F.B.,Q.C.,J.Q., J.G., and J.L.; Writing–Original Draft Preparation, F.B., X.Z., Q.C., and J.L.; Writing–Review & Editing, F.B., X.Z.,Q.C., and J.L.; Visualization, F.B.,Q.C.,X.Z.,W.W., and J.L.; Supervision, Q.C., F.B.; Project Administration, Q.C.and F.B.; Funding Acquisition, F.B.and Q.C. All authors have read and agreed to the published version of the manuscript.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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