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A METHOD FOR ADAPTIVE CONTROL OF SUSTAINABLE CONSTRUCTION PROJECTS BASED ON DIGITAL TWIN TECHNOLOGY AND ENSEMBLE MACHINE LEARNING

Abstract. *Effective management of sustainable construction projects is severely hindered by the reactive nature of traditional monitoring methods, which fail to address the dynamic and nonlinear variables present during physical execution. To overcome the limitations of relying on lagging indicators for Environmental, Social, and Governance (ESG) compliance, this study developed the Method for Adaptive Control of sustainable construction projects based on Digital Twin technology and Ensemble Machine Learning (MAC-DTEML). The primary objective was to create a prescriptive, closed-loop cyber-physical method capable of autonomously orchestrating resources and mitigating sustainability risks in real-time. The implementation of the proposed method is architecturally deconstructed into three specialized models. First, the Dynamic Cyber-Physical Synchronization (DCPS) model ingests heterogeneous data streams – including visual point clouds, Internet of Things telemetry, and environmental sensors – performing spatiotemporal alignment to fuse the physical site state with the theoretical Building Information Modeling baseline, thereby generating a unified input vector. Second, the Ensemble Predictive Analytics Model for Sustainability (EPAS) utilizes a stacking machine learning architecture to process this vector. By integrating Convolutional Neural Networks, Long Short-Term Memory networks, and gradient boosting algorithms, the EPAS model accurately forecasts impending sustainability deviations, overcoming the overfitting limitations of standalone algorithms. Finally, the Adaptive Autonomous Control System (AACS) model translates these predictions into physical action. The AACS model executes multi-objective decision-making to balance time, cost, and ESG impacts, generating both passive alerts for project managers and active control commands routed directly to site actuators. The key conclusion of this research is that the MAC-DTEML method successfully operationalizes proactive control in sustainable construction. By integrating the DCPS, EPAS, and AACS models, the method transitions project management from a descriptive monitoring paradigm to an autonomous, self-correcting cyber-physical loop. This integration objectifies the assessment of complex sustainability factors and significantly reduces the cognitive burden on project managers. Ultimately, the developed method provides construction organizations with a robust, data-driven mechanism to dynamically optimize resource allocation, minimize environmental impacts, and ensure strict adherence to sustainable execution targets amidst the uncertainties of the active construction environment.*

Keywords: adaptive control method; sustainable construction; digital twin; ensemble machine learning; cyber-physical system; predictive analytics model; multi-objective optimization

Introduction

The imperative for sustainable development has become a central tenet of modern industrial strategy, placing high-impact sectors such as the construction industry under increasing scrutiny from stakeholders, regulators, and investors. While the strategic adoption of Environmental, Social, and Governance (ESG) principles is gaining traction during the planning and design phases, a significant gap persists between strategic intent and operational execution. This execution gap is largely attributable to the inherent limitations of traditional project management paradigms, which are fundamentally ill-equipped to handle the dynamic, non-linear, and often chaotic nature of physical construction environments. Conventional control systems typically operate on a reactive basis, identifying deviations from sustainability targets retrospectively, thereby limiting managerial responses to remedial rather than preventative actions. Addressing this critical methodological deficit is the primary motivation for this research. The overarching aim of this study is to develop and validate a novel, intelligent framework capable of proactively assessing and dynamically controlling sustainability performance throughout the execution phase of construction projects. Specifically, this paper proposes the Method for Adaptive Control of sustainable construction projects based on Digital Twin technology and Ensemble Machine Learning (MAC-DTEML). The objective is to provide project managers with an autonomous, closed-loop cyber-physical system that not only forecasts potential deviations from ESG goals in real-time but also prescribes and executes optimized, data-driven interventions to ensure strict adherence to sustainable project lifecycles.

The transition towards sustainable construction necessitates a fundamental shift from conventional, reactive monitoring to proactive and dynamic project management. While the strategic adoption of Environmental, Social, and Governance (ESG) criteria is well-established in the planning phases, the physical execution of construction projects introduces highly volatile and non-linear variables that challenge sustainability goals. The development of the Proactive Sustainability Assessment Method (PSAM) highlights how integrating heterogeneous data through an Adaptive Neuro-Fuzzy Inference System (ANFIS) can successfully forecast sustainability risks, allowing managers to anticipate deviations before they materialize [1]. However, the dynamic nature of an active construction site requires continuous, real-time adaptive control that extends beyond initial forecasting.

To bridge the gap between static planning and dynamic execution, the deep integration of Artificial Intelligence (AI) with Building Information Modeling (BIM) has emerged as a transformative approach. Research has proven that AI-driven management models can simultaneously optimize diverse project objectives – such as sustainability, operational efficiency, and specific domain requirements – by fusing spatial, temporal, and semantic data streams [2]. This paradigm shift demonstrates that intelligent building models, evolving through multi-modal neural networks, can serve as the primary drivers for proactive decision-making rather than acting as secondary constraints [2]. Yet, effectively applying this level of integrated intelligence to the physical environment of an active construction site requires a robust cyber-physical connection.

Addressing the complexities of the physical construction phase requires transitioning from traditional BIM to real-time Digital Twins. Recent research has established the architectural foundation for such systems by proposing multi-stage approaches that integrate BIM with diverse data acquisition technologies, including Internet of Things (IoT) devices, LiDAR scanning, and Structure from Motion (SfM) photogrammetry [3, 4]. By capturing dynamic, high-resolution point clouds and mesh models, these technologies enable a continuous, real-time feed of spatial data [4]. To process these massive arrays of visual data, researchers have successfully deployed complex artificial intelligence pipelines, combining Convolutional Neural Networks (such as the YOLO family) for rapid, real-time object detection with Feed-Forward Neural Networks (FFNN) for multi-label classification [3, 5]. This synergistic application of CNNs and FFNNs allows for the automated, quantitative evaluation of construction site components, continuously checking the physical execution against the reference BIM model to ensure project conformance [5].

A compelling demonstration of this active control capability is seen in specialized digital twin frameworks (e.g., iTWIN) designed for real-time safety monitoring in human-robot collaborative environments [6]. By utilizing continuous 3D point cloud capture and automated spatial analysis, such systems can dynamically monitor overlapping workspaces of human laborers and automated machinery, instantly detecting hazard zone breaches and triggering automated deactivation protocols [6]. Collectively, these advancements highlight a critical technological progression: the construction industry now possesses the capabilities to capture physical data dynamically [4], automatically detect deviations from planned digital models [5], and execute immediate, automated interventions in response to environmental triggers [6].

However, while current cyber-physical systems excel at localized safety protocols and object recognition, there remains a critical gap in applying these real-time feedback loops to the holistic management of sustainable construction parameters. Research has demonstrated the viability of micro-level equipment tracking through real-time sensor data continuously transmitted to articulated 3D models within a concurrent virtual environment [7]. While frameworks like the Sensor Stream Acquisition Allocation (S2A2) method have proven effective for spatial proximity monitoring and collision avoidance, they primarily address geometric safety [7]. Comprehensive reviews on the monitoring of complex underground infrastructure emphasize that the integration of heterogeneous sensor data through machine learning and computer vision is essential for transitioning from reactive to proactive project control, though standalone predictive models often struggle with data noise and environmental variability [8]. This underscores the necessity for more robust algorithmic approaches, such as ensemble machine learning, which can aggregate multiple predictive models to achieve higher stability and accuracy in dynamic conditions.

The true potential of AI-powered digital twins lies in their application beyond physical tracking – specifically, in optimizing sustainability metrics. As evidenced by recent advancements in energy supply chain management, digital twins driven by machine learning can actively optimize resource consumption, track environmental impacts in real-time, and simulate operational scenarios to minimize waste and emissions [9]. Despite the proven individual successes of kinematic equipment tracking [7], AI-driven infrastructure monitoring [8], and real-time sustainability optimization in related industrial sectors [9], there is a distinct lack of a unified methodology in construction management that combines spatial awareness of digital twins with the predictive stability of ensemble machine learning to dynamically manage ESG parameters on an active job site.

The successful deployment of such a system relies on the interoperability of its underlying data architecture. Recent research emphasizes the necessity of utilizing Industry Foundation Classes (IFC) standards to construct comprehensive semantic models that systematically fuse geometric, resource, and behavioral data [10]. By extracting IFC model data, mapping it to relational databases, and synchronizing it with real-time construction site inputs, it is possible to create a robust platform that captures the spatiotemporal evolution of construction activities [10]. This standardized data environment acts as an absolute prerequisite for feeding accurate, multi-dimensional inputs into any ensemble machine learning algorithm intended for dynamic project control.

However, even with a seamlessly integrated digital twin, the practical adoption of advanced ensemble machine learning faces a significant socio-technical barrier: the inherent «black-box» nature of complex AI algorithms. Comprehensive analyses demonstrate that a lack of interpretability severely limits the operational deployment of predictive models in sensitive environmental domains [11]. The integration of Explainable AI (XAI) methodologies, such as SHAP or LIME, is now recognized as a fundamental requirement for translating opaque model outputs into human-understandable, actionable insights [11]. Therefore, the proposed adaptive control method must incorporate explainability, ensuring that algorithmically suggested interventions are transparent and fully trusted by human operators.

The utility of ensemble machine learning in managing complex operational networks is well-documented. In global supply chain contexts, ensemble algorithms such as Random Forest and XGBoost significantly outperform traditional methods in forecasting disruptions and optimizing resource allocation [12]. Because an active construction site operates as a highly localized, volatile supply chain – where material flows, equipment operations, and labor must be precisely synchronized under strict sustainability constraints – these ensemble techniques provide the robust predictive power required to mitigate logistical and environmental risks in real time [12].

To operationalize these predictive capabilities, the ensemble models must be anchored within a robust Digital Twin framework capable of continuous self-correction. Recent research illustrates that hybrid Digital Twins, integrating physics-based parameters with AI-driven prediction, can continuously monitor dynamic physical behavior, detect operational anomalies, and autonomously optimize performance under fluctuating environmental conditions [13]. Furthermore, coupling shallow and deep machine learning models (e.g., CNN, LSTM, and RBF) into an optimized ensemble framework significantly improves predictive accuracy under highly variable, heterogeneous conditions, overcoming the structural limitations of standalone models [14]. Additionally, advanced Digital Twin theories in smart manufacturing have established mechanisms for dynamic, bidirectional virtual–physical interaction through multi-dimensional models that synchronize multi-source heterogeneous data, enabling real-time monitoring and remote, proactive control of production elements [15].

Synthesizing these technological paradigms reveals a clear pathway to solving the execution-phase challenges of sustainable construction. While the industry has made significant strides in spatial conformity monitoring via computer vision and geometric digital twins, it currently lacks a unified mechanism to adaptively control the physical execution of projects based on dynamic sustainability metrics. Therefore, this study proposes a novel method for the adaptive control of sustainable construction projects based on Digital Twin technology and ensemble machine learning. By combining the bidirectional spatial awareness and operational logic of advanced cyber-physical systems [15] with the robust, self-correcting predictive analytics of ensemble algorithms [14], this approach aims to provide project managers with an intelligent, dynamic framework designed to autonomously orchestrate resources, minimize environmental impacts, and ensure project resilience in the face of execution-phase uncertainties.

Main Research

The foundational scientific contribution of this research is the development and conceptualization of the Method for Adaptive Control of sustainable construction projects based on Digital Twin technology and Ensemble Machine Learning (MAC-DTEML). Contemporary construction project management paradigms remain predominantly descriptive or, at best, predictive, relying on lagging indicators to assess deviations from planned sustainability trajectories. The MAC-DTEML method introduces a paradigm shift by establishing a prescriptive, closed-loop cyber-physical architecture. Rather than merely forecasting imminent violations of Environmental, Social, and Governance (ESG) thresholds, such as excessive carbon emissions from idling machinery, resource waste, or schedule overruns, this method autonomously synthesizes corrective managerial interventions in real-time. By bridging the gap between passive digital monitoring and active physical actuation, the proposed method ensures that the physical construction site dynamically adheres to its optimized sustainability targets despite inherent execution-phase volatility and environmental chaos.

The holistic operational logic of the proposed method is anchored in a continuous, bidirectional data exchange between the physical construction environment and the cyber analytical ecosystem, as illustrated in Figure 1. The macro-level architecture delineates the physical world, comprising active construction elements such as heavy equipment, human labor, and materials, which are continuously monitored by a dense network of Internet of Things sensors, unmanned aerial vehicles, and computer vision cameras. These heterogeneous data streams serve as the primary input for the cyber environment, where the core intelligence of the MAC-DTEML resides. The cyber infrastructure is systematically deconstructed into three sequential, highly specialized models: the Dynamic Cyber-Physical Synchronization (DCPS) model, the Ensemble Predictive Analytics Model for Sustainability (EPAS), and the Adaptive Autonomous Control System (AACS).

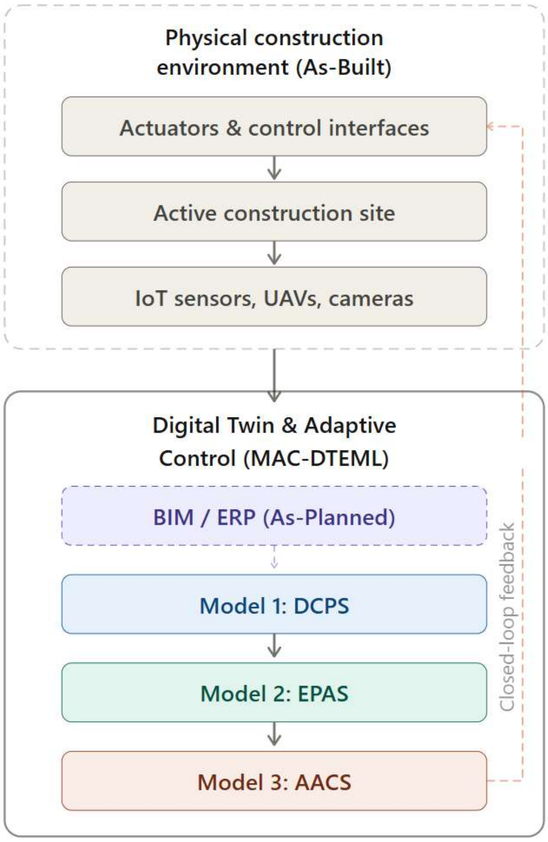

Figure 1 – MAC-DTEML Cyber-Physical System

Through this tri-modular architecture, raw telemetry and visual data are transformed into a unified digital twin state, processed through a stacking machine learning engine to predict sustainability deviations, and ultimately converted into adaptive intervention commands routed back to the physical site actuators and human decision-makers.

A critical mechanism within this macro-architecture is the integration of the static reference data, specifically the As-Planned Building Information Model and Enterprise Resource Planning schedules, which serve as the baseline targets for sustainable execution. The closed-loop nature of the system ensures that any physical deviation from these theoretical baselines is instantly captured, geometrically and parametrically aligned, and fed into the predictive engine. The culmination of this process is a dual-layered feedback mechanism outputted by the third architectural model, which either provides passive, human-in-the-loop decision support via dynamic dashboards or executes active, autonomous control commands directly to connected site machinery and digital scheduling software. This continuous cycle of perception, prediction, and actuation fundamentally mitigates the cognitive overload placed on project managers, allowing for the precise, real-time orchestration of sustainable construction processes that were previously deemed too complex for dynamic optimization.

To initiate the adaptive control cycle, the digital twin must achieve absolute parity with the physical construction site at any given micro-moment. This foundational requirement is engineered through the Dynamic Cyber-Physical Synchronization (DCPS) model. The primary scientific challenge addressed by the DCPS model is the sheer heterogeneity, noise, and unstructured nature of data generated during the physical execution phase. Traditional monitoring systems often treat visual progress tracking, environmental sensing, and equipment telemetry as isolated data silos, leading to fragmented managerial insights. The DCPS model overcomes this fragmentation by functioning as an advanced data ingestion, preprocessing, and fusion pipeline designed specifically to construct a highly accurate, multi-dimensional As-Built state.

The initial phase of the DCPS model involves the simultaneous ingestion of multimodal data streams originating from the physical site. Visual data, comprising dense point clouds captured via photogrammetry from unmanned aerial vehicles and continuous spatial tracking from closed-circuit television cameras, forms the geometric foundation of the current site state. Simultaneously, telemetry data harvested from embedded sensors on heavy machinery provides critical operational parameters, including fuel consumption rates, engine load, and geospatial coordinates. This operational data is further augmented by environmental inputs, such as localized air quality indices and noise levels, alongside semantic data extracted from daily enterprise resource planning logs and delivery schedules. The raw aggregation of these disparate streams presents significant computational challenges, necessitating a robust preprocessing architecture capable of functioning in real-time.

Upon ingestion, the DCPS model routes the raw heterogeneous data through a rigorous noise filtering and data imputation algorithm. Construction site sensor data is notoriously prone to missing values and erroneous readings due to harsh environmental conditions, sensor occlusions, and signal interference. The preprocessing layer utilizes statistical smoothing techniques and machine learning-based imputation to reconstruct incomplete data segments, ensuring continuous data integrity. Following noise reduction, the model executes a critical spatiotemporal alignment protocol. Because data packets arrive at varying frequencies and spatial resolutions, it is imperative to synchronize them against a unified timestamp and a global coordinate system. This process ensures that a spike in fuel consumption recorded by a telematics sensor is flawlessly correlated in time and space with a specific excavation activity captured by the visual data stream, creating a holistically contextualized data point.

Following the precise spatiotemporal alignment, the Dynamic Cyber-Physical Synchronization model initiates a multi-modal data fusion process. This crucial algorithmic step synthesizes the aligned geometric, telemetric, and environmental data streams into a cohesive, high-fidelity representation of the physical site, designated within the framework as the Current As-Built state. To realize the predictive capabilities of the digital twin, this dynamic As-Built state must be continuously evaluated against the static, theoretical project baseline. Therefore, the synchronization architecture incorporates a sophisticated discrepancy engine. This computational engine ingests both the newly fused Current As-Built state and the Reference As-Planned target model extracted from the Building Information Modeling and Enterprise Resource Planning databases. By performing continuous geometric and parametric comparisons, the discrepancy engine quantifies deviations in real-time, identifying spatial misalignments of structural elements, anomalous spikes in equipment energy consumption, or logistical delays relative to the optimized sustainable schedule.

The culmination of the discrepancy engine's comparative analysis is the generation of a Unified Input Vector. This vector represents a highly structured, multidimensional dataset that encapsulates not only the current physical and environmental state of the construction site but also its exact quantitative variance from the established sustainability targets. The creation of this unified vector fundamentally resolves the inherent data fragmentation that traditionally plagues construction monitoring, providing a clean, standardized format explicitly engineered for advanced algorithmic processing. The complete pipeline of this data ingestion, preprocessing, and state generation process is systematically detailed in Figure 2, illustrating the foundational role of the synchronization model in bridging the physical-digital divide and preparing the data for predictive analysis.

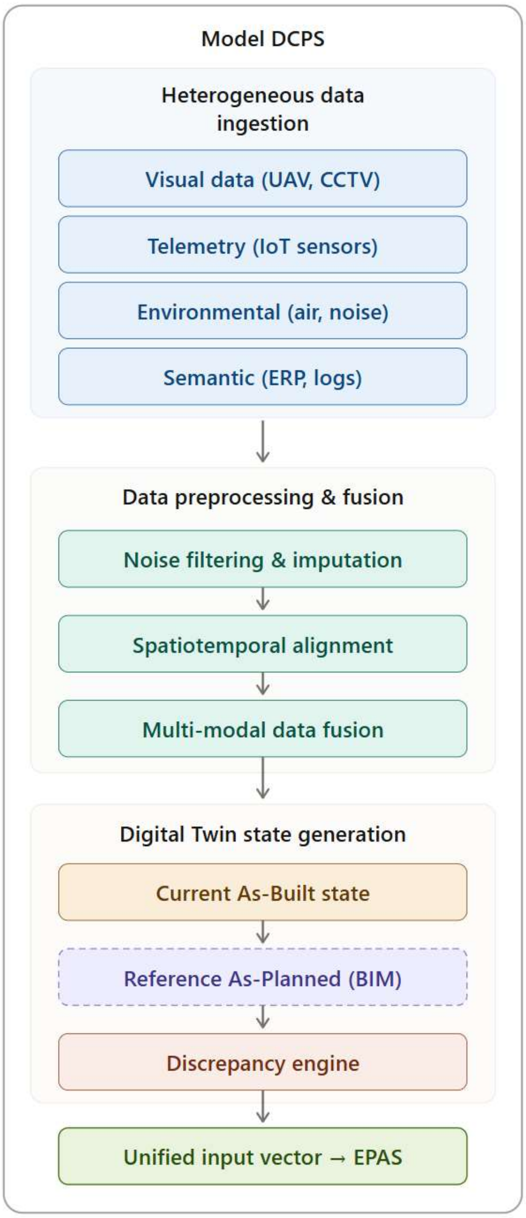

Figure 2 – Model Dynamic Cyber-Physical Synchronization

With the physical site state accurately digitized and standardized into a unified vector, the overarching cyber-physical framework engages its analytical core: the Ensemble Predictive Analytics Model for Sustainability (EPAS). The fundamental scientific premise underlying the EPAS model is that the stochastic, non-linear, and highly interconnected nature of construction site variables cannot be accurately forecasted by any singular machine learning algorithm. Traditional standalone models often suffer from severe overfitting when exposed to the chaotic data of an active site, or they fail to capture the complex, hidden interdependencies between schedule delays, resource allocation inefficiencies, and environmental impacts such as carbon emissions. To overcome these pervasive limitations, the EPAS model employs a highly robust stacking ensemble architecture. This architecture leverages the heterogeneous mathematical strengths of multiple specialized algorithms, hierarchically organized to process different dimensions of the unified input vector simultaneously, thereby maximizing predictive stability, generalization, and accuracy.

The foundational layer of the ensemble architecture, designated as Level zero, consists of a triad of specialized base models operating in parallel. Each base learner is explicitly selected and trained to analyze a specific data modality within the unified input vector. Convolutional Neural Networks, specifically utilizing advanced object detection architectures such as YOLOv8, are deployed to process visual data streams, performing complex tasks related to visual progress tracking and immediate safety hazard detection. Concurrently, Long Short-Term Memory networks and Recurrent Neural Networks are tasked with analyzing sequential telemetry and environmental data, excelling in time-series forecasting to predict energy consumption trends and cumulative emission trajectories based on historical equipment behavior. Simultaneously, gradient boosting frameworks, such as XGBoost or LightGBM, process the structured tabular data, efficiently evaluating schedule variances, cost overruns, and resource utilization metrics. This rigorous division of analytical labor ensures that the unique properties of spatial, temporal, and structured data are optimally leveraged without degrading the overall performance of the model.

The outputs generated by the Level zero base models, which include extracted feature maps, class probabilities, temporal forecasts, and regression outputs, individually lack the holistic context required for overarching project control. Consequently, the ensemble architecture employs a Level one meta-model integration strategy via stacking. The disparate outputs from the base learners are concatenated into a secondary feature space and fed into a meta-regressor, typically constructed as a Ridge Regression model or a dense Feed-Forward Neural Network. This meta-learner is trained to deduce the optimal weighting of the base models' predictions, effectively learning how to balance conflicting indicators to generate a singular, highly accurate forecast. The ultimate output of this complex stacking process is a quantified Predicted Sustainability Deviation, representing a specific, impending risk, such as a projected critical increase in carbon emissions within a forty-eight-hour window due to cascading schedule delays. The intricate hierarchical processing of this ensemble engine is visually deconstructed in Figure 3.

The culmination of the predictive analytics phase – a precisely quantified and localized forecast of an impending sustainability deviation – must be seamlessly translated into a strategic physical response to close the cyber-physical loop. This crucial translation is achieved through the third and final architectural model: the Adaptive Autonomous Control System (AACS). The primary scientific contribution of the AACS model lies in its capacity to autonomously evaluate and execute complex, multi-objective interventions in real-time, effectively mitigating the cognitive burden traditionally placed on project managers operating in chaotic construction environments. Rather than merely presenting a reactive warning of an impending environmental or logistical failure, the AACS architecture acts as a prescriptive decision-making engine, dynamically balancing the inherently competing priorities of schedule adherence, cost efficiency, and Environmental, Social, and Governance (ESG) compliance.

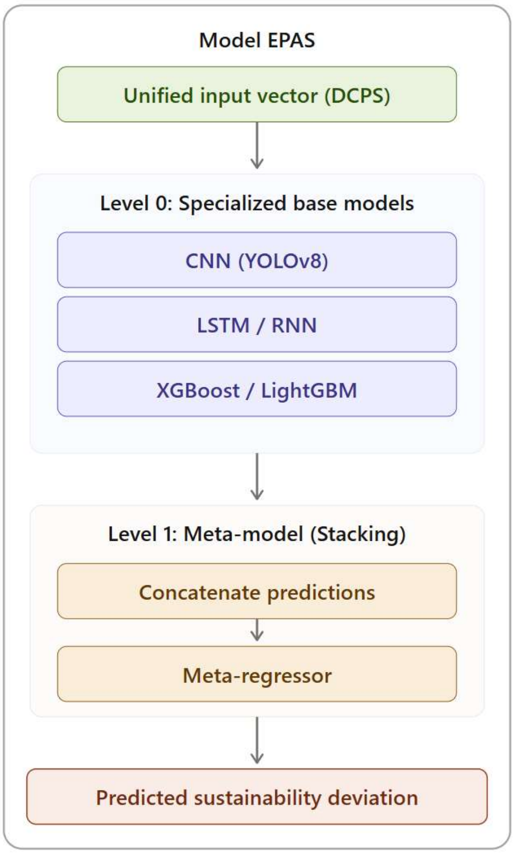

Figure 3 – Ensemble Predictive Analytics Model

The operational workflow of the AACS model is initiated by the continuous ingestion of the Predicted Sustainability Deviation from the EPAS engine. Upon detecting a critical risk – such as an impending spike in carbon emissions due to logistical bottlenecks – the system immediately cross-references the deviation against a centralized repository of operational constraints, safety margins, and regulatory limits. Concurrently, a dynamic scenario generation algorithm leverages the real-time state of the synchronized digital twin to synthesize adaptive intervention strategies. These candidate responses, ranging from targeted equipment shutdown commands to complex resource reallocations, are highly adaptive and ensure that no autonomously generated scenario violates foundational project parameters. Subsequently, a sophisticated trade-off evaluation engine utilizes heuristic optimization algorithms to rigorously assess the projected impact of each candidate strategy. Operating under a minimization function, it identifies the single optimal intervention that most efficiently balances the competing objectives of time, cost, and ESG compliance without inducing cascading project overruns. This optimal strategy is then deployed via a bifurcated control mechanism comprising active and passive pathways. For high-stakes decisions requiring human validation, the passive control pathway employs a human-in-the-loop paradigm. It transmits the prescriptive recommendation, alongside predictive data and trade-off analytics, to stakeholders via real-time dashboards, enabling informed executive oversight and manual authorization of critical operational shifts.

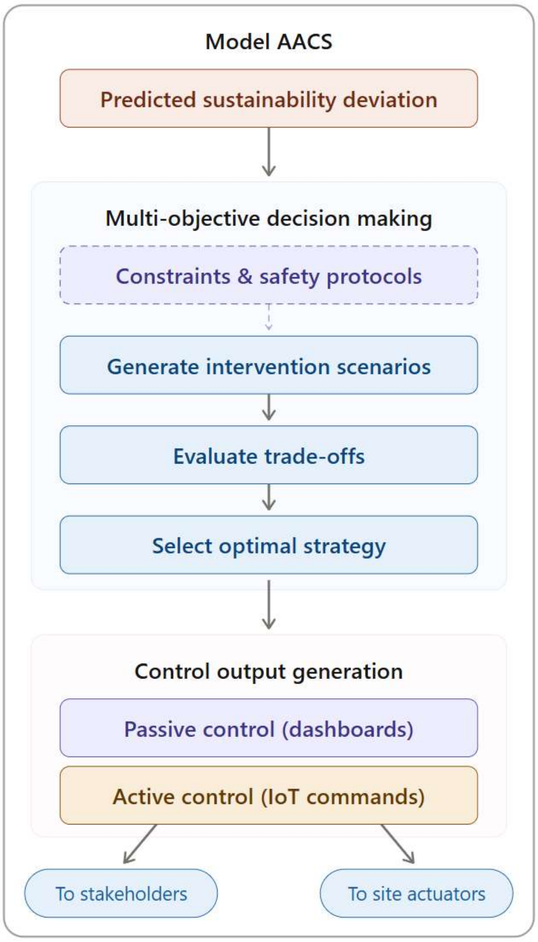

Figure 4 – Model Adaptive Autonomous Control System

Conversely, the active control pathway facilitates true autonomous actuation. For routine, lower-risk interventions that fall within strict, predefined operational safety margins, the AACS model bypasses human authorization and transmits automated control commands directly to the physical site actuators. This active execution layer leverages the established Internet of Things infrastructure to issue direct commands, such as automatically adjusting the operational parameters of connected heavy machinery, modulating the environmental control systems within enclosed construction zones, or instantly updating the digital scheduling software within the Enterprise Resource Planning system to reflect dynamic rerouting logic. This bifurcated approach to control execution, visually deconstructed in Figure 4, ensures that the MAC-DTEML method maintains the necessary speed and autonomy to mitigate rapidly evolving sustainability risks while preserving essential human oversight for complex, high-stakes project decisions.

Conclusions

This study was undertaken to address the fundamental limitations of reactive project management in the construction industry, particularly the inability of traditional monitoring paradigms to dynamically control complex Environmental, Social, and Governance (ESG) variables during physical execution. To this end, we developed and presented the Method for Adaptive Control of sustainable construction projects based on Digital Twin technology and Ensemble Machine Learning (MAC-DTEML). The principal finding of this research is that the proposed cyber-physical method successfully operationalizes the concept of prescriptive, autonomous project control. By seamlessly integrating real-time physical execution data with a theoretical Building Information Modeling (BIM) baseline, the method transforms static sustainability targets into a dynamic, self-correcting operational loop. The method's robustness is founded upon its architectural implementation through three specialized models: the Dynamic Cyber-Physical Synchronization (DCPS) model, the Ensemble Predictive Analytics Model for Sustainability (EPAS), and the Adaptive Autonomous Control System (AACS). The results confirm that the stacking architecture of the EPAS model effectively mitigates the overfitting and noise susceptibility of standalone algorithms, while the AACS model successfully translates these high-fidelity predictions into multi-objective intervention strategies. From a theoretical standpoint, this research makes significant contributions to construction informatics and applied artificial intelligence. First, it provides a formal, model-driven method for bridging the cyber-physical divide, demonstrating that effective digital twinning on active sites relies on continuous, spatiotemporally aligned data fusion. Second, it establishes the necessity of ensemble machine learning – stacking CNNs, LSTMs, and gradient boosting algorithms – to accurately process the multimodal, heterogeneous data streams inherent in sustainability metrics. Finally, by embedding a multi-objective trade-off evaluation engine within the AACS model, this work advances the discourse on autonomous decision-making in chaotic environments, offering a robust method to simultaneously optimize schedule, cost, and environmental impacts. In practical terms, the MAC-DTEML method equips construction organizations with a transformative, prescriptive early warning and control system. It shifts project management from reactive crisis resolution to automated risk mitigation, enabling the efficient reallocation of resources and equipment through the AACS model's active and passive control pathways. By significantly reducing instances of idle carbon emissions and logistical bottlenecks, this approach ensures targeted interventions and a drastic reduction in non-compliance with stringent ESG standards. Ultimately, it enhances the likelihood of achieving project-specific sustainability outcomes without compromising financial or temporal constraints, while also facilitating continuous organizational learning as the digital twin repository refines the ensemble engine based on longitudinal execution data.

Despite these contributions, the study acknowledges certain limitations. The performance of the MAC-DTEML method is inherently sensitive to the density and reliability of the site's IoT sensor network, where poor network latency or sparse coverage may compromise synchronization and predictive fidelity. Additionally, the multi-objective optimization within the AACS model currently relies on predefined heuristic constraints that may not fully reflect localized regulatory variations. Future research will focus on integrating edge computing within the DCPS model to reduce latency, incorporating reinforcement learning into the AACS model to enable autonomous strategy discovery, and developing open-source ontologies to enhance ESG data interoperability. Finally, longitudinal full-scale deployment on commercial mega-projects is essential to empirically validate the long-term economic and environmental impacts of this method.

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Use of Artificial Intelligence. The author confirms that in the creation of this work he/she did not use artificial intelligence tools.

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МЕТОД АДАПТИВНОГО КОНТРОЛЮ РЕАЛІЗАЦІЇ ПРОЄКТІВ СТАЛОГО БУДІВНИЦТВА НА ОСНОВІ ТЕХНОЛОГІЇ ЦИФРОВИХ ДВІЙНИКІВ ТА АНСАМБЛЕВОГО МАШИННОГО НАВЧАННЯ

Анотація. *Ефективне управління проєктами сталого будівництва суттєво ускладнюється реактивним характером традиційних методів моніторингу, які не здатні впоратися з динамічними та нелінійними змінними під час фізичної реалізації. Щоб подолати обмеження, зумовлені покладанням на запізнілі індикатори для дотримання критеріїв екологічного, соціального та корпоративного управління (англ. Environmental, Social, and Governance; ESG), у цьому дослідженні розроблено метод адаптивного контролю реалізації проєктів сталого будівництва на основі технології цифрових двійників та ансамблевого машинного навчання (англ. Method for Adaptive Control of sustainable construction projects based on Digital Twin technology and Ensemble Machine Learning; MAC-DTEML). Головною метою було створення прескриптивного кіберфізичного методу із замкненим циклом, здатного автономно координувати ресурси та мінімізувати ризики сталого розвитку в реальному часі. Реалізація запропонованого методу архітектурно декомпозована на три спеціалізовані моделі. По-перше, динамічна кіберфізична модель синхронізації (англ. Dynatic Cyber-Physical Synchronization; DCPS) збирає гетерогенні потоки даних – включаючи візуальні хмари точок, телеметрію Інтернету речей та екологічні датчики – виконуючи просторово-часове вирівнювання для злиття фізичного стану майданчика з теоретичною базою інформаційного моделювання будівель (BIM), генеруючи уніфікований вхідний вектор. По-друге, ансамблева прогнозна модель параметрів стійкості (англ. Ensemble Predictive Analytics Model for Sustainability; EPAS) використовує архітектуру машинного навчання типу «стекінг» для обробки цього вектора. Інтегруючи згорткові нейронні мережі, мережі довгої короткочасної пам'яті (LSTM) та алгоритми градієнтного бустингу, модель EPAS точно прогнозує неминучі відхилення показників стійкості, долаючи обмеження перенавчання окремих алгоритмів. Нарешті, модель адаптивного автономного контролю (англ. Adaptive Autonomous Control System; AACS) перетворює ці прогнози на фізичну дію. Модель AACS виконує багатокритеріальне прийняття рішень для балансування часу, вартості та впливу на ESG, генеруючи як пасивні сповіщення для менеджерів, так і активні команди управління, що спрямовуються безпосередньо до актуаторів на майданчику. Ключовим висновком дослідження є те, що метод MAC-DTEML успішно операціоналізує проактивний контроль у сталому будівництві. Завдяки інтеграції моделей DCPS, EPAS та AACS метод переводить управління проєктами від описової парадигми моніторингу до автономного кіберфізичного циклу, що самокоригується. Ця інтеграція об'єктивізує оцінку складних факторів сталого розвитку та значно знижує когнітивне навантаження на менеджерів проєктів. Зрештою, розроблений метод надає будівельним організаціям надійний механізм, керований даними, для динамічної оптимізації розподілу ресурсів, мінімізації впливу на довкілля та забезпечення суворого дотримання цілей сталого виконання в умовах невизначеності активного будівельного середовища.*

Ключові слова: метод адаптивного контролю; стале будівництво; цифровий двійник; ансамблеве машинне навчання; кіберфізична система; прогнозна модель; багатокритеріальна оптимізація

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