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BIM-Based Integrated Model for Project Cost Estimation: A Case Study for Concrete Elements

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Abstract

Construction projects often struggle to align design models, cost estimates, and scheduling processes. To address this challenge, this study presents an integrated 5D BIM model that automates cost and schedule estimation by linking 3D BIM components to a structured database of historical productivity and activity data. A unique coding system connects each BIM object to its corresponding construction tasks, enabling automatic generation of resource-loaded schedules with associated durations, costs, and crews based on the selected construction method. The workflow integrates Autodesk Revit, Navisworks, a relational (SQL) database, and Primavera P6 to achieve seamless interoperability across design, estimating, and scheduling tools. The model is validated through a case study of a six-story reinforced concrete building. Findings show that the approach significantly improves estimation, accuracy, and efficiency. Predicted costs closely match actual values, thereby reducing dispersion among estimates. The automated process minimizes manual data handling while keeping cost and schedule outputs synchronized. Novel contributions include the incorporation of detailed historical productivity data, construction method alternatives, and structured cost/activity records into a unified framework, representing a methodological advance in 5D BIM that bridges the design, estimating, and scheduling domains for more reliable and automated project planning.

Keywords: Building Information Modeling (BIM); 5D BIM; Cost Estimation; Construction Scheduling; Productivity Data; Automated Scheduling; Relational Database.

1. Introduction

Accurate cost estimation is paramount in construction projects because even minor errors can jeopardize a project's success and overall quality outcomes [1, 2]. Traditionally, estimators relied on manual quantity take-offs from 2D drawings – a labor-intensive process prone to human error. Measuring quantities from 2D drawings introduces a high risk of duplication or omission. When this data is moved into spreadsheets, additional errors can occur. Even minor mistakes and small discrepancies in quantity can lead to inaccurate budgets, resulting in unreliable cost estimates and potential overruns [3, 4]. To overcome these recurring issues, researchers have developed more precise and automated methods. Building Information Modeling (BIM) has emerged as a leading tool in this area, addressing many limitations of traditional estimating practices [5]. BIM-based approaches have been shown to improve cost management in construction. Empirical studies confirm that BIM adoption enhances overall project cost control and accuracy [6]. For instance, one study reported that using 5D BIM (3D design + cost + schedule) yielded cost estimates within 5% of actual

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costs, compared to a 12% error for traditional methods [7]. Likewise, BIM-based quantity takeoffs have been found to match the accuracy of manual take-offs while also reducing the time and human effort required [8]. These improvements result in more reliable budgets and fewer unexpected issues during project execution.

Recent findings indicate that the advantages of 5D BIM grow with project complexity. Larger-scale projects benefit more from BIM's time savings and cost efficiency [9]. Reflecting these advantages, industry experts increasingly forecast that 5D BIM will become indispensable for effective project cost management and schedule optimization [9, 10]. Broad multi-project studies back up these expectations: for example, across a set of construction projects, BIM implementation reduced project durations by roughly 20% on average while cutting overall costs by approximately 15% [11]. Combining BIM with other best practices can amplify these benefits; integrating BIM into the value engineering process for a residential project resulted in approximately 35% total cost savings and a 15% reduction in project duration [12]. Similarly, utilizing BIM for detailed cost planning and cash-flow forecasting has been demonstrated to provide more accurate real-time financial information, enabling better oversight and scenario-based decision-making [13]. Collectively, this evidence indicates that BIM offers a significantly more reliable and efficient platform for construction cost estimation and control—especially for large or complex projects that would strain traditional manual methods.

However, current BIM-based cost estimating practices still face significant limitations. Typically, the cost outputs from BIM models remain static quantities tied to building components, without consideration of the construction tasks or project schedule [14]. In other words, a 5D BIM model can generate a list of component costs, but it is often isolated from any consideration of when those costs will occur during construction. In detailed project planning and control, cost information needs to be time-phased and linked to the sequence of construction activities to forecast cash flows and manage resources across the project’s duration [15]. Researchers have emphasized that 5D BIM-based cost management necessitates integrating the cost estimate with the schedule [16, 17]. For example, recent research confirms that the BIM-based cost literature predominantly focuses on automated quantity take-off (QTO) and component-level estimating, with few approaches incorporating scheduling data into the process [14]. Without this linkage, cost figures and timelines remain in separate silos. In fact, industry surveys note that practitioners often still estimate costs and schedules independently, then manually merge the two—a slow, error-prone process that usually leads to inconsistencies [18]. Consequently, many experts have concluded that linking BIM-derived cost data with the project schedule is imperative for robust project control and decision-making [19, 20].

In response to these challenges, researchers have explored various approaches to enhance the integration of BIM with cost and schedule information. Broadly, recent studies in 5D BIM can be grouped into three main streams: (i) automating BIM-based quantity take-off and cost estimation, (ii) extending 5D BIM with external cost databases and real-time cost updates, and (iii) linking BIM models with construction schedules to automatically generate or optimize project timelines. Examples of each include model-based QTO systems that improve estimating efficiency and consistency [13], BIM platforms connected to cost libraries for instant budget recalculations [21-23], and 4D/5D BIM workflows that derive construction activity sequences directly from design models [24, 25].

One line of research connects BIM models to external cost databases using standardized classification codes (such as UniFormat or MasterFormat) [21-23]. This approach enables automatic retrieval of unit prices from historical cost libraries and instant recalculation of project costs whenever the BIM design changes, greatly streamlining the estimating process and improving consistency across projects. However, achieving seamless real-time synchronization between BIM and cost data remains a challenge. Most such database-driven 5D BIM solutions still require periodic manual data refreshes or are confined to specific regional cost libraries, meaning that the vision of a fully continuous, universally integrated BIM–cost platform has not yet been realized.

Another line of work aims to integrate BIM with construction scheduling. Early 4D BIM prototypes demonstrated the concept of linking 3D models to project schedules [24, 26-27]. For example, Jrade & Lessard [28] built an integrated system that combined a BIM model with earned value management techniques to track construction time and cost performance in a virtual environment. These pioneering efforts showed that it was possible to synchronize design, schedule, and cost data. However, they also highlighted limitations: the implementations often relied on separate scheduling software or predefined activity templates that were only loosely connected to the BIM model. Any change in the project or construction method requires manual updates in multiple systems (the BIM, the cost estimate, and the schedule) to maintain consistency. In summary, these initial solutions treated cost estimation and scheduling as parallel processes connected through ad-hoc mappings or one-off data exchanges. These solutions fall short of providing the fully integrated, dynamic data framework needed for continuous, automated alignment of cost and schedule information.

Beyond linking BIM to external data sources, recent work has sought to enrich BIM-driven estimation by incorporating construction methods and historical performance data. Several studies incorporate these factors into BIM-based cost models. For example, Banihashemi et al. [29] developed a “5D BIM informatics” prototype that connects a BIM model to a construction cost data platform and uses machine learning to classify detailed material cost components. In this approach, each BIM element is linked to itemized cost components, a step toward automating cost breakdowns. Yet the proposal still falls short of decomposing model-derived quantities into executable schedule activities with assigned crews and productivity rates—an essential step for computing both durations and unit costs at the activity level—and the proposal remains agnostic about construction methods that drive crew productivity and thus affect time and cost. Khodabakhshian & Toosi [30] proposed a BIM-based life-cycle cost framework that defines a cost breakdown structure (CBS), creates phase-specific material takeoff and cost schedules directly from the BIM model, and aggregates life-cycle cost by discipline/element across project stages. This enables cash-flow curves over the project timeline and links element-level estimates to the schedule. However, the implementation relies on spreadsheet exports, which fragment the workflow and move analysis outside the integrated environment. Moreover, it aggregates costs at stage totals, whereas construction schedules are managed at the activity/work-package level. Alzraiee [31] developed a BIM-linked cost estimation system using a SQL relational database of work items and unit costs. The system generates estimates directly from model quantities, improving organization and reuse; however, it does not incorporate crew productivity or link costs to activity durations, resulting in a static estimate that cannot adjust to the actual construction sequence. Project teams must therefore manually combine the cost output with a separate schedule to derive cash flow, creating potential inconsistencies between the estimate and the plan. Taken together, these strands enrich 5D BIM while keeping cost and time on parallel tracks and relying on manual handoffs—underscoring the need for a unified, resource-loaded, time-phased workflow that operates directly from the BIM model.

In parallel, considerable effort has been devoted to automating the generation of construction schedules and corresponding cost estimates directly from BIM information. Some approaches leverage libraries of typical activities and productivity rates. For example, systems have been created that take a building's BIM-derived quantities and automatically generate a preliminary set of construction tasks and durations for specific trades [32, 33]. These automatically generated schedules can then be optimized using algorithms. For instance, Elbeltagi et al. [24] applied a genetic algorithm within a BIM-based scheduling framework to refine the sequence of activities for greater efficiency. Hong et al. [34] developed a graph-based automated scheduling (GAS) model that learns from patterns in past project schedules and recommends efficient activity sequences for new projects, resulting in schedules that were significantly closer to actual project performance than those made manually [34]. At the design stage, Lee and Kang (2025) infer "activity units" directly from 3D models, enabling automatic generation of corresponding construction tasks for scheduling, which reduces reliance on manual templates and moves toward native model-to-schedule generation [35]. While these methods improve the automation of schedule creation, they often operate somewhat independently of cost estimation (or assume cost loading is done in a separate step). They may not fully integrate with real-time design changes. They also typically assume fixed productivity rates that do not reflect project-specific site conditions. Recognizing this limitation, Khataei et al. [36] developed a 4D BIM approach that revises activity productivity using visual programming and BIM-derived geometric context (e.g., adjacency/space constraints), making cost and schedule more sensitive to field conditions. By linking the model's geometry with dynamic production-rate adjustments, their prototype made cost and schedule more sensitive to field conditions. Such efforts reflect a push to make BIM-based planning more context-aware by accounting for variability in construction means and methods.

To further advance integration, other studies leverage modern data standards and technologies for real-time 5D BIM. For instance, some researchers have extended the Industry Foundation Classes (IFC) schema (e.g., adding an IfcCostItem entity) to embed cost items and other project data directly into BIM models, thereby facilitating seamless information exchange between design and estimating systems [18]. Similarly, semantic web frameworks have been employed to ensure that any change in the BIM model automatically triggers updates to the associated cost data, enabling live synchronization between design modifications and their cost implications [37]. Fürstenberg et al. [38] demonstrated an ontology-based reasoning system that matches BIM components to standard construction work items and cost entries, effectively enabling intelligent context-aware cost estimation and planning directly from the model's data. Parallel efforts connect BIM platforms to cloud-based cost databases via application programming interfaces (APIs), ensuring that adjustments in model quantities instantly propagate to cost estimates and that updates in the cost database feed back into the BIM model [19].

A related focus area is establishing unified coding systems to further enhance BIM integration. Pishdad-Bozorgi & Onungwa [39] observed that current 5D BIM applications lack integration with real-time project controls such as progress tracking and cost control, and they advocate assigning consistent classification codes to every BIM component, schedule activity, and cost item to enable different software tools and stakeholders to share data without loss of context [39]. If implemented within a relational database, such standardization could allow 5D BIM platforms to autonomously adjust project budgets and cash-flow projections in response to design changes or real-time field updates, providing stakeholders with up-to-date insights throughout the construction lifecycle. In line with this view, recent studies underscore the importance of data interoperability and intelligent automation in achieving a truly integrated cost–schedule control system [40]. For example, Pal et al. [40] integrated BIM with image-based reality capture and deep-learning segmentation to compute activity-level progress and compare it against the planned schedule, enabling automated detection of schedule deviations and showing how field data can feed BIM-based project control.

Cutting-edge research is also exploring the use of artificial intelligence to achieve fully automated 5D BIM. Al-Sinan et al. [41] proposed a machine learning framework for generating a resource-loaded construction schedule directly from a BIM model's geometry and metadata. Likewise, Pham et al. [42] developed a prototype that uses trained models on prior BIM projects to output a complete schedule—including activities, durations, crews, and costs—directly from the design model [42]. These AI-driven approaches represent the forefront of 5D BIM innovation, hinting at a future where a BIM model could autonomously produce a complete, resource-loaded project plan. However, most such concepts remain at the prototype stage, and significant challenges (such as interoperability issues and the need for extensive high-quality training data) must be addressed before truly seamless design–cost–schedule integration can be achieved in practice [40].

Despite these advances, no existing approach yet provides a fully unified solution, and key gaps remain in the current state of 5D BIM. Notably, none of the prior studies offers a mechanism to reuse detailed historical productivity data at the level of individual BIM components and their associated construction activities. Nor does any current approach integrate cost estimation with scheduled generation in a single, seamless workflow. As a result, project teams still rely on manual or semi-manual steps to synchronize data between estimating and scheduling systems, which can introduce errors and inefficiencies whenever the project scope or construction method changes. This apparent shortcoming underscores the need for a comprehensive 5D BIM solution that integrates design, cost, and schedule information within a single model.

This study proposes such an integrated 5D BIM approach to address the aforementioned gap. In the proposed workflow, detailed historical project data (including activity-level production rates and costs) are leveraged to estimate construction durations and costs for each BIM element, and a resource-loaded construction schedule is generated directly from the BIM model. The system maintains a seamless data flow from design (Autodesk Revit) to simulation (Navisworks) to scheduling (Oracle Primavera P6), ensuring that cost and schedule information remain dynamically linked to the BIM design. By reusing past project knowledge and integrating cost estimation with schedule generation, the approach aims to enhance the accuracy and efficiency of project planning and control, surpassing the current capabilities of 5D BIM practices.

2. Material and Methods

2.1. Research Aim and the Structure of the Proposed Model

Current BIM-based cost estimation approaches still face limitations that can impact accuracy and efficiency. Most existing models rely on building components without leveraging detailed historical information for each element. They typically do not account for differences in construction methods or crew configurations, even though such differences can change the required crew and execution duration and, thus, both direct and indirect costs. Because traditional cost estimation methods estimate at the whole-component level (independent of the project schedule), they often require re-analysis when linking costs to a project schedule, which can introduce errors. Moreover, a few prior approaches integrate cost databases or store actual project performance data for reuse. These shortcomings highlight the need for a more integrated and data-driven solution to 5D BIM (3D design + time + cost) in construction project management.

In response to the aforementioned gaps, this research aims to develop an integrated BIM cost estimation model that seamlessly links the 3D building model with scheduling and cost information in an automated manner. The goal is to produce a system that can generate more accurate time and cost estimates by considering each BIM element's construction method, required resources, and historical performance data. To achieve this aim, the study pursues three key objectives: (1) design a unique custom coding system for project entities, (2) develop an object-oriented cost database integrated with the BIM model, and (3) validate the proposed 5D BIM model through case study experimentation. These objectives ensure that the proposed model is conceptually sound, practical, and proven in a real-world scenario. The proposed model workflow is shown in Figure 1.

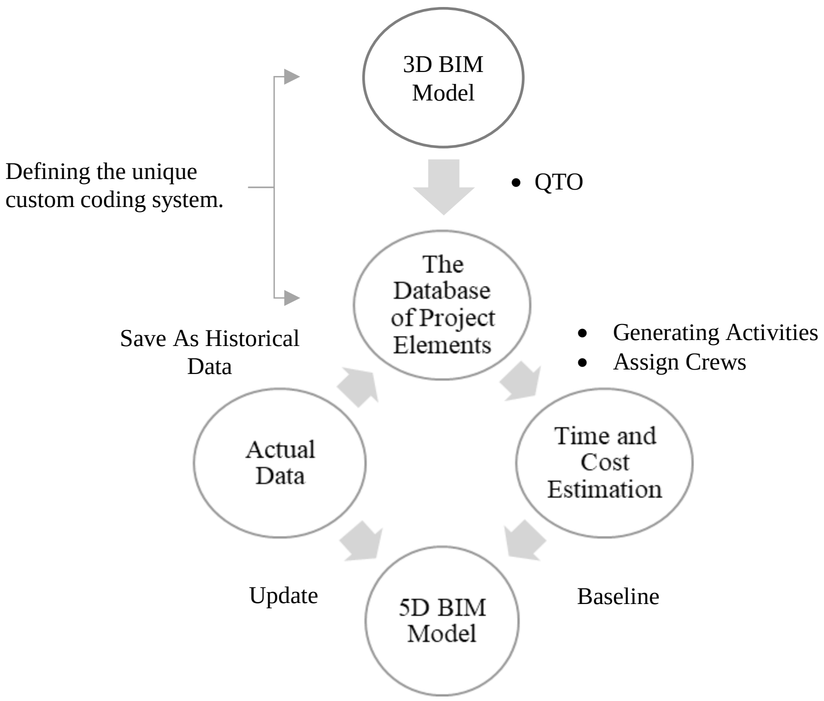

Figure 1. BIM-Based Integrated Proposal Workflow Model

The integrated BIM-based model proposed in this research differentiates itself from previous approaches by directly addressing existing limitations through a holistic integration of design, cost, and scheduling domains. Building upon insights from earlier BIM 5D methodologies—such as automated quantity take-off (QTO), database-driven estimating, and algorithmic scheduling—this study introduces an advanced object-oriented database that explicitly links BIM elements to detailed construction activities, methods, and associated productivity metrics derived from historical project data. A critical contribution is the development of a unique, unified coding system that ensures high software interoperability by systematically mapping each BIM component to its corresponding execution tasks, construction methods, and required resources within the database. This coding system enables the automatic generation of activities and ensures seamless integration across various software platforms, thereby significantly enhancing system interoperability.

Furthermore, the proposed model leverages detailed historical data, enabling it to learn from actual project outcomes—precisely crew productivity rates and material unit costs based on specific execution tasks from past projects—addressing the limitation of previous models that lacked historical performance memory. The model explicitly accounts for variations in construction methods, recognizing that different methods for the same building element, such as casting a concrete slab either in situ or using post-tension techniques, result in different resource requirements and activity durations. The system dynamically adjusts crew requirements, durations, and associated costs by linking BIM elements directly to method-specific data in the database.

Moreover, cost estimation in this model is performed at the execution-activity level, where each construction task required for an element at a specific location is individually identified and estimated, adopting a rigorous bottom-up estimation approach. This detailed, activity-level costing eliminates the need for later decomposition of lump-sum component costs, inherently synchronizing cost and schedule data from the outset. Consequently, the system automatically generates a comprehensive, resource-loaded construction schedule directly from BIM-derived quantities, selected construction methods, and applicable historical productivity rates. This schedule is structured to facilitate immediate integration with standard scheduling software. The proposed model achieves higher accuracy in estimating time and cost by accounting for variations in construction methods and historical performance data. The outcome is a dynamic 5D BIM solution that continuously updates estimates in response to design changes, thereby streamlining project planning and significantly enhancing the reliability and efficiency of cost and schedule management practices.

2.2. Theoretical Foundation

This study adopts an activity-based theoretical lens for 5D BIM in which the 3D design model serves as the source of quantities and the primary index for linking time and cost. Each BIM element (e.g., a column or slab) is first associated with a feasible set of construction methods (e.g., cast-in-situ, precast, post-tension). The chosen method determines a method-specific decomposition into execution tasks (formwork, reinforcement, concreting, curing, etc.). A task becomes a schedule activity only after contextualization by (i) the work zone/location (e.g., ground floor, typical floor, roof), and (ii) the element code that ensures traceability to the originating BIM object. This element → method → task → activity mapping formalizes how design quantities are translated into process-oriented units that can be planned, resourced, and controlled.

Within this lens, activities are not abstract placeholders but resource-bearing work packages that inherit their required crews and materials from standardized mapping tables and historical records. Crucially, the productivity associated with each activity is context-specific: it varies by construction method and by location/zone, because location constraints materially affect the achievable output. Unit costs for crew and materials are drawn from the same historical database, ensuring that time and cost are inferred consistently from shared evidence rather than assembled in parallel.

The theoretical framework is underpinned by a unified coding system that binds design, schedule, and cost into a single, auditable chain. Every activity is assigned a composite identifier composed of the element code, the location/zone code, and the task code. This identifier performs two roles. First, it guarantees bidirectional traceability from the activity back to the originating BIM element and forward into the control system. Second, it enables continuous learning: as actual site performance is recorded against the activity, that data can be stored and retrieved with the same identity in later projects.

A central element of the framework is an online SQL database that operates as the model's institutional memory. It stores the mapping tables (element↔methods, method↔tasks, task↔resources), historical productivity and unit-rate records, and the actuals streamed from the jobsite during execution. Because all activities share the composite identifier, the system can (i) reuse historical performance data when producing new estimates for similar elements, methods, and locations; (ii) ingest external or newly observed values when a scenario falls outside current experience; and (iii) evolve its norms as projects unfold, thereby refining both duration and cost predictions over time. In this way, the database is not a static library but a feedback-driven repository that tightens the loop between planning and control.

Uncertainty is addressed at the activity level by eliciting optimistic, most likely, and pessimistic inputs for the key drivers (productivity and unit rates) and aggregating them into an expected value and dispersion for planning purposes. This choice maintains the transparency of uncertainty treatment and decision orientation while remaining compatible with industry practices.

Finally, the framework is designed for operational integration across common project-control platforms. The 3D model is authored in Revit; quantities are extracted (e.g., via Navisworks) and bound to method- and location-aware activities through the database; and the resulting activity set is exported to Primavera P6 as a resource-loaded, time-phased baseline. Because all elements, tasks, and activities share consistent codes, subsequent design changes or field updates propagate coherently through the same chain—from element to activity to cost and time—enabling a single, auditable workflow rather than two disconnected streams.

2.3. Proposed Model and Methodology

The proposed model establishes an automatic, two-way connection between the BIM environment and the cost estimation-oriented database. Using consistent, unique codes across the BIM model and the database, the model can seamlessly exchange information, generate results with minimal manual intervention, and remain up-to-date as the project evolves. The process begins by analyzing the elements of the 3D model and the workflow design to produce BIM-based cost estimation. The proposed oriented database is developed, and the Entity-Relationship Diagram is implemented using Microsoft SQL. In this phase, a workflow should be designed to integrate with BIM, and the database should be populated with historical data, allowing the user to select various parameters to generate the 5D-BIM cost estimation process.

The architecture of the proposed 5D-BIM model is organized into four main modules (as illustrated in Figure 2). (1) BIM Model Module: This module encompasses the creation of the 3D BIM model in modeling software (e.g., Autodesk Revit). Here, each building element in the model is annotated with three custom codes – an Element Code (E-Code) that uniquely identifies the type of element, a Location Code (L-Code) denoting its location or section in the project, and a Material Code (M-Code) specifying the material or specification. These codes are defined using special BIM templates and become attributes of the BIM elements. Embedding these codes ensures that the BIM model carries rich information that will later drive the cost estimation process. (2) Database Module: This object-oriented database forms the knowledge backbone of the model (implemented, for example, in Microsoft SQL). The database stores multiple linked tables for construction tasks, methods, crews, and historical costs. It uses its own set of unique codes corresponding to execution details: for instance, Task Codes for different construction activities, Crew Codes for other types of work teams, and possibly a Method Code for various execution methodologies. The elements, locations, and material codes of the BIM model are linked in the database to specific tasks and crew entries.

This structured repository allows the system to retrieve the correct construction method and resource information for each model element and to record actual project data for future use. (3) Estimation Module: The estimation component is the processing module that connects the BIM data with the database to perform calculations. It takes the BIM model (with its codes and quantities) and, through the code relationships, generates the list of execution activities required for the project. The module assigns the appropriate crew and resources from the database for each activity. Then, it calculates the duration (using historical productivity rates from the database's records) and the cost (using unit cost information for labor, equipment, and materials, also drawn from historical data). This module's work results in an integrated project schedule and cost estimate. (4) Actual Data and Execution Tracking Module: This final module is dedicated to tracking actual project performance and feeding the collected information back into the system for continuous improvement. As construction progresses, all relevant performance data are systematically collected and entered into the model via this module. The model captures these inputs and archives them in the database's historical records. This feedback loop keeps the database current and enriched for future projects, enabling the model to learn from actual outcomes and progressively improve its estimation accuracy over time.

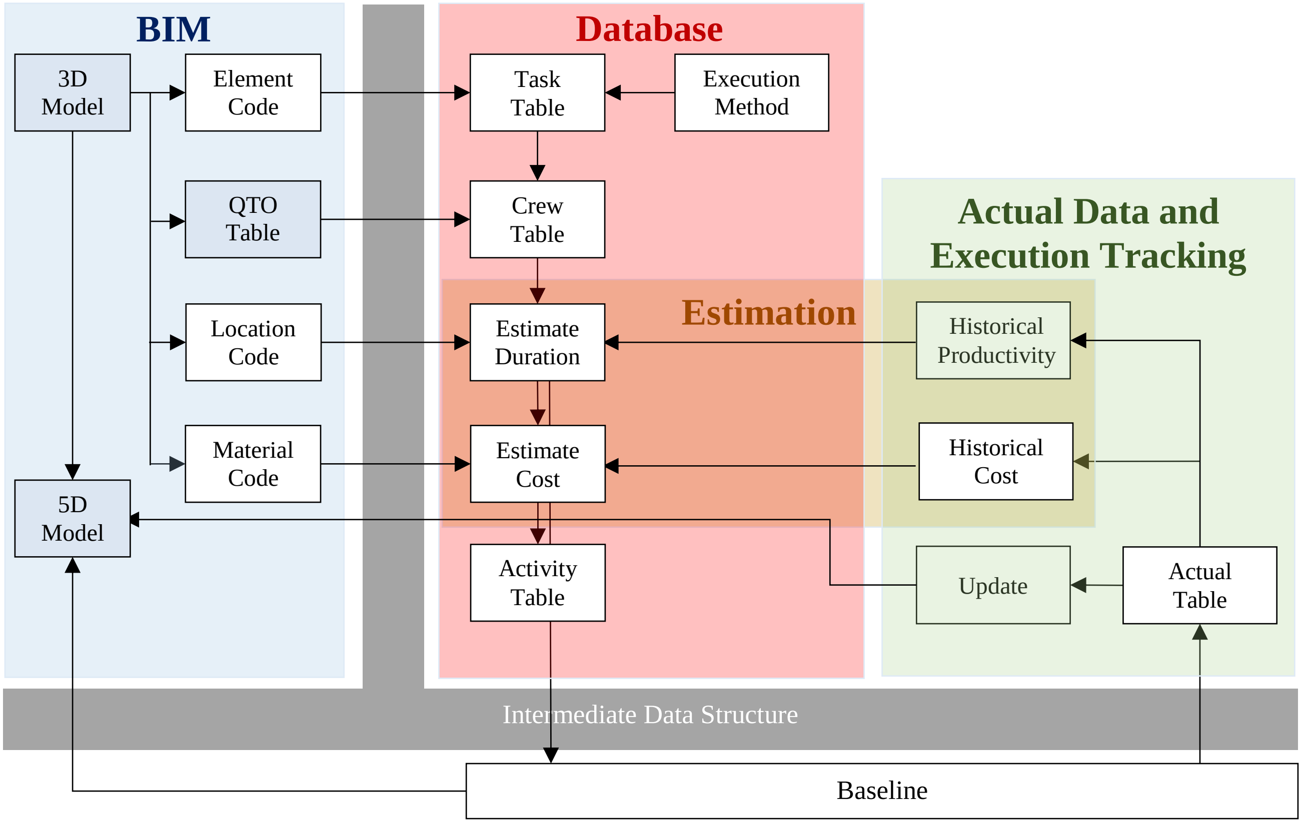

Figure 2. BIM-based cost estimating architecture

2.3.1. BIM Model

Software Interoperability and Code Design

In developing the integrated 5D BIM model, a key methodological focus was on software interoperability, ensuring seamless data exchange between the BIM modeling software (Autodesk Revit) and external databases and scheduling tools. The proposed model establishes a custom unified coding system that serves as a common language across the BIM platform, database, and scheduling software. This coding system enables different applications to recognize and exchange data about the same building elements, locations, and materials without ambiguity. In practice, this means that as information flows from the BIM model to the database (and onward to scheduling tools), the unified codes preserve the identity of each element, thereby maintaining consistency in cost and schedule information across platforms. The unified codes serve as primary keys, linking BIM objects to database records and scheduling entries, thereby forming the backbone of interoperability in the proposed model. Three codes were created in 3D BIM templates for the database and scheduling processes.

Figure 3 demonstrates that the proposed codes guide the estimation process by linking the model data to the database. The left side of the diagram (BIM environment) lists the element, location, and material codes coming from the BIM 3D model, while the right side (database environment) shows the database codes and the generating codes as follows:

- ECode (Element Code): A unique identifier for each element type in the BIM model.
- LCode (Location Code): A code designating the location of an element in the project's breakdown.
- MCode (Material Code): A code specifying the material used in a particular element or component.
- Construction Method Code (CCode): a generated code to identify the construction method based on the element code.
- Task Code (TCode): a generated code to identify the execution tasks based on the element and construction method.
- Activity Code (ACode): a generated code to identify the schedule activities based on the tasks and location.

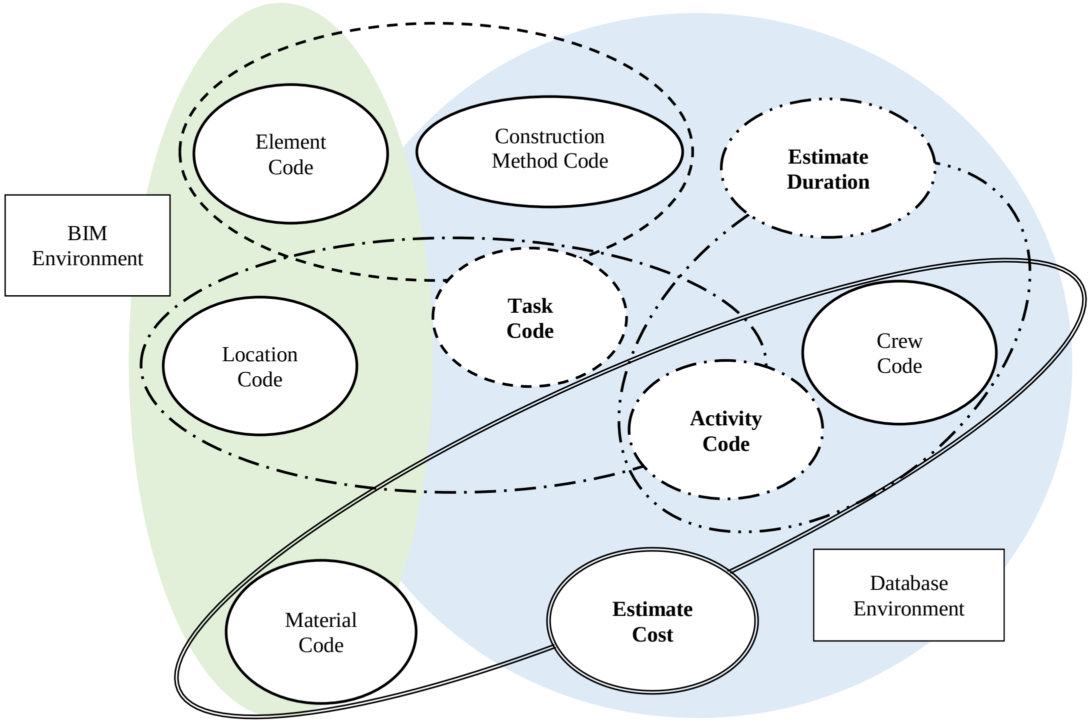

Figure 3. The Proposal Codes' Role in Estimation Process

3D Modeling and Quantity Take-off

In the proposed integrated model, the 3D modeling phase enables seamless linkage between the BIM environment and the oriented cost/scheduling database. Autodesk Revit was selected as the primary modeling tool due to its parametric modeling capabilities and broad adoption in the industry. Once the 3D model was validated, the quantity take-off process was conducted. The structured QTO output included not only the quantities of building elements and materials but also the associated codes (ECode, LCode, and MCode). These codes ensured that every quantity entry could be traced back to its origin within the BIM model and mapped accurately within the database environment.

Due to the absence of a direct API-based link between Navisworks and the SQL-based database, an intermediate data structure was implemented using Microsoft Excel. The QTO results were exported from Navisworks in spreadsheet format. This Excel-based intermediary served as a universal data exchange format, allowing for flexible inspection, correction, or enrichment of the extracted data before importing it into the SQL Server database.

2.3.2. The Database of Project Elements

The integrated model is supported by an object-oriented database (implemented on an SQL Server platform) that serves as a centralized store for all project-related cost and schedule information. Each entity is represented as a table and organized in relational tables linked to the aforementioned unified codes. Figure 4 provides an entity-relationship diagram of the database structure, depicting the tables and their interconnections through primary/foreign keys. In total, fourteen tables form the core of the database, each playing a distinct role in the integrated model. To clarify the design, the database tables can be grouped into four main categories based on their function and the type of data they store:

Core Definition Tables: These tables define the primary entities. For example, an Elements table lists all building element types included in the model, each element's unique ECode, and a descriptive name or category. A Locations table similarly enumerates all distinct project locations (e.g., levels or zones) with their LCodes and names. Likewise, a Construction Methods table contains all possible construction methods (CCode) with a description of each method (e.g., "Cast in Place" vs "Precast" for concrete work).

Relationship/Mapping Tables: A set of tables is devoted to mapping relationships between the core entities, reflecting how different aspects of the project interact. One important example is the Construction Methods–Elements mapping table, which defines which construction methods apply to each element type. For instance, a column element (ECode for column) might have two possible methods (CCode "CP" for cast-in-place and "PC" for precast), whereas another element type might only have one valid method. Another critical relationship table is the Element Method–Tasks table, which links each element-method combination to the execution tasks required to build that element using that method. This table is essentially the expansion of the work breakdown structure for the element: if an element of type X with method Y requires tasks A, B, and C, the table records that mapping by linking the element's ECode and method's MCode to each relevant execution task code (TCode). There are also tables mapping resources to tasks in context; for example, a Crew–Tasks–Element–Location table maps available crew types (crew codes) to specific execution tasks under particular element and location conditions. This enables the system to determine which crew options are feasible or typical for a specific task to a particular element in a given location.

Resource and Historical Data Tables: These tables store information about resources and their cost/productivity metrics, forming the historical knowledge base the model draws upon for estimation. A Crew table, for instance, lists each crew type with a Crew Code and a description (e.g., "Crew 5: 3 carpenters + 2 laborers" might be an entry, identified by a code). Correspondingly, a Crew Costs table stores the unit cost (e.g., hourly or daily cost) for each crew type – in this research, possibly split into internal crew costs vs. subcontractor costs in separate tables, as indicated in the database structure. A Materials table holds all material types, and a Material Prices table provides unit costs for each material code (ensuring that if the QTO identifies a specific material code, the database can supply the latest price per unit for cost calculation). A Crew Productivity table is included to capture historical labor productivity data. This table typically records the production rate of each crew for a given element type and location context, using the element's ECode and location's LCode as keys. For example, Crew A (code CA01) might be able to pour X cubic meters of concrete per day for foundation elements (ECode EF01) in ground floor conditions (LCode L1). Such entries come from past project data or field estimates. They are invaluable for predicting durations: when a new project has a foundation element with that code and location, the system can retrieve the productivity rate to calculate how long the task should take with Crew A. By structuring this historical data by codes.

Project-Specific Activity and Schedule Tables*:* These tables capture the dynamic output of the model for the project and schedule information that gets generated. The activities table lists all scheduled activities, including unique activity IDs and names generated for the project. Additionally, a Logical Relationships table stores any predecessor-successor links between activities (for example, if task "formwork for column X" must precede "concrete pour for column X", that relationship is recorded here). Some relationships may be predefined by templates (e.g., within the set of tasks for one element, there is an intrinsic order), and others might be added depending on the project sequence (like story-level dependencies). There is also a table for Resource Assignments to Activities, which links each Activity ID to the needed resources (crews or materials) by their codes.

Integration between Construction Methods and BIM Elements: Each BIM element in the model is linked to all feasible construction methods as a part of the integrated database. The database enumerates the possible method options for every element type, ensuring that appropriate execution tasks can be assigned based on the chosen method. Table 1 presents the construction method alternatives for each structural element in the case study. For example, a standard reinforced concrete column (ECode "RC") can be constructed either by cast-in-place concrete (CCode "CP") or by using a precast component (CCode "PC"). Recording such alternatives for all elements means the model can dynamically adjust the project plan and required tasks when a different construction technique is selected for a given element.

By integrating construction methods with BIM elements in this way, the model provides a flexible foundation for scheduling and cost estimation. When a specific method is chosen for an element in the BIM environment, the system automatically knows which sequence of tasks to generate (since each method–element combination is predefined in the database). This approach eliminates the need to maintain multiple schedule templates for different construction scenarios; a single unified database can handle variations like cast-in-place versus precast or post-tensioned versus pre-tensioned without manual reconfiguration. In summary, linking construction methods to BIM elements ensures that the downstream scheduling logic always reflects the actual construction approach, thereby improving the accuracy and adaptability of time and cost estimates.

Integration between Execution Tasks and BIM Elements based on Construction Methods: Building on the element-method link, the model defines all necessary execution tasks required to construct each type of BIM element. These tasks are set up as master data in the database, meaning that for every element (ECode) and *construction* method (CCode), there is a predefined list of task codes (TCodes) representing the tasks needed to build that element under that method. Once an element and its method are selected, the model uses this master data to generate the specific execution tasks for that element instance automatically, ensuring that no required task is overlooked.

Table 2 illustrates the mapping between execution tasks and BIM elements under different construction methods. In this table, each row corresponds to an execution task (identified by a TCode and description), and the columns represent element categories (ECode) under particular methods. A binary indicator in each cell, 1 or 0, denotes whether a given task is required (1) or not required (0) for that element-method combination. By reading the table horizontally, one can see all the elements that require a particular task; vertically, one can see all the tasks needed for a specific element under a specified method.

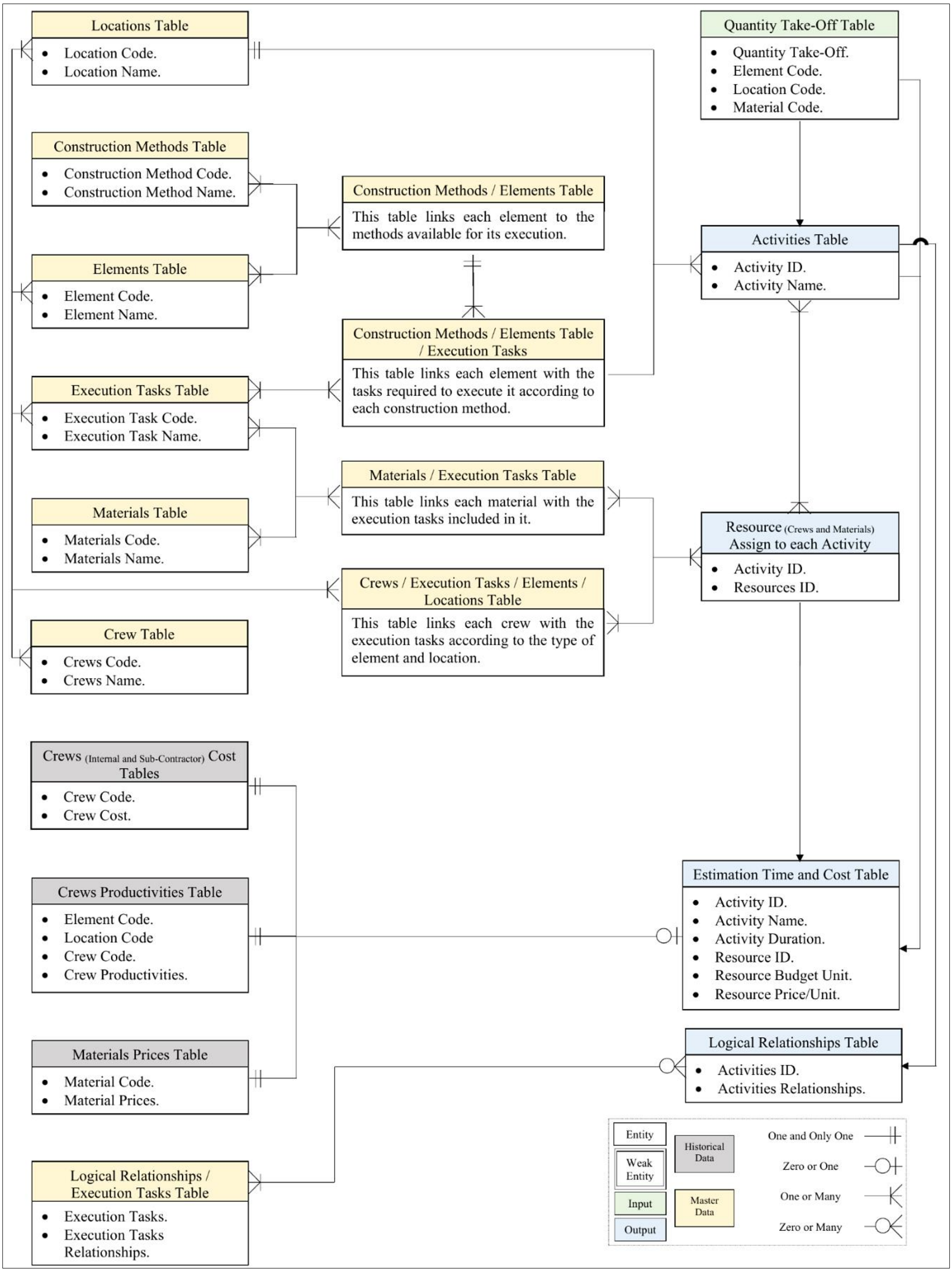

Figure 4. Proposal Database Tables Structure

Table 1. The Possible Construction Methods for each Element

Element Description	ECode	Construction Method	Construction Method Code
Blinding Concrete Under Foundation	BF	Cast in Place	CP
Reinforced Concrete for Foundation	RF	Cast in Place	CP
Reinforced Concrete for Foundation	RF	Precast	EC
Reinforced Concrete for Columns	RC	Cast in Place	CP
Reinforced Concrete for Columns	RC	Precast	EC
Reinforced Concrete for Walls	RW	Cast in Place	CP
Reinforced Concrete for Walls	RW	Precast	EC
Reinforced Concrete for Beams	RB	Cast in Place	CP
Reinforced Concrete for Beams	RB	Precast	EC
Reinforced Concrete for Beams	RB	Pot-Tension	OT
Reinforced Concrete for Beams	RB	Pre-Tension	ET
Reinforced Concrete for Slabs	RS	Cast in Place	CP
Reinforced Concrete for Slabs	RS	Precast	EC
Reinforced Concrete for Slabs	RS	Pot-Tension	OT
Reinforced Concrete for Slabs	RS	Pre-Tension	ET
High Tensile Steel for Foundation	TF	Install on Site	IS
High Tensile Steel for Columns	TC	Install on Site	IS
High Tensile Steel for Walls	TW	Install on Site	IS
High Tensile Steel for Beams	TB	Install on Site	IS
High Tensile Steel for Slabs	TS	Install on Site	IS

Table 2. Integrated Element Code with Task Code

TCode	Execution Task Description	Element Descriptions / ECode												
		Blinding Concrete Under Foundation	Reinforced Concrete for Foundation	Reinforced Concrete for Columns	Reinforced Concrete for Walls	Reinforced Concrete for Beams	Reinforced Concrete for Beams	Reinforced Concrete for Slabs	Reinforced Concrete for Slabs	High Tensile Steel for Foundation	High Tensile Steel for Columns	High Tensile Steel for Walls	High Tensile Steel for Beams	High Tensile Steel for Slabs
		BF	RF	RC	RW	RB	RB	RS	RS	TF	TC	TW	TB	TS
		Construction Method / Construction Method Code												
		Cast in Place	Cast in Place	Cast in Place	Cast in Place	Cast in Place	Pot Tension	Cast in Place	Pot Tension	Cast in Place	Cast in Place	Cast in Place	Cast in Place	Cast in Place
		CP	CP	CP	CP	CP	OT	CP	OT	CP	CP	CP	CP	CP
FS	Formwork Setup	1	1	1	1	1	1	1	1	0	0	0	0	0
IR	Install Rebar	0	0	0	0	0	0	0	0	1	1	1	1	1
TT	Placing Pot-Tension Tendon	0	0	0	0	0	1	0	1	0	0	0	0	0
AB	Fixing Anchorage Bursting Reinforcement	0	0	0	0	0	1	0	1	0	0	0	0	0
AF	Placing Anchorage Pocket Former and Grout Vent	0	0	0	0	0	1	0	1	0	0	0	0	0
EF	Fixing Slab Edge Formwork	0	0	0	0	0	1	0	1	0	0	0	0	0
ER	Slab Edge Formwork and Pocket Former Removal	0	0	0	0	0	1	0	1	0	0	0	0	0
AW	Placing Anchorage Head and Wedge	0	0	0	0	0	1	0	1	0	0	0	0	0
CP	Concrete Placing	1	1	1	1	1	1	1	1	0	0	0	0	0
CF	Concrete Finishing	1	1	0	0	1	1	1	1	0	0	0	0	0
CU	Concrete Curing	1	1	1	1	1	1	1	1	0	0	0	0	0
SS	Stressing	0	0	0	0	0	1	0	1	0	0	0	0	0
XD	Cutting End of Strand	0	0	0	0	0	1	0	1	0	0	0	0	0
GR	Grouting	0	0	0	0	0	1	0	1	0	0	0	0	0
FR	Formwork Removal	1	1	1	1	1	1	1	1	0	0	0	0	0

Integration between Tasks with Crews and Materials: Once execution tasks are identified for each element, the model integrates the resources by linking each task with the necessary crews and materials. For every construction task in the database, there are entries assigning one or more suitable crews to perform that task. The database distinguishes between internal and subcontractor crews, allowing the model to account for different cost rates. It also accommodates multiple crew options for the same task to cover scenarios where, for example, either a two-person or a three-person crew could be deployed based on project needs. Alongside the crew assignment, the model stores productivity rates for each crew performing each task – often multiple productivity values keyed to different contexts. These productivity rates are derived from historical data and can vary by element type or location. Table 3 provides a sample of this task–crew mapping: each row lists a task for an element at a location, along with columns for productivity (Productivity1, Productivity2, …) under different conditions. By linking crews to tasks with consideration of the element and location in this detailed way, the model can automatically calculate task durations and task costs.

To distinguish between sub contractors and internal resources

To cove the possibility of more than one crew executing the same tasks

Productivities according to historical data

Table 3. Sample of a Crew and its Links with the Tasks

Resource Type	Crew Code	Crew No.	Crew Name	ECode	LCode	TCode	Task Description	Productivity1 (Unit/Day)	Productivity2 (Unit/Day)	ProductivityN (Unit/Day)
Internal Resource	FA	01	Formwork Carpenter	BF	0F	FS	Formwork Setup	4.0	7.0	5.0
				BF	0F	FR	Formwork Removal	12.0	15.0	13.0
				RF	0F	FS	Formwork Setup	3.0	5.0	3.0
				RF	0F	FR	Formwork Removal	9.0	11.0	10.0
				RC	0F	FS	Formwork Setup	1.2	3.2	2.2
				RC	0F	FR	Formwork Removal	3.6	4.6	3.6
				RC	any	FS	Formwork Setup	1.2	4.2	3.2
				RC	any	FR	Formwork Removal	3.6	6.6	5.6
				RW	0F	FS	Formwork Setup	2.5	3.5	1.5
				RW	0F	FR	Formwork Removal	7.5	9.5	7.5
				RW	any	FS	Formwork Setup	2.5	5.5	4.5
				RW	any	FR	Formwork Removal	7.5	8.5	6.5
				RB	0F	FS	Formwork Setup	3.0	5.0	4.0
				RB	0F	FR	Formwork Removal	9.0	12.0	11.0
				RB	any	FS	Formwork Setup	1.0	4.0	3.0
				RB	any	FR	Formwork Removal	3.0	4.0	3.0
				RS	0F	FS	Formwork Setup	3.0	4.0	2.0
				RS	0F	FR	Formwork Removal	9.0	10.0	9.0
				RS	any	FS	Formwork Setup	1.0	4.0	3.0
				RS	any	FR	Formwork Removal	3.0	5.0	4.0

In parallel, the model links the required materials to each execution task. Every material that appears in the quantity take-off (QTO) from the BIM model is assigned a material code (MCode), and these codes correspond to entries in the database that map materials to the tasks in which they are used. The database carries the historical unit costs of each material (updated via a materials cost table), so when a task is generated and a quantity for that material is known from the BIM model, the cost for that material on the task can be automatically calculated and assigned to the related task. Table 4 illustrates a sample mapping where common construction materials are associated with the relevant tasks.

Table 4. Sample of a Group of Materials and Linking Them to Their Execution Tasks

MCode	Material Descriptions	TCode	Task Descriptions
C18YS	Concrete 18 MPa (Cylinder) Sulphate Resisting Cement	CP	Concrete Placing
C25YP	Concrete 25 MPa (Cylinder) Ordinary Portland Cement	CP	Concrete Placing
C30YS	Concrete 30 MPa (Cylinder) Sulphate Resisting Cement	CP	Concrete Placing
C30YP	Concrete 30 MPa (Cylinder) Ordinary Portland Cement	CP	Concrete Placing
T08	Reinforcing Steel Diameter of 8 mm	IR	Install Rebar
T10	Reinforcing Steel Diameter of 10 mm	IR	Install Rebar
T12	Reinforcing Steel Diameter of 12 mm	IR	Install Rebar
T14	Reinforcing Steel Diameter of 14 mm	IR	Install Rebar
T16	Reinforcing Steel Diameter of 16 mm	IR	Install Rebar
T20	Reinforcing Steel Diameter of 20 mm	IR	Install Rebar
T25	Reinforcing Steel Diameter of 25 mm	IR	Install Rebar

By tying both crews and materials to execution tasks, the model achieves a seamless integration: any change in the BIM model (such as altering an element's dimensions or construction method) triggers an update in the tasks, which in turn updates the required crew assignments, durations, quantities, and costs.

Logical Relations: The proposed model manages the sequencing logic between tasks centrally through predefined logical relationships in the database. Instead of defining predecessor and successor relations separately for every activity in each new project schedule, the model stores these logical relations at the level of execution tasks. If one task must always precede another, that rule is recorded once in a master "logical relationships" table and applies universally. For example, consider the generic tasks "Install Reinforcement" and "Place Concrete": if, for any structural element, rebar installation should be completed before the concrete pour, the database captures this dependency as a rule linking the task code for "Install Reinforcement" to the task code for "Place Concrete" with a finish-start relationship. Later, when these tasks are instantiated as specific activities in a project (e.g., "Install Reinforcement for Column C1" and "Place Concrete for Column C1"), the system automatically assigns the correct predecessor-successor relationship based on the master rule. This way, without a planner specifying that link, "Install Reinforcement for Column C1" would be scheduled to finish before "Place Concrete for Column C1" starts, without a planner specifying this way.

This approach drastically reduces repetition and the potential for error; planners do not need to recreate standard logic links for every element or rely on duplicating schedule templates, as the relations are assigned automatically. All such nuances are defined once in the database and consistently applied wherever relevant.

2.3.2.1. Execution Activities

Once the BIM model has been developed and linked to the oriented database, the system automatically generates a list of scheduled activities based on the construction method by combining the Element Code (ECode), Task Code (TCode), and Location Code (LCode). Each activity is uniquely identified using an Activity Code (ACode), which reflects the element type, the construction task, and the location within the project. This structure ensures that even repetitive tasks across different elements or locations are distinguishable, as shown in Figure 5. For example, the task "Concrete Placing" (TCode: CP) for a foundation element (ECode: RF) at the ground level (LCode: 0F) would result in the activity code "RF-CP-0F".

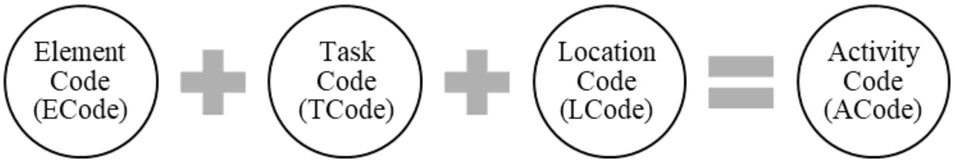

Figure 5. Activity Code (ACode)

2.3.2.2. Crews and Materials

After activities are generated, the model automatically assigns crews and materials to each task using predefined mappings stored in the database. Productivity rates are retrieved from historical records based on the task, element type, and location, allowing the estimation of task durations accurately.

2.3.3. Cost and Duration Estimation

Having established the BIM model integration with a cost/schedule database and defined all execution activities and resource assignments in previous sections, the proposed model can automatically generate detailed cost and time estimates. This section presents the methodology for computing direct costs and activity durations. The model leverages the quantities extracted from the 3D BIM model, links them to unit rates for materials and crew, and applies crew productivity rates to estimate the time and cost. This integration ensures that any changes in the 3D BIM model are consistently reflected in the cost and duration, eliminating the need for manual data transfer and potential discrepancies.

The following subsections outline how the system calculates the direct costs for each construction activity and estimates the corresponding durations, including the handling of uncertainty through three-point estimation and probabilistic formulas. The database produces three values based on historical data: P = Pessimistic value, M = Most Likely value, and O = Optimistic value. The values of estimations are then calculated using either the Triangular distribution Equation 1 or the Beta distribution Equation 2. The standard deviation that measures the amount of variance or uncertainty for each estimated value can be calculated using Equation 3 in the case of the Beta Distribution.

$$Estimation\ Value = (P + M + O)/3 \tag{1}$$

$$Estimation\ Value = (P + 4M + O)/6 \tag{2}$$

$$SD = (O - P)/6 \tag{3}$$

Cost Estimation Procedure

In the integrated 5D BIM model, cost estimation is performed at the level of individual execution activities (as defined earlier in the workflow). The 3D BIM model provides the quantity of work via automated quantity take-off for each activity. These quantities are then mapped to the relevant cost items in the object-oriented project database using unique codes. The database stores the unit rates for all required resources (materials and crews), which have been derived from historical data stored in the system. Material costs are computed by multiplying the BIM quantity of each material by its unit price. In contrast, crew costs are calculated by estimating the effort required and multiplying it by the crew's cost rate. By performing these computations for every activity (rather than at a coarse component level), the model produces a cost breakdown linked to the project schedule. This bottom-up approach means that the total direct cost is simply the aggregate of all activity costs, ensuring consistency between the cost estimate and the work plan, as each cost item is tied to a scheduled task from the outset. Figures 6 and 7 illustrate examples of the model's cost estimation output. Figure 6 shows a sample material cost calculation for a structural element; Figure 7 presents the corresponding crew cost estimation. In these examples, the model retrieves the relevant material and crew entries by their codes, applies the BIM quantities and unit rates, and computes the cost for each activity, demonstrating the automation of the process.

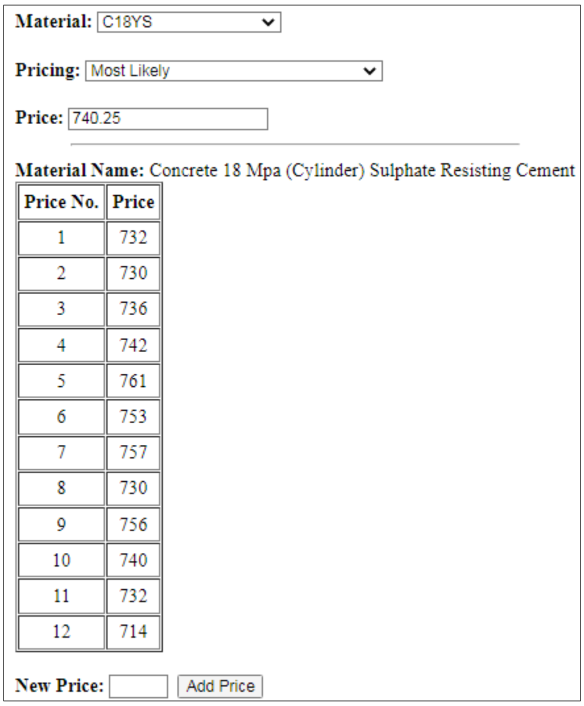

Figure 6. Material Estimation

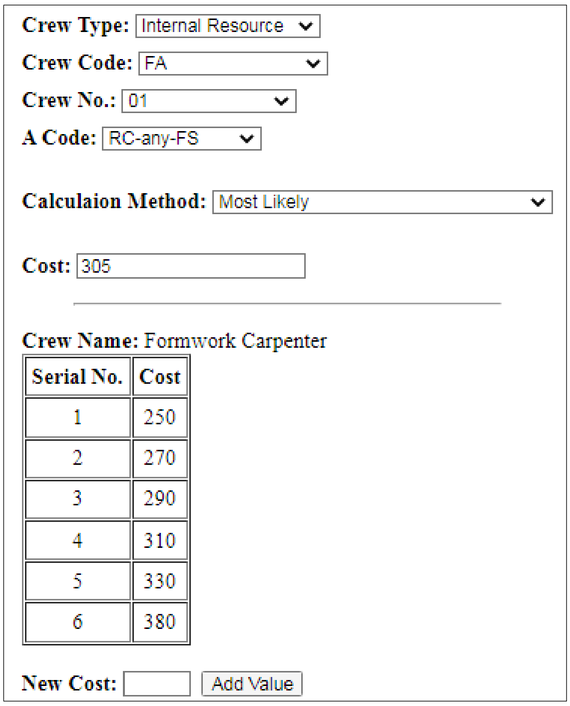

Figure 7. Crew Estimation

A significant advantage of the proposed model is its ability to incorporate historical data and uncertainty into the cost estimates. For each resource (material or crew) involved in an activity, the database not only contains a single unit cost value but can also provide three data points reflecting uncertainty: an optimistic cost (O, the lowest reasonably observed cost), a most likely cost (M, the typical or expected value), and a pessimistic cost (P, the highest observed cost). These three-point estimates are derived from a statistical analysis of past project records, allowing the model to perform a more robust estimation by accounting for price variability. By default, the model can calculate an expected cost for each activity using either a triangular distribution or a beta distribution (PERT) formula applied to O, M, and P. In the triangular case, the expected value is the simple average of the three points (Equation 1). In contrast, in the PERT beta distribution, the most likely value is given additional weight (commonly using the formula $(O + 4M + P) / 6$, as shown in Equation 2).

The choice between these methods is left to the estimator. In both cases, the model can also compute the standard deviation of the estimated cost as a measure of uncertainty (using the PERT formula $[P – O] / 6$, represented by Equation 1). Including these equations allows the estimator to quantify the confidence range of each cost estimate, supporting risk analysis and contingency planning. For instance, if a particular crew's cost has high variability in the historical data, the model will reflect a larger standard deviation for activities utilizing that crew, signaling higher cost risk. It should be noted that the estimator has flexibility in using this information – they can either take the expected costs as the basis for budgeting or choose a more conservative value (e.g., the pessimistic cost) if a safer estimate is desired. Moreover, suppose historical data for a particular resource is not available or deemed irrelevant. In that case, the model permits the manual input of unit costs or adjustments to the three-point values, ensuring that the model remains practical in a variety of scenarios. This automated linkage between BIM and cost data accelerates the estimating process. It improves accuracy by minimizing human errors and ensuring that every cost is tied to a defined scope of work. The result is an estimation that can be trusted as the basis for financial planning and that can be easily updated if the project scope or design changes, simply by re-running the BIM-to-cost calculation workflow.

Duration Estimation Procedure

In parallel with cost estimation, the model computes the duration estimation for each activity using the BIM quantities and resource productivity data. The goal is to determine a realistic duration for every scheduled activity, which allows the assembly of a complete project timeline when all activities are linked in sequence. Time estimation also begins with the fundamental relationship between the quantity of work and the rate at which that work can be completed. For a given activity, the required quantity of work is known from the BIM's quantity take-off. The activity has a crew assigned (as determined in the earlier integration steps), and the productivity rate of the crew is obtained from the historical database. Productivity is the amount of work a crew can perform per unit time. The database stores actual achieved productivity from past projects for each type of activity and crew, improving the estimates' realism by basing them on empirical data. Like cost, the model accounts for variability in productivity by retrieving three-point estimates: for each crew-task combination, an optimistic productivity (O, fastest rate), a most likely productivity (M, average rate), and a pessimistic productivity (P, slowest rate) are determined from historical records. These values reflect how quickly or slowly the work might be done under different field conditions or assumptions.

The estimator using the model can also specify the number of crews deployed for the activity (for example, using two parallel crews to expedite work). Given these inputs, the model calculates the activity duration by dividing the total quantity by the total production rate of the crews. In a simple deterministic scenario, if a single crew is assigned, the duration D would be calculated as D = Q / M (with M being the most likely productivity, in consistent units). More generally, if (n) identical crews work in parallel, the effective productivity becomes (n) multiplied (productivity per crew), and thus D = Q / (n * productivity per crew). This formula is applied within the model to derive an initial duration for each task. However, to incorporate the three-point data and obtain a more robust estimate, the model can perform a three-point duration calculation: the optimistic duration D_O is computed using the optimistic productivity (i.e., D_O = Q / (n * O), representing the shortest plausible duration), the most likely duration D_M = Q / (n * M), and the pessimistic duration D_P = Q / (n * P), representing the longest plausible duration. Using these three values, an expected duration can be calculated via the triangular formula or PERT beta formula analogous to the cost estimation (Equations (1) and (2) applied in time domain). In practice, the PERT approach is commonly recommended for schedule estimation, yielding an expected duration D{exp} = (D_O + 4D_M + D_P) / 6 and a standard deviation for the activity duration sigma = (D_P - D_O) / 6 (per Equation (3)). The model thus provides not only a single estimated duration for each activity but also an indication of the uncertainty or confidence range, which is invaluable for schedule risk analysis.

Once the durations for all activities are determined, the model integrates them into the project schedule by placing each activity in its proper sequence as defined by the project's logic (predecessor–successor relationships). Because the cost estimation was done at the same activity level, each scheduled activity in this 5D model carries its associated cost and resource, enabling time-cost analyses such as cash flow projections. This provides a basis for comparing expenditure with funding or income schedules, helping identify potential financing gaps. Figure 8 illustrates the duration estimation interface of the model for a sample activity; the estimator selects the relevant task and inputs the number of crews, upon which the system retrieves the corresponding productivity values from the database and computes the activity's duration. As shown in the figure, the interface guides the user through confirming the task details (1), choosing the crew deployment (2), and then displaying the calculated duration along with possible variation ranges (3). This example underscores the model's interactive yet automated nature of the time estimation process. By leveraging actual productivity data and allowing scenario adjustments (e.g. adding an extra crew to see its effect on duration), the model ensures that the schedule is data-driven and flexible to user inputs.

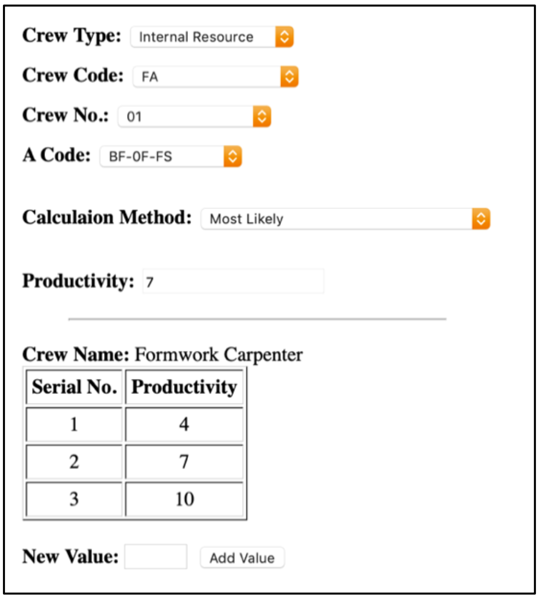

Figure 8. Duration Estimation

In summary, integrating BIM and the database greatly enhances automation and consistency in project planning. This approach eliminates the traditional templates where estimators and schedulers work separately with duplicate data; instead, a change in the BIM model will automatically trigger updates in the related activities' quantities, costs, and durations. The result is a more efficient and reliable estimation process. The integrated time and cost estimation streamlines the planning phase and forms a solid foundation for ongoing project monitoring and management in a BIM environment

2.3.4. Actual Data Integration and Execution Tracking

The proposed BIM-based model provides a real-time module for integrating planned and actual project data to support rigorous monitoring. It enables continuous tracking of actual progress and directly compares these metrics against the baseline estimates. During construction, site engineers and project staff input field updates into a centralized online database, for example, recording each activity's start and finish dates, work performed, and the resources consumed. The model then automatically aligns and compares these actual performance metrics with the corresponding planned values from the 5D BIM baseline. While the activities and resources carry the same coding system during the estimation and execution phases, every reported on-site data point is accurately mapped to its planned counterpart [33], ensuring that any deviation between the plan and reality is immediately detected. In essence, the model serves as an early-warning system: discrepancies such as emerging schedule delays or cost overruns are flagged at their onset, enabling project managers to respond with informed decisions before such issues escalate [28, 43].

Figure 9 illustrates the workflow of this integrated monitoring and control process. The cycle continues after establishing the baseline schedule in the project management software (Primavera P6), fully loaded with the estimated durations, costs, and assigned resources for all activities. As construction progresses, actual performance data are continuously collected on-site and fed into the online database. These updated actuals are regularly exported from the database into the scheduling software, which updates the project schedule to reflect the work accomplished to date. This bi-directional data flow automatically generates up-to-date cost and schedule performance reports. It facilitates systematic comparisons between the evolving actual progress and the original plan. The continuous feedback loop, thereby created, allows stakeholders to identify any variances promptly and formulate corrective actions or recovery plans as necessary.

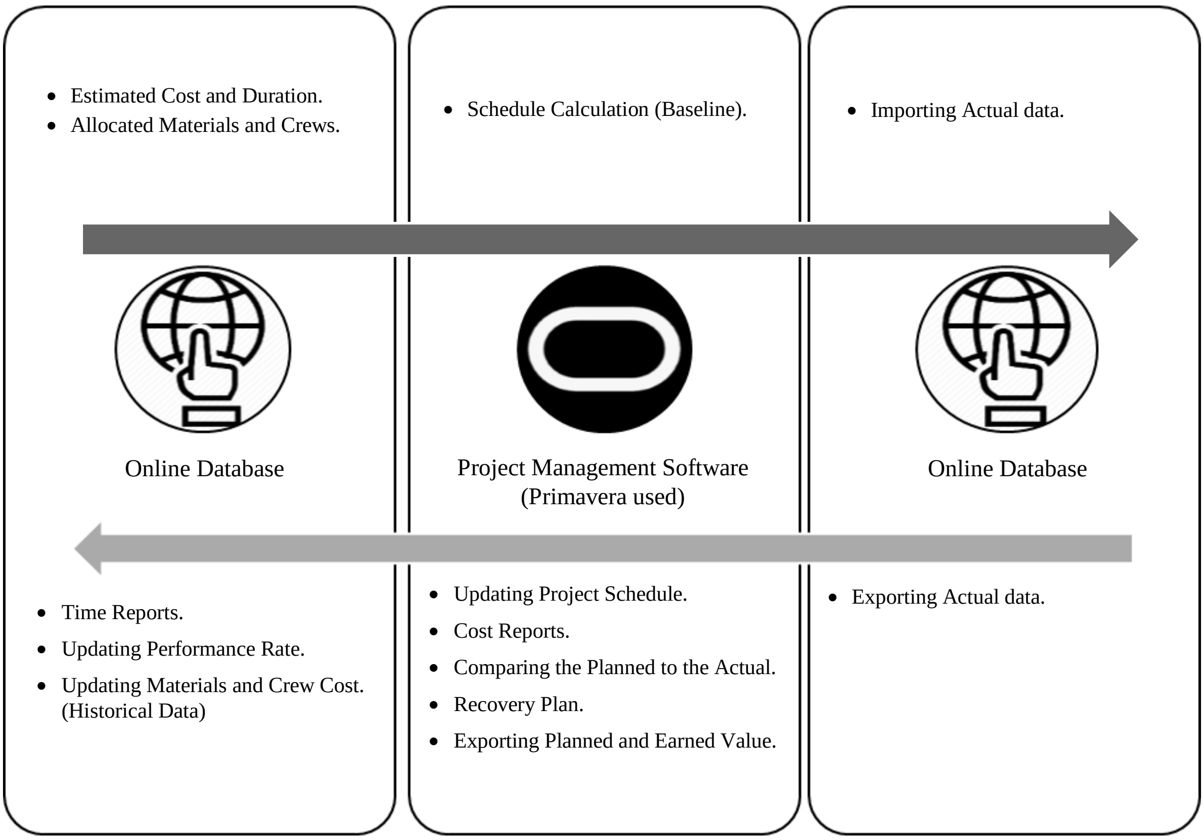

Figure 9. The Proposal for the Project Control Cycle Framework

Moreover, each iteration of this cycle enriches the project's knowledge base: the actual performance information is continually fed into the central database, augmenting the repository of historical data. Over time, this accumulation of real project data improves the accuracy of subsequent estimates by providing more reliable reference points. Overall, the structured approach to data integration and execution tracking markedly enhances project management effectiveness. It provides decision-makers with accurate, real-time insights into project performance and fosters proactive control measures to mitigate the risk of schedule delays and budget overruns.

3. Case Study

To validate the proposed BIM-based cost estimation and scheduling model, we applied it to an actual six-story reinforced-concrete residential building. This building is one of 36 similar structures in a development, and we obtained its actual construction schedule and cost data for comparison. The case study focuses on the concrete structural work of one building, allowing us to demonstrate how the model generates a detailed cost-loaded schedule and to compare the model's outputs with what was achieved on-site. Using an actual project, we ensure the example reflects practical complexities and provides a meaningful test of the model's effectiveness.

Modeling and Data Extraction: The building's structural elements were first modeled in detail using Autodesk Revit, creating a full 3D BIM of the concrete components (Figure 10). All beams, slabs, columns, footings, and walls were defined with their geometric and material properties. We performed an automatic quantity take-off (QTO) from this Revit model using Autodesk Navisworks. The QTO data was then exported to Microsoft Excel as a structured report (Figure 11), organized by ECode, LCode and MCode. These quantities served as the primary input for our cost and scheduling database. By leveraging Revit and Navisworks for modeling and QTO, we ensured that the quantity data was accurate and consistent with the design and avoided manual take-off errors. Any change in the BIM would automatically update the quantities, which is one of the key advantages of maintaining estimate accuracy.

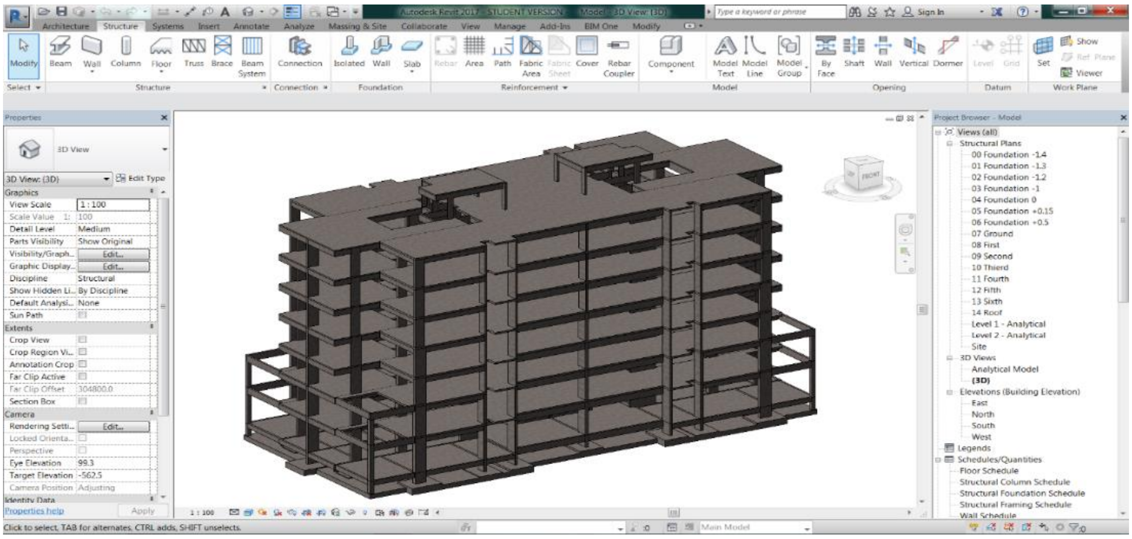

Figure 10. The 3D View for Building Project

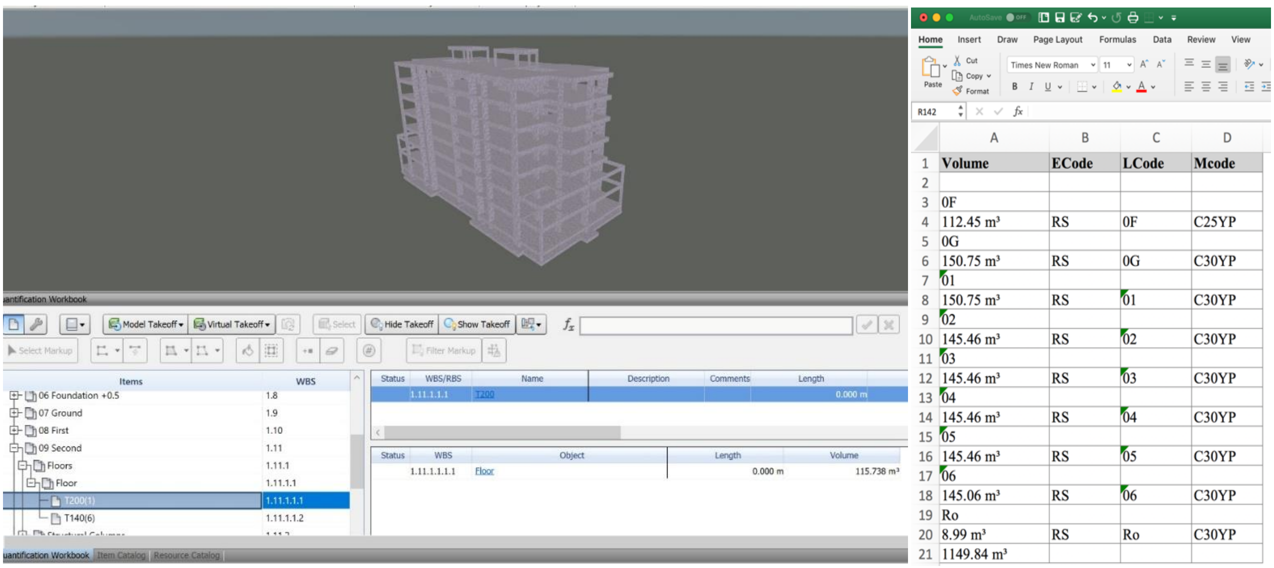

Figure 11. Quantities Take-off (Output of Navisworks)

Applying Coding: The proposed coding system was used to link the BIM elements with the external database. In Revit, each element was tagged with an Element Code (ECode) representing its structural category (e.g. "RC" for column, "RB" for beam, "RS" for slab, "RF" for footing), and a Location Code (LCode) indicating its location or level in the building. The ECode was set as a type parameter (so all instances of a given element type share the same code) while the LCode was an instance parameter (since, for example, identical columns appear on different floors and need location distinction). Figure 12 shows a snapshot of the BIM model with these codes assigned to the elements. It is worth noting that this coding was embedded directly into the 3D BIM model, so no manual re-entry of codes was needed during data transfer; the codes automatically exported with the QTO tables. This ensured a seamless identification of each element in the database, which was used to assign the correct construction tasks and resources for that element.

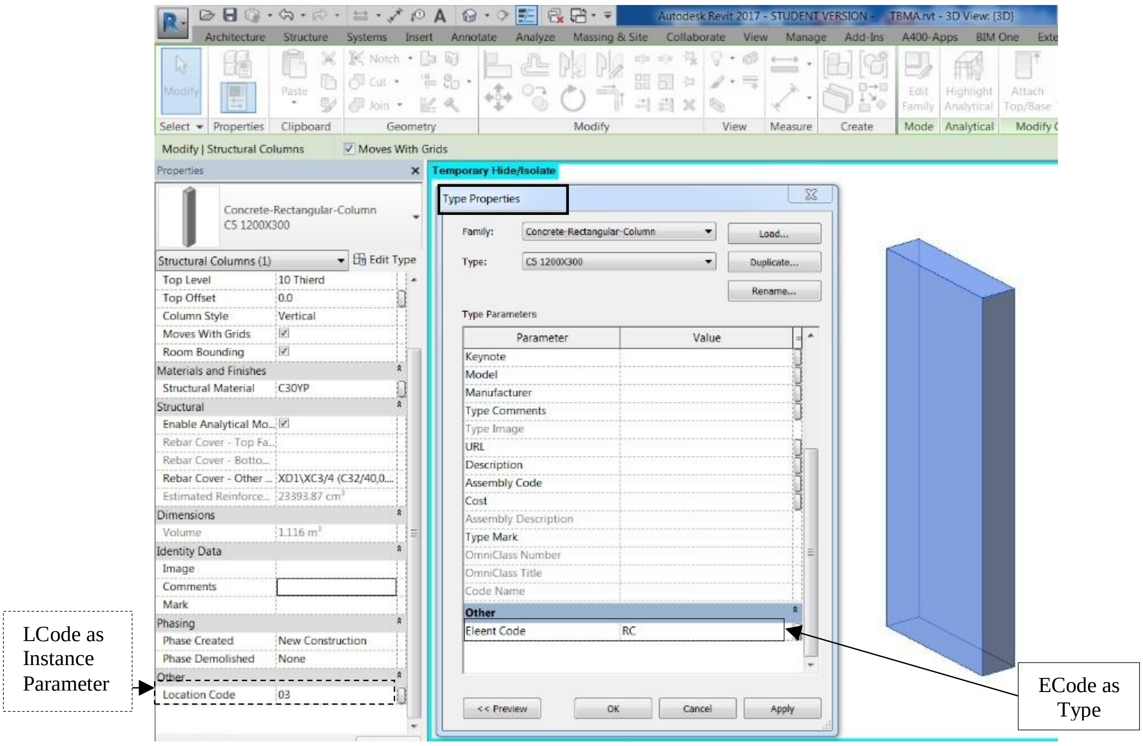

Figure 12. Element Code (ECode) and Location ode (LCode) (Output of Autodesk Revit)

Execution Method Selection and Activity Generation: With the quantities and codes in the database, the next step was to generate the scheduled activities for each element. The model's SQL-based database contains a library of execution methods and associated tasks for each element type (as defined in the methodology). We selected the construction method for each element in a user interface linked to the database. In this case study, cast-in-place was chosen as the execution method for all concrete elements (the model supports alternatives like precast, but the actual project used cast-in-place for its structure). Once the method was selected, the system automatically retrieved the list of execution tasks from the database corresponding to that element type and method. For example, for a reinforced concrete column (ECode "RC") with a cast-in-place method, the database generates tasks such as formwork setup, concrete placing, formwork removal, etc., each with a predefined code and description. Figure 13 illustrates this process of selecting an element (by its ECode and LCode) and the construction method, after which the relevant tasks are generated. The tasks are generated by a Task Code (TCode) (e.g. "FS" for Formwork Setup, "CP" for Concrete Placing, etc.), and the model combines the ECode, LCode, and TCode to form a unique Activity Code (ACode) for each activity.

These ACodes ensure each activity is distinctly tied to a specific element and location. The output of this stage was an activity list for the entire building's concrete works, as summarized in Table 5. Table 5 shows a portion of this list: for instance, it includes activities like RF-0F-FS (Formwork Setup for a foundation footing), RF-0F-CP (Concrete Placing for a footing), and so on, with their descriptions. Each row in the table represents an activity that will appear in the schedule. In total, dozens of activities were generated (covering foundations, columns, beams, and slabs across all floors). Notably, the model performed this step automatically as soon as the element code and method were known; the system looked up a template of tasks and created all necessary activities with no manual schedule drafting. This ensured that no required task was omitted and that the naming and coding of activities were standardized. By avoiding a manual activity definition, we reduced the risk of human oversight and maintained consistency across similar elements.

Figure 13. Getting the Schedule Activities

Table 5. Activities List Example

ECode	Lcode	Construction Method	TCode	ACode	Description
RF	0F	Cast in Place	CP	RF-0F-CP	Concrete Placing for Reinforced Concrete for Foundation in Foundation Level
RF	0F	Cast in Place	CF	RF-0F-CF	Concrete Finishing for Reinforced Concrete for Foundation in Foundation Level
RF	0F	Cast in Place	CU	RF-0F-CU	Concrete Curing for Reinforced Concrete for Foundation in Foundation Level
RF	0F	Cast in Place	FR	RF-0F-FR	Formwork Removal for Reinforced Concrete for Foundation in Foundation Level
RF	0F	Cast in Place	FS	RF-0F-FS	Formwork Setup for Reinforced Concrete for Foundation in Foundation Level
RC	0F	Cast in Place	CP	RC-0F-CP	Concrete Placing for Reinforced Concrete for Columns in Foundation Level
RC	0F	Cast in Place	CU	RC-0F-CU	Concrete Curing for Reinforced Concrete for Columns in Foundation Level
RC	0F	Cast in Place	FR	RC-0F-FR	Formwork Removal for Reinforced Concrete for Columns in Foundation Level
RC	0F	Cast in Place	FS	RC-0F-FS	Formwork Setup for Reinforced Concrete for Columns in Foundation Level

Integration of Cost and Productivity Data: Once the list of activities was generated, the model assigned the required resources to estimate each activity cost and duration. This was achieved by using the stored historical data in the database (Figure 14). The model assigns the relevant materials and unit costs for cost estimation for every activity. In our case, the footing RF-0F-CP had a quantity of about 689 m³ of concrete (MCode "C30YS" concrete 30 MPa cylinder sulphate resisting cement), and the database unit price for this specified concrete mix was around 740 SAR/m³ after choosing the probable estimation technique. Multiplying these, the model computes the material cost for that activity. Table 6 shows an example of the materials assignment; each activity's code is listed with the material code, unit price, quantity, and resulting cost calculated by the model. In addition to materials, the model also considers crew costs. After choosing a specific crew type (internal, sub-contractor, crew number and a probable estimation technique), the model calculates crew costs by estimating the labor hours needed and multiplying by the crew cost rate. This produces a cost for the crew, which is added to the activity's cost. The model obtains the total cost for each activity by summing the material and crew costs. These costs are inherently linked to the BIM quantities and the chosen execution method, so they reflect the specific project conditions.

In parallel with cost calculation, the model determines each activity's duration using the productivity data. For each task, the required quantity of work (from QTO) and the crew's productivity (from historical records) are used to compute how long that task should take. Table 7 presents how the model estimated activity durations based on crew productivity. The first part shows the scheduled activities, the middle part shows the assigned crews for each activity, and the third part shows the duration and cost estimates based on the productivity and costs of the crews assigned in the middle part.

Figure 14. Pricing a Material

Table 6. Assign the Materials with unit and cost

ACode	Description	MCode	Material	Material Price	Budget Unit	Unit	Material Cost
RF-0F-CP	Concrete Placing for Reinforced Concrete for Foundation in Foundation Level	C30YS	Concrete 30 MPa (Cylinder) Sulphate Resisting Cement	740.25	689.02	m³	510047.1
RC-0F-CP	Concrete Placing for Reinforced Concrete for Columns in Foundation Level	C30YS	Concrete 30 MPa (Cylinder) Sulphate Resisting Cement	753.41	16.21	m³	12212.78
RB-0F-CP	Concrete Placing for Reinforced Concrete for Beams in Foundation Level	C30YS	Concrete 30 MPa (Cylinder) Sulphate Resisting Cement	753.41	43.83	m³	33021.96
RW-0F-CP	Concrete Placing for Reinforced Concrete for Walls in Foundation Level	C30YP	Concrete 30 MPa (Cylinder) Ordinary Portland Cement	740.25	10.75	m³	7957.69
RS-0F-CP	Concrete Placing for Reinforced Concrete for Slabs in Foundation Level	C25YP	Concrete 25 MPa (Cylinder) Ordinary Portland Cement	741	112.45	m³	83325.45
TB-01-IR	Instal Rebar for Reinforcing Beams in First Floor Level	M3508	Mild Steel 35/33 Diameter of 8 mm	10811.4	1.75	Ton	18920
TB-01-IR	Instal Rebar for Reinforcing Beams in First Floor Level	T5212	High Tensile Steel 52/36 Diameter of 12 mm	11124.3	0.5	Ton	5562.14
TB-01-IR	Instal Rebar for Reinforcing Beams in First Floor Level	T5216	High Tensile Steel 52/36 Diameter of 16 mm	11124.3	6	Ton	66745.74

Table 7. Estimate the Activities Duration based on Crews Productivity

Part 1						Part 2				Part 3					
ECode	**LCode**	**Construction Method**	**TCode**	**ACode**	**Description**	**Crew Type**	**C Code**	**Crew No.**	**Labor Crew Name**	**Budget Unit**	**Unit**	**Productivity / Day**	**No. of Crew**	**Estimated Duration (Day)**	**Crew Cost**
TF	0F	Install in the Site	IR	TF-0F-IR	Install Rebar for Reinforcing Foundation in Foundation Level	Internal Resource	TX	1	Steel Fixer	48	Ton	0.3	20	8	2493
RC	0G	Cast in Place	CP	RC-0G-CP	Concrete Placing for Reinforced Concrete for Columns in Ground Floor Level	Internal Resource	OP	1	Concreters Placing	47.24	mł	63.33	1	1	0
RC	0G	Cast in Place	CU	RC-0G-CU	Concrete Curing for Reinforced Concrete for Columns in Ground Floor Level	Internal Resource	OU	1	Concreters Curing	47.24	mł	173.33	1	1	140
RC	0G	Cast in Place	FR	RC-0G-FR	Formwork Removal for Reinforced Concrete for Columns in Ground Floor Level	Subcontractor	FA	1	Formwork Carpenter	47.24	mł	4.7	4	3	1535
RC	0G	Cast in Place	FS	RC-0G-FS	Formwork Setup for Reinforced Concrete for Columns in Ground Floor Level	Subcontractor	FA	1	Formwork Carpenter	47.24	mł	1.57	6	6	6496

Automated Schedule Creation: The model assembled the entire schedule once every activity had an estimated duration and cost. The predefined templates in the database determined the logical sequence of activities. The database encoded these dependencies so the model could automatically assign predecessors and successors to each activity. At the end of the process, we had a complete set of scheduled activities with IDs, descriptions, durations, costs, assigned materials, and assigned crews, all generated from the initial BIM input. The final step was to export this information to project management and BIM tools for review and visualization. We exported the activities, durations, and costs to Primavera P6, which produced a detailed Gantt chart schedule of the project (Figure 15). Simultaneously, we linked the activities to the BIM in Navisworks to create a 5D simulation model. Figure 16 shows the Navisworks 5D model timeline, where we can visualize the construction sequence and see the cumulative costs at each timeline step. This confirms that the data flow was successful, starting from Revit to Navisworks/Excel (quantities) to the database (activities, resources) and, finally, to Primavera/Navisworks (schedule and 5D model). The case study thus demonstrates the end-to-end capability of the proposed integrated model in a real-world scenario. A fully cost-loaded schedule and a 5D BIM simulation were produced using a BIM design, either automated or semi-automated. Throughout this process, we avoided duplicating data entry and leveraged historical information to make the outputs realistic. The building was constructed using traditional planning methods; after applying our model, we can compare how the model's automatically generated estimates and schedule would have performed versus the actual outcomes, as discussed in the next section.

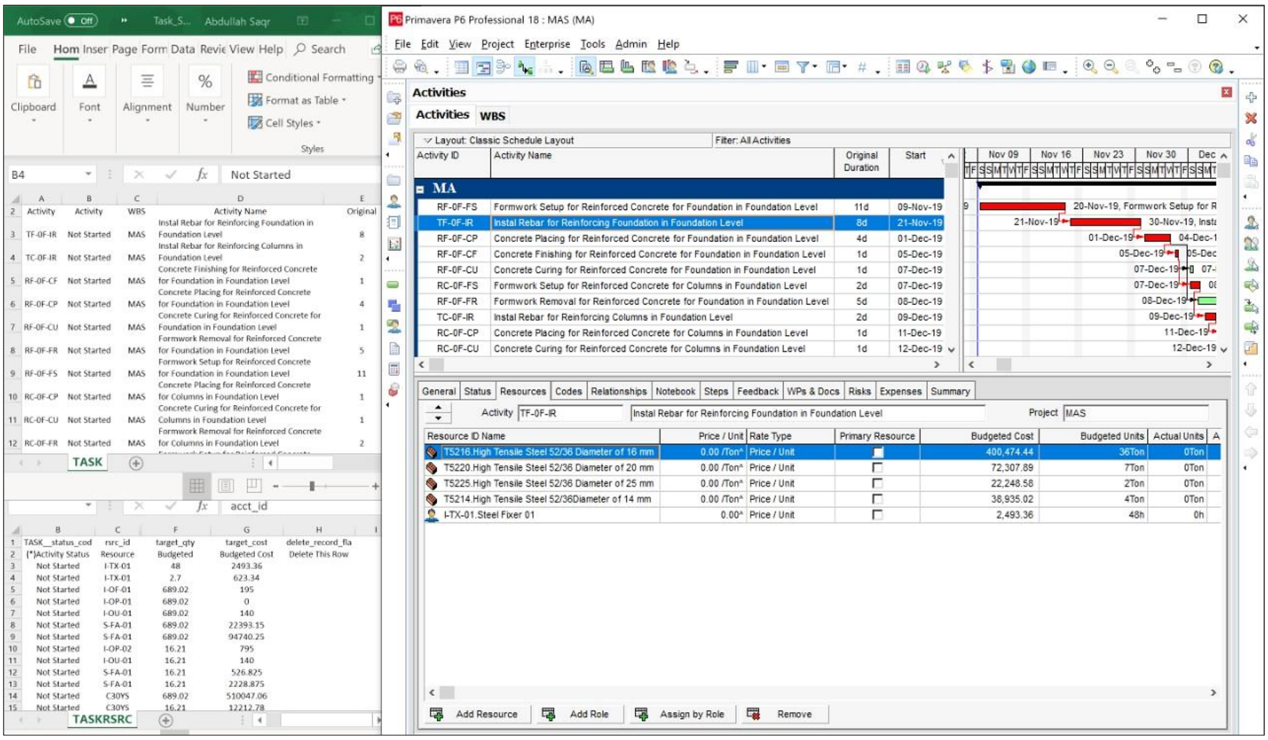

Figure 15. Export Estimation Data from Database to (Primavera)

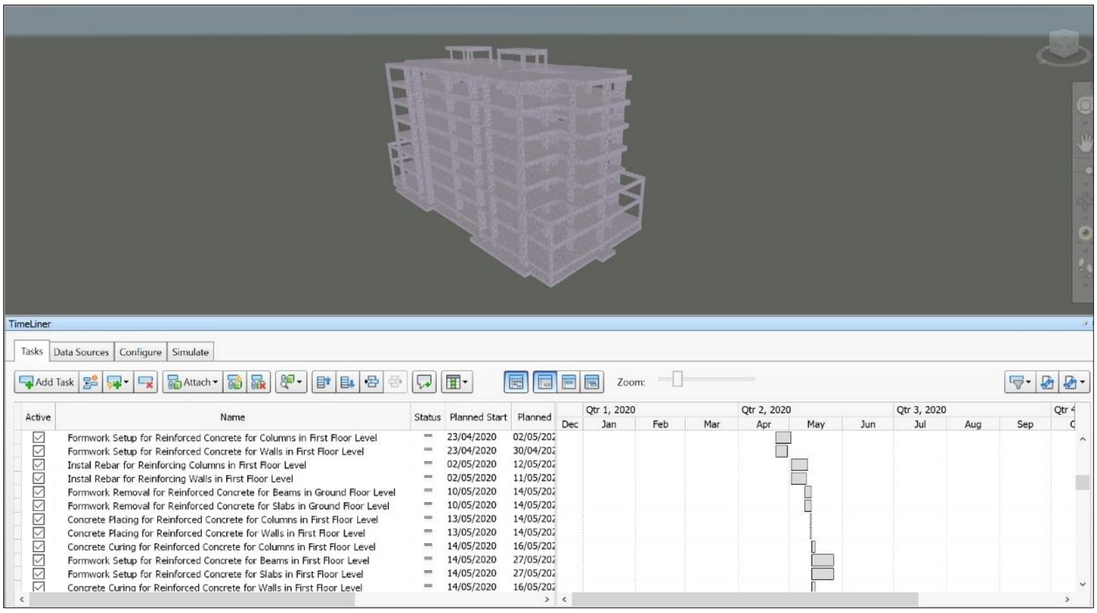

Figure 16. 5D BIM Model

4. Results and Discussion

The case study results indicate that the BIM-based integrated model improves the accuracy of cost estimation and execution schedule compared to traditional methods. We compared the model's estimated costs for each activity against the actual costs incurred on-site and against the project's original cost estimate (which was done using the traditional method at the whole-element level). A useful metric for comparison is the Cost Performance Index (CPI), defined as the ratio of budgeted cost to actual cost for a given activity. In the actual project (using the original estimates), the CPI values varied widely, ranging from around 0.60 to 1.25. In other words, some activities cost nearly 40% more than the traditional estimate predicted (CPI ~0.6 indicates a major overrun cost), while others cost about 25% less than estimated (CPI ~1.25 indicates the estimate was too high). This large variance suggests that the conventional estimating approach was inconsistent in accuracy. By contrast, if the proposed BIM-based model's estimates are used as the budget, the CPI for all activities falls in a much tighter band, roughly from 0.91 to 1.08. This means that every activity's cost would have fallen within ±8% of the actual cost. Beyond numerical improvement, this tighter CPI band signals a more systematic accuracy: the model produces consistent estimates across heterogeneous tasks because the element → method → task → activity mapping preserves context (method and location) rather than assuming one-size-fits-all productivities. Table 8 presents the CPI comparison in detail for a sample of activities (database estimate vs. actual vs. traditional estimate). These findings validate that incorporating detailed historical productivity and cost data and estimating at the activity level provides more accurate results. Our outcome aligns with prior studies; for example, Abdel-Hamid & Abdelhaleem [7] reported that using a 5D BIM approach for cost estimating reduced the variance between estimated and actual costs to about 4.8% compared to 11.9% under traditional methods. More broadly, single-digit cost-variance bands are commonly reported when 5D controls are adopted, though many such workflows still depend on external BoQs/Excel with manual reconciliation to scheduling tools; in contrast, the present model achieves comparable variance while internalizing unit rates and historical productivities in an SQL repository and exporting a resource-loaded baseline to P6, thereby eliminating re-entry between cost and time.

Notably, the model achieves high systematic accuracy; the estimates are reliable for different tasks. The model accounts for specific factors that traditional estimation might overlook. For example, the model recognizes that installing rebar in a confined foundation footing (column neck) is more labor-intensive than installing rebar in a typical upper-floor column. In the case study, the historical data in the database indicated a lower productivity rate for rebar installation at the foundation level, so the model appropriately allocated more hours and higher cost to that task. The traditional estimate, by contrast, had assumed a uniform productivity for rebar work in all columns. As a result, the original estimate under-budgeted the foundation column rebar work, whereas the model's estimate was much closer to the actual cost. This was evident in the CPI values – the rebar installation activity for foundation columns showed a large cost overrun in the original plan, but the model's prediction for the same activity was almost spot on. Considering these differences (task type, element type, location), the model achieves a high accuracy that would be difficult to achieve manually. This pattern precisely aligns with the theoretical foundation's expectations. Once a task is elevated to an activity with a specific method and zone, it inherits the appropriate crew mix and historical productivity for that context. Importantly, this internal, activity-level costing contrasts with external price-book integrations that can automate item mapping yet do not natively yield resource-loaded schedules or co-inferred durations and costs [44]. We expect that as we collect more historical data for various activities, this accuracy will further improve. In our prototype database, some activities had as few as three historical data points to draw from, yet the model still performed well. With a growing repository (dozens of data points per element, task, location and construction method), the statistical confidence in the estimates will increase, potentially narrowing the error margin even more.

Although the primary focus of our evaluation was cost, the integrated nature of the model also improved schedule accuracy. Based on realistic crew productivities, the automatically generated durations for activities led to a construction schedule that closely mirrored the actual duration. The total duration for the structural work predicted by the model was within a few days of the actual duration executed on-site (approximately 4 months for the concrete frame). Many individual activity durations matched what happened. It is worth noting that the original project schedule (planned without our model) did see some deviations; specific tasks took longer or shorter than planned because the planners had to make assumptions on productivity. By using actual productivity metrics, the model essentially "plans with reality," reducing guesswork. Thus, a project team using this model would likely have a more reliable baseline schedule and could better forecast the project finish date. Although we have not conducted a comprehensive critical path analysis, it can be inferred that improved activity duration estimates would enhance overall schedule accuracy. These observations are consistent with reported coordination and planning benefits in infrastructure applications—e.g., 4D/5D simulation for rail stations and structured mitigation of scheduling deficiencies in road projects—while our model adds an internalized cost/time data spine so that schedule realism and cost coherence are maintained through one traceable chain [45, 46]. Likewise, whereas several studies advance automation primarily at the QTO or classification level, often stopping short of internal, activity-level resource loading, the present study extends automation through the element → method → task → activity mapping with crews and rates drawn from a single database [47, 48].

The integrated model also demonstrated substantial efficiency benefits in the planning process itself. Traditionally, preparing a detailed cost estimate and schedule for a project like this requires many labor hours: quantity surveyors measure drawings, estimators price the bills of quantities, and schedulers develop Gantt charts and assign the activities relations. Using the proposed model, once the BIM model was ready, the effort to generate the resource-loaded schedule was minimal, and the software integration automated the complex tasks. Quantities were generated directly from the BIM model, and activity-level durations and costs were subsequently generated through integrated mapping and estimation logic. The human effort was to review the outputs and make necessary adjustments or validations. This represents a significant reduction in manual work compared to traditional methods. Prior research confirms that automating BIM-based quantity takeoff not only accelerates the estimation process but also reduces human error and improves accuracy and consistency [8, 49]. The findings from this case study further extend that benefit by demonstrating that schedule generation can likewise be automated. Unlike conventional workflows where planners must manually define each activity and re-enter quantities into scheduling tools, the proposed model relies on an integrated database that directly links BIM-derived quantities to construction methods and execution logic. As a result, both the cost estimate and project schedule are generated simultaneously from the same data source rather than through parallel, disconnected processes. One of the key advantages of this integration is consistency: task definitions and sequencing in the schedule are derived from the same structured logic used in cost estimation. This eliminates discrepancies commonly observed in traditional workflows, where the cost breakdown created by estimators may not align with the activity structure used by schedulers—creating challenges in tracking and managing cost at the activity level. In the proposed approach, data structure unification ensures coherence between estimated costs and scheduled activities, significantly reducing manual reconciliation effort. This end-to-end coherence also addresses a recurrent limitation identified in practice reviews, where 5D is frequently bounded to pre-GMP phases and post-GMP cost control is handled outside the 5D stack; by maintaining a single data backbone across estimate and schedule, the present model retains fidelity into execution [39].

One of the most powerful advantages observed is how the model creates a tight alignment between the planning phase and the project's execution phase. Because the model's outputs are structured the same way as field data would be, the tracking progress becomes straightforward. In an actual project, the activities and codes from our model would be used for planning and reporting actual progress. Site engineers could update the status of each activity in the system so the model can automatically compute updated performance work. Our case study was retrospective, but we simulated how tracking would work using the actual project data. We could input the actual costs and durations for each activity back into our database and instantly compare them against the model's baseline. The integrated nature of the model means these comparisons are apples-to-apples; every activity in the field has a corresponding entry in the plan with the same identifier. This facilitates real-time performance monitoring. Prior studies emphasize the importance of integrating planned and actual project data within a unified BIM-based environment. Vassena et al. [43], highlight that having a unified platform for planned and actual data enables the timely detection of schedule delays or cost overruns. Our model implements such a platform. During the case study, if an activity's actual cost came in higher than estimated, the CPI turned red (less than 1.0), and we could identify precisely which task and why. This information would prompt managers to investigate a live project – perhaps the crew was slower than the historical average or there were site difficulties.

The model's ability to incorporate those actual productivity rates into the database means it "learns" over time, continuously improving its predictions for future tasks. In essence, the case study shows that the proposed model is not just a planning tool but also forms the backbone of a project cost control system. It links the 3D BIM, the estimate, and the schedule with the actual performance data in one coherent framework. This leads to better alignment with what happens on site; the plan is realistic from the start, and any deviations can be tracked methodically. Such alignment greatly aids decision-making; rather than dealing with abstract cost accounts or aggregated budget lines, managers see cost and schedule performance per activity, which is how work is executed. Moreover, by continuously feeding actual data back into the model's database, the accuracy of future forecasts is enhanced (a concept akin to machine learning/improvement of estimates over multiple project cycles). In operational terms, the online SQL database functions as institutional memory: it standardizes identifiers, captures actuals in the same structure as the baseline, and makes those records immediately reusable when generating the next estimate. In that sense, this approach operationalizes ideas seen in IFC/ontology frameworks that conceptually couple cost and schedule but does so with a project-ready SQL→P6 stack; and it aligns with the direction of ML-enabled scheduling by learning productivity at the activity level from accumulated actuals [41].

To assess robustness, we conducted three practical checks aligned with typical estimating decisions. First, we compared two common three-point aggregations (triangular vs. PERT) and observed that headline accuracy metrics changed modestly; the distributional choice had a smaller effect than the inclusion of zone-specific productivity. Second, we ran a "zone ablation" by replacing zone-aware productivities with a single project-wide rate; accuracy degraded, confirming that location contextualization is a key driver. Third, we perturbed the construction method assignment for a subset of elements (e.g., cast-in-situ ↔ precast) where feasible; as expected, tasks and resource composition changed, and accuracy moved accordingly. These checks (summarized in Table 8) indicate that the model's gains stem primarily from the activity-level mapping and context (method and zone), while the precise three-point aggregation rule plays a secondary role within the observed ranges. A full Monte Carlo simulation could provide richer uncertainty propagation; given scope and data granularity, we treat it as future work and, in this paper, report empirical variability alongside CPI.

Table 8. Comparison of Cost Estimates and CPI for Selected Activities

#	ACode	Description	Database Estimated	Traditional Estimated	Actual Cost	Database CPI	Actual CPI
1	RF-0F-FS	Formwork Setup for Reinforced Concrete for Foundation in Foundation Level	189,481	168,638	195,165	1.03	0.89
2	RF-0F-CP	Concrete Placing for Reinforced Concrete for Foundation in Foundation Level	510,047	504,947	515,148	1.01	0.99
3	RF-0F-CF	Concrete Finishing for Reinforced Concrete for Foundation in Foundation Level	390	386	390	1.00	0.99
4	RF-0F-CU	Concrete Curing for Reinforced Concrete for Foundation in Foundation Level	280	277	280	1.00	0.99
5	RF-0F-FR	Formwork Removal for Reinforced Concrete for Foundation in Foundation Level	44,786	40,756	48,369	1.08	0.91
6	RC-0F-FS	Formwork Setup for Reinforced Concrete for Columns in Foundation Level	4,458	3,789	4,413	0.99	0.85
7	RC-0F-CP	Concrete Placing for Reinforced Concrete for Columns in Foundation Level	12,213	11,602	12,091	0.99	0.95
8	RC-0F-CU	Concrete Curing for Reinforced Concrete for Columns in Foundation Level	280	280	280	1.00	1.00
9	RC-0F-FR	Formwork Removal for Reinforced Concrete for Columns in Foundation Level	1,054	896	1,043	0.99	0.85
10	RC-0G-FS	Formwork Setup for Reinforced Concrete for Columns in Ground Floor Level	12,991	11,692	12,861	0.99	0.90
11	RC-0G-CP	Concrete Placing for Reinforced Concrete for Columns in Ground Floor Level	35,950	32,355	35,590	0.99	0.90
12	RC-0G-CU	Concrete Curing for Reinforced Concrete for Columns in Ground Floor Level	280	280	280	1.00	1.00
13	RC-0G-FR	Formwork Removal for Reinforced Concrete for Columns in Ground Floor Level	3,071	2,764	3,040	0.99	0.90

While the proposed framework demonstrates technical feasibility and measurable accuracy gains, several practical barriers could influence its real-world adoption. Populating and maintaining the historical productivity and cost database requires initial data collection and standardization, which can be resource-intensive. Successful deployment also depends on adequate training of estimators, planners, and field engineers to correctly use the coding system and sustain data quality over time. Moreover, organizations may face resistance to abandoning traditional BoQ- and spreadsheet-based workflows, making change management and phased implementation strategies essential. Finally, integration with existing enterprise systems and IT governance (e.g., data security and version control) may require additional support. These challenges suggest that pilot implementation followed by gradual scaling is the most practical path for industry adoption.

Two limitations qualify these findings. First, the case study involves a single project and a prototype database, so some activities had limited historical samples; accuracy is expected to tighten as the database densifies. Second, transferability across contractors and regions requires mapping local methods, codes, and unit-rate structures into the same schema. Nevertheless, the observed reduction in CPI dispersion and the schedule alignment suggest that the activity-based mapping, coupled with a learning database, is a viable path to more reliable planning in similar building projects. Overall, the comparative evidence situates these gains within a wider body of 4D/5D research while clarifying that the pathway—internalized, activity-level cost–time integration over a single data backbone—is pivotal to achieving them [7, 24, 41, 50].

5. Conclusion

This study introduced an integrated 5D BIM model that unifies the design, cost estimation, and scheduling processes in a single automated framework. A case study of a six-story reinforced concrete building validated this approach, demonstrating substantial improvements over traditional estimation and scheduling methods. Notably, the model improved cost estimation accuracy; its predicted costs closely matched actual costs for each activity, resulting in more reliable budgeting and fewer cost overruns. It also significantly reduced the manual effort and time required to produce the project's cost estimate and schedule by automating those processes, thereby minimizing human error and ensuring that the cost and schedule outputs remained synchronized. Furthermore, the model supported progress tracking and the computation of performance metrics (e.g., the Cost Performance Index, CPI) within a unified system, allowing for early detection of deviations during project execution. The model's use of actual project historical data ensures that the planning is based on realistic assumptions, and that monitoring is based on detailed element-task-location-construction method specific metrics. These results demonstrate the efficacy of tightly linking rich BIM design data with cost and schedule information to achieve more accurate, efficient, and controlled project planning.

Despite these promising results, the study has certain limitations. It primarily focused on the structural concrete work of a single mid-sized project, which may constrain the generalizability of the findings. However, extending it to additional trades or materials follows the same steps—augment the element–method–task codes, add the execution method and task, and populate the associated resource, productivity, and unit-rate records. Future research should apply the model in a broader range of construction scenarios and incorporate additional project management dimensions (for example, linking the 5D BIM framework with procurement workflows or cash flow forecasting) to enhance its capabilities further and validate its generalizability. Such efforts will help establish the model's robustness and contribute to more comprehensive, automated 5D BIM practices in construction management. Still, the core finding remains: By linking BIM, cost, and schedule data in an automated workflow, project teams can achieve more accurate, efficient, and controlled outcomes. The case study gives clear proof-of-concept of these advantages, bridging the model's theoretical framework and its practical effectiveness on an actual construction project.

6. Declarations

6.1. Author Contributions

Conceptualization, A.E., I.M., and A.S.; methodology, A.E. and A.S.; software, A.S.; validation, A.E. and A.S.; formal analysis, A.E. and A.S.; investigation, A.E. and A.S.; resources, A.S.; data curation, A.S.; writing—original draft preparation, A.S.; writing—review and editing, A.E. and A.S.; visualization, A.S.; supervision, A.E. and I.M.; project administration, A.E., I.M., and A.S.; funding acquisition, A.S. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available in the article.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Conflicts of Interest

The authors declare no conflict of interest.

7. References

[1] Akbari, S., Pour Rahimian, F., Sheikhkhoshkar, M., Banihashemi, S., & Khanzadi, M. (2020). Dynamic sustainable success prediction model for infrastructure projects: a rough set based fuzzy inference system. Construction Innovation, 20(4), 545–567. doi:10.1108/CI-04-2019-0034.

[2] Yılmaz, İ. C., Yılmaz, D., Kandemir, O., Tekin, H., Atabay, Ş., & Bulut Karaca, Ü. (2024). Barriers to BIM Implementation in the HVAC Industry: An Exploratory Study. Buildings, 14(3), 788. doi:10.3390/buildings14030788.

[3] Olsen, D., & Taylor, J. M. (2017). Quantity Take-Off Using Building Information Modeling (BIM), and Its Limiting Factors. Procedia Engineering, 196, 1098–1105. doi:10.1016/j.proeng.2017.08.067.

[4] Lee, S. K., Kim, K. R., & Yu, J. H. (2014). BIM and ontology-based approach for building cost estimation. Automation in Construction, 41, 96–105. doi:10.1016/j.autcon.2013.10.020.

[5] Sayed, M., Abdel-Hamid, M., & El-Dash, K. (2023). Improving cost estimation in construction projects. International Journal of Construction Management, 23(1), 135–143. doi:10.1080/15623599.2020.1853657.

[6] Shaqour, E. N. (2022). The role of implementing BIM applications in enhancing project management knowledge areas in Egypt. Ain Shams Engineering Journal, 13(1), 101509. doi:10.1016/j.asej.2021.05.023.

[7] Abdel-Hamid, M., & Abdelhaleem, H. M. (2023). Project cost control using five dimensions building information modelling. International Journal of Construction Management, 23(3), 405–409. doi:10.1080/15623599.2021.1880313.

[8] Al-Musawi, R., & Naimi, S. (2023). Evaluation of Construction Project’s Cost Using BIM Technology. Mathematical Modelling of Engineering Problems, 10(2), 469–476. doi:10.18280/mmep.100212.

[9] Hosamo, H. H., Rolfsen, C. N., Zeka, F., Sandbeck, S., Said, S., & Sætre, M. A. (2024). Navigating the Adoption of 5D Building Information Modeling: Insights from Norway. Infrastructures, 9(4), 75. doi:10.3390/infrastructures9040075.

[10] Agwa, T. C., & Celik, T. (2025). From Barriers to Breakthroughs: A Deep Dive into BIM Integration Challenges. Buildings, 15(7), 1116. doi:10.3390/buildings15071116.

[11] Das, K., Khursheed, S., & Paul, V. K. (2025). The impact of BIM on project time and cost: insights from case studies. Discover Materials, 5(1), 25. doi:10.1007/s43939-025-00200-2.

[12] Gouda Mohamed, A., Alqahtani, F. K., Ismail, E. R., & Nabawy, M. (2024). Synergizing BIM and Value Engineering in the Construction of Residential Projects: A Novel Integration Framework. Buildings, 14(8), 2515. doi:10.3390/buildings14082515.

[13] Mahboob, A., Rathnasinghe, A., Ekanayake, A., & Tennakoon, P. (2024). Evaluating BIM’s Role in Transforming Cash Flow Forecasting Among Construction SMEs: A Saudi Arabian Narrative. Sustainability (Switzerland), 16(23), 10221. doi:10.3390/su162310221.

[14] Farouk, A. M., & Rahman, R. A. (2025). Integrated applications of building information modeling in project cost management: a systematic review. Journal of Engineering, Design and Technology, 23(1), 287–305. doi:10.1108/JEDT-10-2022-0538.

[15] Lu, Q., Won, J., & Cheng, J. C. P. (2016). A financial decision making framework for construction projects based on 5D Building Information Modeling (BIM). International Journal of Project Management, 34(1), 3–21. doi:10.1016/j.ijproman.2015.09.004.

[16] Forgues, D., Iordanova, I., Valdivesio, F., & Staub-French, S. (2012). Rethinking the Cost Estimating Process through 5D BIM: A Case Study. Construction Research Congress 2012, 778–786. doi:10.1061/9780784412329.079.

[17] Li, J. (2016). Integrating building information modelling (BIM), cost estimating and scheduling for buildings construction at the conceptual design stage. Master Thesis, University of Ottawa, Ottawa, Canada.

[18] Cassandro, J., Mirarchi, C., Zanchetta, C., & Pavan, A. (2024). Enhancing Accuracy in Cost Estimation: Structured Cost Data Integration and Model Validation. Journal of Information Technology in Construction, 29, 1293–1325. doi:10.36680/j.itcon.2024.058.

[19] Rahimi, M. Z. (2023). Building Information Model for cost estimation and scheduling in building architecture. SSRN Electronic Journal, 1-17. doi:10.2139/ssrn.4665581.

[20] Yarnold, J., Banihashemi, S., Lemckert, C., & Golizadeh, H. (2023). Building and construction quality: systematic literature review, thematic and gap analysis. International Journal of Building Pathology and Adaptation, 41(5), 942–964. doi:10.1108/IJBPA-05-2021-0072.

[21] Fazeli, A., Dashti, M. S., Jalaei, F., & Khanzadi, M. (2021). An integrated BIM-based approach for cost estimation in construction projects. Engineering, Construction and Architectural Management, 28(9), 2828–2854. doi:10.1108/ECAM-01-2020-0027.

[22] Le, H. T. T., Likhitruangsilp, V., & Yabuki, N. (2021). A BIM-database-integrated system for construction cost estimation. ASEAN Engineering Journal, 11(1), 45–59. doi:10.11113/AEJ.V11.16666.

[23] Esteban, J., & Mesa, O. (2021). Cost Estimation of Construction Projects Using 5D BIM: Integrating the cost engineer in BIM-based processes through activity theory. Master Thesis, Delft University of Technology, Delft, Netherlands.

[24] Elbeltagi, E., Hosny, O., Dawood, M., & Elhakeem, A. (2014). BIM-based cost estimation/monitoring for building construction. International Journal of Engineering Research and Applications, 4(7), 56-66.

[25] Wefki, H., Elnahla, M., & Elbeltagi, E. (2024). BIM-based schedule generation and optimization using genetic algorithms. Automation in Construction, 164, 105476. doi:10.1016/j.autcon.2024.105476.

[26] Liu, H., Lu, M., & Al-Hussein, M. (2014). BIM-Based Integrated Framework for Detailed Cost Estimation and Schedule Planning of Construction Projects. Proceedings of the 31st International Symposium on Automation and Robotics in Construction and Mining (ISARC), 38. doi:10.22260/isarc2014/0038.

[27] Wang, X., Yung, P., Luo, H., & Truijens, M. (2014). An innovative method for project control in LNG project through 5D CAD: A case study. Automation in Construction, 45, 126–135. doi:10.1016/j.autcon.2014.05.011.

[28] Jrade, A., & Lessard, J. (2015). An Integrated BIM System to Track the Time and Cost of Construction Projects: A Case Study. Journal of Construction Engineering, 2015, 1–10. doi:10.1155/2015/579486.

[29] Banihashemi, S., Khalili, S., Sheikhkhoshkar, M., & Fazeli, A. (2022). Machine learning-integrated 5D BIM informatics: building materials costs data classification and prototype development. Innovative Infrastructure Solutions, 7(3), 215. doi:10.1007/s41062-022-00822-y.

[30] Khodabakhshian, A., & Toosi, H. (2021). BIM-based Life Cycle Cost Estimation Framework for Construction Projects. International Congress on the. Phenomenological Aspects of Civil Engineering, 20-23 June, 2021, Ataturk University, Erzurum, Turkey.

[31] Alzraiee, H. (2022). Cost estimate system using structured query language in BIM. International Journal of Construction Management, 22(14), 2731–2743. doi:10.1080/15623599.2020.1823061.

[32] ElMenshawy, M., & Marzouk, M. (2021). Automated BIM schedule generation approach for solving time–cost trade-off problems. Engineering, Construction and Architectural Management, 28(10), 3346–3367. doi:10.1108/ECAM-08-2020-0652.

[33] Sbiti, M., Beladjine, D., Beddiar, K., & Mazari, B. (2022). Leveraging Quantity Surveying Data and BIM to Automate Mechanical and Electrical (M & E) Construction Planning. Applied Sciences (Switzerland), 12(9), 4546. doi:10.3390/app12094546.

[34] Hong, Y., Xie, H., Agapaki, E., & Brilakis, I. (2023). Graph-Based Automated Construction Scheduling without the Use of BIM. Journal of Construction Engineering and Management, 149(2), 05022020. doi:10.1061/jcemd4.coeng-12687.

[35] Lee, J. H., & Kang, L. S. (2025). Generation of construction schedule information through activity unit recognition of 3D models created at the design phase. KSCE Journal of Civil Engineering, 29(8), 100175. doi:10.1016/j.kscej.2025.100175.

[36] Khataei, S., Akcamete, A., & Sonmez, R. (2020). 4D BIM integrated productivity estimation of construction projects. 6th International Project and Construction Management Conference (IPCMC2020), 12-14 November, 2020, Istanbul, Turkey.

[37] Jia, J., Ma, H., & Zhang, Z. (2024). Integration of Industry Foundation Classes and Ontology: Data, Applications, Modes, Challenges, and Opportunities. Buildings, 14(4), 911. doi:10.3390/buildings14040911.

[38] Fürstenberg, D., Wikström, L., Hjelseth, E., & Lædre, O. (2021). Enabling automation of BIM-based cost estimation by semantic web technology. Proceeding of the Conference CIB W78 2021, 11-15 October, 2021, Luxembourg, Luxembourg.

[39] Pishdad, P., & Onungwa, I. O. (2024). Analysis of 5D Bim for Cost Estimation, Cost Control, and Payments. Journal of Information Technology in Construction, 29, 525–548. doi:10.36680/j.itcon.2024.024.

[40] Pal, A., Lin, J. J., Hsieh, S. H., & Golparvar-Fard, M. (2024). Activity-level construction progress monitoring through semantic segmentation of 3D-informed orthographic images. Automation in Construction, 157, 105157. doi:10.1016/j.autcon.2023.105157.

[41] Al-Sinan, M. A., Bubshait, A. A., & Aljaroudi, Z. (2024). Generation of Construction Scheduling through Machine Learning and BIM: A Blueprint. Buildings, 14(4), 934. doi:10.3390/buildings14040934.

[42] Pham, V. H., Chen, P. H., Nguyen, Q., & Duong, D. T. (2024). BIM-Based Automatic Extraction of Daily Concrete and Formwork Requirements for Site Work Planning. Buildings, 14(12), 4021. doi:10.3390/buildings14124021.

[43] Vassena, G. P. M., Perfetti, L., Comai, S., Mastrolembo Ventura, S., & Ciribini, A. L. C. (2023). Construction Progress Monitoring through the Integration of 4D BIM and SLAM-Based Mapping Devices. Buildings, 13(10), 2488. doi:10.3390/buildings13102488.

[44] Solla, M., Derbi, D., Alosta, M., Al Kazee, M. F., Hayder, G., & Milad, A. (2025). Integrating price guideline and building information modeling for construction project cost estimation a case study. Discover Civil Engineering, 2(1), 151. doi:10.1007/s44290-025-00309-6.

[45] Inzerillo, L., Acuto, F., Pisciotta, A., Mantalovas, K., & Di Mino, G. (2024). Exploring 4d and 5d analysis in bim environment for infrastructures: A case study. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLVIII-2/W4-2024, 233–240. doi:10.5194/isprs-Archives-XLVIII-2-W4-2024-233-2024.

[46] Castañeda, K., Sánchez, O., Peña, C. A., Herrera, R. F., & Mejía, G. (2025). BIM Uses for Mitigating Deficiencies in Road Scheduling Planning. Sustainability (Switzerland), 17(6), 2729. doi:10.3390/su17062729.

[47] Valinejadshoubi, M., Moselhi, O., Iordanova, I., Valdivieso, F., & Bagchi, A. (2024). Automated system for high-accuracy quantity takeoff using BIM. Automation in Construction, 157, 105155. doi:10.1016/j.autcon.2023.105155.

[48] Zhang, C., Kumar, D., Li, H., Zhou, R., Lv, L., & Tian, J. (2023). Development of a BIM-Enabled Automated Cost Segregation System. Buildings, 13(7), 1805. doi:10.3390/buildings13071805.

[49] Khosakitchalert, C., Yabuki, N., & Fukuda, T. (2020). Automated modification of compound elements for accurate BIM-based quantity takeoff. Automation in Construction, 113, 103142. doi:10.1016/j.autcon.2020.103142.

[50] Rashidi, A., Chan, D. W. M., Ravanshadnia, M., Sarvari, H., & Tajaddini, A. (2024). Applying Building Information Modelling (BIM) Technology in Pre-Tender Cost Estimation of Construction Projects: A Case Study in Iran. Buildings, 14(5), 1260. doi:10.3390/buildings14051260.