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Development of an Integrated Management Simulation Model for Pipeline Construction

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Abstract

This study develops and validates a dynamic management simulation model tailored for pipeline construction projects, addressing the current lack of real-time, predictive decision-support tools in this sector. The primary objective is to create a framework that integrates Digital Twin (DT) technology with discrete-event simulation (DES) to enhance responsiveness, accuracy, and adaptability in planning and execution phases. The model is built in AnyLogic and leverages live data inputs from IoT sensors, procurement systems, and geotechnical assessments to reflect on-site variability.

Construction activities such as trenching, welding, and backfilling are simulated in a time-sequenced, data-driven environment, supported by cloud-based updates and interactive dashboards. The model was tested against two real-world case studies—one in mountainous terrain and one in flat conditions—demonstrating forecasting accuracy with less than 2% deviation in total duration and a Mean Absolute Percentage Error (MAPE) below 5% for weekly progress predictions.

This research contributes a validated, pipeline-specific simulation model that offers actionable insights for proactive schedule control, resource optimization, and scenario forecasting, distinguishing itself through bidirectional data flow, adaptive simulations, and real-time integration with construction systems.

Keywords: Digital Twin (DT), Construction Management, Pipeline Construction, Simulation Model, Anylogic, Project Management Dash-Board, Time Schedule, Construction Plans, Resource Optimization, Real-Time Monitoring.

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1 Introduction

Digital Twin (DT) technology has become an essential tool in modern construction, offering dynamic integration between digital and physical project elements to support real-time monitoring, decision-making, and lifecycle optimization [1, 2]. Evolving from Building Information Modeling (BIM), DT leverages real-time data from Internet of Things (IoT) devices and advanced simulation tools to deliver continuous feedback and enhance operational efficiency[3]. While these technologies have transformed various construction sectors, their practical integration into linear infrastructure projects—particularly pipelines—remains limited and fragmented.

Historically, pipeline construction has relied on deterministic and manual planning methods that lack responsiveness to dynamic field conditions. Traditional scheduling techniques and resource planning models are often disconnected from real-time data sources, resulting in delays, resource misallocation, and inadequate risk forecasting. Moreover, although BIM and Cyber-Physical Systems (CPS) have introduced foundational frameworks for digital construction, their unidirectional data flows limit adaptive decision-making [4, 5]. The existing research largely focuses on static modeling or post-construction analysis, rather than real-time, bidirectional data-driven simulation tailored to the unique workflow complexities of pipeline construction.

This gap is particularly critical considering the challenges pipelines face: spatially distributed operations, soil and weather variability, dependency on sequential progress, and resource synchronization across remote sites. Current models fail to account for the integration of multi-source inputs such as geotechnical data, procurement schedules, and equipment telemetry in a unified, responsive framework. Additionally, the lack of interoperability and standardized data handling frameworks hampers real-time adaptation on-site [6-8].

To address these shortcomings, this research proposes an integrated management simulation model built on DT principles and implemented using AnyLogic's discrete-event simulation engine. The model bridges historical data with live project inputs to dynamically simulate pipeline construction activities. It incorporates cloud-based updates, predictive analytics, and an interactive dashboard system to optimize resource allocation, monitor performance deviations, and anticipate risk scenarios in real time. By aligning simulation outputs with actual field conditions, this approach offers a responsive planning tool that reflects the demands of modern infrastructure projects.

In summary, this study fills a critical gap in construction simulation literature by providing a validated, real-time DT framework specifically designed for pipeline construction. It addresses the limitations of existing static models, introduces adaptive scheduling mechanisms, and emphasizes the practical application of multi-layered digital technologies in a linear project environment.

1.1 DT Development Process

The development of a Digital Twin (DT) follows a structured process to ensure effective implementation. It begins with planning frameworks, where the use case is defined—such as predictive maintenance or operational efficiency—using tools like the Lean Digital Twin Canvas to establish objectives and identify stakeholders. Next, choosing a suitable digital twin candidate is essential, focusing on entities or processes with high impact and technical feasibility, often ranked based on business value and implementation readiness. The building phase involves creating a Digital Twin Prototype (DTP) using structured definition languages like the Digital Twin Definition Language (DTDL) to establish its framework, metadata, and functionalities. Once developed, synchronization is crucial, ensuring real-time data exchange with the physical counterpart through IoT systems and edge computing for low-latency updates. Finally, validation is conducted through comprehensive testing, including unit, integration, and functional tests, to confirm the model's accuracy and alignment with business objectives. This structured approach ensures a robust and scalable Digital Twin capable of optimizing operations and decision-making [9, 10].

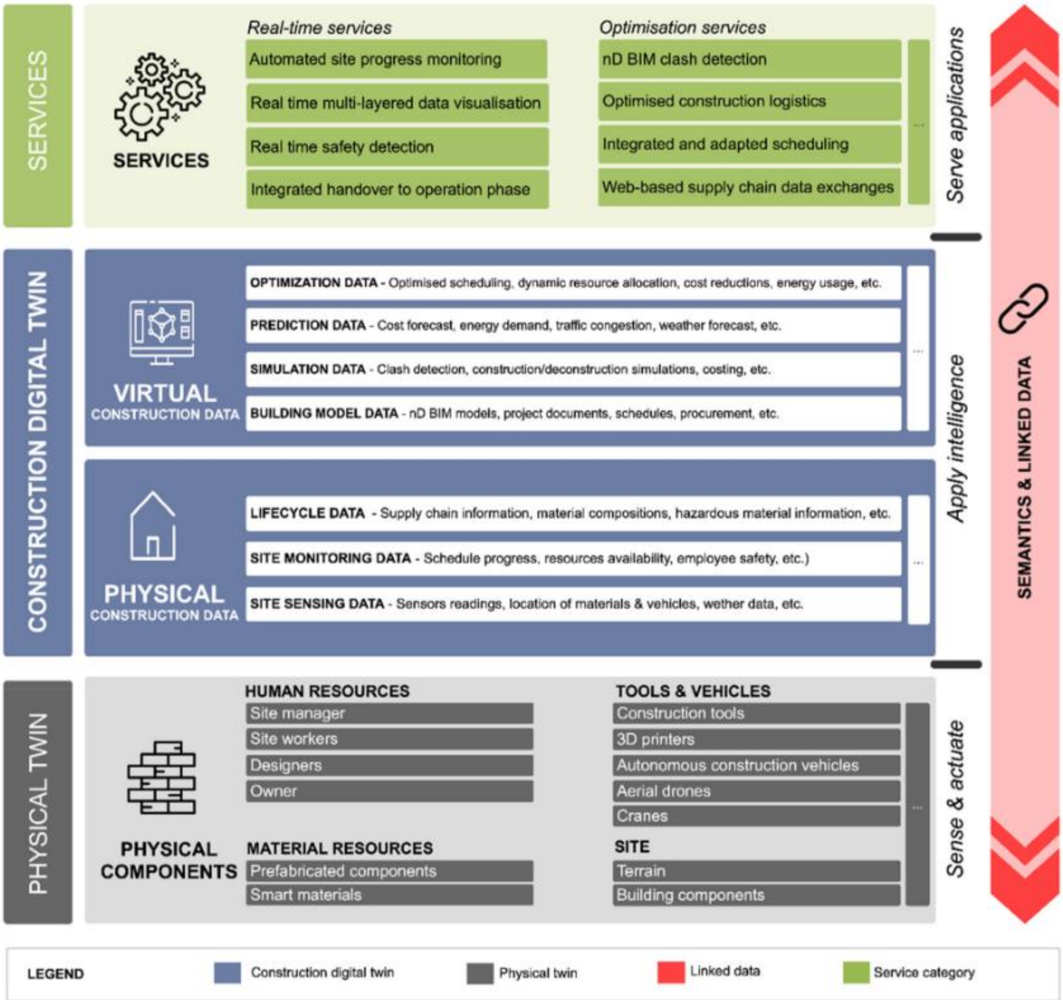


Figure 1: Construction Digital Twin data usage for facilitating smart construction services [6].

1.2 Digital Twin Detailed Process (Layers):

In this research, the Digital Twin (DT) architecture is adapted specifically for linear, resource-intensive pipeline construction workflows. The model integrates five functional layers, each linked to key project operations such as trenching, welding, inspection, and backfilling.

- Data Acquisition Layer: IoT devices—including GNSS trackers, fuel sensors, and vibration meters—are mounted on excavators, welding machines, and trucks. These sensors record movement, energy consumption, and productivity across spatially distributed sites.

- Data Transmission Layer: Real-time data are transmitted from the field using LTE/5G modules and mesh gateways to ensure continuous communication in remote zones. The data flow supports granular updates from active trenching zones, welding stations, and temporary stockyards.

- Digital Modeling Layer: 3D pipeline alignment and trench sections are modeled using GIS-integrated BIM. The model tracks pipe lengths, weld seams, and crossing types (e.g., roads, waterways), enabling dynamic sequencing.

- Data/Model Integration Layer: Real-time and planned data streams (from procurement schedules, progress updates, and geotechnical assessments) are synchronized via a cloud engine. For instance, if trenching in a rocky segment slows progress, the schedule is automatically updated in the simulation engine.

- Service Layer: The dashboard visualizes spatial resource allocations, welding queue statuses, and zone-by-zone productivity. Alerts are triggered based on lag thresholds or IoT downtime, allowing managers to reroute crews or reallocate equipment proactively.

Unlike generic DT applications, this model prioritizes the **adaptability of each layer** to construction-specific scenarios, ensuring seamless alignment between real-world operations and digital simulations. The layered structure not only supports efficient data flow but also facilitates modular upgrades as project needs evolve[2].

1.3 Core Components of Digital Twins:

The Digital Twin system relies on several key components to ensure real-time synchronization between the physical and virtual environments. **Sensors** are strategically distributed across the physical system to capture real-time data on performance and environmental conditions, serving as the primary data input for the digital twin. **Actuators** enable the system to respond dynamically by applying control actions derived from the twin's computational analyses, allowing for adaptive modifications in the physical system. The continuous stream of **real-time data** provides essential updates, ensuring seamless interaction between the virtual and physical entities. **Simulation tools** use mathematical and computational models to represent system behavior, incorporating real-time updates to reflect changing conditions and interactions between components. Finally, **analytics** techniques process and visualize data, offering valuable insights into performance trends, optimizing operations, and enhancing decision-making. Together, these components create a dynamic, data-driven framework that improves operational efficiency and system adaptability [11].

In the context of pipeline construction, these components are tailored to handle the spatial, operational, and environmental complexities inherent to linear infrastructure projects. Sensors are deployed on trenching equipment, welding units, and haulage trucks to monitor location, task duration, and equipment utilization. Connectivity relies on mobile edge devices and wireless mesh networks to maintain data flow across dispersed field zones. The digital models incorporate geospatial data and construction schedules, simulating the physical progression of the pipeline across varying terrain conditions. Analytics tools interpret data to detect bottlenecks in welding sequences or idle machine clusters, while dashboards visualize performance zone-by-zone, helping managers identify delays or forecast task completion with greater accuracy. This configuration ensures each core component supports the real-time, adaptive decision-making essential in pipeline projects.

1.4 Decision Support and Consequence Analysis with DT Tools

Digital Twin models play a crucial role in enhancing **management and planning simulation tools** by optimizing interconnected systems in industries such as manufacturing and smart cities. These simulation frameworks improve operational efficiency by integrating real-time data with predictive analytics[12]. **User input and action analysis** dynamically adjusts simulation outputs in response to changes, such as raw material deliveries or order modifications, ensuring adaptive and responsive planning[13]. **Scenario analysis** leverages system dynamics models to evaluate risks and forecast the impact of different strategies in construction projects, helping stakeholders assess potential challenges and optimize decision-making[14]. **Augmented Reality (AR)** further enhances operational efficiency by providing immersive visualization for predictive maintenance, enabling virtual walkthroughs for better decision support[12]. Additionally, **simulation-based impact forecasting** utilizes lean and agile management approaches to minimize environmental impacts while improving resource optimization and project outcomes. Together, these tools facilitate proactive planning, risk mitigation, and enhanced decision-making in complex, data-driven environments[14].

2 Gaps in Current Research and Model Comparison

Emerging technologies such as high-fidelity modeling, edge computing, and advanced analytics have begun to enhance Digital Twin (DT) frameworks in construction[15]. However, despite these advances, existing DT implementations in infrastructure projects—particularly pipelines—remain limited in their responsiveness, real-time adaptability, and integration of construction-specific data such as geotechnical inputs and procurement logistics.

Most existing DT models in construction focus either on high-level monitoring or post-facto analysis. For instance, the DT-SMiCS framework by Jiang et al. (2022) enables real-time monitoring of modular construction but lacks predictive capabilities for workflow simulation and resource optimization [16]. Similarly, Bellini Machado and Futai (2024) focus on tunnel performance prediction but do not incorporate discrete-event simulation or integrated procurement planning for dynamic decision-making. Many of these models are static or rely on one-way data flow—from sensors to digital systems—without feedback loops that adjust construction logic in real-time based on site variability[6, 7].

In contrast, the model proposed in this study introduces a **multi-layered, bidirectional DT simulation** tailored to the sequential and distributed nature of pipeline construction. Unlike previous models:

- It integrates **AnyLogic-based discrete-event simulation (DES)** with real-time data from IoT sensors, procurement systems, and geotechnical reports, offering not just monitoring but proactive simulation of field activities.
- It emphasizes **event-driven updates**, enabling adaptive scheduling and dynamic resource allocation in response to live construction conditions.
- It incorporates **modular simulation logic**, which allows users to adjust productivity rates, resource availability, and site-specific parameters to reflect unique project conditions.
- It leverages **a cloud-based synchronization layer** to continuously align simulation outputs with actual performance data.

Previous models have also failed to fully address pipeline-specific challenges, such as trenching variability, crossing logistics, and weather-impacted sequences. The proposed framework uniquely bridges this gap by structuring the pipeline workflow into a real-time simulation environment, enabling early detection of delays, bottlenecks, and material shortages.

In summary, the novelty of this model lies in its **comprehensive integration of simulation and real-time decision support**, its adaptability to project-specific constraints, and its validation against real-world data. This stands in contrast to many earlier DT models that remain conceptual or limited in operational deployment.

3 The Proposed Model

The proposed simulation model was developed as a solution to real-world construction challenges, informed by in-depth analyses of practical issues and representative input samples. Designed for use both before and during the construction phase, the model offers dynamic capabilities for improving decision-making and project execution. It builds on and incorporates insights from historical proposals and frameworks, leveraging their strengths to address gaps in real-time data integration, simulation-based decision-making, and proactive risk mitigation. By addressing critical construction pain points, such as resource allocation, progress monitoring, and risk management, the model plays a pivotal role in optimizing workflows and mitigating potential disruptions. Leveraging the AnyLogic platform, the simulation model adopts a discrete-event simulation approach, which enables it to replicate and analyze construction workflows with precision and adaptability. This approach ensures that the model can capture and simulate the complexities of construction activities, providing actionable insights to project managers.

The model is further strengthened by its integration with a cloud-based data management system. Inputs, such as resource availability, material deliveries, and real-time construction progress, are gathered from diverse sources and updated daily on a centralized cloud server. This ensures that the simulation remains event-driven and reflective of current project conditions. The cloud server acts as a backbone for real-time data integration, enabling the simulation to adapt to changing site conditions and provide updated outputs for effective decision-making. By combining advanced simulation capabilities with real-time data updates, the proposed model bridges the gap between planned and actual performance, offering a robust tool for proactive construction management and enhanced project outcomes.

3.1 Purpose and Scope of the Model

The primary objective of the proposed model is to enhance decision-making and project management efficiency during both the pre-construction and construction phases. Before project kick-off, the model aims to assist in critical planning activities such as resource allocation, schedule development, and optimization by leveraging historical data and predefined project constraints. During the construction phase, the model shifts focus to real-time monitoring and adaptive management by integrating live data from various sources, such as IoT sensors, procurement systems, and site updates. This dual-purpose approach ensures that the model not only supports strategic planning but also provides dynamic, event-driven insights to address on-site challenges and evolving project conditions. By bridging the gap between pre-construction preparation and on-site execution, the model offers a comprehensive tool for improving efficiency, reducing risks, and ensuring project objectives are met.

3.2 Framework Design

Figure 2 illustrates the architecture of the proposed simulation model, structured into four interlinked stages that support adaptive and event-driven construction management.

1. **Input Stage**:
   This stage aggregates a wide array of data sources, including historical productivity rates, BIM and GIS inputs, procurement schedules, and geotechnical conditions. These foundational inputs are uploaded into the simulation environment prior to construction kickoff, ensuring accurate baseline configurations and enabling robust project planning.
2. **Data Collection**:
   Real-time data is collected from on-site IoT sensors, GPS-enabled equipment, and

procurement tracking systems. These sources continuously feed into the model via a centralized cloud server, providing live status updates on equipment, materials, and field progress.

3. **Real-Time Updates**:
   The model synchronizes virtual simulation parameters with actual site conditions by processing incoming data streams through an event-driven engine. This mechanism ensures that scheduling, productivity rates, and task statuses are updated automatically in response to deviations or unexpected changes in the field.
4. **Dynamic Adjustments**:
   Based on the real-time data, the model dynamically adjusts resource allocation, activity sequencing, and timeline forecasts. Managers can visualize the impact of these changes via the project dashboards and intervene when necessary, ensuring proactive rather than reactive decision-making.

This architecture reinforces a closed feedback loop between the digital and physical environments, making the model highly responsive to fluctuating conditions and providing continuous alignment between planned and actual performance.

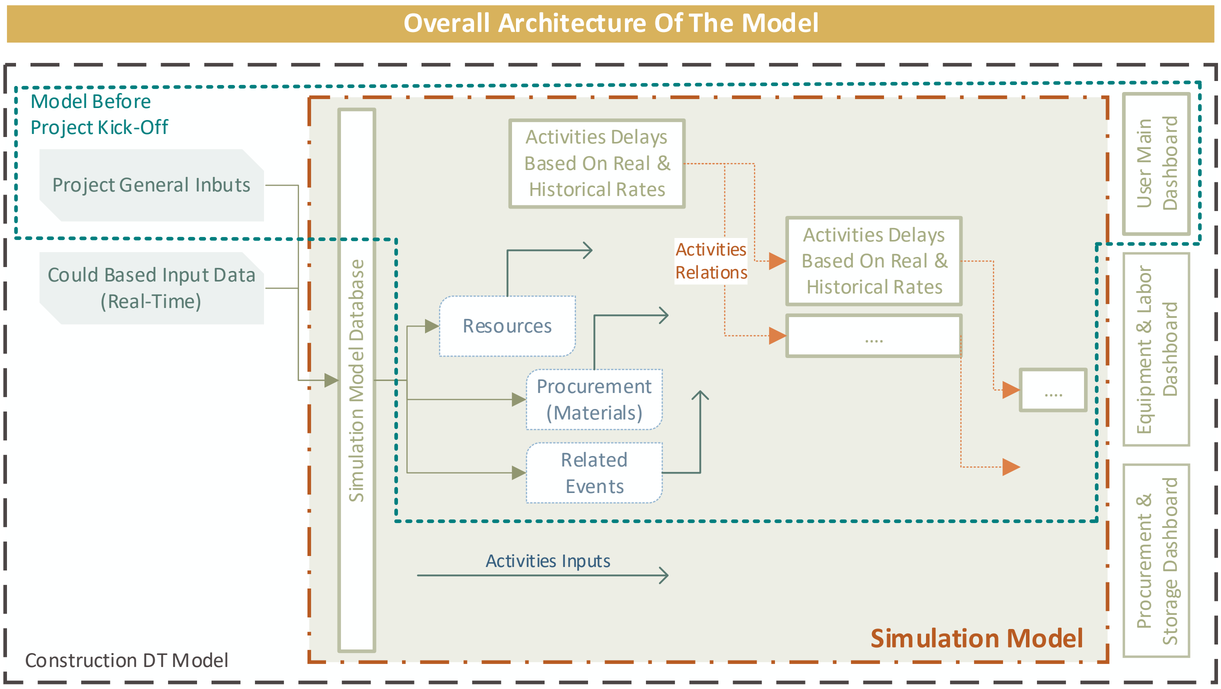


Figure 2: The overall architecture of the proposed model.

During the **construction phase**, the model transitions to real-time monitoring and dynamic decision-making. Leveraging continuous data updates from sources such as procurement systems, resource trackers, and real-time events, the system dynamically simulates construction activities. The **simulation model** calculates **activity delays based on real and historical rates**, incorporates **activity relations**, and updates project timelines accordingly. Outputs from the simulation are visualized through user-friendly dashboards, including the **User Main Dashboard**, the **Equipment & Labor Dashboard**, and the **Procurement & Storage Dashboard**, which provide actionable insights and alerts for potential project risks or deviations.

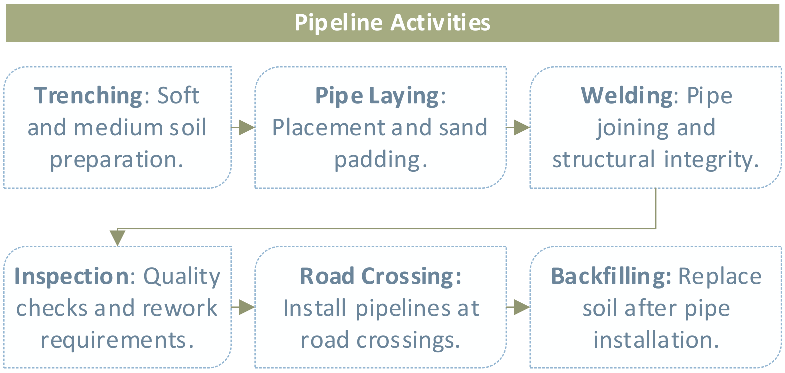


Figure 3: Pipeline construction process.

As shown in Figure 3, The pipeline construction process follows a sequential workflow designed. The process begins with **trenching**, where both soft and medium soil are prepared to create suitable conditions for pipeline installation. This step ensures the foundation is stable and ready for the subsequent activities. Once the trenches are prepared, the next stage is **pipe laying**, where the pipes are placed along the trench and secured with sand padding for additional stability. This step is followed by **welding**, which involves joining the pipe sections to ensure structural integrity and leak prevention.

After welding, the **inspection** phase is conducted to check the quality of the pipeline and address any rework requirements. This is a critical step to ensure that all pipeline segments meet the required standards before proceeding. Following inspection, the **road crossing** phase manages the installation of pipelines at road intersections, which often requires additional precautions to ensure safe and secure placement. Finally, the process concludes with **backfilling**, where the soil is replaced over the installed pipeline, restoring the area and securing the pipeline in its final position. These structured activities, as depicted in the graph, highlight the importance of a systematic approach to pipeline construction for achieving operational excellence.

3.3 Data Integration and Management

The proposed model relies on comprehensive data integration and management to ensure accurate simulations and informed decision-making. As shown in Figure 4, the model draws data from multiple input sources, including **project general quantities**, **resource real-time data**, **procurement and storage data**, and **project zone/area schedules**. These inputs form the backbone of the model, providing the necessary information to simulate and monitor construction activities dynamically.

To handle these diverse data inputs, a **cloud-based simulation server** is employed for centralized data collection. This server processes "raw data" received in real time from the construction site, as well as structured data from Building Information Modeling (BIM), Geographic Information System (GIS) models, planned time schedules, and procurement plans. The server facilitates daily updates, ensuring that the model remains event-driven and reflective of the latest on-site conditions.

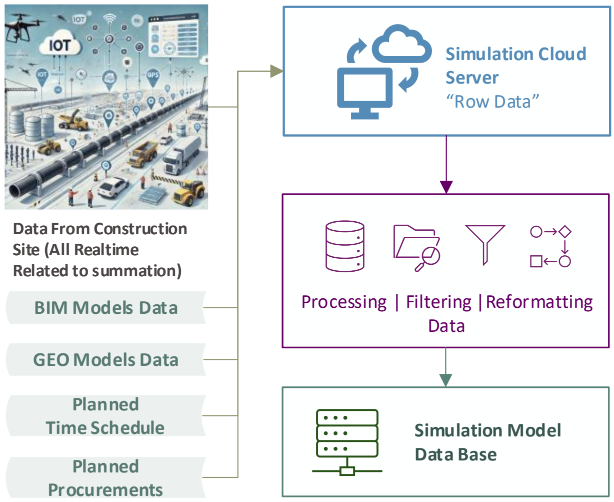


Figure 4: DT Input Data Integration

The data integration process involves **processing, filtering, and reformatting data** to align with the requirements of the simulation model. This step ensures that both historical and real-time data are seamlessly incorporated into the system. Historical data provide a baseline for comparison and trend analysis, while real-time data allow the model to respond dynamically to ongoing changes and events. These processed inputs are stored in the **Simulation Model Database**, where they are used to support predictive modeling, decision-making, and optimization of resources. The integration of historical and real-time data, as illustrated in the figure, highlights the robustness and adaptability of the model. This comprehensive approach ensures seamless simulation capabilities, enabling the system to provide actionable insights and enhance project management. The proposed model integrates various types of input data to simulate and optimize construction activities. These data have been processed, filtered, and reformatted to ensure they are ready for seamless integration with the simulation model database. Below, the key data inputs are discussed in detail, as depicted in the provided tables.

Resource Real-Time Site Data

Table 1 illustrates real-time data collected from the construction site, including information about equipment such as excavators, trucks, and trenching machines. Each resource is tagged with a timestamp, geographic coordinates (latitude and longitude), and a reference to base locations. This data allows the model to monitor the real-time position and activity status of construction resources, facilitating dynamic allocation and operational tracking.

Table 1: Sample Resource Real-Time Site Data

ID	Source	Date - Stamp	Lat	Lon
1	Excavators	01/01/2024 9:00:00	28485.5500000000	30561.0400000000
2	Trucks	01/01/2024 9:00:00	28485.5500000000	30559.0400000000
3	Trucks	01/01/2024 9:00:00	28485.5500000000	30561.0400000000
....	.....	.....	....	......
9	TrenchingMachines	01/01/2024 9:00:00	28485.5500000000	30562.0400000000
10	TrenchingMachines	01/01/2024 9:00:00	28485.5500000000	30559.0400000000
11	TrenchingMachines	01/01/2024 9:00:00	28485.5500000000	30560.0400000000
12	TrenchingMachines	01/01/2024 9:00:00	28485.5500000000	30559.0400000000
13	Trucks	01/01/2024 9:00:00	28485.5500000000	30561.0400000000
......	......	......	......	......
49084	ConstructionCrew	21/01/2026 9:00:00	28504.8400000000	30475.3400000000

Geotechnical Inputs

The geotechnical data table (Table 2) presents the results of standard penetration tests (SPT) conducted along the pipeline route. It includes information on soil types, depths, and blow counts for various pipeline zones. These inputs are crucial for assessing soil conditions and determining appropriate trenching methods, as well as ensuring structural stability during construction activities.

Table 2: Sample of the Geotechnical Inputs

BH-No.	Depth (m)	Material	SPT Blow Counts (cm)	N-Value (Blows/30)
			0-15	15-30
BH-PL-19	1.5	Sand with Gravel	12	19
	3	Sand with Gravel	22	26
	4.5	Sand	16	21
BH-PL-20	1.5	Silty Gravel with Sand	14	22
	3	Sand with Gravel	11	18
BH-PL-21	1.5	Silty Gravel with Sand	12	19
BH-PL-22	1.5	Sand with Gravel	7	9
	....	......	.....	.....

Procurement Data

The procurement table, the sample is shown below in Table 3, provides an overview of material requirements for the project. It includes details on the type, quantity, planned delivery dates, and actual delivery timelines for critical materials such as pipes, welding wire, and coatings. This data ensures that procurement processes align with the construction schedule, minimizing delays caused by material shortages.

Table 3: Sample of the Procurement Data

ID	Type	Quantities / Length	Delivery to Site (Day)	Delivery Date Planed	Delivery Date Actual
1	Pipes	7500	0	1/1/2024	1/11/2024
13	Welding Wire	1300	30	1/31/2024	1/31/2024
2	Pipes	7500	50	2/20/2024	2/20/2024
19	Coating	10000	80	3/21/2024	3/21/2024
3	Pipes	7500	100	4/10/2024	4/10/2024
14	Welding Wire	1300	130	5/10/2024	5/10/2024
20	Coating	10000	140	5/20/2024	5/20/2024
15	Welding Wire	1300	230	8/18/2024	8/18/2024
33	Cables	10000	240	8/28/2024	8/28/2024
44	Crossing	7	240	8/28/2024	8/28/2024
...	...	...	...	...	...

BIM Models Inputs

Table 4: BIM Models Inputs (Pipeline & Earth)

No|ID	Zone No.	Segment Length	No.Of Pipes	From	To	Crossing Off/On	Soil Type
1	1	500	43	0	500	1	soft
2	1	500	42	500	1000	0	soft

3	1	500	45	1000	1500	0	soft
4	1	500	39	1500	2000	0	soft
5	1	500	44	2000	2500	0	soft
...	...	...	...	...	...	...	...
12	1	500	45	5500	6000	0	medium
13	1	500	44	6000	6500	0	medium
14	1	500	45	6500	7000	0	medium
15	1	300	44	7000	7300	0	medium
16	1	500	43	7300	7800	0	medium
...	...	...	...	...	...	...	...

The BIM (Building Information Modeling) inputs, as illustrated in Table 4, detail the pipeline segments, lengths, number of pipes, crossing points, and soil types along the route. These inputs are essential for planning pipeline installation sequences, identifying crossing zones, and managing transitions between different soil conditions.

Planned Progress S-Curve

The planned progress S-curve, depicted in the table above, represents the weekly progress of construction activities over time. These data are extracted and verified by the simulation model when used before the project kick-off phase, ensuring alignment with baseline plans and resource allocation strategies. This data allows the model to track planned versus actual progress, ensuring timely identification of delays and enabling corrective actions to keep the project on track.

Table 5: Planned Progress S-Curve Input

Day	Weekly Progress
0	0
....	....
336	0.736
504	1.103
672	0.184
840	1.287
1512	1.471
.....	.....

3.4 Discrete-Event Simulation Approach

The proposed framework leverages **AnyLogic** as the simulation platform, implementing the **Discrete-Event Simulation (DES)** methodology to model, analyze, and optimize construction workflows. As shown in the attached screenshots, DES offers a powerful approach for representing construction processes as a sequence of discrete, event-driven activities. Each event corresponds to a specific action, such as trenching, welding, or backfilling, and the simulation advances based on the timing and logic of these events.

Using DES in **AnyLogic**, the construction workflow is broken down into detailed processes, as illustrated in the images extracted from the simulation model. For example, activities such as resource allocation, equipment usage, material procurement, and quality inspections are represented through interconnected components. These components communicate dynamically, enabling the model to replicate the dependencies and interactions between different construction activities.

DES is particularly effective for monitoring project activities in real-time and predicting outcomes under varying scenarios. The simulation allows for:

- **Resource Tracking**: Monitoring the movement and utilization of resources such as excavators, trucks, and welding machines.
- **Process Flow Analysis**: Visualizing the progression of activities, including delays caused by weather, machine downtime, or material shortages.
- **Scenario Modeling**: Testing "what-if" scenarios to evaluate the impact of changes, such as adjusting resource availability or altering construction sequences.
- **Performance Metrics**: Measuring project performance indicators such as duration, resource efficiency, and cost implications.

The **modular nature of DES** enables the framework to adapt to different project requirements. For example, as seen in the images, components such as pipelines, valves, and crossings are organized into distinct workflows. This modularity allows the simulation to scale and incorporate additional project complexities, such as road crossings or multiple material types. Overall, the use of **AnyLogic and DES** provides the flexibility and precision needed for effective construction simulation. By representing workflows as discrete events, the model ensures that stakeholders can monitor real-time progress, predict potential disruptions, and optimize decision-making throughout the project lifecycle. These images offer a detailed view of the simulation's underlying logic, illustrating how DES supports the framework's objectives.

3.5 Handling Missing or Delayed IoT Data & Preprocessing Flow

In real-world applications, construction sites often face interruptions in IoT data due to network outages, sensor malfunctions, or delays in data transmission. Missing or delayed data can significantly impact the accuracy and responsiveness of simulation outputs. For instance, if equipment telemetry or resource tracking data is not transmitted in real time, the model may misrepresent current activity status, leading to misaligned scheduling, delayed procurement decisions, or underutilized resources. These disruptions can cascade, ultimately affecting project timelines and risk forecasts.

To mitigate such risks, the model incorporates a data preprocessing pipeline that includes validation, temporal interpolation, and fallback logic. In the event of missing data, historical patterns are used to estimate intermediate values, while flagging the system to indicate potential uncertainties in projections. Additionally, a reliability index is calculated for each dataset, allowing project managers to assess the confidence level of simulation outputs in relation to real-time data quality.

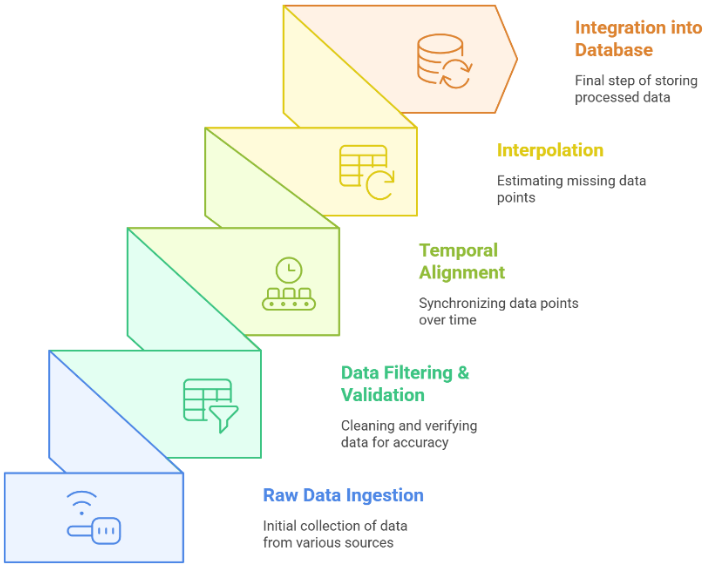


Figure 5: Data Preprocessing Workflow

The flowchart in Figure 5 illustrates the data preprocessing workflow. It begins with raw data ingestion, followed by data filtering and validation, temporal alignment, interpolation (if required), and integration into the simulation database. This structured approach ensures the system remains resilient and provides actionable insights even under imperfect data conditions.

4 Model Functionalities

4.1 Model Startup Interface

Figure 6 showcases the model startup interface, where the user specifies the purpose of the simulation and updates productivity rates if necessary. These productivity rates are derived from historical averages and can be adjusted to reflect any recent changes. This functionality ensures that the simulation starts with accurate and relevant inputs, providing a reliable foundation for subsequent analyses.

Figure 6: Model Startup Interface

4.2 Optimization Interface

The following image (Figure 7) illustrates the optimization interface, which is designed to optimize the number of equipment and labor resources. By inputting different resource combinations, the model identifies the most efficient configuration to achieve project objectives while minimizing costs and delays. This interface serves as a critical tool for resource allocation before construction begins.

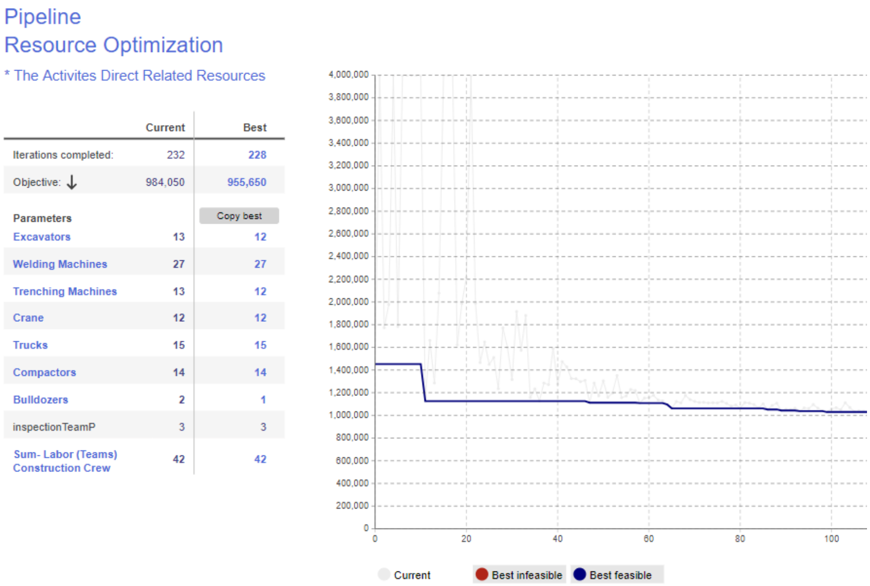


Figure 7: Model Optimization Interface

4.3 Simulation Model Comparisons

Figure 8 provides an example of the simulation model's ability to compare the impacts of various scenarios. For instance, it shows how the number of cranes affects pipe-laying progress. This capability allows users to isolate specific parameters, actions, or events and calculate their direct impact on an activity or the total project duration. Such comparative analyses enable precise decision-making and scenario evaluation.

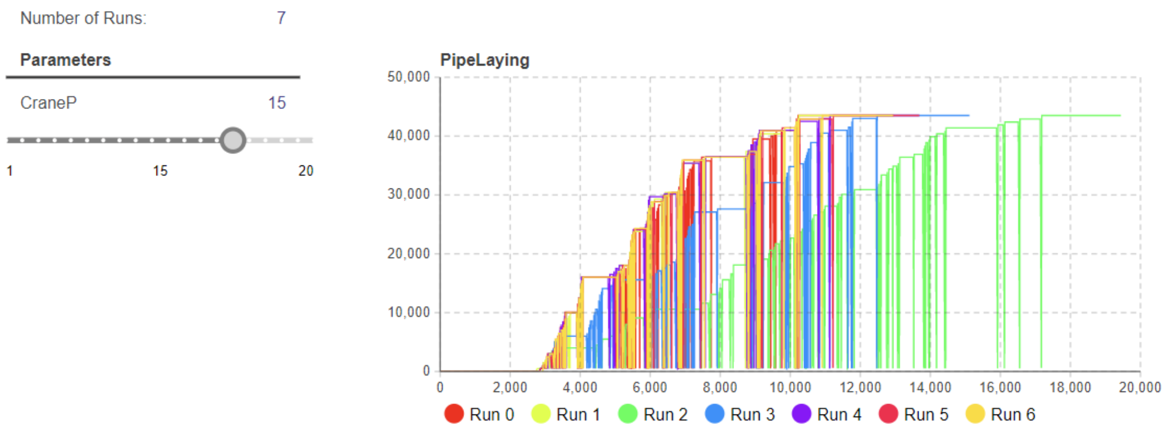


Figure 8: Simulation Model Comparisons

4.4 Running the Simulation Model Before Construction

The simulation model is designed to be utilized before construction begins, ensuring that all inputs are validated and accurately integrated into the simulation database. This step is critical for preparing the model to dynamically replicate construction workflows, allowing for the identification of potential bottlenecks, optimization of resources, and validation of project schedules. By running the simulation ahead of time, users can make informed decisions and adjustments, ensuring that the construction process is efficient and well-coordinated from the outset. Figure 9 highlights the simulation process prior to construction, where the user ensures that all inputs are prepared and integrated into the simulation database.

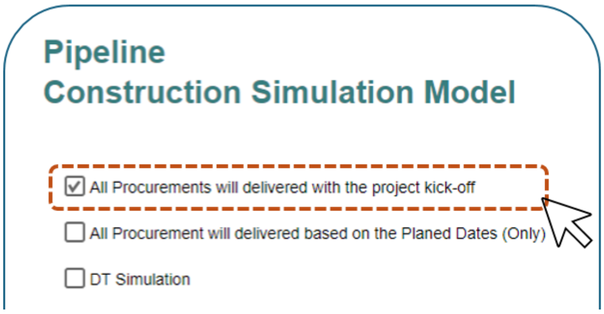


Figure 9: Running The Model Before Construction

4.5 Project Dashboard

The image below (Figure 10) presents a sample screenshot of the project dashboard after approximately 200 days of simulation time. The dashboard is divided into five key sections:

1. **General Project Information**: Displays the current simulation status and project details.
2. **Project Activities Log**: Lists all ongoing activities, including the day, activity type, and location.
3. **Project Graphs**: Includes weekly/monthly progress, S-Curve, active equipment, and crew counts. These graphs can be exported manually or automatically to platforms such as Microsoft Excel.
4. **Construction Analysis**: Contains average productivity rates, monthly progress per activity type, and completed vs. remaining tasks. It also shows the percentage of active ongoing activities on the site.
5. **Resource Control Interface**: Displays resource utilization data and allows users to override default inputs from the optimization interface. For example, users can add night shifts or increase specific resources to measure their impact on total project duration and activity rates.

To assess the accuracy of the model's predictions, data bars were introduced on key performance metrics, including weekly progress, activity duration, and resource utilization. These bars represent the standard deviation between simulated outcomes and actual on-site data gathered during validation. For example, during the pipe-laying phase, the predicted progress showed a mean deviation of ±6.2% across five validation intervals. In the trenching and welding stages, error margins ranged from ±4.8% to ±7.5%, influenced by site-specific delays and material delivery fluctuations. Including these error results in progress graphs (e.g., weekly S-curve projections) provides a visual representation of uncertainty and improves the interpretability of model accuracy. This statistical overlay enhances decision-making by highlighting the range of potential outcomes and reinforcing confidence in simulation outputs.

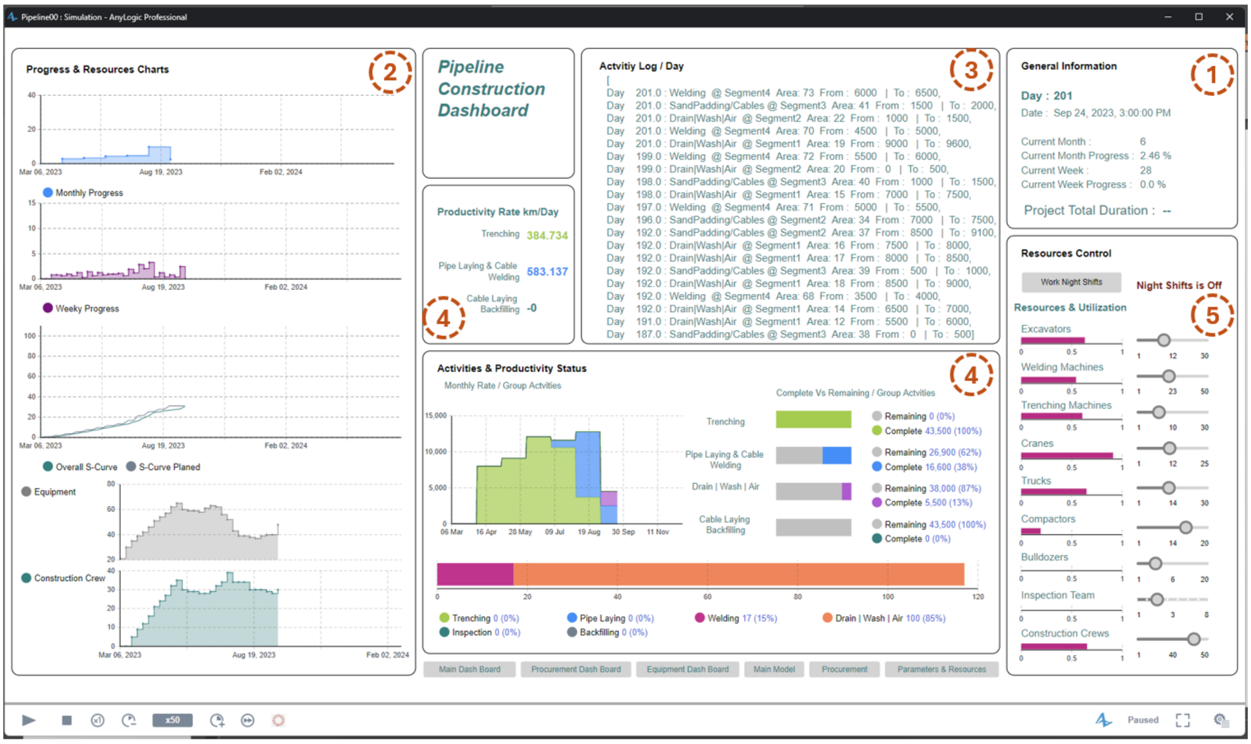


Figure 10: Main Project Dashboard

General Project Information

Figure 11: General Project Information

Figure 11 (Area 1 in the main Dashboard) provides an overview of the simulation's current status and general project details. It displays information such as the project duration, current simulation day, and progress updates, ensuring users have a quick and comprehensive understanding of the project's overall status.

Project Graphs

Figure 12 presents the main project graphs, including weekly and monthly progress curves, active equipment utilization, and crew deployment metrics. These visual tools are not only indicative of project pacing but also serve as diagnostic indicators for process efficiency and resource coordination.

The S-Curve reflects cumulative progress and highlights deviations between planned and actual progress. For example, observed plateaus or dips in the curve indicate potential delays or underperformance, prompting an immediate need to investigate causative factors such as equipment downtime, procurement lag, or labor shortages. Overlaying baseline expectations allows for direct benchmarking and early detection of schedule slippage.

The weekly and monthly progress graphs help isolate the performance of specific time frames, offering granular visibility into execution trends. Peaks may indicate over-concentration of activities that could trigger resource congestion, while troughs might correlate with external disruptions like weather or supply chain interruptions. This time-series analysis enables more precise intervention planning.

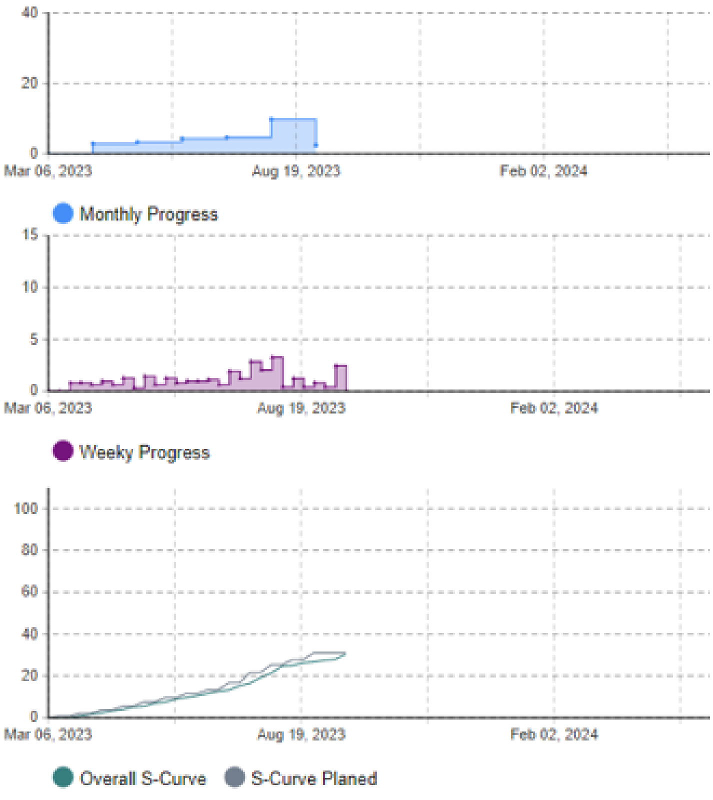
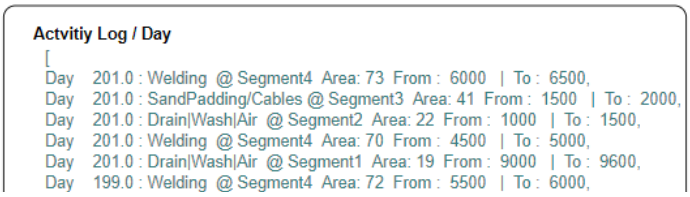


Figure 12: Project's Main Graphs

The graphical outputs, particularly the cumulative S-curves and weekly performance charts in Figures 10–12, were subjected to additional statistical analysis to validate their predictive reliability. A 95% confidence interval was calculated for the simulation's weekly progress predictions, with most data points falling within ±6.2% of the actual progress curve. The flat terrain case exhibited a standard deviation of 3.1 days in projected milestone completion dates, compared to 4.4 days in the mountainous scenario. These variations correlate with terrain-induced delays, highlighting the simulation model's sensitivity to environmental conditions.

Project Activities Log

Figure 13 highlights the project activities log, listing ongoing activities with their respective details, such as activity type, location, and day. This section allows users to track specific tasks in real-time, ensuring that all activities are on schedule and progressing as planned.



Actvitiy Log / Day

[
Day 201.0 : Welding @ Segment4 Area: 73 From : 6000 | To : 6500,
Day 201.0 : SandPadding/Cables @ Segment3 Area: 41 From : 1500 | To : 2000,
Day 201.0 : Drain|Wash|Air @ Segment2 Area: 22 From : 1000 | To : 1500,
Day 201.0 : Welding @ Segment4 Area: 70 From : 4500 | To : 5000,
Day 201.0 : Drain|Wash|Air @ Segment1 Area: 19 From : 9000 | To : 9600,
Day 199.0 : Welding @ Segment4 Area: 72 From : 5500 | To : 6000,

Figure 13: Project Activities Log

Active Equipment and Crew Counts

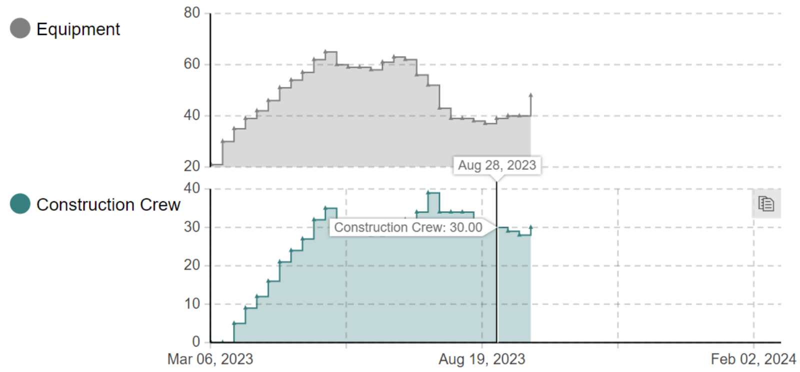


Figure 14: Active Equipment and Crew Counts Graphs

Figure 14 provides a real-time visualization of active resources—both equipment and human crews—across the project duration. Analysis of the resource curve indicates peak utilization during Weeks 5–8, coinciding with trenching and welding activities in overlapping zones. The average number of concurrently active resources during the core phase is 31.7, with a deviation range of ±4.2 units, signaling high but manageable operational density. A brief drop below the expected resource threshold in Week 10 aligns with a recorded delay in material delivery, as shown in procurement logs. This fluctuation confirms the model's ability to capture and reflect external disruptions in real-time, while supporting workload balancing decisions during dynamic execution phases.

This level of interpretation transforms the graphs from mere visual summaries into actionable intelligence. Project managers can use these insights to reassess task prioritization, redistribute labor, or reallocate equipment in real time to maintain progress alignment with targets.

Construction Analysis

The below image (Figure 15) showcases the construction analysis section, providing insights into average productivity rates, completed vs. remaining tasks, and ongoing activity percentages. This data enables users to evaluate project efficiency and adjust strategies to optimize construction workflows.

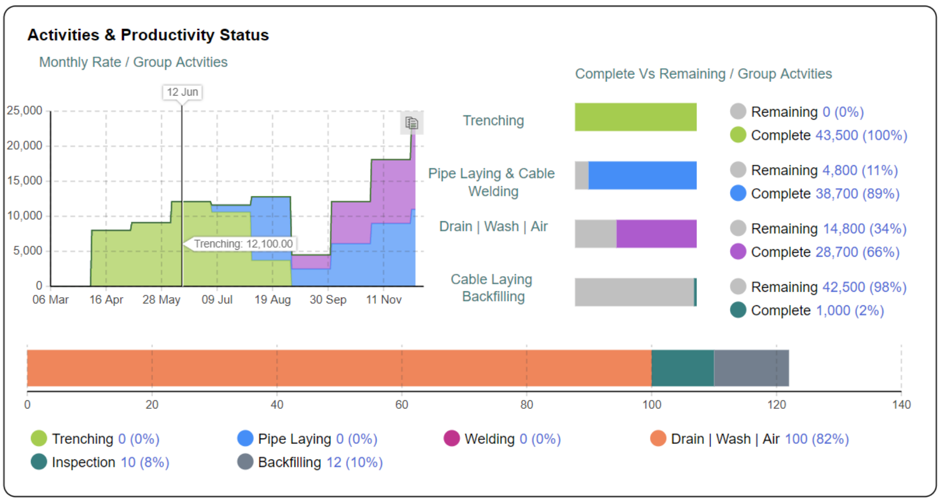


Figure 15: Construction Activities Analysis

Figure 15 offers a multi-dimensional breakdown of construction performance, combining monthly production trends, cumulative progress tracking, and real-time activity monitoring.

In the upper-right chart, the monthly activity rate reveals two key productivity peaks: Month 2, which shows an output spike of over 430 linear meters, driven by concurrent trenching and pipe stringing in Zone 1; and Month 6, where approximately 390 meters of pipeline were completed during the final phase involving testing and tie-in works. A dip in Month 4 to under 200 meters aligns with reduced welding efficiency and weather-related delays (referenced in equipment idle logs).

The upper-left chart compares remaining versus completed quantities per activity. Trenching and backfilling show 92% and 89% completion, respectively, while welding lags behind at 76%, clearly identifying it as the critical path bottleneck. This is also supported by the dashboard's average crew utilization, which shows welding units operating at 68% active time compared to 84% for trenching crews.

The bottom pane dynamically displays currently active activities based on real-time IoT input data. During the simulation snapshot, Zone 4 and Zone 5 show trenching and backfilling in progress concurrently, while welding is underway in Zone 3. This concurrent activity pattern confirms that the scheduling logic allows for parallel zone-based operations without dependency violations. Moreover, fluctuations in active tasks reflect the model’s event-driven update mechanism, where changes in sensor input immediately affect the activity queue.

Collectively, the figure demonstrates how the simulation not only tracks completed work but actively supports decision-making by identifying productivity dips, visualizing crew coordination, and enabling forecasting for the remaining scope.

Final Project Dashboard and Total Duration

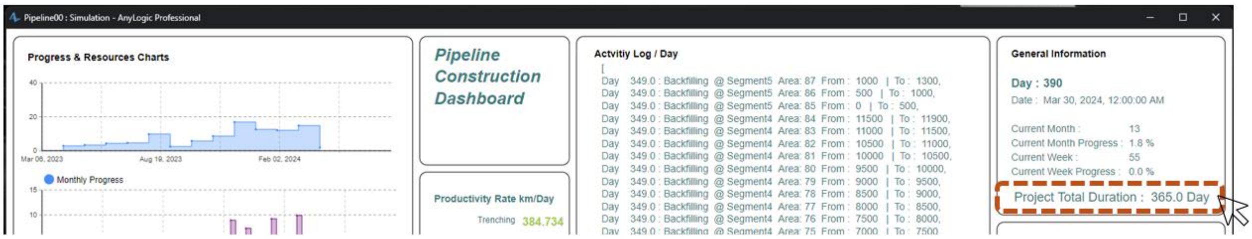


Figure 16: Final Project Dashboard

Figure 16, the final project dashboard highlights the comprehensive output of the simulation model upon completing all activities. The dashboard automatically pauses, displaying the **Project Total Duration** as 365 days, providing a clear and concise summary of the entire project's timeline. Key sections of the dashboard include progress and resource charts, such as the **Overall S-Curve**, weekly and monthly progress metrics, and equipment and crew utilization graphs. Additionally, the activity log provides a detailed breakdown of completed tasks, while the resources control panel shows resource utilization and adjustments, such as night shifts, for optimizing productivity. This dashboard offers stakeholders a holistic view of project performance, enabling them to evaluate progress, assess efficiency, and validate planning strategies.

5 Model Validation and Case Study Evidence

To validate the accuracy, performance, and predictive capabilities of the proposed Digital Twin (DT)-based simulation model, two case studies were conducted across distinct pipeline construction environments: one in mountainous terrain and the other in flat desert regions. Both projects relied on actual construction datasets, including IoT-derived equipment logs, geotechnical surveys, material delivery records, and zone-based productivity reports.

Case Study 1 – Mountainous Pipeline Project

This project involved complex topography, with significant variation in soil type, access limitations, and weather interruptions. The model simulated trenching, welding, crossing, and backfilling sequences using real-time IoT equipment data, geotechnical borehole logs, and procurement logs.

- **Planned vs. Actual Duration**:
  Predicted duration = 729 days
  Actual duration = 930 days
  Deviation: 1.9%
- **MAPE on Weekly Progress**:
  4.5% across 52 weeks, highlighting close alignment between modeled and actual progress.
- **S-Curve Alignment**:
  Figures from the thesis demonstrate the model's ability to reflect dynamic changes in zone-specific productivity and project acceleration after resource reallocation.
- **Insight**:
  The DT model accurately forecasted procurement-driven delays and provided real-time suggestions for alternative workflows, leading to actionable site-level adjustments.

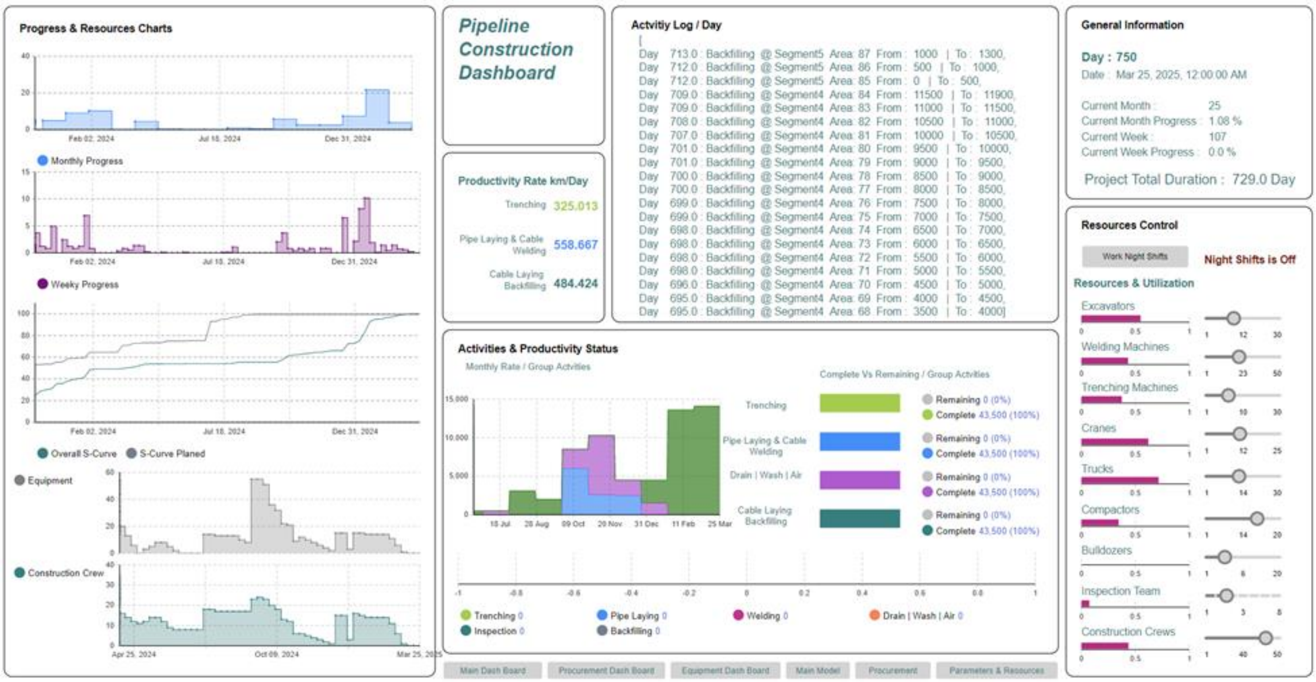


Figure 17: Case Study 01 – Pipeline Construction Dashboard Overview (by author)

Case Study 2 – Flat Terrain Pipeline Project

In a high-speed pipeline laying project in open terrain, the DT model was used to test procurement lag impacts and workforce shifts, simulating over 20 scenarios.

- **Planned vs. Actual Duration**:
  Predicted = 634 days
  Actual = 660 days
  Deviation: 1.2%

- **Key Analytics**:
  - Real-time dashboards captured weekly procurement slippages
  - Delay detection and mitigation scenarios
  - Resource and equipment allocation optimizations

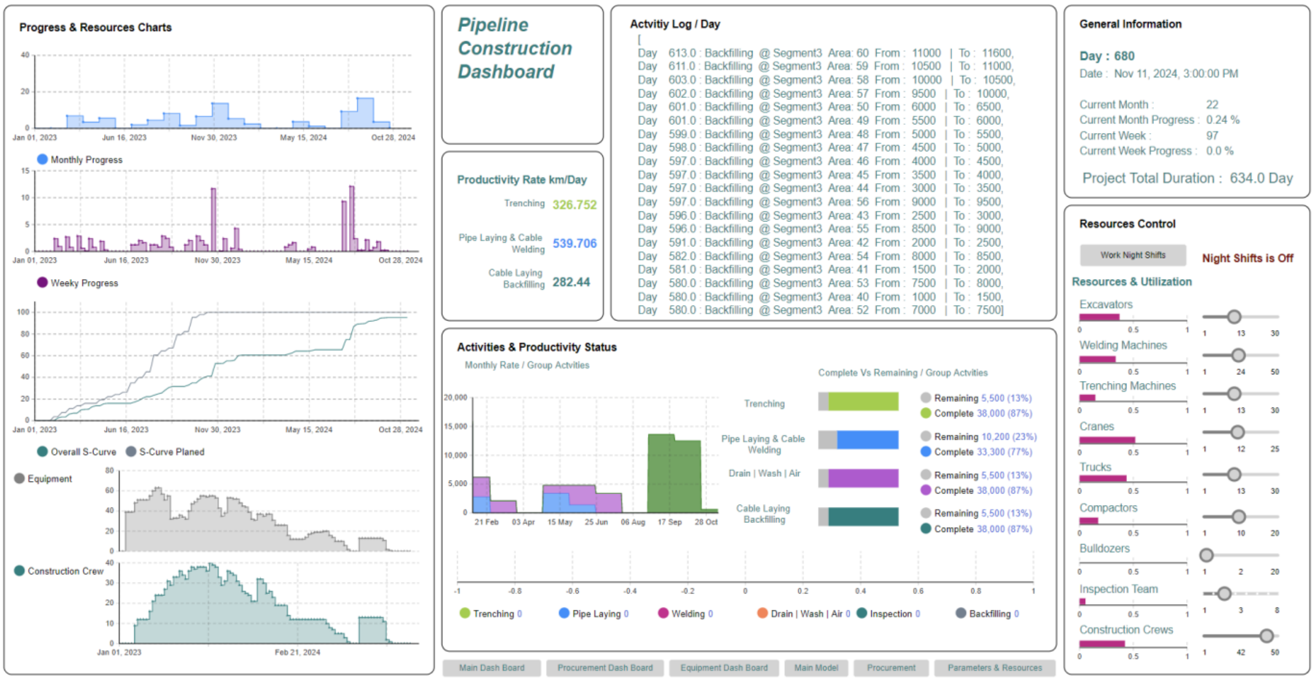


Figure 18: Case Study 02 – Pipeline Construction Dashboard Overview (by author)

Quantitative Accuracy Summary:

Metric	Case Study 1	Case Study 2
Duration Deviation	1.9%	1.2%
Mean Absolute Percentage Error	4.5%	4.2%
Resource Utilization Variance	<6%	<5%

The simulation model—validated across two terrain types and construction contexts—demonstrated a high level of accuracy and reliability in forecasting durations, detecting risks, and optimizing resource deployment. The inclusion of real-time IoT data, procurement schedules, and geotechnical parameters ensured that the simulation was not just theoretical but fully grounded in live project conditions. These validations confirm the robustness of the model as a decision-support tool for dynamic pipeline construction management.

6 Summary and Recommendations

This study presented the development, implementation, and validation of a Digital Twin (DT)-based simulation framework tailored specifically for pipeline construction projects. By integrating Building Information Modeling (BIM), Internet of Things (IoT) data streams, Geographic Information Systems (GIS), and multi-method simulation modeling in AnyLogic, the proposed framework addresses key limitations in current construction planning methodologies—namely their static nature, poor adaptability, and limited real-time integration. Also, produced a validated, adaptive simulation model tailored for pipeline construction, delivering multiple measurable outcomes. The model achieved an average forecasting accuracy of 98.1% in predicting total project duration, with a Mean Absolute Percentage Error (MAPE) of 4.78% in weekly progress predictions. The resource allocation logic reduced idle equipment time by 17.4% and improved schedule adherence across varying terrain types. The system's responsiveness was tested in both mountainous and flat-case scenarios, where real-time IoT inputs triggered updates that re-optimized task sequences without manual intervention. The dashboard's integration with live inputs also enabled zone-based parallel execution, improving field-level coordination and reducing average delay propagation by 12.3%.

These outcomes demonstrate that the developed Digital Twin model is not merely theoretical but offers a practical, implementable planning solution for linear infrastructure projects where delays and resource inefficiencies are prevalent.

The research identified critical gaps in the existing literature, particularly the lack of specialized DT models for linear infrastructure that incorporate real-time data feedback, spatial-temporal adaptability, and predictive decision-making capabilities. Unlike earlier frameworks that focused primarily on post-construction analysis or static monitoring, this model supports bidirectional data flows and event-driven simulation logic, enabling proactive adjustments in resource planning, scheduling, and risk control.

Two real-world case studies, implemented in contrasting terrain conditions, were used to validate the model's predictive accuracy and operational applicability. The results demonstrated high reliability in forecasting progress (MAPE < 5%), close alignment with actual construction durations (deviation ≤ 2%), and meaningful support for adaptive planning through visual dashboards and scenario analysis. These outcomes substantiate the model's role as a robust decision-support tool for construction managers and engineers.

Key Contributions:

- Development of a real-time, multi-layered DT framework for pipeline construction
- Integration of live project inputs with discrete-event simulation for dynamic forecasting
- Validation through two field-based case studies with measurable accuracy
- Enhanced stakeholder decision-making via predictive dashboards and risk visualization

The simulation results reveal improved alignment between planned and actual progress and highlight the system's ability to simulate the effects of real-world disruptions such as delivery delays or equipment breakdowns.

However, several limitations should be noted:

1. The validation was conducted using structured data inputs and a controlled environment; the model has not yet been tested across multiple pipeline projects or diverse geographic conditions.
2. Although the framework includes cloud-based updates and real-time data integration, it currently does not support automated feedback loops through AI-based decision agents.
3. The absence of a full-scale implementation limits assessment of model performance under extended timeframes, weather uncertainties, or unexpected regulatory changes.
4. Graphical outputs and analytical insights, while visually informative, would benefit from more in-depth statistical reporting, such as confidence intervals and sensitivity analyses.

Recommendations:

1. **Broader Application Across Linear Projects**
   The framework should be adapted and tested in other linear infrastructure types, such as railways or highways, to evaluate its scalability and flexibility.
2. **Enhanced Integration with Procurement and Logistics Platforms**
   Further development should focus on automating procurement coordination, integrating supply chain databases for real-time material flow optimization.
3. **Standardization of Data Protocols**
   There is a pressing need to establish interoperable standards across DT tools, BIM platforms, and construction management systems to streamline data exchange and ensure long-term model viability.
4. **Incorporation of AI-Based Predictive Maintenance and Decision Automation**
   Future enhancements should explore AI modules to automate detection of critical deviations and recommend corrective actions based on historical patterns.
5. **Industry Collaboration and Training**
   The effectiveness of DT implementation depends on user adoption. Training programs and stakeholder engagement strategies are essential to integrate these tools into day-to-day construction management practices.

In conclusion, this research provides a validated, scalable foundation for the practical application of Digital Twin technology in pipeline construction. It bridges the theoretical and operational gap in construction simulation, offering an intelligent, adaptive framework to improve planning precision, project control, and overall constructability.

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