OPTIMIZING LINEAR CONSTRUCTION PROCESSES: A SIMULATION-BASED APPROACH TOWARDS AI-SUPPORTED DECISION MAKING

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Abstract

Large-scale linear construction projects involve complex interdependencies, extended sites, and numerous execution variants, while existing approaches lack personalized recommendation systems for trenching applications. This paper presents a simulation-based framework conceptually enabling AI-driven optimization methods to support data-informed planning under limited historical data availability. A bottom-up simulation model captures process-specific dynamics and enables synthetic data generation, forming the basis for proposing focused parameter ranges with promising execution variants. Parametric validation across 3,200 simulation runs confirms realistic system behavior. The results indicate that AI-integrated simulation frameworks represent a viable and transferable approach for optimization in data-scarce linear construction environments.

Introduction

The European Union has established comprehensive guidelines for trans-European energy infrastructure to achieve climate neutrality by 2050 while ensuring energy security and market integration across Member States (European Parliament and Council, 2022). Priority electricity transmission corridors have been defined, particularly North–South interconnections in Central and South Eastern Europe, to support renewable energy integration into the internal market. To support this European objective, the Federal Requirements Plan Act has promoted 35 projects totaling approximately 14,000 km since 2013, yet by 2023 only about 4,000 km had been approved or completed (enercity, 2025). This discrepancy reflects persistent challenges in the planning, approval, and execution of large-scale linear infrastructure projects.

The scale and complexity of these projects limit the availability of robust empirical reference data and standardized methods for performance assessment and optimization. Construction processes are highly dependent on site-specific conditions such as geology, logistics, and resource availability, complicating systematic evaluation of alternative construction strategies. Simulation-based methods provide a promising means to address these challenges. By representing construction processes as parameterized models, simulation enables systematic analysis of construction sequences, resource interactions, and logistical dependencies. When combined with optimization methods, such approaches can support informed decision-making and contribute to the timely implementation of projects critical to achieving national and European climate and energy objectives.

Given the complexity of large-scale construction sites operated by numerous crews simultaneously, the integration of Artificial Intelligence (AI) for decision support represents a promising extension of simulation-based planning. Recent surveys indicate growing industry interest in AI applications for optimization tasks. While German construction companies increasingly employ data analysis and predictive modeling, personalized recommendation systems remain largely unimplemented despite planned investments by over one-third of surveyed firms with more than 250 employees (Engels et al., 2025). This indicates substantial development potential and demand for AI-supported optimization tools. Consequently, this work investigates whether AI-integrated simulation can effectively address the variant generation and optimization challenges inherent in large-scale linear construction projects.

State of the Art

In order to contextualize this paper within the existing body of research, relevant literature on simulation-based decision support and AI-integrated optimization methods is reviewed. Particular emphasis is placed on applications in industrial manufacturing and their transferability to construction domains. While construction projects present distinct challenges due to site-specific variability and data scarcity, methodologies proven in manufacturing environments provide valuable foundations for developing simulation-based planning approaches in linear infrastructure construction.

Relevant Related Work

In industrial manufacturing, the discrete event simulation (DES) is a well-established tool for decision support, system analysis, and performance evaluation. Negahban and Smith (2014) identify three primary areas of application:

- Manufacturing system design
- Manufacturing system operations
- Simulation language/package development

These categories can also be applied in the construction industry, as relevant construction literature subsumed under these categories can be found. With respect to manufacturing system design, simulation-based approaches have been adopted to address construction site layout planning. This aspect is particularly critical for linear construction projects, where site layouts continuously evolve along the project corridor and material transportation distances represent a major cost and performance driver. Petroutsatou et al. (2021) proposed an algorithm for optimizing construction site layouts by dynamically relocating site facilities and storage areas, demonstrating reductions in transportation effort and overall operating costs. Similarly, RazaviAlavi and AbouRizk (2021) developed a simulation-based decision-support tool to evaluate alternative site layouts based on on-site transportation, construction logistics, and safety considerations.

Analogous to manufacturing system operations, simulation has also been applied to the analysis and optimization of construction processes themselves. Typical approaches vary equipment capacities, crew sizes, or task sequences and analyze resulting impacts on process performance through repeated simulation runs. König et al. (2007) applied this principle to drywall construction by simulating processes to analyze the impact of resource constraints and scheduling on efficiency.

More recent work extends this paradigm by systematically exploring large sets of feasible construction schedules instead of isolated scenarios. Morkos (2014) presents an approach that automatically generates schedules while enforcing precedence, resource, and spatial constraints. Rather than identifying a single optimal solution, the method enables the exploration of the feasible solution space and the analysis of trade-offs across multiple alternatives.

Within the category of simulation language and package development, a trend toward hybrid simulation frameworks can be observed, combining generic models, comprehensive system architectures, and integrated optimization methods. A similar development can be observed in construction-related research. Early work by Weber (2007) focused on the evaluation of logistics and site layout strategies for material flow in building construction. The developed tool, *SIMUBAU*, utilized CAD models to derive geometric and semantic model components and integrated these with databases and external programs for logistics and planning data. Within the research project *ForBAU*, a further framework was developed for earthworks in road construction. This approach employed CAD-based tools to generate voxel-based earthwork models and linked them with external databases providing simulation parameters, thereby improving both visualization and result analysis capabilities (Günthner et al., 2013).

More recent research extends these frameworks toward data-driven and continuously updated simulation environments. Jungmann (2025) proposes a digital twin-based approach in which real-time data collected on construction sites are processed to extract activity durations, calibrate stochastic simulation models, and generate key performance indicators (KPIs) for decision support. The approach further integrates machine learning-based activity recognition, stochastic productivity modeling, and DES to enable continuous model calibration and more accurate forecasting of construction processes.

While such approaches significantly enhance the realism and timeliness of simulation models, they primarily focus on improving model accuracy and enabling data-driven evaluation of predefined decision alternatives. Although multi-criteria optimization techniques are applied to identify promising solutions, these approaches do not inherently generate or adapt decision alternatives through learning-based mechanisms.

Addressing this gap as well as the third area of application, research has increasingly focused on integrating optimization methods with simulation frameworks. In construction, hybrid approaches combining simulation with genetic algorithms have been applied particularly for site layout planning, jointly addressing cost efficiency, safety, and productivity objectives (Said and El-Rayes, 2013; Papadaki and Chassiakos, 2016). However, these approaches remain largely static and do not adapt to changing site conditions. Evidence from related fields suggests that a more dynamic integration is feasible. In industrial manufacturing, Choi et al. (2024) and Klar et al. (2024) demonstrate that combining simulation with learning-based optimization enables continuous performance improvement. Kandemir et al. (2025) on the other hand, integrates DES with AI methods to optimize job scheduling under uncertainty. These results highlight the broader potential of adaptive, data-driven optimization, which remains largely untapped in construction site management.

Despite considerable progress in simulation-based decision support, the reviewed literature reveals limitations that need further investigation. Particularly in the construction domain, the integration of optimization methods with simulation frameworks remains underexplored compared to manufacturing applications. Moreover, recent advances in AI-driven optimization show promising results, yet their practical application in construction site management, particularly for personalized recommendation systems, remains limited.

Limitations and Open Directions in the Current State of the Art

A review of existing approaches indicates limitations concerning practical applicability, integration challenges, and data availability.

While numerous simulation frameworks have been developed for construction site management, their practical deployment remains limited. The *ForBAU* project's demonstrator exemplifies this challenge: despite representing a powerful approach, Wimmer et al. (2010) explicitly stated that expert knowledge is necessary to utilize the tool effectively. Most existing systems are developed primarily in research environments rather than for practical use by site managers, who would benefit most from them in daily operations. Future research should therefore emphasize user-friendly interfaces and intuitive workflows that enable construction professionals without extensive expertise to apply these tools effectively for decision-making.

Despite significant advances in AI-driven optimization and their successful application in industrial manufacturing, the integration of these methods with construction site simulation frameworks appears to be an emerging area of research. While several studies have explored AI-based optimization using parametric BIM models (Hoeng et al., 2025; Wiederer et al., 2025), these primarily focus on optimizing building geometry, site layout, or isolated aspects such as resource allocation and scheduling. To the best of the authors' knowledge, comprehensive frameworks systematically integrating AI-based optimization with construction execution processes within a simulation environment are scarce in the current literature. Such frameworks would need to simultaneously consider dynamic scheduling, task allocation, resource constraints, logistical dependencies, and overall project costs while accounting for the strong interdependencies between site layout, transportation processes, and resource utilization.

A key barrier to AI adoption in construction is the lack of structured historical data for training machine learning models. Unlike manufacturing, where data is consistently captured in standardized environments, construction projects involve heterogeneous processes, site-specific conditions, and high contextual variability. This challenge is especially pronounced in linear infrastructure projects due to long durations, spatially distributed work fronts, and continuously changing site conditions.

Simulation-based approaches provide a way to potentially overcome this challenge through synthetic data generation. By simulating diverse construction scenarios with varying parameters and constraints, researchers can create comprehensive training datasets that capture complex interdependencies (Chan et al., 2022). Future research should investigate methodologies for generating high-quality synthetic construction data based on simulations that accurately reflect real-world variability, including validation frameworks and transfer learning approaches that effectively leverage synthetic data alongside limited real-world observations.

Within the specific domain of resource allocation optimization for linear construction sites using simulation-based approaches, several research opportunities emerge: (i) development of user-friendly simulation tools tailored to construction practitioners; (ii) integration of AI-based optimization methods with comprehensive construction process simulation; (iii) systematic approaches to synthetic data generation and validation; (iv) holistic frameworks capturing interdependencies across planning, scheduling, and execution; and (v) real-time adaptive optimization capabilities for dynamic construction environments.

In addressing the aforementioned opportunities, this work presents a framework that enables the concept of AI-based optimization in conjunction with construction site simulation by generating synthetic training data.

Methodology: Integrated Simulation Framework for Process Optimization

The methodology presented in the following is built upon a modular, process-oriented simulation framework specifically designed for open-cut trench construction in energy transmission projects. It provides the foundation for an AI-supported decision-making approach aimed at improving the allocation and coordination of earthwork resources. Figure 1 illustrates the overall structure and workflow of the proposed framework. The process begins with the collection and preprocessing of project-specific input data provided by the user.

The framework follows a hierarchical modeling strategy in which individual subprocesses are initially represented in a structured and modular form. These representations are used to derive simplified performance estimates that capture the essential behavior of each process step. The resulting information is then aggregated to form an abstracted representation of the overall construction workflow, linking the subprocesses in a sequential manner. Based on this abstraction, an AI-based component defines a constrained parameter space that focuses on promising execution strategies. Instead of evaluating isolated process steps, the simulation is applied at the level of the integrated system, allowing interactions between subprocesses to be considered. Within this reduced solution space, parametric simulations are conducted to assess different resource allocation strategies and their system-wide effects, from which KPIs are derived.

Finally, an iterative validation and refinement loop involving the user ensures the resulting scenarios are realistic, comparable, and optimized.

Input Information and Preprocessing

The proposed framework requires a set of project-specific input information provided by the user, which is accessible through an intuitive graphical user interface. The project's geometric and spatial characteristics must be specified, including segment cross-sections, lengths, radii, and gradients, as well as the intermediate storage location. Project-specific construction alternatives may also be considered, such as whether to improve existing soil in place or replace it entirely. Additional restrictions, such as the availability of machinery and labor, can likewise be incorporated. The user is further able to specify overarching project goals, for example maximum allowable cost or target construction duration. On the basis of these inputs, the simulation model as well as the appropriate parameter ranges for an optimized execution are subsequently generated.

Generation of the Parameter Space

Large scale linear construction projects are characterized by a high number of interdependent decisions. Even individual construction steps provide numerous configuration

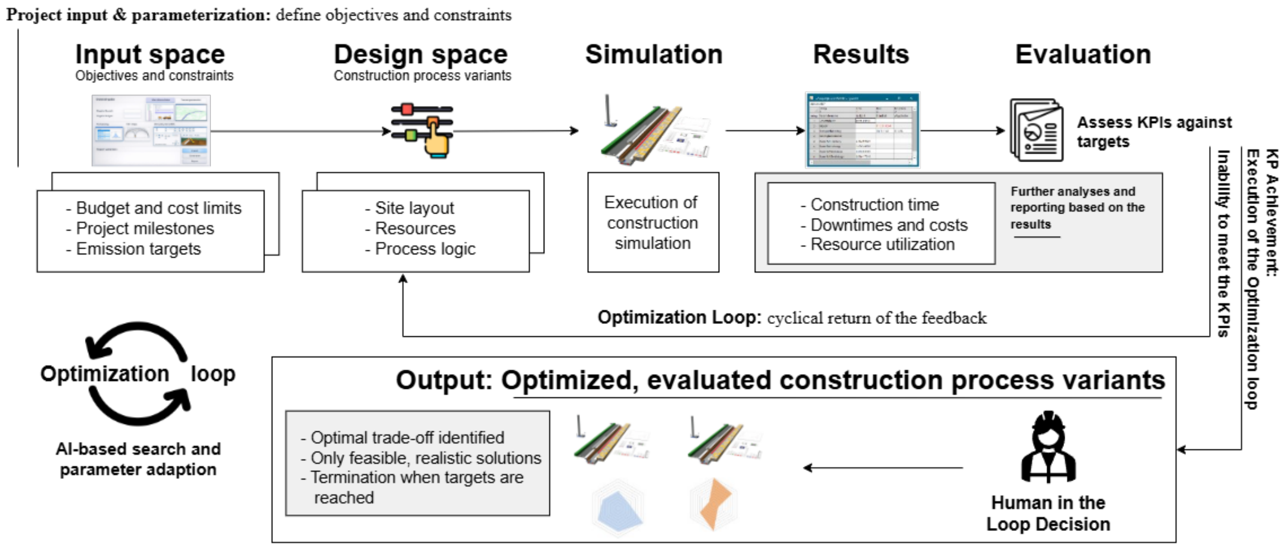

Figure 1: Holistic framework for AI-based parameter space generation and parametric simulation

options depending on equipment selection and logistical setup. When multiple crews operate simultaneously, identifying efficient task allocation and coordination strategies becomes increasingly difficult, making a comprehensive exploration of all possible configurations impractical.

To address this challenge, the proposed approach combines data-driven prediction with hierarchical aggregation to reduce the solution space. At its core, the method follows a bottom-up principle, first evaluating individual process steps independently. For each subprocess, a regression-based model is trained to predict the duration and cost based on the given input parameters. Processes that do not require logistical coordination can be evaluated through direct performance predictions. In contrast, logistics-dependent processes are further refined by optimizing relevant parameters using a differential evolution algorithm. This enables the identification of efficient equipment configurations and transport strategies.

This step provides KPIs for each individual process, including estimated duration and cost factors. Where applicable, it also provides optimized logistical configurations, all without requiring simulation at the subprocess level.

A higher-level learning component then aggregates these subprocess KPIs to derive system-level predictions, including overall project duration, cost development, task allocation, machinery utilization, and process synchronization. Although subprocess characteristics such as duration may initially serve as input variables, the model is also intended to capture inverse relationships. This indicates that adjustments at the subprocess level, such as longer execution times, may improve overall system performance. One example of this would be stabilizing process synchronization. In such cases, sub-processes can be re-evaluated in light of these updated objectives. This results in an abstract yet consistent representation of the overall construction workflow and defines a constrained parameter space that is likely to contain promising execution variants. Based on this reduced solution space, the simulation model is applied exclusively at the level of the integrated system to evaluate and compare these variants in detail.

In order to enable this predictive capability, the AI system must learn the complex interdependencies inherent to large-scale linear construction processes, which require sufficient high-quality training data. However, as previously mentioned, adequate volumes of such data are not available in a structured form. Therefore, synthetic training data is generated by systematically varying project and execution parameters in order to capture the underlying process interactions. This enables the AI models to generalize from limited empirical data and supports robust and optimized decision making.

Parametric Simulation for Energy Transmission Lines

To evaluate the parameter space proposed by the AI system and derive KPIs for execution variants, a parametric simulation model for energy transmission line construction is employed. The simulation follows a bottom-up approach and comprises three main components: a parametric representation of the working corridor, detailed models of individual process steps, and a holistic model of the entire open-cut construction process.

The working corridor model forms the foundation of the simulation and includes the trench cross-section, construction road, and soil storage areas. Key parameters such as trench depth, width, slope angles, layer heights, and number of pipes can be adjusted, ensuring broad applicability across different scenarios and projects.

This geometric representation provides the basis for calculating earthwork volumes and material quantities. Rather than deriving soil conditions from continuously updated 3D models, as demonstrated by Ji et al. (2009), they are provided directly by the user as input parameters. To ensure practical applicability, subsoil categories have been developed in collaboration with domain experts based on the traditional German classification system for earthworks (DIN 18300, 2019). The categories are designed for rapid and reliable field assessment by construction personnel. Based on user-specified soil class percentages, stochastic models simulate the spatial distribution and behavior of different soil types within the trench.

Based on the project-specific working corridor, individual processes of open-cut construction are modeled separately. Five main processes have been identified: (1) topsoil removal, (2) trench excavation, (3) pipe zone construction, (4) trench backfilling, and (5) topsoil replacement. Each process model centers on an excavator that traverses the trench and moves material to its designated location. During (2) trench excavation and (3) pipe zone construction, additional transport vehicles are required to remove or deliver materials, as exemplarily shown for process (3) in Figure 2. Various logistic parameters can be adjusted within these individual process simulations. To ensure realistic representation, machinery does not operate at full capacity continuously. Instead, randomly distributed disruptions are integrated to reflect actual field conditions. Each process is simulated independently, allowing process duration and downtime to be determined individually based on the input parameters of each section.

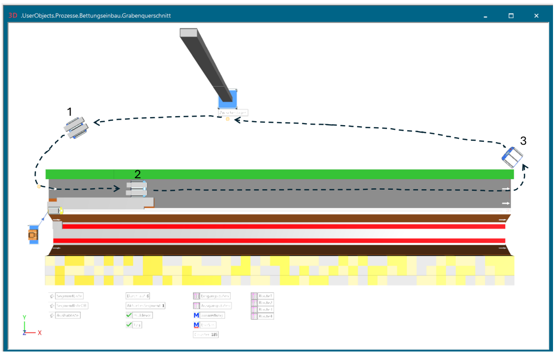

Figure 2: Parametric simulation of the pipe zone construction

These detailed process simulations provide the foundation for a holistic model that analyzes the interdependencies between different execution steps. This higher-level model is intentionally kept at a greater level of abstraction, using effort values and average durations derived from the process simulations as input parameters rather than replicating their logistical detail. At this level, tasks can be distributed across varying numbers of excavators and scheduled with different timing patterns, enabling identification of the fastest and least disruption-prone construction sequence. This combination of detailed process-level and abstract system-level simulation has proven effective for optimizing earthwork processes, as Ji et al. (2011) have similarly shown.

Simulation-Based Performance Metric Derivation

Each simulation yields performance metrics related to time, economics, and sustainability. Following the framework's bottom-up structure, these metrics are first determined for each process step based on the deployed equipment and project parameters. Then, they are aggregated at the system level. The calculations are based on a comprehensive database of effort values, cost factors, and machinery emission data provided by industry partners. This allows for the systematic comparison and evaluation of different execution variants.

Human Validation, Refinement and Final Output

The derived KPIs are evaluated based on predefined project goals by combining quantitative criteria with qualitative user judgment about the plausibility of each variant. If the resulting variants do not satisfy the specified criteria, the relevant parameters are adjusted iteratively, and a new optimization loop is initiated. This process continues until either a sufficient number of viable execution variants have been generated or the predefined termination criteria have been met. The result is a set of feasible, optimized construction scenarios that align with project-specific requirements.

Verification of the Simulation

The simulation model was developed using *Tecnomatix Plant Simulation*, with most methods implemented in the platform's native programming language, *SimTalk*. Technical verification was conducted iteratively throughout the development process using integrated debugging tools. This iterative verification process ensured that the model implementation accurately reflected the intended conceptual design.

Structured historical performance data for linear construction processes is scarce, and existing documentation is influenced by numerous confounding factors, such as weather conditions, regulatory delays, and crew-specific practices. This makes it difficult to isolate baseline process performance. Consequently, traditional validation approaches relying on historical performance data were not fully applicable. To address these limitations, the simulation model was developed in close collaboration with construction personnel, ensuring alignment with practical experience. Performance factors were verified through spot checks on active sites, and experienced professionals confirmed that the simulation produces plausible results, including realistic daily work targets.

Table 1: Simulation parameters and their value ranges

Logistic Parameter	Lower Limit	Upper Limit	Steps
Vehicle Count	1	10	1
Cycle Time [min]	15	120	15
Distance to Storage [km]	5	40	5

To further validate the realism of the simulation, systematic experiments were conducted by varying key input parameters. At this stage, only the temporal output is fully implemented, therefore, the experiments focus exclusively on construction time as the performance metric. The input parameters including vehicle count, cycle time, and distance to the intermediate storage facility were varied across the ranges shown in Table 1. These were defined by experienced site personnel to represent realistic conditions. Each parameter combination was simulated with five different random seed values to account for stochastic variability in simulation outcomes. This yielded a total of 3,200 simulation runs, covering a comprehensive and structured parameter space. The resulting simulation outputs were subjected to comparative sensitivity analyses to verify whether parameter variations produced effects on construction time and resource utilization consistent with empirical expectations and practical construction experience.

Due to their independence from logistic parameters, the processes of (1) topsoil removal, (4) trench backfilling, and (5) topsoil replacement displayed only limited temporal variability, driven primarily by randomly distributed disruptions. The resulting standard deviation was approximately 20 minutes for trench backfilling and about 9 minutes for topsoil removal and replacement. In contrast, (2) trench excavation and (3) pipe zone construction exhibited substantially higher temporal variability due to multiple logistical influences, with a standard deviation of approximately 3.5 hours for pipe zone construction and around 21 hours for trench excavation. Consequently, trench excavation emerges as the process with the greatest influence on overall schedule variability.

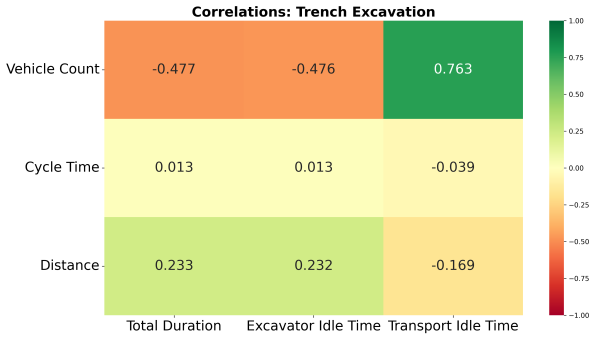

Figure 3: Heatmap of the trench excavation parameter space

To reveal the influence of different logistic parameters more clearly, a correlation analysis was conducted. The results are presented in Figure 3 and Figure 4.

The vehicle count shows a strong negative correlation with total duration (r = -0.477 for trench excavation, r = -0.464 for pipe zone) and excavator idle time (r = -0.476 and r = -0.464), and a strong positive correlation with transport idle time (r = 0.763 and r = 0.751). The parameter cycle time demonstrates minimal correlation with all output metrics in trench excavation (|r| < 0.04). In the pipe zone process, correlations are slightly higher (r ~ 0.09 for duration and excavator idle time, r = -0.312 for transport idle time). Distance to storage location shows moderate positive correlations with total duration and excavator idle time (r = 0.23 for trench excavation and r = 0.454 for pipe zone), and negative correlations with transport idle time (r = -0.169 and r = -0.179).

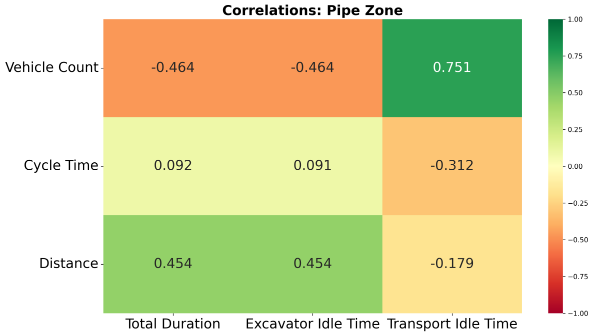

Figure 4: Heatmap of the pipe zone parameter space

Discussion and Result Analysis

The parametric validation confirmed that the modeled relationships between parameters and system behavior are plausible and aligned with observed construction practices. Increasing vehicle count effectively reduces construction time and excavator idle time by ensuring continuous excavator operation. However, beyond a certain threshold, adding more vehicles results in smaller reductions in duration while substantially increasing idle time for the vehicles. This reflects a fundamental trade-off between excavator utilization and transport fleet efficiency.

The analysis of cycle time and distance to storage reveals distinct operational characteristics between trench excavation and pipe zone construction. In trench excavation, transport vehicles travel alongside the excavator during continuous loading, making the excavator's digging speed the limiting factor regardless of vehicle timing or transport distance. In contrast, pipe zone construction involves rapid unloading where vehicles simply discharge embedment material next to the trench and depart, operating independently of the excavator. Poorly synchronized cycle times in relation to storage distance can cause multiple vehicles to arrive simultaneously, creating bottlenecks and increased idle time. Nevertheless, the influence of the cycle time remains largely negligible except for its impact on transport vehicle idle time. This is particularly favorable from a practical standpoint, as cycle time is difficult to control in real construction scenarios due to synchronized work schedules and operational constraints.

The reliance on expert judgment and parametric validation does highlight limitations imposed by the absence of comprehensive historical performance data. Ongoing efforts focus on establishing structured documentation protocols for future construction phases, enabling more rigorous quantitative validation and supporting continuous model refinement.

Table 2: Comparison with existing tools

Criterion	proposed tool	ForBAU	Jungmann
Framework type	AI-integrated simulation-based optimization	3D simulation and decision support	Digital twin-based decision support
Domain focus	Linear construction sites (trenching)	Earthwork (road construction)	Repetitive construction site processes
Primary objective	automated generation, evaluation and optimization of resource- and schedule-related execution variants	integrated data management, simulation-based process optimization, dynamic 4D construction site information modeling	real-time data-driven simulation, KPI generation and decision support through continuous model calibration
Key innovation	Automated AI-supported variant generation and optimization	Resistance coefficient-based process modeling, holistic machine fleet interaction simulation	ML-based activity recognition and real-time model calibration
Spatial resolution	process - / segment-based	voxel-based	process-based

Conclusions and Scientific Contribution

This work introduces a framework combining parametric simulation with AI-enhanced parameter optimization to support decision-making in large-scale linear trenching projects. By enabling the automated generation and evaluation of execution variants, the framework addresses a key limitation of existing decision support tools, which typically rely on manually defined scenarios.

Compared to existing approaches such as ForBAU and the digital twin-based framework of Jungmann (2025), the proposed framework is specifically tailored to linear construction sites. While ForBAU applies voxel-based terrain models for road earthworks and Jungmann focuses on continuous model calibration from real-time sensor data, the proposed approach adopts a process- and segment-based spatial resolution aligned with the characteristics of trenching projects. This reduces data requirements and model complexity while maintaining practical relevance for construction planning.

A central contribution of the framework is the generation of synthetic training data through systematic simulation of diverse construction scenarios, addressing the lack of structured historical data. This potentially enables the AI component to learn process interdependencies and identify promising parameter ranges. Parametric analyzes show that the simplified simulation captures essential dynamics, while a user-oriented design based on familiar soil classifications ensures practical applicability without requiring detailed geotechnical input.

Despite promising results, several limitations remain. Cost and sustainability indicators are only partially integrated, and validation relies primarily on expert assessment and sensitivity analysis due to limited empirical data availability. Rather than adopting a sensor-based approach as proposed by Jungmann (2025), this work relies solely on simulated synthetic data, for which initial tests deliver encouraging results. Terrain and soil modeling remains simplified, restricting the representation of spatial heterogeneity, and the framework currently covers only the open-cut construction phase.

Two directions for future work deserve particular attention. First, the AI models must be trained across a sufficiently diverse set of cross-sections and project configurations to ensure robust generalization. Should the underlying construction processes or project characteristics change significantly, retraining may be required. Ongoing efforts therefore focus on making the data generation and training workflow as reproducible as possible to minimize the overhead of future retraining cycles. Second, the current workflow depends on licensed simulation software, which may limit accessibility. Once AI models are sufficiently trained, bypassing the simulation for routine optimization tasks represents a promising step toward broader practical applicability.

Overall, the results indicate that AI-integrated methods based on simulation frameworks offer a viable path toward data-driven optimization in linear construction, even under significant data scarcity. The proposed methodology for simulation-based synthetic data generation is transferable to other construction or production processes with similarly definable constraints, providing a solid foundation for more informed planning of large-scale linear infrastructure projects.

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