Towards AI-based Optimization of human-centered and robot-assisted construction processes

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Abstract -

This research explores an innovative AI-driven approach to optimizing construction processes with a focus on human-centered design, addressing key challenges in the construction industry, such as skilled labor shortages and ergonomic risks associated with work-related musculoskeletal disorders. By integrating process design with AI-based algorithms into simulation tools, various construction process layout variants including robot-assisted scenarios can be simulated and evaluated based on user-specific key performance indicators (e.g., ergonomic score, layouting parameters) to identify optimized solutions. A data processing algorithm automates the process, eliminating the need for manual simulation variations and resulting in increased operational productivity. The AI-based system evaluates and optimizes process layouts by adjusting control parameters. A case study on a brick laying process serves as an exemplary use case, highlighting the necessity and impact of adopting process optimization. The findings emphasize the transformative potential of automated process optimization within simulation environments to rethink existing construction practices, enhance worker well-being, and boost operational productivity.

Keywords -

AI-based Learning; Simulation; Process optimization; Human Factors; Parametric Design Automation

1 Introduction

The construction industry is a crucial contributor to global economics [1]. However, it faces arising multifaceted challenges such as economic or demographic change, which worsens existing challenges [2]. In addition to inefficiencies and the slow adoption of digitalization and automation, the construction industry confronts an acute and growing shortage of skilled workers. The declining appeal of construction work as a field of employment exacerbates the physical demands on the existing workforce – who are essential to many construction processes – thereby significantly increasing the risk of work-related musculoskeletal disorders (WRMD) [3]. This widely prevalent health issue can result in premature retirement due to health reasons [4], thus aggravating the existing lack of skilled workers. To sustainably utilize human labor, construction processes must be optimized to minimize the risk of medium- and long-term health issues for workers. Hereby, Computer-Aided Process Planning (CAPP) offers a methodical option, combining a digital twin of the process containing the working tasks, which enables a realistic simulation [5]. The subsequent analysis of the simulated process gains insight to various predefined criteria. Advanced process simulations using the CAPP methodology can identify risks such as musculoskeletal disorders and serve as a foundation for human-centric optimization of construction processes. Human-centric optimized processes may represent a crucial element in addressing the aforementioned increasing shortage of skilled workers. This optimization efforts through simulation currently rely on manually iterations due to insufficient innovative approaches. Thus, each simulative change is implemented and evaluated individually, which involves a high time expenditure and complexity.

In addition to the human factors, a multitude of challenges exist in manual construction processes that can be described parametrically and, depending on the software solution, optimized in a suitable digital environment. With this premise, the number of practicable variants remains limited due to the manual processing of such simulations, which in many cases leads to suboptimal solutions and requires an innovative solution.

2 State of the Art

Process simulation is a digital tool currently implemented in various fields, such as the automotive industry [6]. This approach allows the digital production and process planning by creation of a digital process twin by the utilization of suitable CAPP software [5]. The ema Work Designer by imk Industrial Intelligence or Tecnomatix by Siemens for instance represent such a CAPP tool including digital human models. Integrating human actions into the digital process enables the evaluation of process ergonomics based on various criteria that represent the physical load on the worker's body, whether caused by motion alone or by external forces acting on it. In the literature, several well-established evaluation criteria are widely recognized. These ergonomic evaluation criteria, which are particularly relevant in the context of this research, include:

- Ergonomic Assessment Worksheet (EAWS) score: Categorized into three groups, the EAWS score within a range of 0 to 25 represents a process without risk to get affected by WRMDs resulting in musculoskeletal damage. The range of 25 to 50 shows middle risk with recommendation to adapt these processes in a human-centered way, whereas values of more than 50 in EAWS score relate to high risk to suffer from WRMDs and therefore indicate the need for urgent process adaptation. Including the process duration, this commonly used criteria considers the posture combined with external loading [6].
- NIOSH: The NIOSH risk index represents a measure for the risk of adopting WRMDs caused by human lifting activities. This approach considers detailed parameters, such as weight of the object or vertical and horizontal location of object and target [7].
- RULA/REBA: The Rapid Upper Limb Assessment (RULA) and Rapid Entire Body Assessment (REBA) scores indicate the risk of getting affected by WRMDs analyzing body and segment angles, and repetitions of movements. RULA and REBA are based on assessment worksheets calculating an index considering single body part postures in addition to loading on the body resulting in a score from 1 (acceptable risk) to 7 in RULA respective 11 and more in REBA (high risk) [8]. In contrast to EAWS, RULA/REBA do not consider body postures and their duration [9].

As the topic of human-centered work process in construction is gaining relevance [10, 11], Kulkani and Devalkar investigated the ergonomic influence on construction workers in various construction tasks (granite cutting, brick work, shuttering, plastering and material transportation) by applying the RULA and REBA index [8]. Resulting in evaluation scores of 6 and 7 in RULA as well as 11 and more in REBA, the investigated construction processes indicate a high risk of the worker adopting WRMDs.

Schmailzl et al. proposed in prior work a framework for decision making regarding the degree of automation of an exemplary brick laying process [12]. To represent a process reproduction as close to reality as possible, motion capturing was used to record the construction worker's movements. Therefore, this approach evaluates the captured brick laying process regarding ergonomics of the worker incorporating the EAWS score as well as task duration within various initial layouts as well as the influence of integration of a robot as assistive technology. The results, showing an EAWS score of up to 154, clearly highlight the need to optimize certain construction processes with a focus on the human worker.

In contrary to standardized production lines, construction sites are characterized by dynamic changing conditions. However, recurring and standardized subprocesses, such as bricklaying, enable the implementation of CAPP software. Currently, even when these types of processes are planned and optimized, they are still manually developed and adjusted by layout designers. A comprehensive parametric design of layouts offers considerable advantages, as changes can be implemented quickly and effectively. Both in production factories and in the construction industry, the ability to make adaptive adjustments is becoming increasingly important, particularly due to the growing demand for customized production and buildings. Despite the great potential of artificial intelligence (AI) and algorithmic approaches in the field of process optimization, there are currently – due to the best knowledge of the authors – a lack of scientific studies that comprehensively address the forementioned process algorithmic approaches combined with ergonomic evaluation scores applied to the construction industry. Parametric design is frequently used in the construction industry, however, mainly in the context of building modelling and less in classical project management. As Abioye et al. showed in their literature review, AI-based optimization seems to be a promising approach for improving processes in the AEC industry [13]. The study by Bergmann shows how parameters simplify the control of an environment and which advantages result from this [14]. The use of generic approaches for optimization can improve the efficiency and performance of production systems significantly. Of particular interest are genetic algorithms (GAs), especially the NSGA-II variant, because they are able to handle numerous parameters and enable multi-objective optimization. Another example from the warehouse sector shows that alternative unconventional layout concepts, such as non-orthogonal shelving arrangements or v-shaped aisle systems, can offer considerable efficiency gains [15]. Investigating different layout options is currently a time-consuming manual task that limits the potential variance of the layout. A tailored algorithm could perform this task in a fraction of the time required by a designer while also identifying irrational but applicable solutions. The use of parametric algorithms in combination with detailed simulations enables the adjustment of critical layout parameters – such as the width of the aisles, the number of racking bays, or the capacities – which optimizes the flow of material and the use of storage space.

Building on the application of AI-driven optimization methods, such as those used in logistics, this research aims to transfer and adapt the concept of automated optimization to the construction industry, focusing on applications where fundamental principles, such as material transportation and storage, are analogous to those in other sectors.

Derivated from, i.a., the findings of Schmailzl et al. [12], this research aims for and proposes a concept for automated generation of process simulation variants, their evaluation as well as AI-based optimization in the field of construction in order to exceed a limited number of simulation cycles as in manual simulation. Additionally, the approach has the potential to reduce the risk of workers developing WRMDs, thereby promoting a more sustainable and attractive utilization of the workforce in the construction industry.

3 Methodology

Given the challenges faced by the construction industry, particularly the high health risks associated with construction work [3] and the limited adoption of digitalization, this research proposes a methodological approach for automated software pipeline encompassing an AI-driven optimization of construction processes with a focus on human-centered design. This section elaborates the concept of parametric process generation, the automation of simulation & evaluation and AI-based optimization.

The presented concept illustrates the intended functionality of a fully automated optimization loop; at this stage, intermediate manual data transfer steps are necessary due to current software capabilities regarding API connectivity, which currently restricts execution to a limited number of optimization cycles. Potential solutions to enable complete automation are discussed further in Section 5.

3.1 Concept

Figure 1 illustrates the proposed methodology. Taking a holistic perspective on construction processes, it presents a workflow comparison between traditional process optimization methods and the enhanced efficiency achievable through AI-based algorithms. With the ongoing digitalization of the construction sector, simulating models and components using advanced software has become a standard practice to optimize building designs prior to physical implementation. This approach extends to factory layout planning, where efficiency improvements are achieved through detailed simulations.

The concept shown in Figure 1 outlines how specific construction tasks, such as bricklaying or concrete pouring, can be integrated into CAPP software. The initial step involves the digital, parametric representation of tasks, incorporating parameters such as object positions and material information. This parametric control can be controlled by a software pipeline and enables a systematic as well as adaptable process. Process layout designers typically create an initial setup based on their expertise, but this manual approach often relies on subjective judgment. Analyzing key performance indicators (KPIs), such as ergonomic factors, material flow efficiency, or pathway criteria, offers a preliminary evaluation of the process. Without a defined baseline incorporating KPIs, comparative assessments regarding the process quality remain limited. The optimization loop in Figure 1 demonstrates two distinct approaches. The dashed line 1 illustrates the traditional method, which is characterized by the manual adjustment of parameters followed by manual repetition of simulations and the comparison of outcomes. Due to the time-intensive nature of this simulation scenario, this restricts the exploration of possible variants. Conversely, the second approach leverages AI-driven algorithms, which autonomously modify parameters and executes numerous simulations. The results are stored systematically and analyzed in relation to the chosen parameters.

By selecting appropriate algorithms, the optimization process achieves superior KPIs and significantly reduces manual work for achieving an optimized solution. AI-based methods are characterized by the recognition of correlations between parameter adjustments and their effects on the results, thus enabling more efficient and precise optimization.

Consequently, this advanced simulation framework provides a robust foundation for optimizing construction sites, enhancing process quality, and improving conditions based on specific KPIs and therefore serves as a basis to prevent the risk of getting affected by WRMDs delineating an approach to reduce the immense lack of skilled workers.

3.2 Structure of the parametric layout

To enable a layout to be fully controlled through parameters, an external structure must first be established that allows such control. This requires assigning unique parameter names to all values within the system, ensuring clear identification and reference. With this parametric structure in place, the entire layout can be adjusted flexibly by simply entering specific values. Moreover, the parametric system should allow the selection of different objects to enhance the realism of the scenario. The selection of specific process components was investigated in prior work [12]. Based on these outcomes, boolean operators must be incorporated to select the desired objects, with all objects existing in parallel within the system to maintain consistent parametric relations.

In case of manual adjustments, these are performed directly within the software and can be tailored to specific needs, offering flexibility, but often at the cost of time and

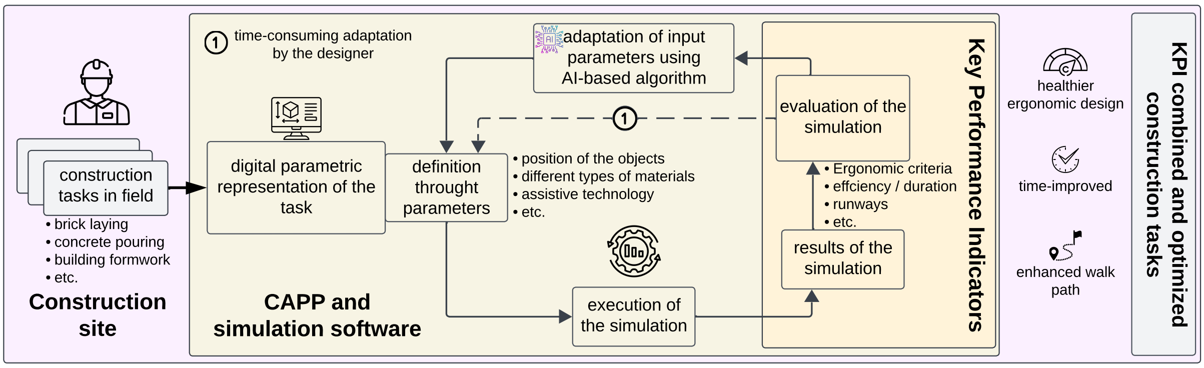


Figure 1. AI-based process optimization method: Is applied to construction tasks (left) optimized by predefined KPIs (right). The green CAPP box represents the automation of the manual workflow, with AI adapting parameters to generate and process multiple variants.

efficiency. To integrate algorithms into this process, an import and export interface for the parameters is essential.

Depending on the software, it may be necessary to export the entire setup or model and reimport it after structural modifications. More advanced software solutions allow the export of parameters alone, which can then be modified and reimported. This leaner approach significantly reduces time intense computational processes and enhances workflow efficiency.

Hereby, a well-developed API interface enables effective collaboration with algorithms and supports streamlined and time-efficient adjustments of parametric structures. Even rudimentary APIs often provide basic import and export functionalities, which are sufficient to implement algorithms into the workflow.

3.3 Validation of the simulation results

The validation is a critical step in process design, it gives value feedback to the planner to improve the setup. For every process, specific KPIs must be defined to serve as measurable benchmarks for future optimization. Efficiency remains a fundamental KPI, often including metrics such as cycle time, resource consumption, and material pathways. In manufacturing, this KPI play a central role in reducing costs and improving production rates. The ergonomic score is meanwhile gaining importance and is increasingly used, especially in manufacturing processes. In Germany, the Load Handling Ordinance requires risk assessments but does not consider details like weight limits or biomechanical impacts on the human [16]. In practice, a 25 kg limit is often used for manual lifting, but factors like carrying distance can greatly affect the biomechanical evaluations. In general, planners must evaluate trade-offs between competing KPIs, as optimizing one parameter may impact other parameters. Storing and documenting process results is essential for thorough validation. This includes capturing input parameters, such as material specifications or positions, alongside output metrics as discussed. Such data build the basis for advanced AI-driven optimization techniques. By analyzing data, AI algorithms can identify patterns and make targeted adjustments, leading to more efficient and streamlined processes.

3.4 Optimization of the results using AI

Optimization tasks require a careful selection of algorithms, each offering distinct advantages depending on the problem and context. For instance, gradient-based algorithms rapidly converge to a single optimal solution by iteratively improving from an initial guess, ideal for clearly defined, differentiable goals. However, for complex problems with conflicting objectives, genetic algorithms (GAs) are particularly effective in finding optimizations due to their inherent capability to manage multiple trade-offs simultaneously. The NSGA-II algorithm applied by Bergmann is a recognized method for multi-objective optimization [14], explicitly chosen in this study for its robust handling of multiple interdependent KPIs and its ability to maintain diverse, balanced solutions.

The NSGA-II algorithm refines a set of solutions step by step using evolutionary principles. Starting with random solutions, each computation repetition represents different combinations of parameters, resulting in specific outcomes. These outcomes are evaluated based on defined KPIs, such as efficiency or human ergonomics. The results are then ranked into groups, so-called Pareto fronts, with the best, non-dominated solutions placed in the first front. To ensure diversity, the algorithm calculates a crowding distance, spreading solutions evenly across the objective space.

The best solutions from the first front are selected and combined to create new combinations of input parameters by recombination. Additional mutations introduce small variations of the parametric to explore new possibilities and avoid premature convergence. This process of evaluation, selection, recombination, and mutation recurs iteratively until a predefined stopping condition is met, such as reaching a set number of generations or achieving convergence.

The result is a Pareto front, a collection of high-quality solutions that balance conflicting objectives. Decision-makers can choose the most suitable solution from this set, depending on their specific priorities and constraints. This choice typically requires additional context-specific criteria or weighting of KPIs – such as prioritizing ergonomics over productivity. This makes the NSGA-II especially effective for problems involving multiple competing objectives. Additionally, the NSGA-II qualifies as an AI-based approach due to its use of evolutionary mechanisms and heuristic search strategies. Instead of exhaustively evaluating all possibilities, it focuses on exploring the most promising regions of the solution space efficiently.

Concluding, this flexibility and efficiency make the NSGA-II a highly promising choice for multi-objective optimization problems, especially in dynamic and constrained environments.

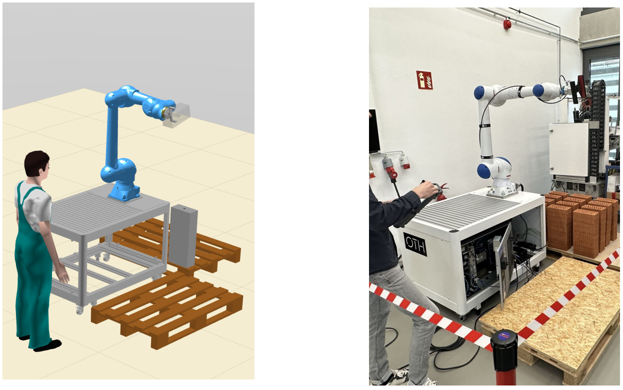
4 Application example: Brick laying process

The potential applications for this concept are diverse and can be implemented across various construction processes. In this section, we present a specific use case as an example of how the concept can be applied. As the initial scenario, we use a brick laying process that has been previously performed and analyzed in prior research.

Incorporating digital human models, the software is capable to consider human process behavior for a more realistic process representation. Besides the standard movements as provided by the algorithms of the software, human motion can be integrated from motion capturing. The motion data was recorded via an Inertial Measurement Unit (IMU) based Motion Capturing system as the orange sensor attachments in Figure 2 represent. The process was developed within the emaWD simulation software, a powerful tool capable of modeling complex setups and offering a range of advanced analytical functions. emaWD is widely utilized for factory layout simulations, providing comprehensive feedback to designers across multiple KPIs, including all those relevant and previously discussed in earlier sections. These sensor units combine an accelerometer, magnetometer and gyroscope to determine the human movements [17].

In manufacturing processes, robots often play a significant role. The software enables the integration of a vast selection of robot models, each with diverse functionalities and gripping mechanisms. Moreover, the software allows

Figure 2. Motion Capturing of a brick laying use case at the Building Lab of Ostbayerische Technische Hochschule (OTH) Regensburg.



(a) Simulation of a brick laying process with the optimization of the integration of the robot HC10 by Yaskawa.

(b) Realization of simulated and optimized brick laying process integrating the Yaskawa HC10 at the Building Lab of OTH.

Figure 3. Optimized robot-assisted brick laying process towards the human well-being.

customization and restrictions for robots, accommodating specific models that may not be natively included. The ability to incorporate and program these robots within the algorithm significantly broadens the scope of potential solutions, potentially leading to entirely novel configurations with drastically altered KPIs. While simply adding a robot to a process might seem to improve performance, it also introduces additional factors such as flexibility, feasibility, and cost, which must be carefully evaluated. These considerations are critical to ensure that the benefits of robot integration outweigh the associated challenges. Later in this section, the parametric integration of robots into the optimization process will be explored in greater detail. Although the software is not originally designed for construction tasks, designers can creatively adapt it to simulate various building processes, including the one described in this study.

Besides the application of robotic devices, the earlier study highlights the significant impact of layout changes on key performance indicators (KPIs). In this process, depending on the four manually implemented layout options, the KPIs EAWS score, process duration and walk length were explored. The four layout variants differed as follows:

1. Original process: The original process describes a brick laying process done by a human worker, who transfers bricks from a pallet to a target position.
2. Repositioning of the pallet: Based on the original process, the pallet position was shifted 2 meters to opposite direction of the brick target position (see Figure 4).
3. Adaptation of brick material: Based on the original process, the brick type was changed resulting in a weight reduction from 4.5 kg to 2.8 kg for a same-sized brick.
4. Combined adaptation of brick material and pallet repositioning: This scenario represents both aforementioned repositioning of the pallet and adaptation of brick material.

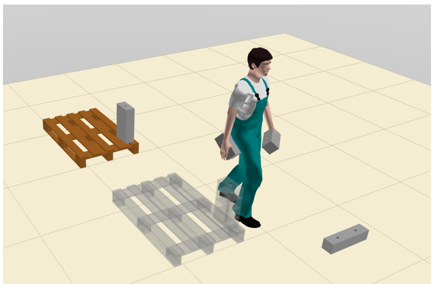


Figure 4. Repositioning of brick storing pallet in a distance of 2.0 m to the original pallet position, depicted as gray copy.

The outcomes were systematically compared, with KPIs serving as the metrics to evaluate the performance of each variation.

Interestingly, the research revealed that certain irrational layout modifications resulted in better outcomes. All exemplary executed layout configurations were manually designed by planners and executed within the emaWD simulation software. The resulting processes exhibited varying KPI outcomes, highlighting the challenge of identifying the optimal layout. This case study demonstrates the complexity of achieving optimal solutions, even for a straightforward and repetitive process. When additional parameters and variables are introduced, finding layouts that improve all required KPIs simultaneously becomes nearly impossible without systematic optimization. This scenario emphasizes the necessity of integrating the proposed concept into the exemplary brick laying process to address these challenges effectively. The software already supports various export and import formats as essential basis for robust data transfer. An export method is provided by the emaWD Wizard, a data transfer assistant that generates an *xlsx*-file to represent the emaWD setup. This file has the capability to define all tasks, objects, and executing agents – whether human models or robots – completely with coordinate information. For the demonstration of the concept, the brick laying process was exported using the Wizard and described in a structured text format. At this stage, the *xlsx*-file can be accessed via a Python script, allowing extraction, manipulation, and adaptation of all relevant data. In this example, product information such as the weight and dimensions of the bricks was modified within the script and reflected in the *xlsx*-file. As noted earlier, every task and component can be adjusted within the spreadsheet. The algorithm modifies these layout parameters and updates the setup within the *xlsx*-file. Upon importing the updated spreadsheet into the emaWD software, a new simulation is executed. The results, expressed as KPIs, provide immediate feedback to the designer through various representations. These KPI outputs can also be exported in simpler formats, such as *csv*-files, given their reduced complexity compared to the process setup. This exported data is then integrated back into the Python script, supplying the algorithm with essential feedback from the results. The connection between input parameters and KPIs is pivotal, as it forms the foundation of the optimization loop. This single optimization cycle, with changed input parameters, is repeated multiple times to generate a diverse and extensive first dataset with different parametric, enabling the algorithm to identify non-dominated solutions across multiple Pareto fronts.

After the initial round of creating a broad dataset, the algorithm proceeds as outlined in subsection 3.4 selecting the most relevant data to further refine and improve the process. Currently, emaWD does not offer a public API interface, which limits its ability to fully support the intended operation of the optimization loop. The absence of an API interface prevents direct control over the software pipeline, hindering the algorithm's ability to efficiently optimize the parametric configurations and limiting its potential to enhance the parameters in a more effective and automated manner.

5 Discussion

This research explores the implementation of an automated AI-based approach for optimizing construction processes with a focus on the human worker.

The application of proposed research within an exemplary brick laying use case as demonstrated in section 4

Table 1. Overview of the simulation results and KPIs corresponding to the four considered design variants.

Design Variant	EAWS Posture Score	EAWS Load Score	**Sum EAWS Score**	Distance [m]	Duration [s]
1	19.5	140	**159.5**	4.7	47
2	8.5	140	**148.5**	16.5	55
3	37	110.5	**147.5**	4.7	47
4	27	110.5	**137.5**	16.5	50

primarily considers human-related KPIs as a measure to optimize construction processes. In particular, the EAWS score as measure for the worker's ergonomics is utilized in the application example. In general, according to the EAWS scores as depicted in Table 1 it seems that the human experiences lower risk of WRMDs when minimizing the load on the human body, as expected. Furthermore the EAWS increases when reducing the pathway as intuitive assumption would suggest. However, the subcategories load score and posture score of the EAWS cannot be explained by intuitive assumptions. Whereas the material handling score decreases from a value of 140 in the original process to a value of 110.5 in the brick weight reduced process as demonstrated in section 4, the relating posture scores show contradictory behavior. Consequently, the optimal resulting EAWS score can hardly be predicted by intuitive assumption of process design variants. Currently, the emaWD software only allows manual import and export of the KPIs and parametric, creating a bottleneck for efficient algorithm implementation. Integrating an automated AI-based process optimization is likely to enable the finding and application of unconventional and unintuitive parameters in design variants within simulation, which is an essential basis for effective process optimization in general.

The proposed algorithm represents an innovative approach to process optimization, enabling the simultaneous optimization of multiple KPIs. Particularly in optimization scenarios involving human factors alongside efficiency and other metrics, it is essential to identify balanced compromises that address all relevant aspects effectively. However, the effective application of AI-based tools relies on seamless data transfer and access through a robust API that allows algorithms to interface directly with simulation software. Despite the growing capabilities of AI-driven approaches, seemingly suitable simulation tools often lack the necessary API functionalities. This limitation significantly constricts the potential for automating and optimizing processes efficiently. Addressing this gap by developing powerful APIs would unlock new possibilities for improving existing workflows and overcoming current time-induced constraints through leveraging AI-based optimization.

Process simulation tools are already commonly used in various industrial fields, such as the automotive industry [18]. Given their ability to optimize production setups before realization, these simulation tools hold great promise for prefabrication processes within the construction sector. Specifically, the proposed optimization approach is particularly suited to prefabricated building components (e.g., wall elements, modular units) or standardized infrastructure elements (e.g., precast bridge segments, tunnel lining segments), where stable, predictable conditions prevail. Direct implementation on traditional, dynamic construction sites remains challenging due to variability; thus, prefabrication represents the primary and most effective context for applying the proposed simulation-driven optimization method.

This work emphasizes the critical role of the human worker, especially in mitigating issues related to health risks and improving working conditions. By automating process simulations, this approach has the potential to contribute to more efficient and effective human-oriented optimization methods.

While AI-driven optimization offers significant advantages, it also involves trade-offs. Implementation costs – such as computational resources and robotics integration – must be weighed against potential efficiency gains. Additionally, selecting appropriate hyperparameters is essential, as improper tuning can compromise algorithm stability and the quality of optimization results.

6 Conclusion

This research highlights the pressing need for automated, AI-based process optimization in the construction industry, emphasizing the importance of human-centered design. The proposed conceptional holistic approach demonstrates the potential to address critical challenges by identifying and analyzing complex parametric structures, simulating diverse scenarios, and evaluating specific construction tasks to achieve optimized process solutions. The ability of such systems to identify unconventional solutions opens up new possibilities for process improvement, alongside with an increase in simulation efficiency. Crucially, the development of robust APIs is identified as a foundational requirement to fully realize the benefits of this approach. When seamless integration via robust APIs becomes available, the proposed approach has the potential to unlock the full capabilities of AI-based optimization, driving a more efficient, adaptive, and sustainable construction sector while significantly improving human factors and fostering safer and more worker-centric construction processes.

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