Evaluating Incremental Automation Strategies in Concrete 3D Printing

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Abstract

Concrete 3D printing has significant potential to automate construction by improving productivity and reducing project costs. However, auxiliary workflows such as filler placement, reinforcement positioning, and grouting are typically performed manually or through semi-mechanized processes, limiting overall automation benefits. This study proposes an automated methodology for the fabrication of reinforced cement concrete (RCC) filler slabs using compressed polyethylene (PE) waste as filler elements. A conceptual dual-gantry Concrete 3D Printing system is proposed, with one gantry dedicated to concrete deposition and the other to automated placement of recycled plastic fillers and reinforcement cages. A case study is used to analytically evaluate the techno-economic performance of the proposed setup. . In the case study, automation features are systematically introduced by integrating additional robotic equipment and tooling modules. The performance of each automation configuration is evaluated using two proposed metrics: the Automation Efficiency Index (AEI) and Marginal Automation Utility (MAU), both formulated as functions of project time and total overhead cost. The results demonstrate the potential of integrated 3D printing and robotic automation to optimize construction time and cost while identifying the automation saturation point beyond which additional automation yields marginal benefits. The proposed evaluation framework provides a generalizable methodology for assessing automation alternatives in construction additive manufacturing workflows.

Keywords – Concrete 3D printing, filler slabs, dual-gantry, Automation Efficiency Index, Marginal Automation Utility.

1 Introduction

Concrete 3D printing has the potential to transform the construction industry in terms of productivity, cost effectiveness, and environmental sustainability. 3D printing can help the construction industry by improving productivity, overcoming skilled labour shortages [1–3], and increasing safety at off-site plants and on-site construction. 3D printing also eliminates the need for formwork, offering geometric flexibility and enabling significant material savings through structural optimization [4, 5]. Though Concrete 3D printing has been highlighted as a construction automation technique, various workflows in it, like picking and placing of reinforcement and grouting, are still done either manually or using mechanized techniques. This limits the potential benefits of automation and reduces the overall productivity gains of concrete 3D printing.

In order to overcome the lack of automation in concrete printing [6] demonstrated a concept for 3D printing an RCC filler slab using a gantry-type 3D printer integrated with a robotic gripper to automate the precise placement of filler elements and reinforcement cages and casting of filler slabs. This study showed the potential of integrating concrete 3D printing and automation, the integration of pick-and-place automation for filler and reinforcement placement was shown to improve process control and reduce manual intervention. However, the automation configuration was limited to a single gantry system performing both printing and auxiliary tasks, which resulted in increased cycle time and overhead cost, limiting practical feasibility. The present study extends this baseline configuration by exploring incremental automation architectures and proposing a quantitative decision-making framework to determine the optimal automation configuration.

Robotic pick-and-place operations are widely used in industrial automation and have been explored in construction robotics and additive manufacturing [7–9]. However, existing studies predominantly treat pick-and-place operations as separate system modules and integrated pick-and-place and dispensing architectures for construction additive manufacturing remain largely unexplored.

Decision-making for automation alternatives has been addressed using financial metrics, multi-criteria decision-making (MCDM) methods, and multi-objective optimization approaches. Financial indicators such as ROI and NPV are widely used but do not capture productivity gains or incremental automation configurations. MCDM techniques such as AHP, TOPSIS, and fuzzy models have been applied in construction automation but rely on subjective expert weighting [10–12]. Multi-objective optimization methods are computationally intensive and rarely translated into actionable automation design tools[10, 11]. Moreover, existing frameworks treat automation as static alternatives and lack marginal decision rules to identify optimal automation levels and saturation thresholds. Therefore, integrated frameworks combining global benchmarking and marginal decision metrics remain lacking, which this study addresses.

This study proposes a dual-gantry robotic concrete 3D printing system with an integrated pick-and-place and filler-dispensing mechanism and introduces a quantitative automation decision framework to evaluate incremental automation strategies. The framework integrates the Automation Efficiency Index (AEI) with a Marginal automation utility (MAU) metric to systematically determine the optimal configuration for automation and techno-economic trade-offs. The framework is analytically evaluated through a simulated case study of concrete 3D printing of a 6m x 6m RCC filler slab.

2 Materials and Methods

2.1 Baseline Automation Configuration

The baseline configuration (ND) is adopted from study conducted by [6]. The authors present an automated methodology for 3D printing reinforced concrete (RCC) filler slabs using mechanically compressed polyethylene (PE) waste as filler material. In this configuration, a single gantry-type 3D printer equipped with a robotic gripper performed all tasks, including concrete extrusion, reinforcement placement, and filler placement. This system represents the minimum automation configuration and is used as the reference case for evaluating incremental automation alternatives in the present study Figure 1 represents plan view of the baseline while Figure 2 and Figure 3 represent the CAD model and an early physical prototype of this baseline single-gantry integrated concrete 3D printer, respectively..

The printing has been carried out in three parts: cover layers, compression zone, and tension zone printing shown in Figure 4 . The sequence of printing which is common for all the alternatives is as follows:

1. Printing of Cover layer
2. Robotic placement of reinforcement cages using a pneumatic gripper.
3. Robotic placement of PE filler elements picking and placing one by one from the recycle plastic filler stack as shown in Figure 1**.**
4. Extrusion printing of top cover and casting of the compression zone.

The study highlighted the sustainability potential of using concrete 3D printing integrated with automation techniques. A case study of printing a 6m X 6m RCC filler slab was used to illustrate the concept proposed. Table 1 highlights the major results of the study.

Table 1 Results of concrete 3D printing of 6m X 6m RCC filler slab using single-gantry 3D printer

Metrics	Unit	Value
Carbon Emission Saving	$kgCO_2$ eq.	1286 (37%)
Time for Printing	hours	42
Time for Placing Rebars	hours	0.5
Time for Placing Fillers	hours	39
Total Time	hours	81.5
Overhead Cost	INR.	2,16,000

Despite achieving 37% carbon emission reduction, the baseline system exhibited limited operational performance, with filler placement time comparable to printing due to sequential placement and single-gantry operation. The total fabrication time of 81.5 h is impractical for industrial deployment, motivating the adoption of parallelized, integrated automation strategies.

2.2 Proposed Dual-Gantry Setup

To overcome the limitations highlighted in section 2.1, this study proposes a conceptual design for a dual-gantry concrete 3D printing setup, as shown in the CAD model in Figure 5. While the baseline ND system relies on a physical prototype, the proposed dual-gantry architecture and filler dispenser are currently evaluated conceptually.This new setup has two gantries one gantry is dedicated for concrete 3D printing and the other gantry consist of a robotic arm with filler dispenser for picking and placing of reinforcement cage and compressed Polyethylene fillers. This introduces parallel operations eventually reducing the overall project duration.

The filler dispensing mechanism shown in Figure 6 enables automated deployment of compressed polyethylene fillers using a vertically stacked storage column and a servo-driven ball screw actuator for controlled single-element release. A robotic gripper places the filler within the printed tension zone. The ball screw mechanism provides accurate and repeatable dispensing under varying stack loads, and synchronization with the gantry controller allows coordinated dispensing and placement, significantly reducing manipulation time and improving system efficiency.

2.3 Incremental Automation Alternatives

While the proposed dual-gantry architecture enables parallel execution of printing and auxiliary manipulation tasks, automation in concrete 3D printing is not binary but exists across multiple possibilities exist for system integration and robotic deployment. This study evaluates incremental automation configurations, ranging from the baseline single-gantry system to dual-gantry systems with integrated dispensing and multiple robotic arms.

To quantify the impact of incremental automation on project time and cost, a resource-constrained scheduling model was developed. The printing gantry, pick-and-place gantry, robotic arms, and dispensing system were modeled as constrained resources with defined task precedence relationships. Project duration was computed considering parallelization and resource dependencies, while overhead costs were estimated from equipment capital cost, energy consumption, and supervisory labor requirements. The interdependencies were modelled based on the task sequencing described in **Section 2.1.**

Although incremental automation is expected to reduce project duration through parallel task execution, it also introduces additional capital and operational costs. Consequently, increasing automation does not necessarily result in optimal techno-economic performance, and a systematic decision framework is required to identify the optimal automation configuration.

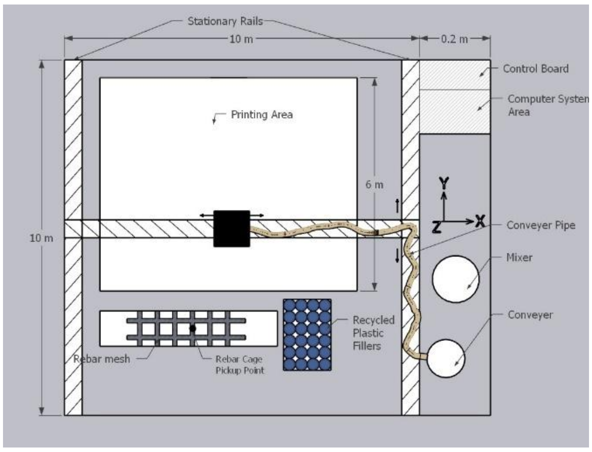

Figure 1 Plan view of the 3D printing system integrated with automated pick and place function.

2.4 Decision-Making Framework for Optimal Automation Configuration

While scheduling-based analysis quantifies time and cost for each automation configuration, these metrics alone do not indicate the optimal automation configuration. Hence, a quantitative decision framework is introduced to benchmark automation performance and identify the techno-economically optimal configuration.

2.4.1 Automation Efficiency Index (AEI)

To benchmark the overall techno-economic performance of different automation configurations, this study introduces the Automation Efficiency Index (AEI). The AEI quantifies the combined effect of productivity improvement and cost reduction relative to the baseline configuration. Let T_0 and C_0 denote the project duration and overhead cost of the baseline (ND) configuration, and T_i and C_i denote the corresponding values for automation configuration i.

Then AEI for the configuration i is defined as:

$$AEI_i = \left(\frac{T_0}{T_i}\right) \times \left(\frac{C_0}{C_i}\right)$$

The AEI is a normalized composite efficiency metric: values greater than unity indicate improved performance relative to the baseline, and higher AEI values correspond to more efficient automation configurations. By integrating both productivity and cost into a single metric, AEI provides a global benchmark for comparing alternative automation architectures.

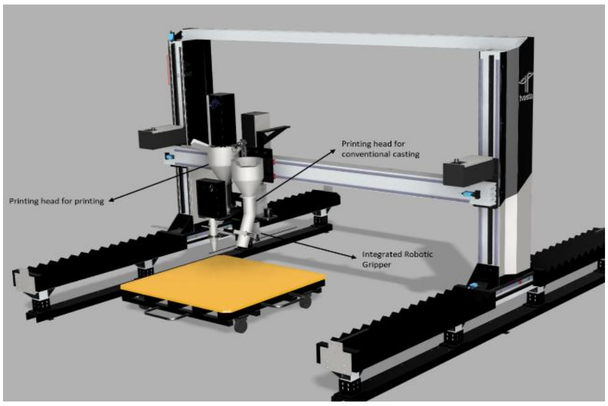

Figure 2 3D CAD model of the baseline single-gantry concrete 3D printing system (ND) integrated with an automated robotic gripper for pick-and-place functions.

Figure 3 An early physical prototype of the baseline single-gantry design (ND) integrating 3D printing with robotic pick-and-place features.

2.4.2 Marginal Automation Utility (MAU)

While AEI provides a global benchmarking metric, it does not capture the incremental benefit of adding automation resources. Therefore, a Marginal Automation Utility (MAU) metric is introduced to evaluate the marginal techno-economic benefit of transitioning from one automation configuration to the next.

First, a normalized utility function is defined to integrate time and cost objectives:

$$U_i = w_t\left(1 - \frac{T_i}{T_0}\right) + w_c\left(1 - \frac{C_i}{C_0}\right)$$

where w_t and w_c are weighting factors representing the relative importance of productivity and cost, respectively, and $w_t + w_c = 1$. In this study, equal weights are assumed.

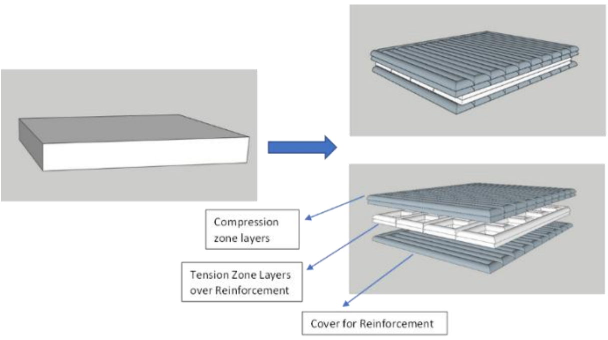

Figure 4 Representation of a Conventional Slab (Left). 3D printed slab (Right Top). Different layers of 3D printed slab (Right Bottom)

The marginal automation utility for configuration i is then defined as:

$$MAU_i = U_i - U_{i-1}$$

Positive MAU values indicate that the additional automation configuration provides net techno-economic benefit, whereas negative values indicate diminishing returns or over-automation. The MAU metric, therefore, serves as a marginal decision criterion for automation expansion.

2.4.3 Integrated Automation Decision Strategy Using AEI and MAU

The AEI and MAU metrics are integrated to support systematic automation decision-making. AEI is used as a global benchmarking indicator to rank automation configurations based on combined productivity and cost efficiency, whereas MAU is used as a marginal decision criterion to determine whether additional automation resources provide meaningful incremental benefits.

The optimal automation configuration is identified by framework combining these metrics as shown in Figure 7. The proposed framework thus provides a quantitative decision-support methodology for automation planning in construction additive manufacturing, enabling stakeholders to balance productivity gains and overhead costs when designing robotic construction systems.

3 Results and Discussions

3.1 Resource-constrained scheduling

A case study is used in this study to analytically evaluate the scheduling and techno-economic performance of the proposed dual-gantry setup and the decision-making framework.

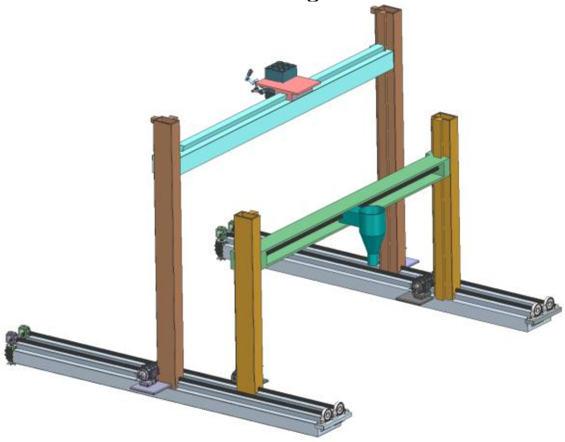

Figure 5 Proposed Dual-Gantry Setup

A 3D-printed RCC filler slab with a width of 6 m and a length of 6 m has been considered. The slab depth is 230 mm. Since physical prototyping and constructing all multi-robot-arm configurations is not economically feasible, the total project duration for the baseline (ND) and incremental automation configurations was estimated using a resource-constrained scheduling software. The printing gantry, pick-and-place gantry, robotic arms, and filler dispensing system were modelled as constrained resources, and task precedence relationships were defined for extrusion printing, reinforcement placement, and filler placement operations. For each automation configuration, tasks were scheduled based on resource availability and parallel execution opportunities, enabling explicit quantification of idle time, resource contention, and parallelization benefits. The resulting project duration represents the makespan of the scheduled task network and is reported for all configurations in Table 2 .

The equipment cost for each automation configuration was decomposed into three components: (i) fixed cost, (ii) idle cost, and (iii) usage cost. This decomposition enables integration of economic modelling with the scheduling framework and provides insight into how automation affects cost structure.

Fixed Cost (C_f): Fixed cost represents the costs incurred because of the installation of the setup, and training and education of the operators and labourers.

Idle Cost (C_i): Idle cost accounts for the cost of automation resources during periods when they are available but not actively performing tasks due to precedence constraints or synchronization delays. Idle cost includes depreciation, standby power consumption, and supervisory labour associated with idle equipment.

Usage Cost (C_u): The operational cost incurred when equipment is actively performing tasks. This includes electricity consumption for motors and actuators, wear-related maintenance cost, and active labour supervision.

The Table 3 shows the costs calculated for each resource used, and the Table 2 shows the total overhead costs for different alternatives.

ND represents 3D printer with single gantry and no filler dispensers, D-xR represents 3D printer with dual gantry having “x” number of robotic arms in the gantry dedicated for pick and place operations. The following nomenclature is adopted to represent the different configurations throughout the paper.

3.2 Automation Efficiency Index and Marginal Automation Utility

3.2.1 AEI-Based Global Benchmarking of Automation Configurations

The Automation Efficiency Index (AEI) was computed for all automation configurations using the project duration and overhead cost values reported in **Table 4**. The baseline configuration (ND) required 80 h and an overhead cost of INR 216,533, whereas automation configurations significantly reduced both time and cost.

Figure 6 Filler Dispenser

The results indicate that the introduction of automation yields substantial improvements in techno-economic performance. The D-0RA configuration reduced the project duration from 80 h to 12 h and overhead costs to INR 27,450, resulting in a major increase in AEI. Further automation with a single robotic arm (D-1RA) reduced the project duration to 9 h and overhead costs to INR 21,075, resulting in the highest AEI improvement among the tested configurations.

However, beyond this level, additional automation led to diminishing efficiency gains. While D-2RA and D-3RA configurations further reduced project duration to 8.5 h and 8 h, respectively, the overhead cost increased to INR 21,483 and INR 22,016. The D-4RA configuration showed no further reduction in project duration (8 h) but exhibited a substantial increase in overhead cost to INR 27,674, resulting in a decline in AEI. This trend indicates that automation does not improve system efficiency in a monotonic manner and that excessive automation can reduce overall techno-economic performance.

3.2.2 Marginal Automation Utility (MAU) and Diminishing Returns Analysis

To evaluate the incremental benefit of new automation configurations, the Marginal Automation Utility (MAU) was computed for successive automation configurations. MAU quantifies the marginal techno-economic benefit of adding automation resources such as additional robotic arms. The MAU for alternatives are shown in **Table 4**.

The transition from ND to D-0RA and from D-0RA to D-1RA resulted in large positive marginal benefits due to significant reductions in project duration and overhead cost. This demonstrates that initial automation investments yield substantial productivity and economic gains, primarily due to parallelization of printing and manipulation tasks and reduced manual intervention.

However, the marginal benefit decreased after first transition from ND to D-0R. Although D-2RA and D-3RA configurations achieved minor reductions in project duration (from 9 h to 8 h), these improvements were accompanied by increased overhead costs. The D-4RA configuration exhibited no time improvement and a significant cost increase, indicating negative marginal utility and over-automation. This negative MAU value is an intended feature of the proposed calculation method, accurately reflecting the physical and economic reality of diminishing returns—where adding redundant equipment increases costs without proportionally improving productivity. These results clearly identify an automation saturation region beyond the D-1RA/D-2RA configurations, where additional automation resources provide limited or negative marginal benefits. These results clearly identify an automation saturation region beyond the D-1RA/D-2RA configurations, where additional automation resources provide limited or negative marginal benefits.

3.2.3 Integrated Automation Decision Making

The integrated AEI–MAU analysis indicates that the D-1RA and D-2RA configurations represent the optimal automation region, providing substantial reductions in project duration with minimal increase in overhead costs. Although D-3RA further reduces project duration, the marginal cost increase outweighs the productivity gain, and the D-4RA configuration clearly represents over-automation with no additional time benefit and increased cost.

These findings demonstrate that the proposed decision framework can systematically identify the techno-economically optimal automation configuration and avoid excessive automation investment. The results also highlight that automation planning in concrete 3D printing should focus on balanced parallelization rather than maximum robotic deployment.

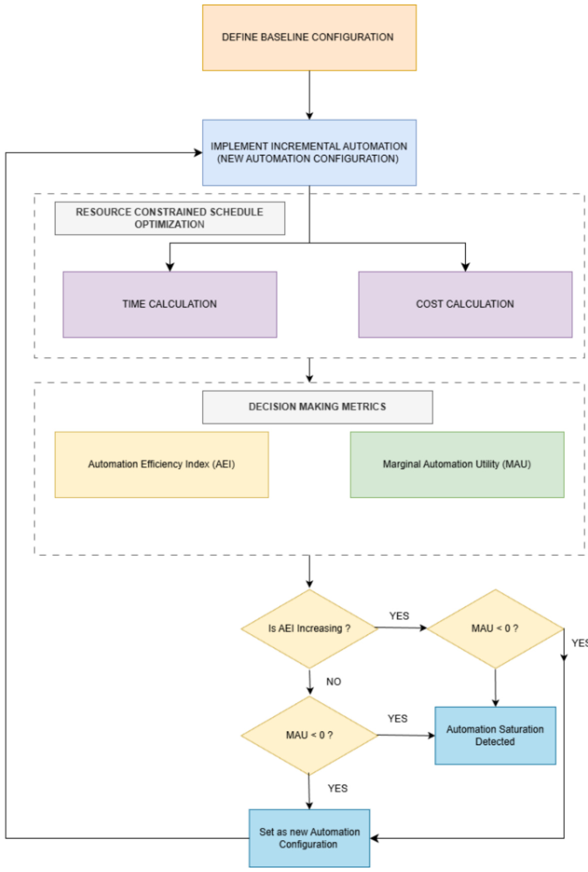

Figure 7 Decision-Making Framework

Table 2 Time and Overhead Cost for Automation Configurations

Automation Configuration	Time (hr.)	Overhead Cost (INR)
ND	80	2,16,533
D-0R	12	27,450
D-1R	9	21,075
D-2R	8.5	21,483
D-3R	8	22,016
D-4R	8	27,674

Table 3 Components of equipment cost

Resource	Fixed Cost (INR per hr.)	Idle Cost (INR per hr.)	Usage Cost (INR per hr.)
Robotic Arm	125	82	160
Printer Head	40	64	250
Operator	20	10	24

Table 4 AEI and MAU for automation configurations

Automation Configuration	AEI	Utility Value	MAU
ND	1	0	0
D-0R	52.58	0.862	0.862
D-1R	91.32	0.895	0.033
D-2R	94.86	0.897	0.002
D-3R	98.35	0.899	0.002
D-4R	78.24	0.886	-0.013

4 Conclusion

Concrete 3D printing improves productivity, cost efficiency, and sustainability; however, reinforcement and filler placement remain key automation bottlenecks. This study proposes a dual-gantry robotic 3D printing system with an integrated filler dispenser and introduces a quantitative decision framework to evaluate incremental automation. Resource-constrained scheduling was used to estimate time and cost, and novel AEI and MAU metrics were developed to identify the techno-economically optimal automation configuration.

The following are the major findings of the case study:

- **Significant reduction in project duration:** The baseline required ~80 h, whereas dual-gantry automation reduced fabrication time to 8–12 h (85–90% reduction), demonstrating the effectiveness of parallelized printing and manipulation.

- **Substantial reduction in overhead cost:** Automation alternatives reduced overhead cost from approximately INR 216,533 in the baseline case to as low as INR 21,075 – INR 27,674 (75-80% reduction) in automated configurations.

- **Global techno-economic benchmarking using AEI:** AEI values increased significantly with increasing automation, indicating substantial efficiency gains compared to the baseline. However, AEI decreased at the highest automation configuration due to increased capital and idle costs, highlighting the non-monotonic relationship between automation and efficiency.

- **Identification of diminishing returns using MAU:** MAU analysis revealed that marginal benefits saturate after intermediate automation configurations, with near-zero or negative marginal utility observed for higher automation configuration. This demonstrates that excessive automation may not yield proportional productivity gains.

- **Optimal automation configuration identification:** The integrated AEI–MAU framework identified intermediate automation configurations (D-1RA/D-2RA) as techno-economically optimal, while higher automation configurations did not provide significant benefits.

The decision framework considers time and overhead cost as primary objectives and does not explicitly incorporate uncertainty, reliability, lifecycle environmental impacts, or variations in the scale and complexity of the printed elements. Future studies will investigate how AEI and MAU perform under different printing scales, as the cost-efficiency and time-related benefits of robotic automation may vary significantly with project size. The primary contribution of this paper is a novel dual-gantry robotic concrete 3D printing architecture with an integrated filler dispensing mechanism, and a quantitative AEI–MAU-based decision framework that provides a systematic approach to identify optimal automation configurations and techno-economic trade-offs in construction additive manufacturing.

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