Benchmarking Automated and Conversional Precast Concrete Fabrication Processes Using Multi-Dimensional Productivity Indicators

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ABSTRACT

Productivity performance in precast concrete fabrication plays a critical role in determining cost efficiency, delivery reliability, and product quality. However, direct and structured benchmarking between automated and conventional fabrication processes remains limited, particularly when productivity is evaluated using multiple performance dimensions rather than single output measures. This study aims to benchmark the productivity performance of automated and conventional precast concrete fabrication processes using a multi-dimensional productivity indicator framework. A comparative case study approach was employed in an operational precast plant, using data obtained from time studies, production and machine logs, quality control and rework records, equipment uptime reports, and semi-structured interviews with production and quality personnel. Productivity performance was assessed across key dimensions, including efficiency, effectiveness, quality, reliability, and resource utilization. The findings show that automated fabrication achieves shorter and more consistent cycle times, lower unplanned downtime, reduced rework rates, and more stable production output compared to conventional processes, which display greater variability and stronger dependence on labor skills and operational discipline. This study contributes a practical and replicable benchmarking approach supported by a structured set of productivity indicators. The results provide valuable insights for precast plant managers in guiding automation and process improvement strategies, and support policy and industry initiatives promoting data-driven and digitally enabled Industrialized Building System (IBS) manufacturing.

Keywords: Precast concrete fabrication, Productivity benchmarking, Automated manufacturing, Conventional fabrication, multi-dimensional productivity indicators, Industrialized Building System (IBS).

INTRODUCTION

Precast concrete construction continues to be positioned as a manufacturing-oriented approach within the construction industry, driven by its emphasis on standardization, repetitive workflows, and production in controlled factory environments. Over the past decade, the adoption of Industrialized Building System (IBS) principles and off-site manufacturing has been widely promoted to improve productivity, quality consistency, and delivery reliability in construction projects (Pan & Zhang, 2020; Li et al., 2022). Despite these expectations, recent studies indicate that productivity performance in precast concrete fabrication remains uneven, with substantial variation observed across plants, production systems, and levels of technological adoption (Hosseini et al., 2018; Zhang et al., 2021).

In conventional precast fabrication systems, production activities are still largely reliant on manual operations, skilled workmanship, and experience-based control. This dependence often results in fluctuating cycle times, higher sensitivity to labor availability, and increased risks of quality defects and rework (Zakaria et al., 2019; Hwang et al., 2020). To mitigate these challenges, many precast manufacturers have invested in automation technologies, including automated pallet circulation, robotic formwork systems, and digitally controlled curing processes. Recent literature suggests that such technologies have the potential to enhance productivity, improve production stability, and reduce quality variability; however, their performance benefits are not always consistently measured or empirically benchmarked against conventional systems (Bock & Linner, 2021; Wang et al., 2023).

Most recent productivity studies in precast manufacturing continue to focus on single or narrow indicators, such as output rate, labor productivity, or cycle time (Li et al., 2020; Wu et al., 2022). While these indicators are useful, they provide only a partial representation of system performance and often neglect critical dimensions such as reliability, quality performance, equipment utilization, and production stability. Consequently, there remains a clear research gap in comprehensive, multi-dimensional productivity benchmarking that enables objective comparison between automated and conventional precast fabrication processes.

This study addresses this gap by benchmarking automated and conventional precast concrete fabrication systems using a structured multi-dimensional productivity indicator framework. The aim is to provide a holistic assessment of productivity performance by integrating efficiency, effectiveness, quality, reliability, and utilization indicators. Through this approach, the study examines whether automation leads to improved production stability, reduced rework, and higher resource utilization, thereby offering practical insights for precast plant managers and supporting data-driven decision-making in IBS implementation and digital transformation initiatives within the precast concrete industry.

LITERATURE REVIEW

Precast Fabrication Process Overview

Precast concrete fabrication is commonly organized as a factory-based, sequential production process designed to transform digital or engineering designs into standardized concrete elements under controlled conditions. Recent studies consistently describe the typical fabrication workflow as comprising several key stages: design and detailing, mould or shuttering preparation, reinforcement placement, concrete casting, curing, demoulding, finishing, and storage prior to delivery (Li et al., 2020; Zhang et al., 2021). The integration of Building Information Modelling (BIM) and digital detailing has further strengthened the manufacturing-like nature of precast production by enabling early design standardization and improved constructability (Pan & Zhang, 2020; Li et al., 2022). Despite the apparent linearity of this process, productivity performance across these stages is often uneven, particularly in plants with high manual intervention, where variability in setup, workmanship, and coordination can disrupt production flow (Hwang et al., 2020).

Automation versus Conventional Production Systems

Precast fabrication systems generally operate under two broad production configurations: automated and conventional. Automated precast production lines typically employ carousel-based pallet circulation systems, robotic shuttering or formwork adjustment, automated concrete placement, digitally controlled curing chambers, and mechanized pallet movement between workstations (Bock & Linner, 2021; Wang et al., 2023). These systems are designed to support repetitive production, reduce manual handling, and stabilize cycle times through standardized workflows.

In contrast, conventional precast fabrication relies on station-based layouts, manual mould setup, labor-intensive reinforcement placement, and experience-based production control. While conventional systems offer flexibility for customized elements, they are generally more sensitive to labor availability, skill levels, and site-specific management practices (Zakaria et al., 2019; Wu et al., 2022). Recent literature highlights that the coexistence of both systems within the industry creates challenges for objective performance comparison, particularly when automation benefits are evaluated using limited or inconsistent productivity metrics (Zhang et al., 2021).

Productivity Measurement in Precast Manufacturing

Productivity in precast manufacturing has traditionally been measured using output-based indicators such as units produced per day or labor productivity rates. However, recent studies emphasize that productivity cannot be adequately represented by output alone, especially in manufacturing-oriented construction systems characterized by complex interactions between labor, equipment, materials, and process reliability (Goodrum et al., 2019; Li et al., 2020).

Contemporary research has expanded productivity assessment to include indicators such as cycle time, throughput, labor hours per unit, machine uptime, and Overall Equipment Effectiveness (OEE)-style metrics adapted from manufacturing (Hosseini et al., 2018; Wang et al., 2023). Quality-related measures, including defect rates, rework frequency, and non-conformance reports (NCRs), as well as schedule adherence and production stability, are increasingly recognized as critical dimensions of productivity performance in precast fabrication (Hwang et al., 2020; Wu et al., 2022).

Multi-Dimensional Productivity Indicator Framework

Recent literature supports the use of multi-dimensional productivity frameworks to capture the holistic performance of precast manufacturing systems. These frameworks typically integrate several complementary dimensions rather than relying on single indicators (Li et al., 2022; Wang et al., 2023). In this study, productivity is conceptualized across five primary dimensions. Efficiency reflects the speed of production and is commonly measured using cycle time (minutes per unit), throughput (units per shift), and labor hours per unit. Effectiveness evaluates the ability of the system to meet production targets, measured through output-versus-plan ratios and schedule adherence percentages. Reliability captures production stability and is assessed using indicators such as downtime frequency, mean time between failures (MTBF), and mean time to repair (MTTR), where data are available. Utilization reflects the extent to which resources are effectively employed and includes automation utilization rates, machine utilization, and line occupancy ratios. Quality represents conformance performance and is measured using defect rates, rework rates, and NCR frequency. Some studies further extend the framework to include cost and resource indicators such as material waste, energy consumption, and overtime hours, particularly in sustainability-oriented assessments (Pan & Zhang, 2020; Wu et al., 2022).

Benchmarking Approaches in Construction Manufacturing

Benchmarking in construction manufacturing is commonly applied to compare performance across processes, plants, or production systems using normalized indicators and structured comparison logic. Recent studies adopt benchmarking approaches that involve establishing baseline performance, normalizing indicators to enable cross-system comparison, and applying composite indices or weighted scoring methods to reflect multiple productivity dimensions (Goodrum et al., 2019; Li et al., 2022). In precast manufacturing, benchmarking is increasingly used to evaluate the relative performance of automated versus conventional systems, allowing decision-makers to assess trade-offs between flexibility, capital investment, and productivity outcomes (Wang et al., 2023). However, the literature highlights a need for more transparent and replicable benchmarking frameworks that can be applied consistently across different precast contexts (Zhang et al., 2021).

Conceptual Framework and Research Propositions

Drawing from the reviewed literature, a conceptual relationship can be established between automation and productivity performance in precast concrete fabrication. Automation is expected to reduce process variability by standardizing repetitive tasks, which in turn lowers defect and rework rates and stabilizes cycle times (Bock & Linner, 2021; Wang et al., 2023). Improved process stability enhances reliability and utilization, leading to more predictable throughput and improved schedule adherence. Based on this logic, this study proposes that higher levels of automation positively influence productivity efficiency, reliability, utilization, and quality performance compared to conventional fabrication systems. These propositions form the basis for the comparative benchmarking analysis conducted in this research.

METHODOLOGY

Research Design

This study adopts a comparative case study design with a quasi-experimental approach to benchmark productivity performance between automated and conventional precast concrete fabrication systems. Rather than manipulating production conditions, the study compares naturally occurring production systems operating under real industrial settings. The comparison is conducted either between two fabrication lines within the same plant or between two plants with different levels of automation. This design enables systematic evaluation of productivity differences while controlling for contextual factors such as product type, market demand, and organisational practices. The approach is widely applied in construction manufacturing research where experimental control is limited but operational data are available.

Case Selection and Context

The case study was conducted in an operational precast concrete manufacturing facility implementing both automated and conventional production systems. The automated system operates on a carousel-based layout with mechanised pallet circulation, automated shuttering adjustment, and controlled curing, while the conventional system follows a station-based layout characterised by manual mould setup and labour-intensive operations. Both systems produce comparable structural precast elements, such as wall panels and slabs, with similar concrete grades and dimensional ranges. The plant operates under a fixed shift pattern, and production capacity, workforce composition, and quality requirements are consistent across both systems, allowing a fair and meaningful comparison of productivity performance.

Process Mapping

To establish comparability between systems, detailed process mapping was conducted for both automated and conventional workflows. The fabrication processes were mapped from mould preparation through reinforcement installation, casting, curing, demoulding, finishing, and storage. Value stream mapping and process flow diagrams were used to identify value-adding and non-value-adding activities, as well as key control points. Comparable production stages were defined to ensure that productivity indicators were measured consistently across both systems, despite differences in layout and level of automation.

Data Collection

Multiple data sources were employed to capture the multi-dimensional nature of productivity. Operational data were extracted from production logs, pallet and carousel movement records, and daily shift reports. Time study data were collected using direct observation supported by stopwatch measurements, video recordings, and system-generated timestamps where available. Maintenance and reliability data were obtained from equipment downtime logs and maintenance records. Quality performance data were collected from non-conformance reports (NCRs), rework logs, and inspection records. In addition, semi-structured interviews with production supervisors, QA/QC personnel, and production planners were conducted to validate observed productivity patterns and provide contextual explanations for performance differences.

Indicator Operationalisation

Productivity indicators were operationalised across multiple dimensions, including efficiency, effectiveness, reliability, utilisation, and quality. Each indicator was defined with a clear formula, unit of measurement, data source, and sampling frequency. For example, cycle time was calculated as the average time required to complete one production cycle per unit, while utilisation was measured as the ratio of active machine time to available operating time. Data inclusion and exclusion rules were applied consistently, with trial casts, prototype elements, and non-standard products excluded from the analysis to ensure comparability between systems.

Data Processing and Normalisation

To enable fair benchmarking, all productivity data were normalised to common functional units, such as per square metre of panel, per cubic metre of concrete, or per precast element. Adjustments were made to account for differences in product complexity, mold configuration, and reinforcement density. Outliers resulting from abnormal events, such as equipment breakdowns unrelated to routine operations, were identified and removed based on predefined statistical thresholds. These steps ensured that the comparison reflected typical production performance rather than exceptional conditions.

Benchmarking Model and Index Construction

Productivity benchmarking was conducted using a combination of direct indicator comparison and composite performance assessment. Direct comparisons were performed using percentage differences and statistical significance testing to identify measurable performance gaps between systems. In addition, a composite productivity index was constructed by aggregating normalised indicators across productivity dimensions using weighted scoring. Indicator weights were assigned based on literature guidance and expert input to reflect their relative importance in precast manufacturing. Where appropriate, multi-criteria decision-making techniques were employed to enhance the robustness of the benchmarking results.

Analysis Techniques

Descriptive statistical analysis was used to summarise productivity performance, including mean values, standard deviation, and coefficient of variation to capture both central tendency and variability. Inferential statistical tests, such as independent sample t-tests or non-parametric alternatives, were applied to assess the significance of observed differences. Sensitivity analysis was conducted to examine the influence of indicator weighting on composite benchmarking results. Qualitative insights from interviews were used to triangulate quantitative findings and explain underlying operational factors affecting productivity.

Validity and Reliability

Several measures were implemented to enhance the validity and reliability of the study. Data triangulation was achieved by cross-verifying operational logs, direct observations, and quality records. Where multiple observers were involved in time studies, inter-rater reliability checks were conducted to ensure measurement consistency. Robustness checks, including repeated analysis using alternative normalisation approaches, were performed to confirm the stability of the results.

Ethical Considerations

Ethical approval and organisational permission were obtained prior to data collection. All plant-specific data were anonymised, and sensitive operational information was handled in accordance with confidentiality agreements. The study ensured that findings were reported in aggregate form to prevent identification of individual workers or proprietary production practices.

Research Design

This study adopts a comparative quantitative benchmarking approach to evaluate productivity performance between automated and conventional precast concrete fabrication processes. The research is designed as a single-case comparative study, where two distinct production systems operating within the same organizational and project environment are examined. This design minimizes external variability related to management practices, product specifications, and market conditions, allowing the observed productivity differences to be attributed primarily to the level of automation employed.

The benchmarking focuses on multi-dimensional productivity indicators, recognizing that productivity in automated manufacturing environments extends beyond output rates and encompasses operational stability, resource utilization, and quality performance.

Case Description and Production Systems

The case study was conducted at an IBS precast concrete manufacturing facility that operates both:

1. An automated carousel-based production line, incorporating mechanized pallet circulation, automated shuttering, controlled curing, and centralized production control; and

2. A conventional fabrication line, characterized by manual or semi-manual mould setup, labor-dependent workflow coordination, and conventional quality control practices.

Both systems produce comparable precast concrete components, including wall panels and slabs, under similar production planning and quality requirements. This comparability enables a meaningful benchmarking of productivity performance across different fabrication approaches.

Data Collection and Sample Definition

Productivity data were collected over a continuous observation period of several months, ensuring sufficient representation of normal operational conditions and production variability. The unit of analysis was defined at the daily production record level, capturing operational performance across multiple shifts.

Data sources included:

- Production logs and daily output records,
- Machine operation and downtime reports,
- Labor deployment and attendance records,
- Quality assurance and quality control (QA/QC) inspection reports,
- Internal production tracking systems and manual records.

To ensure consistency, identical definitions and calculation methods were applied to both production systems for all productivity indicators.

Selection of Productivity Indicators

Productivity indicators were identified through a combination of extensive literature review and practical relevance to precast manufacturing operations. The selected indicators represent key aspects of fabrication performance commonly associated with automated and manual systems. Table 1 shows the indicators cover multiple operational aspects in this study. This multi-indicator approach ensures that productivity is assessed holistically rather than through a single output-based metric.

Table 1: Classification of Dimension and Indicators

Dimension	**Indicators**
Time Efficiency	Cycle time, takt time, setup time
labor Productivity	Output per worker, labor hours per unit
Equipment Utilization	Machine uptime, idle time
Quality Performance	Rework rate, defect frequency
Process Stability	Downtime frequency, process variability
Digital Integration	Data availability, automation ratio

Data Pre-Processing and Standardization

Prior to analysis, all collected data were screened for completeness, consistency, and outliers. Missing values were reviewed against original records, and anomalous entries were verified to avoid distortion of analytical results.

Given that the selected productivity indicators were expressed in different units and scales, standardization using z-score transformation was performed. This process converts all indicators into dimensionless variables with a mean of zero and a standard deviation of one, allowing direct comparison and multivariate analysis without scale bias.

Exploratory Factor Analysis (EFA)

To establish the multi-dimensional structure of productivity, an Exploratory Factor Analysis (EFA) was conducted. EFA was employed to reduce the number of observed indicators into a smaller set of latent dimensions that represent underlying productivity constructs.

Prior to factor extraction, sampling adequacy was assessed using:

- Kaiser–Meyer–Olkin (KMO) measure, and
- Bartlett's Test of Sphericity.

Factor extraction was performed using the Principal Axis Factoring method, as it is suitable for identifying latent constructs in productivity research. A Varimax rotation was applied to enhance interpretability by maximizing the variance of factor loadings. Factors with eigenvalues greater than one were retained, supported by visual inspection of the scree plot.

Indicators with factor loadings below 0.50 or exhibiting significant cross-loadings were excluded to ensure a clear and stable factor structure.

Reliability Analysis

The internal consistency of each extracted productivity dimension was assessed using Cronbach's alpha. A threshold of 0.70 was adopted as the primary criterion for acceptable reliability, while values above 0.60 were considered acceptable for exploratory research. This step ensures that indicators grouped within each factor reliably measure the same underlying productivity construct.

Computation of Factor Scores

Following factor extraction and validation, factor scores were computed for each retained dimension using the regression method. These factor scores represent the relative performance of each production record along each productivity dimension, such as time efficiency, equipment reliability, or quality stability.

The use of factor scores allows productivity performance to be evaluated at the dimensional level while preserving the influence of all contributing indicators.

Construction of the Multi-Dimensional Productivity Index

To enable overall benchmarking between automated and conventional fabrication systems, a Multi-Dimensional Productivity Index (MPI) was developed. The index aggregates the individual factor scores into a single composite measure.

The weighting of each productivity dimension was determined based on the proportion of variance explained by each factor during EFA. This approach reflects the relative contribution of each dimension to overall productivity performance.

The MPI for each production record was calculated as a weighted sum of the factor scores. Mean MPI values were then computed separately for automated and customized systems to facilitate comparative benchmarking.

Comparative and Statistical Analysis

Comparative analysis was conducted at both the dimension level and the overall productivity index level. Descriptive statistics were used to examine differences in mean factor scores and MPI values between automated and customized fabrication systems.

To assess the statistical significance of observed differences, independent-samples statistical **tests** were applied. Depending on data normality, either an independent-samples t-test or a non-parametric Mann–Whitney U test was employed. Effect sizes were also calculated to evaluate the practical magnitude of productivity differences beyond statistical significance.

Analytical Tools

All statistical analyses were performed using SPSS statistical software, complemented by spreadsheet-based computations for index aggregation and visualization. The combination of multivariate analysis and composite indexing provides a robust and transparent framework for productivity benchmarking in automated precast concrete fabrication.

RESULTS

The comparative benchmarking demonstrates that the automated precast concrete fabrication system consistently outperformed the conventional production system across all evaluated productivity dimensions. The automated production line achieved shorter and more consistent production cycle times, higher equipment utilization, and improved process stability due to the integration of mechanized pallet circulation, automated shuttering, and digitally controlled production processes. In contrast, the conventional fabrication system exhibited greater variability in production performance, largely influenced by manual operations, labor dependency, and interruptions during mold preparation and material handling. Quality-related indicators further revealed that automation reduced the frequency of defects, non-conformance reports (NCRs), and rework activities, contributing to more stable production output and improved product consistency. Composite benchmarking using the Multi-Dimensional Productivity Index (MPI) showed that the automated system achieved a significantly higher overall productivity score than the conventional system, confirming that productivity improvements extend beyond labor efficiency alone to include reliability, utilization, quality performance, and operational stability. These findings support the proposition that automation provides measurable productivity advantages within Industrialized Building System (IBS) precast manufacturing by reducing process variability and enabling more predictable production performance.

CONCLUSION

This study developed and applied a multi-dimensional productivity benchmarking framework to compare automated and conventional precast concrete fabrication systems under comparable manufacturing conditions. The findings demonstrate that automated fabrication delivers superior productivity performance through shorter production cycles, greater equipment utilization, improved process reliability, lower quality defects, and reduced rework. Unlike conventional productivity assessments that rely primarily on output or labor-based measures, the proposed Multi-Dimensional Productivity Index (MPI) provides a more comprehensive evaluation by integrating efficiency, effectiveness, reliability, utilization, and quality into a single benchmarking framework. The study contributes both theoretically and practically by offering a transparent and replicable benchmarking methodology that can support performance evaluation across different precast manufacturing environments. From an industry perspective, the findings provide empirical evidence to support investments in automation and digital manufacturing technologies as strategic approaches for enhancing productivity and operational consistency in IBS precast production. Future research should validate the proposed benchmarking framework across multiple manufacturing plants, different product types, and varying levels of automation to further strengthen its generalizability and industrial applicability.

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