Performance Evaluation Model to Enhance Life Cycle Productivity in Modular and Off-Site Construction: A Process-Oriented Approach

Babak Manouchehri [a], Sang Hyeok Han [a], and Fuzhan Nasiri [ap]

[a] Department of Building, Civil and Environmental Engineering, Concordia University, Montréal, Canada
Email: Babak.manouchehri@mail.concordia.ca, sanghyeok.han@concordia.ca, fuzhan.nasiri@concordia.ca

Abstract

The construction sector has long faced low productivity relative to other industries. Modular and off-site construction (MOC) offers a promising solution by assembling modules in a controlled facility environment and benefiting from repetitive nature of operations and the ability to conduct processes simultaneously. These features increase process flow continuity and enhance productivity across the life cycle. However, MOC has not yet realized its full potential, mainly due to the influence of conventional construction mindsets and the ineffective integration of lean practices, leading to process disruptions and persistent waste throughout the life cycle. To address this, a process-oriented performance evaluation (PE) model is introduced, using system dynamics to model life cycle processes and the existing interactions among different life cycle stages. This approach systematically evaluates life cycle productivity by accounting for the state of utilized resources (workers and workspace) and employing proposed MOC key performance indicators (MOC-KPIs) to identify the root causes of process waste with respect to resources utilization.

Keywords

Off-site construction, Key performance indicators, System dynamics, Productivity evaluation, Process waste.

1 Introduction

Over the past two decades, global construction productivity has remained stagnant, increasing by only 10% (0.4% annually) between 2000 and 2022, while the global economy and manufacturing sectors grew by 50% and 90%, respectively. Productivity further declined by 8% between 2020 and 2022, causing significant value loss, project delays, and cost overruns [1]. Despite rising demand for housing, the industry struggles with workforce shortages, escalating costs, and affordability challenges. Rising inflation and interest rates have exacerbated the disparity between housing costs and incomes, with homeownership now consuming up to 54% of household income in Canada [2]. Improving life cycle productivity is critical to addressing these challenges and enhancing housing availability. MOC, which shifts traditional on-site activities to controlled off-site environments, offers potential solutions by adopting lean manufacturing principles. It aims to boost productivity, quality, safety, and cost efficiency [3, 4]. However, MOC adoption remains limited, holding only 6.03% market share in 2022, and faces challenges such as high installation and transportation costs and inefficient lifecycle performance [3]. Many stakeholders report higher-than-expected costs compared to conventional methods, limiting MOC's ability to achieve widespread cost reductions and productivity improvements [5, 6].

MOC leverages lean manufacturing principles to reduce costs, minimize waste, and maintain quality. While research has demonstrated its potential in applications like high-rise buildings and manufactured housing [8], MOC often fails to fully benefit from lean practices. Conventional methodologies and fluctuating market demands requiring complex customization have hindered its adoption, leaving processes dominated by traditional construction mindsets [9]. These issues result in unbalanced lifecycle workflows and inefficiencies unique to MOC, such as repetitive operations and simultaneous activities across workstations. Current PE tools like the Balanced Scorecard, conventional construction KPIs, and Earned Value Management fail to effectively assess MOC projects [10]. Their limitations include poor tracking of concurrent activities, inadequate resource utilization assessment, inability to identify waste causes, and failure to address logistics challenges critical to MOC's success. These gaps impede precise PE and hinder the industry's shift toward more efficient, lean-driven practices. This paper introduces a process-oriented PE approach, using System Dynamics Modeling (SDM) to assess MOC lifecycle productivity through proposed MOC-KPIs in order to identify the root causes of process waste. SDM is a simulation-based approach used to understand and analyze complex systems over time. It employs feedback loops, stock-and-flow structures, and time delays to model real-world processes dynamically. The approach involves three key steps: (1) proposing KPIs to analyze resource utilization and identify process waste; (2) developing an SDM simulation to map MOC lifecycle dynamics and evaluate current-state life cycle productivity; and (3) testing intervention scenarios to validate the KPIs' effectiveness in identifying waste and improving life cycle process efficiency.

2 Literature Review

2.1 Measuring progress in conventional construction

Progress measurement involves quantifying the effectiveness and efficiency of actions to assess a project's current state [11]. As projects grow in size and complexity, they require more resources, generating vast amounts of data [12]. To obtain accurate performance outcomes, it is essential to analyze this data using specific indicators to identify root causes of problems promptly [14]. KPIs play a crucial role in improving project efficiency by supporting decision-making, identifying areas for improvement [15]. Literature reveals that KPIs in construction and related fields (e.g., manufacturing, road transportation) often focus on sustainability and productivity [16, 17]. These efforts primarily introduce new indicators for PE in areas such as time and cost. Mellado et al. [18] ranked commonly used KPIs, while Orgut et al. [11] identified factors to enhance project control reliability at different phases of the construction lifecycle. Habibi et al. [19] also explored phase-based KPIs and their impact on cost and schedule. However, due to the project-oriented nature of conventional construction, KPIs vary significantly between projects, making performance comparisons and future forecasts challenging. Efforts to reduce inefficiencies on construction sites have led to the development of various performance metrics to improve progress measurement [20, 21].

Furthermore, conventional KPIs related to lean manufacturing, road transportation, and on-site construction, focusing on productivity and process flow, are investigated. For example, KPIs include defect per unit which tracks errors in products, aiming to reduce rework and scrap costs [22]; overall equipment effectiveness that measures manufacturing equipment efficiency to enhance productivity [22]; loading/unloading time, focusing on minimizing delays in transportation operations [7, 13]; and on-site rework rate which measures defects and reworks during construction to minimize delays and the related costs [23, 24]. However, these KPIs may not fully address the unique needs of MOC projects, such as work sequence and resource flow, and may overlook key factors like laydown area availability. They may also struggle to accommodate MOC's dynamic nature, where disruptions in manufacturing (e.g., material shortages) affect on-site installation. Additionally, they may not pinpoint root causes of waste (e.g., rework due to module misfit or damage during shipment) or provide a complete view of resource allocation, especially for tasks like module repairs. Furthermore, traditional road transportation KPIs often fail to capture transportation processes across the MOC life cycle, such as the duration modules spend in staging areas before shipment.

2.2 Evaluating productivity in MOC

Effective resource planning is essential in construction management to meet project constraints and maintain process flow, as its absence can lead to productivity losses [25]. Concepts such as optimal-size capacity buffers and multi-skilled resources have been proposed to improve flexibility and productivity [25, 26]. Using multi-skilled resources enhances process integration and production efficiency [26]. Arashpour et al. [27] examined various cross-training strategies in MOC, finding they address capacity imbalances and time variability, measured by indicators like throughput rate and cycle time. However, these strategies are costly due to workforce turnover and resource availability [28].

Arashpour et al. [28] proposed a customized methodology for tracking the MOC production workflow, using discrete event simulation (DES) to reveal that production output is nonlinear due to variability in the MOC environment. To address this, they recommended setting a capacity buffer rather than aligning production targets with capacity. Manouchehri [29] applied a dynamic productivity model using SDM to MOC, estimating productivity in labor cost per ton of module installed on-site. By modeling the impact of performance factors (e.g., waiting times for transit) through causal loop diagrams and Stock and Flow diagrams, the model predicted future productivity and provided more accurate estimates for integrated project phases. Wang et al. [30] proposed an optimization model for the precast concrete component production line, incorporating lean production theory and Value Stream Mapping (VSM). They developed current- and future-state value maps and introduced KPIs such as delivery cycle, value-added time ratio, number of personnel, and production line balance rate. The model demonstrated improvements in production line balance, reduced delivery cycle, decreased value-added time ratio, and fewer workers. Similarly, Garza-Reyes et al. [17] developed a methodology combining time-based study, DES, and trial and error to optimize line balancing in manufacturing. The study identified workload distribution and process flow performance, with DES models assessing different scenarios to determine the optimal balance. They introduced the "balancing loss" indicator to measure idle time, achieving reductions in balancing losses ranging from 1.82 to 36.32 percent. The KPIs developed for MOC are listed in Table 1.

Table 1. Overview of existing KPIs for assessing productivity and resource allocation in MOC

MOC Phase	MOC KPI
Manufacturing	Workforce density Workload density Production line balance rate Value-added time ratio Balancing loss

In reviewing previous studies, several key gaps were identified in the evaluation of MOC performance: (1) Many studies relied on conventional construction KPIs that fail to account for the unique workflow and sequencing of MOC, leading to ineffective assessments of productivity and resource utilization; (2) Most studies focused solely on the manufacturing phase, neglecting the integrated nature of MOC across all life cycle stages; (3) They often overlooked on-site installation dynamics, such as site-specific constraints; (4) The interaction between life cycle processes, like delays in module quality inspections affecting on-site installation, was not adequately considered; (5) There is a lack of methodologies that compare actual performance with predefined benchmarks, hindering performance comparisons across projects; and (6) Existing methods, like VSM, do not effectively address concurrent activities or identify root causes of inefficiency in MOC life cycle performance. Given the differences between off-site and on-site construction methods, MOC should be treated as a process-oriented approach, leveraging repetitive operations throughout its life cycle. As a result, the literature supports the need for a dedicated PE framework for MOC, which should: (1) adopt a process-oriented approach that supports repetitive operations and the distinct flow of MOC processes; (2) incorporate MOC life cycle and resource leveling to identify waste and improve efficiency; and (3) include KPIs to assess MOC life cycle performance.

3 Proposed Method

This paper introduces a process-oriented approach to systematically evaluate the MOC life cycle productivity (MOC-LCP), using proposed MOC-KPIs. The approach aims to help production managers efficiently identify root causes of process waste related to resource utilization (e.g., workforce and workspace). As illustrated in Figure 1, the methodology involves three key steps: (1) developing MOC-KPIs tailored to various life cycle phases to measure resource utilization (e.g., workforce); (2) creating a simulation model integrated with these KPIs to assess life cycle productivity while considering resource allocation; and (3) run intervention scenarios using the simulation model to analyze the effectiveness of the proposed MOC-KPIs in identifying root causes of waste.

3.1 MOC-KPIs proposal

The proposed MOC-KPIs enable a detailed analysis of resource utilization to identify inefficiencies and the root causes of process waste. Grounded in lean principles, the approach aims to enhance life cycle efficiency through continuous improvement and waste minimization, transforming MOC into a more efficient and cost-effective construction method. While tools like VSM offer useful metrics for performance measurement [9], they have notable limitations: (1) an incomplete set of metrics for systematically assessing life cycle performance; (2) an inability to capture complex interdependencies among life cycle processes, such as the ripple effects of delays across stages; (3) insufficient capacity to model and analyse parallel workflows that require precise coordination (e.g., interactions between manufacturing and site operations); and (4) limited capability to guide investigations into root causes of waste (e.g., rework) to improve the efficiency and effectiveness of operations, particularly regarding resource utilization (e.g., workforce and workspace).

To propose KPIs aligned with the MOC life cycle processes, the delivery flow of a single module at the MOC system level was analyzed. A detailed process flow was constructed using insights from MOC literature, published MBI reports, and interviews with industry professionals (e.g., Stack Modular, MODLOGIQ, Smart Modular Canada). However, the MOC life cycle process is prone to disruptions that introduce significant waste, hinder operational efficiency, and increase resource utilization, thereby reducing MOC-LCP and escalating project costs. To address these challenges, MOC-KPIs are essential for identifying, measuring, and diagnosing the root causes of process waste. They enable recognizing issues, quantifying their impact, and analyzing contributing factors, facilitating the timely detection of inefficiencies. This improves resource utilization across life cycle stages, streamlines process flow, and supports continuous improvement. Ultimately, these efforts enhance MOC-LCP and lower overall project costs.

The proposed KPIs include workflow interruption (WFI), module defect modification (MDM), module quality inspection release (MQIR), staging area occupancy (SAO), at-factory module loading (AFML), module travelling time (MTT), shipment damage inspection (SDI), module lift handling (MLH), module in-place alignment (MIPA), module connection work (MCW), and site-fit rework (SFR).

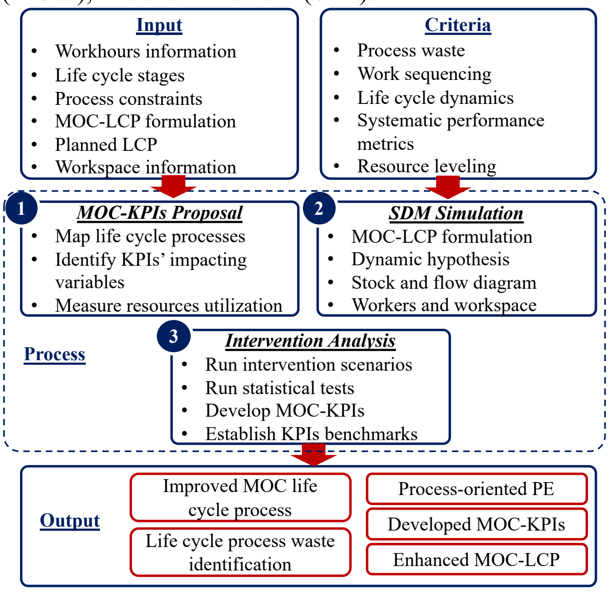

Figure 1. MOC-LCP evaluation process

3.2 SDM Simulation

Simulation is recognized as an effective technique for tasks such as productivity assessment and resource planning. However, before developing a life cycle simulation model, it is essential to formulate an equation capable of efficiently estimating current-state productivity in MOC. The MOC-LCP is represented by Equation 1.

$$MOC - LCP = \frac{S_{inst}}{T_{MOC}} \quad (1)$$

Where S_{inst} = surface area of all modules installed on-site per square feet; T_{MOC} = total MOC project spent workhours.

Additionally, further literature review was conducted to identify factors influencing the proposed KPIs and constraints affecting module delivery within the modular project life cycle. Further, SDM is used which is an efficient tool that enables evaluating a system's ability in coping with the incurred changes (i.e., most-contributing KPIs functionality), while examines new scenarios that could be implemented within the system's environment (i.e., life cycle process) for the sake of effective decision-making process (i.e., identification of root cause of process waste with respect to resources utilization). To better understand the interrelated processes within the MOC life cycle and visually depict the dependencies among various KPIs and their parameters, a causal loop diagram of the module delivery process flow model is developed [20]. (Figure 2).

Moreover, building on the established CLD, a stock and flow diagram (SFD) is subsequently formulated. It is divided into five interconnected sub-SFDs to model process of module (*i*) manufacturing, including module assembly and quality inspection; (*ii*) transportation; (*iii*) on-site installation; and (*iv*) MOC-LCP assessment. To effectively represent the dynamic relationships among various life cycle processes, additional key components and their interactions are integrated into the SFD diagram. These relationships are articulated through mathematical equations and a set of defined rules.

3.3 Intervention Analysis

The objective of scenario analysis is to evaluate the impact of various interventions on a system's KPIs [25]. This involves several key steps: (*i*) identifying interventions and their boundaries, with the proposed MOC-KPIs serving as response variables, and employing the developed and validated SDM to examine the behavior of MOC-KPIs under each scenario; (*ii*) performing statistical tests to assess whether the interventions significantly affect overall life cycle performance, explore relationships among the proposed MOC-KPIs, evaluate the combined effects of interventions, and test hypotheses regarding the impact of each intervention on individual MOC-KPIs; and (*iii*) analyzing MOC-KPIs' behavior across different interventions to verify which one efficiently identifies root causes of process waste within each phase of the MOC. To conduct intervention analysis, various scenarios, as shown in Table 2, were identified through literature review and interviews with MOC experts.

Table 2. Scenarios studied for intervention analysis

Intervention type	Intervention scenario
Manufacturing (assembly and quality inspection)	S1: Ramp up module production S2: Apply overtime policy S3: Reduce rework during module assembly and quality inspection S4: Reduce quality inspection space unavailability
Transportation (truck-trailer and crane)	S5: Increase transportation fleet availability S6: Timely crane preparation at factory S7: Reduce lack of space on laydown area
On-site installation	S8: Timely crane preparation S9: Speed up lift preparation S10: Boost module alignment

	process
	S11: Accelerate module connection
	S12: Reduce site-fit rework

4 Case Example

A residential modular project located in Kenora, Ontario, was selected as the case study. The project involved the construction of a single building using six wooden-framed modules, manufactured by Smart Modular Canada. These modules, each weighing 14 tons and measuring 14 feet by 50 feet, were fabricated at a factory in Thunder Bay, Ontario, and fully equipped with mechanical, electrical, and plumbing systems, as well as internal finishes. Although the installation of the final module was initially planned to be completed within 242 workhours, the process ultimately required 268 workhours due to various challenges encountered throughout the project life cycle, including detected defects during assembly, delays in truck availability, and damages sustained during shipment.

Moreover, the scenarios were simulated using the SDM, and the resulting MOC-KPI data were analysed to assess normality. This analysis employed Quantile-Quantile (Q-Q) plots, kurtosis, skewness, and the Shapiro-Wilk test. Q-Q plots were constructed for each MOC-KPI to visualize their distribution (11 plots). Figure 3 presents the Q-Q plots for the manufacturing proposed KPIs (module assembly and inspection), namely, WFI, MQIP, and MDM. The Q-Q plots reveal that the datasets for each MOC-KPI deviate from normality, as the data points cluster away from and do not align closely with the 45-degree reference line. To provide a more comprehensive assessment of normality, additional statistical measures, including kurtosis, skewness, and the Shapiro-Wilk test, were employed, as summarized in Table 3. The skewness and kurtosis values exceeded the acceptable thresholds for some MOC-KPIs, thereby violating the normality assumption (thresholds: −2 to +2 for skewness and −7 to +7 for kurtosis). These values are highlighted in Table 3. Furthermore, the Shapiro-Wilk test yielded *p*-values below the significance level of 0.05, leading to the rejection of the null hypothesis (normal distribution). This result corroborates that the dataset deviates significantly from normality. Therefore, non-parametric statistical tests were subsequently employed at this stage of the analysis.

Table 3. Statistical measures and test for data normality assessment

Independent variables (MOC-KPIs)	Skewness	Kurtosis	Shapiro-Wilk *p*-value
WFI	**-0.700**	7.470	2.008×10^{-9}
MQIR	2.478	12.133	1.591×10^{-9}
MDM	4.885	27.870	4.132×10^{-11}
WFD	4.401	25.909	1.693×10^{-11}
SAO	**-0.211**	**4.552**	1.430×10^{-8}
AFML	5.375	31.888	3.577×10^{-12}
MTT	4.115	21.327	1.677×10^{-10}
SDI	3.861	16.086	3.437×10^{-9}
MLH	2.787	**6.999**	2.014×10^{-10}
MIPA	3.337	21.307	3.154×10^{-11}
MCW	5.388	32.000	2.794×10^{-12}

Spearman's Rank Correlation Coefficient analysis was conducted to examine the strength and direction of relationships among the proposed MOC-KPIs, as summarized in Table 4. The results reveal an acceptable level of linear relationship between certain MOC-KPIs ($0.2<r<0.9$). However, the correlation between some variables, such as MDM and MTT is less than 0.2, indicating a very weak and negligible relationship. The strongest correlation is observed between AFML and MIPA (r=0.64). Interestingly, while MIPA shows no correlation with other KPIs (r = 0.0), it exhibits the second-highest correlation with AFML (r = 0.642). These correlations, though weak in some cases, underscore the interconnected nature of various processes across the MOC life cycle, highlighting the factors and MOC-KPIs that are influenced by these operations. Furthermore, since all coefficients fall within the acceptable range, the proposed MOC-KPIs are deemed suitable for inclusion in the developed model, supporting their potential relevance in capturing the dynamics of the life cycle processes.

At this stage, quantile regression analysis was utilized to assess the robustness of the proposed MOC-KPIs and to define a reliable framework for identifying those that significantly contribute to MOC-LCP. The analysis involved multiple iterative rounds, during which the *p*-value for each MOC-KPI was computed. KPIs with *p*-values exceeding 0.05, signifying a lack of statistical significance, were systematically excluded from subsequent iterations. This process continued until all remaining MOC-KPIs demonstrated statistical significance, confirming their importance to MOC-LCP and their effectiveness in identifying and evaluating root

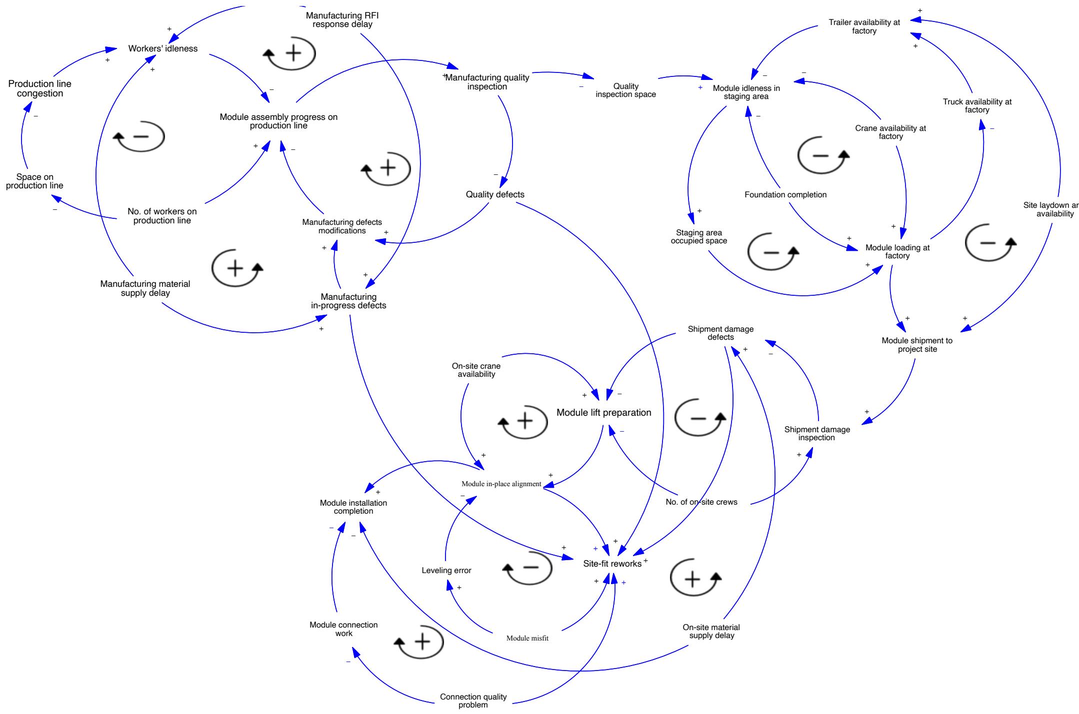

Figure 2. The causal loop diagram of MOC process flow to evaluate life cycle productivity

Table 4. Correlation between MOC-KPIs using Spearman Rank Correlation Coefficient

	WFI	MDM	MQIR	SAO	AFML	MTT	SDI	MLH	MIPA	MCW	SFR
WFI	1										
MDM	0.0	1									
MQIR	0.0	**0.49**	1								
SAO	0.0	-0.03	-0.07	1							
AFML	0.0	**0.6**	**0.5**	-0.03	1						
MTT	0.0	-0.01	-0.02	0.23	-0.01	1					
SDI	0.0	-0.02	-0.04	-0.44	-0.02	-0.02	1				
MLH	0.0	-0.03	-0.07	-0.10	-0.03	-0.03	-0.06	1			
MIPA	0.0	0.00	0.00	0.00	**0.64**	0.00	0.00	0.0	1		
MCW	0.0	-0.02	-0.04	-0.06	-0.02	-0.02	-0.03	-0.06	0.0	1	
SFR	0.0	-0.01	-0.02	-0.03	-0.01	-0.01	-0.02	-0.03	0.0	**-0.45**	1

causes of process waste with respect to resource utilization. The outcomes of the quantile regression analysis are detailed in Table 5.

Table 5. Results from multiple iterations of quantile regression analysis (pp-value)

MOC-KPI	*p*-value				
	R1	R2	R3	R4	R5
WFI	0	0	0	0	0
MQIR	0	**0.586**	-	-	-
MDM	0	0	0	0	0
WFD	0	0	0	0	0
SAO	0	0	0	0	0
AFML	0	0	0	0	0
MTT	0	0	0	0	0
SDI	**0.596**	-	-	-	-
MLH	0	0	0	**0.999**	-
MIPA	0	0	**0.991**	-	-
MCW	0	0	0	0	0

As shown in Table 5, five rounds of quantile regression analysis identified WFI and MDM in manufacturing, SAO, AFML, and MTT in transportation, as well as SDI and SFR in the on-site installation stages, as statistically significant at the 95% confidence level. These findings indicate that these factors play a critical role in influencing MOC life cycle performance. The statistical significance at the 95% confidence level suggests a strong correlation between these variables and overall project efficiency. Further analysis is required to explore the extent of their impact and potential strategies for optimizing these key indicators across different project phases. These MOC-KPIs are deemed robust, as they contribute meaningfully to identifying the root causes of waste across the MOC life cycle by accounting for resource utilization and enabling an effective and efficient evaluation of the MOC-LCP.

5 Conclusion

Certain studies have proposed mathematical and simulation models to evaluate productivity and process flow in MOC, focusing on minimizing variability. Other research works have developed KPIs in manufacturing to enhance MOC operational efficiency. However, few studies have addressed the root causes of process waste related to resource utilization (e.g., workers and workspace), nor have they proposed MOC-KPIs and considered the dynamic interactions among life cycle stages. This study fills this gap by proposing a process-oriented PE model that incorporates the proposed MOC-KPIs. Using SDM, the model simulates the interactions among life cycle stages and their processes, systematically assessing the current-state life cycle performance in terms of productivity (i.e., MOC-LCP) by comparing it to a baseline while considering process constraints and resource utilization (workers and workspace). The study also introduces new MOC-KPIs to identify, quantify, and diagnose the root causes of waste and enhance coordination across life cycle stages in MOC. The results show that MOC-KPIs such as WFI and MDM in manufacturing, SAO, AFML, and MTT in transportation, and SDI and SFR in on-site installation phases can effectively assess the state of resource utilization and identify process inefficiencies. Future research should explore the impact of applying the model to projects with a larger number of modules, as its calibration was based on a 6-module project, which may affect result reliability. Additionally, further studies should investigate the relationship between MOC-LCP improvement and project cost savings. Also, social indicator (e.g., employee turnover) are excluded due to their subjective and qualitative nature, as well as the lack of standardized assessment methods. This research improves the understanding of the key factors affecting MOC life cycle performance, helping general contractors and modular developers manage constraints and optimize project outcomes.

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