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AGENT-BASED MODELING AND SIMULATION OF MULTIDIMENSIONAL IMPACTS OF CONSTRUCTION LABOR PRODUCTIVITY FACTORS

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ABSTRACT

Despite numerous attempts to quantify the impacts of factors influencing productivity in the construction industry, such factors are still perceived as static and independent, resulting in unrealistic productivity estimates. Therefore, this paper investigates the different factors' impacts on not only productivity, but also each other. The objective is to highlight the necessity of perceiving the already heavily researched factors affecting productivity as dynamic and interdependent through a multidimensional lens. Two generic agent-based models are built to simulate the outcomes of a project through varying levels of detail, each investigating a certain set of impacts. The first model includes the quantified impacts of the factors on productivity (traditional approach), while the second encompasses all quantified impacts of the factors on productivity and on each other (comprehensive approach). Findings proved the accuracy of the proposed comprehensive approach in estimating durations compared to planned durations and to those obtained from the traditional approach.

1 INTRODUCTION

Labor productivity is an essential aspect of the construction industry; it is simply defined as output per labor hour (Shashank et al. 2008), but it strongly correlates with project duration and cost (Hasan et al. 2018). Basically, human resources exhibit a pivotal role in construction project cost, which drives the companies to maximize their workers' productivity in an attempt to maintain their survival and profitability (Ghoddousi and Hosseini 2012). As a matter of fact, the success of a construction project is heavily dependent on maintaining high productivity throughout different phases of the project (Nasirzadeh and Nojedehi 2013). Having acknowledged this, seeking continuous productivity improvement has long been lingering in researchers' minds, triggering their contribution to eliciting an ample pool of factors affecting construction productivity over the years. In particular, the past three decades have witnessed extensive efforts to lavish productivity on sites (Naoum 2016). However, even with major and continuous endeavors, labor productivity remains in a position where much research effort must be exerted to exploit its full potential in the practical industry (Hasan et al. 2018). Low productivity can actually be attributed to various components including but not limited to technical ones such as poor planning, social such as low labor motivation, managerial such as weak leadership, and contractual ones such as improper procurement methods (Naoum 2016).

Among studies addressing labor productivity factors, most have addressed the impacts of factors on productivity independently. Failing to incorporate the cascading impacts of factors on each other, and consequently on productivity, would result in unrealistic productivity estimates. Accordingly, this paper proposes a novel approach where various factors' impacts on productivity on one hand, and on each other on the other hand, are investigated. The objective is to highlight the necessity of perceiving the already heavily researched factors affecting construction productivity as dynamic and interdependent through a multidimensional (various factors together) lens. Therefore, two generic agent-based models (ABM) are built to simulate the outcomes of a project through varying levels of detail, each considering a certain set of impacts to be investigated. ABM simulation approach allows mimicking and replicating a real-world scenario through constructing a simulation experiment around a collection of autonomous agents which interact with one another and with the environment they belong to (Sanchez and Lucas 2002). In this study, ABM is chosen as it allows modeling the emergent behavior of the different agents within the model, in addition to modeling the interactions of the agents living in the same environment. This modeling process eventually allows users to study the effects of the modeled agents' decisions, behaviors, and interactions on their performance. The developed models are described as generic as they are not tailored to a specific project. In other words, they may be used by different users working on different projects by inserting a project's databases for the crews, tasks, and areas. The first simulation model includes the quantified impacts of the factors on productivity. As for the second simulation model, it encompasses all quantified impacts of the factors on productivity and on each other. This study's contribution to research and practice lies in (1) demonstrating the criticality of incorporating the impacts of the influencing factors on each other rather than on productivity only and (2) proving the accuracy of the duration results obtained from the model that incorporates the aforementioned impacts, compared to planned durations and to those obtained from the model considering the impacts on productivity only. This approach paves the road for a comprehensive investigation of the interdependent impacts of labor productivity factors.

2 LITERATURE REVIEW

2.1 Factors Affecting Productivity

Various methodologies have been employed in exploring potential factors that affect productivity and for modeling productivity in construction. For instance, aiming at tackling low productivity, Ghoddousi and Hosseini (2012) conducted a survey to evaluate the factors impacting the sub-contactors' productivity via a structured questionnaire. Their results revealed that the most important factors in ascending order are jobsite condition, weather, reworks, supervision system, planning, construction technology and method, and materials/tools. A similar study is done by Toan et al. (2020) who clustered 45 factors into six primary groups which are work conditions, management, manpower, external, and project. These factors were compiled into a structured questionnaire survey that was distributed among project managers. The analysis of their collected surveys showed that the most critical factors affecting productivity are availability of material, availability of workers, lack of supervision, design changes, accidents, work discipline, timeliness of remuneration, ability of construction management, financial status of stakeholders, and economic conditions. Nasirzadeh and Nojedehi (2013) went further to model the complex interrelated structure of factors affecting productivity via a system dynamics-based approach that accounts for the highly dynamic nature of various factors. The model was tested on a housing project where it showed that the full impact of various influencing factors can be predicted by assessing the direct and indirect effects of each factor.

Psychological and even psychosocial factors' effects on labor productivity have been also investigated by many researchers. Hashiguchi et al. (2020) presented a study for identifying the relationships among psychological factors impacting productivity such as feeling safe on site, skills, proactive behavior, and team performance. A structural equation modeling approach is adopted in investigating the health risk's effect on young and older workers' perceptions. Their results revealed that the body mass index negatively affects proactive behavior and safety feeling among older workers, but no noticeable relationship was found among younger workers. Bayesteh et al. (2022) argued that productivity modeling is oversimplified due to the subjectivity of information given by experts, so they integrated two approaches for developing a framework aimed at reducing subjectivity linked to labor productivity modeling. The interrelationships between various factors influencing labor productivity were explored and results from that study are used in this research. However, such interrelationships have not yet been employed in the duration estimation process on construction projects, presenting a visible research gap in this area.

2.2 Agent-Based Modeling in Construction

ABM simulation has been applied for diverse purposes in a variety of industries including construction. In particular, the construction management domain has seen an abundance of ABM applications around labor productivity and performance subject. As such, Kiomjian et al. (2020) argued that learning in construction is not an individual process, but rather crew dynamics impact learning through knowledge transfer, thereby affecting productivity. They proposed an ABM approach to derive the effect of project schedule and crew composition on knowledge sharing and task duration. Their results revealed that crews which are more diverse tend to experience greater levels of knowledge sharing and better productivity gains. Raoufi and Robinson Fayek (2018) integrated ABM with fuzzy logic to consider subjectivity in modeling motivation for predicting crew performance. They suggested that integrating fuzzy with ABM expands the domain of applicability of ABM to include subjective and probabilistic uncertainty, providing a novel methodology to be used in assessing construction practices and processes. Khanzadi et al. (2018) presented a hybrid simulation approach amalgamating system dynamics and ABM to predict labor productivity while considering the continuous impacting factors and interactions among various agents on the project. It was revealed that, in addition to the number of working crews, the pattern of their movement also affects the severity of crews' interferences, affecting thereby labor productivity. Binhomaid and Hegazy (2021) proposed a framework for modeling a site that accommodates productivity-hindering and danger zones, and for quantifying site productivity and potential accidents based on the site configuration. The framework was implemented as an ABM, and the results showed that simulating aggressive and avoider workers' behaviors about different site obstacles helps modelers propose realistic solutions for site improvement. Despite the mentioned approaches through ABM in construction, no study has yet modeled the quantified and multidimensional impacts of the influencing factors on productivity and on one another through ABM. Therefore, this paper addresses this gap by employing these interrelationships through modeling and simulation to quantify their impacts and estimate task and project durations.

3 MODEL DEVELOPMENT AND APPLICATION

After a careful selection of relevant factors to be included in this study is performed, two generic simulation models are developed to underline the importance of investigating the different factors' impacts on project and task durations on one hand (Model 1), and on other factors on the other hand (Model 2). This study employs ABM to fulfill this objective. ABM is chosen as it allows modeling the emergent behavior of the different agents within the model, in addition to modeling the interactions of the agents living in the same environment. The emergent behavior in the case of this study is the changing values of construction workers' fatigue, congestion in working areas, chances of accidents, and so on. As ABM is characterized by the heterogeneity of its agents, heterogeneity in this study is in the agent characteristics (differences in task, worker, and area attributes on one hand, and differences among the various task agents themselves in the task population, worker agents themselves in the workers' population, and area agents themselves in the area population on the other hand). The heterogeneity is also in the behavior of the agents, where workers behave differently due to their different experience and fatigue levels, and due to the different site layout conditions. Communication is another main pillar in ABM, and it is represented by the different communication means such as messages sent between the different agents during the process of assigning workers to tasks and the process of initiating task execution. After building both simulation models, model verification and validation are performed, followed by a case study is used to prove the model's applicability and to analyze the obtained results for further interpretations. Finally, the results that are obtained from both models are analyzed.

3.1 Factors and links

Numerous studies have addressed investigating factors that affect labor productivity on construction projects, including one by Bayesteh et al. (2022), where several factors were classified into nine categories. However, even though modeling all factors ensures accurate reflection of the reality of labor productivity in construction projects, not all investigated factors were included in the model developed in this study. This is attributed to the requirements of any simulation model, where abstraction is needed for feasible simulation and analysis. Also, the study's goal is not to provide a holistic productivity analysis model, but to show the effect of incorporating factors' interrelationships on each other's and on the overall project. Therefore, the selection of factors was subject to satisfying two major constraints. The first is the need to obtain proven mathematical formulae that quantify the impacts of the factors to be modeled on productivity. Otherwise, there would be no proof of how each factor affected the productivity that is the core interest of this study. The second constraint is selecting factors that may be modeled computationally, i.e., factors whose aspects may be represented by movements through states, changes in variables, triggering of events, or any other simulation feature. Both constraints significantly limited the availability of factors that may be included in this simulation model. Therefore, six factors were selected to be modeled in this study along with their impacts on task and project durations on one hand, and their impacts on other factors on the other hand. These factors and impacts are derived from the aforementioned study by Bayesteh et al. (2022). The six selected factors are deemed sufficient to prove their interdependencies and their impacts on project performance, and they are: Safety, Experience, Congestion, Fatigue, Site Layout, and Resource Availability. The relationships linking the different factors in terms of impacts are also acquired from the mentioned study as shown in Figure 1. Fatigue, congestion, experience, and site layout affect workers' individual performances, which in turn impacts the duration needed to complete a task, while accidents and resource availability affect the total project duration rather than individual task durations. Accidents cause a sudden pause during the project for a specified period of time, and lack of resource availability leads to a delay in the start time of a task rather than an extension to the task duration itself. Mathematical equations that quantify the impacts of the factors that affect task durations (fatigue, congestion, experience, and site layout) are discussed in this section.

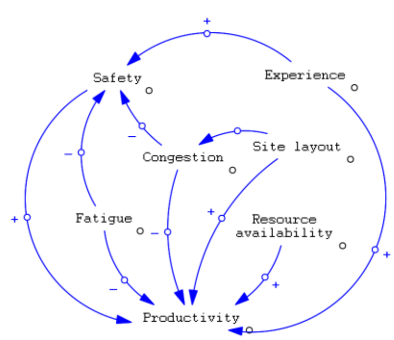


Figure 1: Labor productivity factors and links.

First, fatigue is quantified through a mathematical equation mentioned in a study by Ferjani et al. (2015). It is represented by an index (I) (Equation 1), where d is a coefficient that indicates how physically demanding a certain task is and w is the duration during which the worker has been previously working.

$$I = 1 - e^{-d.w} \tag{1}$$

Using index (I), an adjusted duration (D_f) that considers fatigue may be calculated using Equation (2), where I is the previously calculated task fatigue index, and D is the originally planned task duration. D_f represents the updated task duration due to fatigue:

$$D_f = (1 + I)D. \tag{2}$$

Regarding congestion, a study by Dabirian et al. (2021) quantified congestion's effect on productivity (Equation 3), where P_h is the updated productivity due to congestion, c is a constant that refers to congestion (greater c values indicate more congestion), and D is the distance between neighboring workers. To convert P_h into duration, Equation (4) is developed, where D_c refers to the updated duration due to congestion.

$$P_h = 1 - (c/D) \tag{3}$$

$$D_c = \frac{D}{1-(c/d)} \tag{4}$$

In this study, c is calculated as the ratio of the number of workers to the area capacity. Accordingly, values lower than or equal to 1 indicate no congestion, while values higher than 1 indicate congestion. When c is lower than or equal to 1, the duration in the model is not affected. Equation (4) is only used when c is higher than 1, and it is normalized to ensure logical congestion and duration results.

As for site layout, working areas are described as either well-planned or poorly planned. The impact of the site layout on the duration is derived from a study by Binhomaid (2019), where productivity, measured by the number of trips a truck could make around the site, was found to decrease by around 10% in poorly-planned sites compared to well-planned sites. This conclusion allowed the development of Equation (5). Well-planned areas do not lead to any delays in the task duration, while poorly planned areas lead to an increase in task duration by an adjustable extent of 10%:

$$D_{sl} = 1.1D \tag{5}$$

Equation (6) represents D_e, or the duration due to experience. "e" is each construction worker's experience level. Different ranges for e may be assigned in the model depending on each crew's experience levels.

$$\begin{aligned} D_e &= 1.2D,\ 0.1 < e < 0.2 \\ D_e &= 1.1D,\ 0.3 < e < 0.4 \\ D_e &= D,\ e = 0.5 \\ D_e &= 0.9D,\ 0.6 < e < 0.7 \\ D_e &= 0.8D,\ 0.8 < e < 1.0 \end{aligned} \tag{6}$$

A worker's actual task duration is calculated as the average of all updated durations due to the different factors as shown in Equation (7).

$$D_{actual} = \frac{D_f + D_c + D_{sl} + D_e}{4} \tag{7}$$

3.2 Agent-Based Simulation Models

In order to highlight the importance of investigating the impacts of different factors on construction productivity and on one another, two simulation models were built. In the first simulation model, the direct impacts of the influencing factors on project duration were modeled by incorporating mathematical equations that quantify the mentioned impacts. As for the second simulation model, the interrelations among the factors that impact and are impacted by other factors are added. This model further underlines the necessity to perceive the heavily researched factors affecting construction productivity as dynamic and interdependent through a multidimensional (various factors together) lens. Both simulation models were built using AnyLogic 8.7.10.

3.2.1 Model 1: Impacts of Factors on Project Duration

This model includes the agents' main environment, three agent populations, two events, and a set of parameters and variables. The three agent populations that are modeled were Workers, Tasks, and Areas. The required agent population inputs are represented in Table 1.

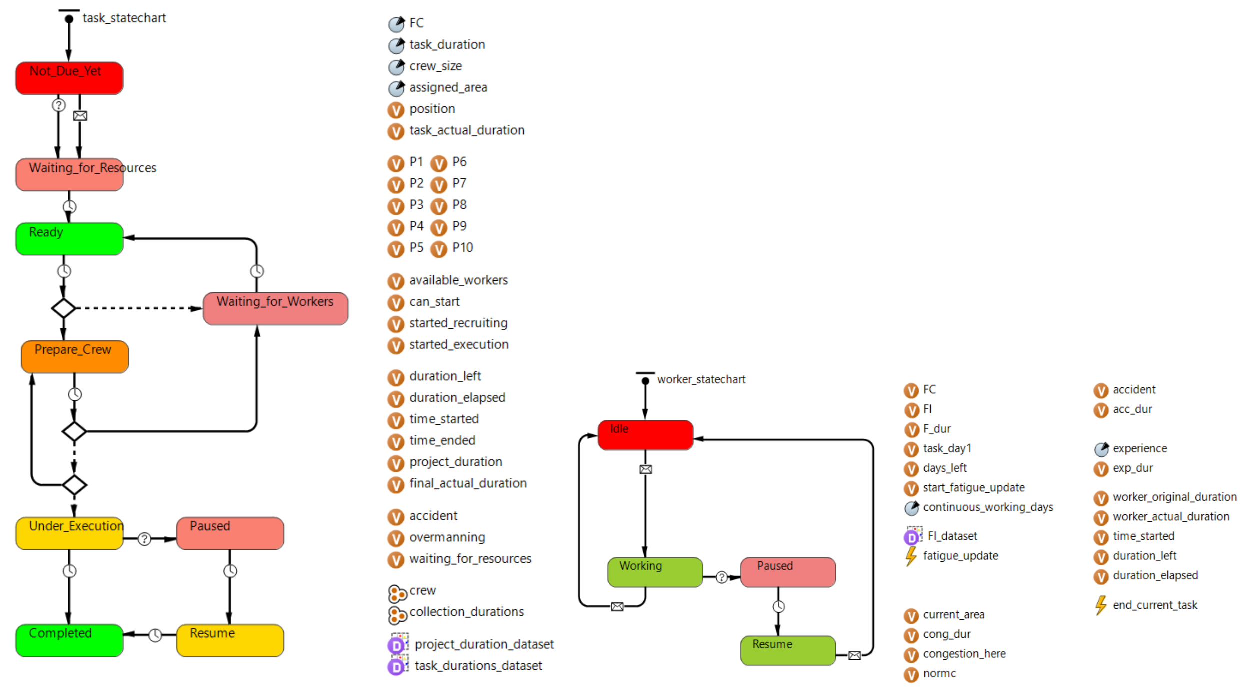
Table 1: Agent population required input.

Agent Population	**Mode of Creation**	**Required Input Parameters**
Workers	Database-loaded	Worker ID Worker Experience
Tasks	Database-loaded	Task ID Task Duration Required Number of Workers Assigned Working Area Predecessors
Areas	Database-loaded	Area ID Vertical Dimension (d_1) Horizontal Dimension (d_2) Area Size Area Capacity

The task agent population includes a set of variables, parameters, collections, and datasets as shown in Figure 2(a). The crew collection is used to collect all worker agents that are assigned to the current task, and the durations collection is used to collect individual worker durations as each worker's duration differs based on experience and fatigue, apart from other common factors among all workers.

Each task agent goes through a "statechart", where they enter the "Not Due Yet" state upon model startup. This state holds all tasks whose predecessors were not completed yet. Once all predecessors are completed, the task agent moves to the "Waiting for Resources" state and stays there until a randomly generated duration representing days waiting for resources is elapsed. Afterward, the task moves to the "Ready" state, where it checks if there are any available workers (not occupied with another task). If so, it moves to the "Prepare Crew" state where it adds workers to its crew collection until the required number of workers is secured. Otherwise, it moves to the "Waiting for Workers" state and keeps checking for available workers until enough workers are assigned. Once the crew is ready, the task moves to the "Under Execution" state and then to the "Completed" state when the last assigned worker completes their work. During execution, if an accident occurs (its occurrence will be discussed shortly), the task moves to the "Paused" state and then resumes by moving to the "Resume" as soon as the accident pause duration is over. It then moves to the "Completed" state when the remaining days are over as well. This process is shown in Figure 2(a). All task durations and the total project duration are added to datasets and exported to excel sheets for analysis at the end of each simulation run.

The Worker agent population included parameters, variables, and events pertaining to different factors that can affect workers' productivities, such as fatigue, accidents, congestion, experience, and site layout (Figure 2(b)). Fatigue, congestion, experience, and site layout affect each worker's duration needed to complete a task, while accidents cause a sudden pause all throughout the project for a specified period of time, thus affecting the total project duration rather than individual task durations. In the statechart, all agents enter the "Idle" state upon model startup. Once a worker is assigned to a task, they move to "Working" state through a message-triggered transition after a message "Start Working" is sent from "assigner" task that assigned a worker to its crew. When the calculated worker actual duration is elapsed, they move back to the "Idle" state and await a new message representing an assignment to trigger their movement to the "Working" state again. If an accident occurs, they move to the "Paused" then "Resume" states until the remaining actual duration is elapsed, and they move back to the "Idle" state. Accidents for both workers and tasks are modeled as an event that is triggered if a "chance of accidents" parameter is greater than a specific value. The value and threshold of this parameter may be specified based on a company's historical data on previous accidents and their frequency, severity, and duration. Two simulation results were recorded: actual task durations and total project duration. Actual task durations indicate duration of each task separately per run, while total project duration indicates total project duration per run.



(a) (b)

Figure 2: Statechart and attributes for the (a) Task agent and (b) Worker agent.

3.2.2 Model 2: Impacts of Factors on Project Duration and Other Factors

A study by Bayesteh et al. (2022) addressed various factors that affect labor productivity and quantified the impacts of the different factors on each other. Therefore, in order to quantify and consequently model the impacts of the factors on one another, the values developed by the mentioned study are used. For example, the impact of fatigue on safety is represented by coefficient "*Cf-s*". Accordingly, in this model, the impact of fatigue on safety is represented by an increase in the value of the "chance of accident" by a percentage of *Cf-s* every time the fatigue index (*I*) explained earlier exceeds a specified threshold. The same concept applies to the impact of experience and congestion on safety, where the "chance of accident" is increased by "*Ce-s*" and "*Cc-s*", respectively. As for site layout, a poorly planned site layout may lead to an increase in *c*, the congestion coefficient, by "*Csl-c*".

3.3 Model Verification and Validation

The model was verified using the dynamic testing approach suggested by Sargent (1992). Dynamic testing entails executing the developed model under various conditions and examining if the values obtained are correct. The techniques adopted in achieving this include traces, internal consistency checks, and investigations of input-output relations. Moreover, all outputs from the used formulas were checked manually. Validation of the proposed simulation model was conducted using three tests suggested by Sargent (1992). The first one is the *Extreme Condition Tests* which examine the structure and output plausibility of the model against an improbable extreme combination of factor levels inside the system. Examples of extreme conditions include a construction project with ideal productivity where all workers are experienced and they do not endure fatigue, workplaces do not get congested, resources are promptly available, work areas are always accessible, and no hazards jeopardize safety on site. In this case, work progress should match the deterministic estimated schedule dates, and it did. The second conducted test was *Face Validity* which calls for asking people knowledgeable about the matter whether the built model and its performance are reasonable. In our study, one expert from the field approved the logic and behavior of the built model. Additionally, *Degenerate Tests* were carried out where the model's behavior degeneracy is tested through selecting appropriate internal and input parameters. When applying factors that negatively impact productivity such as congestion and fatigue, duration of performing a task should increase which was true in the model. Finally, an illustrative example was applied to test the logic and reliability of the model as shown in the following section.

4 CASE STUDY

To verify the feasibility and workability of the developed models on one hand, and to highlight the importance of considering the impacts of the different factors on each other on the other hand, a case study is conducted. In the case study, data were obtained from an ongoing residential gated community project spread over 475,000 square meters, including a variety of building types, such as townhouses, twin houses, and condominiums. The portion of the project that was included in model validation included 52 tasks and 9 working areas. Task relationships, durations, required number of workers, and assigned areas were obtained from the project data. Based on the task types, task fatigue coefficients were estimated to be between 7.5 to 9.9 when compared to task fatigue coefficients per task type obtained from Roja et al. (2006). Fatigue coefficient values were inserted as stochastic values. Finally, the delays in task start dates were obtained from the historical data of the company and inserted as stochastic values as well. The original project duration with no factors taken into account was 68 days. Model 1 (impacts of factors on durations) and Model 2 (impacts of factors on durations and other factors) were each run 100 times with varying random values of parameters, and two results were recorded per run: actual task durations and total project duration. After 100 runs, the change in averages of task durations and the project duration was negligible.

4.1 Discussion

The discussion will tackle two main purposes: (1) to highlight the significant differences in durations between Model 1 that only considers the impacts of the factors on durations and Model 2 and considers the impacts of the factors on each other as well, and (2) to prove the accuracy and reliability of the results of Model 2 compared to actual results. The average task duration was obtained for each task among all 100 runs from each model. An average of 8.8% increase in task duration was detected among all 52 tasks between Model 1 and Model 2 (Table 2). This value is obtained by calculating the percent increase of each task duration among both models and then obtaining their average, not by calculating the percent increase of the average task durations of each model. Such an increase is the result of considering the impacts of the factors on each other and on the duration in contrast to considering their impacts on the duration only. Boxplots shown in Figure 3 and Figure 4 for Model 1 and Model 2 respectively were also generated showing all task durations. It can be noticed that most task durations' 25th and 75th percentiles varied considerably in Model 2 compared to Model 1, in addition to significant changes in the medians. Taking Task 6 as an example, its 25th and 75th percentiles moved from 10 and 11 days, respectively, in Model 1, to 10 and 16.5 days in Model 2. Such observation was only made possible through considering the impacts of the factors on one another. Had their impacts on the duration been considered solely during planning, major deviations and failures during execution could have occurred, possibly leading to claims and disputes among project participants.

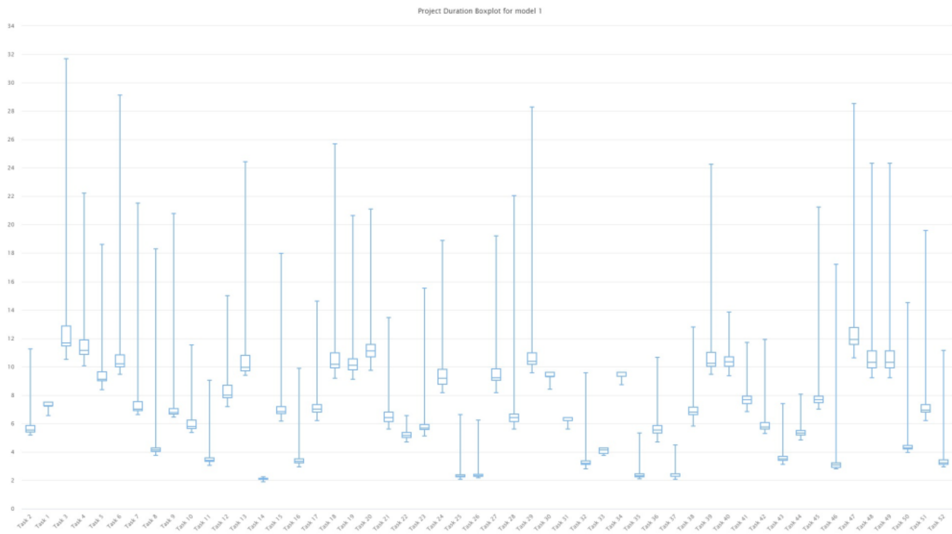


Figure 3: Task durations boxplot for model 1.

As for average project durations, the values from both models for the total project durations were obtained. An average increase of 9.8% was observed between the durations obtained from both models (Table 2). The difference between the average increase in task durations and the average increase in total project durations may be attributed to the two factors whose impacts are on the total project duration only. Accidents and lack of resource availability cause a sudden pause in the project and a delay in the start date of a task, respectively. Therefore, they do not extend the durations of the tasks themselves.

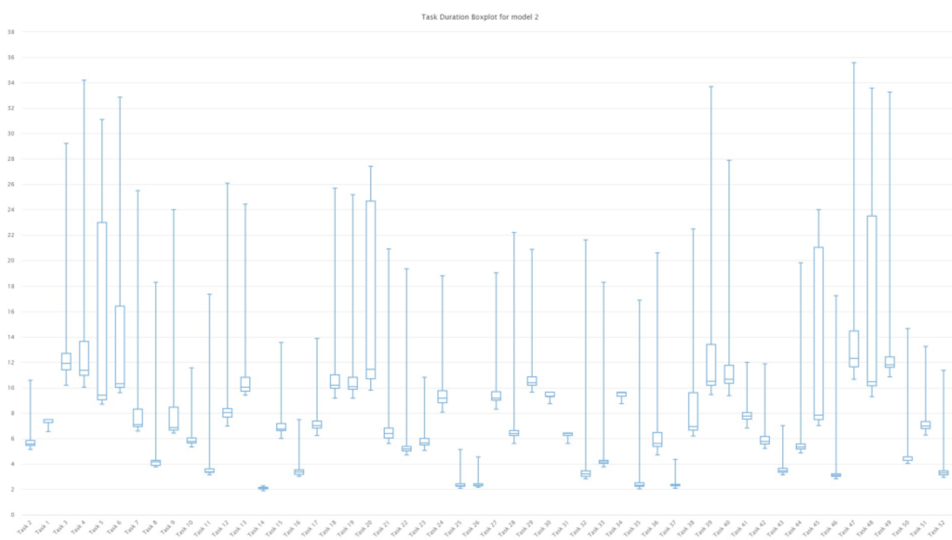


Figure 4: Task durations boxplot for model 2.

Table 2: Average task and project durations and percent increase among models 1 and 2.

	Average Tasks Durations	**Average Total Project Duration**
Model 1	7.71	125.5
Model 2	8.65	139.1
Percent Increase	8.8%	9.8%

The presented results show the differences between the results obtained from Model 1 and Model 2, which proves that considering the impacts of the factors on each other leads to significant changes in the estimation of task and project durations. However, to prove the accuracy of Model 2 results compared to planned durations and Model 1 results with respect to actual durations, project participants were asked to provide actual task and project durations. Table 3 shows the planned, Model 1, and Model 2 results compared to actual results of task and project durations. It may be deduced that Model 2 generated the most accurate task and project durations when compared to actual durations, with 8.9% and 3.03% relative changes, respectively. This further underlines the accuracy and reliability of the developed model (Model 2) that not only takes some of the most prominent factors influencing productivity into consideration, but also investigates their interdependencies and their impacts.

Table 3: Planned, model 1, and model 2 results with respect to actual results.

	Average of Task Durations Relative Change Compared to Actual	**Project Duration Relative Change Compared to Actual**
Planned	32.99%	49.62%
Model 1	16.8%	7.03%
Model 2	8.9%	3.03%

The obtained results further highlight the importance of considering the impacts of the factors on one another rather than only on the productivity or duration for a more accurate and reliable planning process on construction projects. Enhancing the planning process can help refine the overall project performance through providing more realistic and achievable plans, while also reducing wastes in time, cost, and resources. Practicing reliable planning also ensures a more efficient project monitoring and control process through allowing for more accurate calculations of control metrics such as the Earned Value Method's Cost Performance Index (CPI) and Schedule Performance Index (SPI) (Kuhl and Graciano 2014) or the Last Planner System's metrics including Percent Planned Complete (PPC), Tasks Anticipated (TA), Tasks Made Ready (TMR), and more (Hamzeh et al. 2019).

5 CONCLUSION

Despite various attempts in quantifying the impacts of factors affecting labor productivity on project duration, the research body still lacks a comprehensive approach that links the different factors and quantifies their impacts on project duration and on each other through a multidimensional perspective. This perspective, where each factor may be affecting more than one outcome or factor, ensures an accurate estimation of task durations and total project durations. This paper employs ABM to address this issue. ABM is chosen as it allows modeling the emergent behavior of the different agents within the model, in addition to modeling the interactions of the agents living in the same environment. The emergent behavior in the case of this study is the constantly changing values of construction workers' fatigue, congestion in working areas, chances of accidents, and so on. This modeling process eventually allows users to study the effects of the modeled agents' decisions, behaviors, and interactions on their performance.

Through ABM, two generic simulation models were developed, where the first one considered the impacts of factors affecting labor productivity on the duration only, while the second considered their impacts on each other as well. The developed models are described as generic as they are not tailored to a specific project. In other words, they may be used by different users working on different projects by inserting a project's databases for the crews, tasks, and areas. The models run and generate results regardless of the data inserted to help estimate accurate task and project durations. Its validity was proved by a set of verification and validation techniques, and its reliability was tested through a retrospective case study. Individual task durations and total project duration results were obtained. By implementing a case study for model validation, an average of 8.8% increase in task duration was detected among all tasks between the two models, and an average increase of 9.8% was observed between the total project durations. These values highlight the significant changes observed in duration results after taking the impacts of the factors on each other. Additionally, results showed that considering the impacts of the factors on each other resulted in a more accurate and reliable duration estimation process for task and project durations, with only 8.9% and 3.3% relative changes, respectively, compared to actual durations. Such an approach allows for more reliable planning, where, as aforementioned, enhancing the planning process can help refine the overall project performance through providing more realistic and achievable plans, while also reducing wastes in time, cost, and resources. Practicing reliable planning also ensures a more efficient project monitoring and control process through allowing for more accurate calculations of control metrics. The paper contributes to research by demonstrating the inaccuracy of basing duration estimates in construction projects on purely deterministic task duration estimates or on durations with the impacts of factors on productivity only. Instead, duration estimates should be based on the aforementioned in addition to the interdependencies of the factors represented by the quantified impact of the factors on each other. As for the paper's contribution to the industry, it lies in providing practitioners with a reliable approach for task and project duration estimates whose accuracy was proven to be higher than that of deterministically estimated planned durations and to traditional approaches that only consider the impacts of the factors on productivity. Future research can address adding more influencing factors as only six factors were selected to be modeled. Additional links among factors may also be included to add a "bidirectional" aspect to this multidimensional approach proposed. Increasing the number of simulation runs can also better enhance model credibility. Finally, more accurate mathematical equations used to quantify the impacts of the factors may be used.

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