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A HYBRID SIMULATION-BASED OPTIMIZATION FRAMEWORK FOR MANAGING MODULAR BRIDGE CONSTRUCTION PROJECTS: A CABLE-STAYED BRIDGE CASE STUDY

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ABSTRACT

Generally, bridge construction is one of the most complex structures in the construction industry due to the higher scalability and supply chain complexity. The modular bridge construction (MBC) technique is considered more advantageous in providing higher productivity, shorter schedules, and better quality. Current practices in managing MBC projects overlook dynamic behaviors among the relevant stakeholders and the interactions among various interacting systems, including manufacturing, logistics, and onsite assembly. To this end, this paper proposes a simulation-optimization framework to enhance MBC project planning. The simulation module comprises discrete event simulation and agent-based modeling to model the interconnected behaviors of the MBC systems. The optimization module aims to improve the key performance indicators (KPIs) of MBC projects, including project cost, schedule, and sustainability. The proposed framework is validated by introducing an MBC case of a cable-stayed bridge. The generated solutions by the optimization model show possible significant enhancements in the identified KPIs.

1 INTRODUCTION

Over the past decade, the construction industry has been witnessing a shift towards Offsite Construction (OSC) methods (Gerth 2013) whereby building elements are manufactured in a factory and then transported to the site for installation and assembly (Jin et al. 2018). It has been adopted in several types of construction projects such as residential and bridge construction projects.

OSC has been associated with several benefits when compared to traditional construction including shortened schedule, reduced cost, better on-site safety, improved product quality, increased productivity as well as reduced negative environmental impact (Kamali and Hewage 2016). Despite such benefits, OSC encounters certain challenges that potentially limit and complicate its successful implementation and thus should be mitigated. These challenges include, for example, the need for intensive pre-project planning to coordinate the different phases of the project (Kamali and Hewage 2016), transportation restraints considering prefabricated units' dimensions and weight (Wei et al. 2014), the need for effective communication and coordination between the different involved stakeholders (Kamali and Hewage 2016) as well as managing the overall supply chain (Wang et al. 2019; Assaf et al. 2023). As a matter of fact, the challenge of managing the OSC supply chain is deeply rooted in the complexity of the OSC supply chain itself and its fragmented nature as compared to that in traditional construction (Wang et al. 2019). Researchers describe the OSC supply chain as a multi-echelon supply chain that involves the structure's components' design preparation and shop drawings detailing, manufacturing in a prefabricated facility, storage, and shipment to the site for installation (Hussein 2021). Adding to the complexity of managing the OSC supply chain, the prefabricated components are uniquely designed to meet the requirements of the project. They are also bulky and heavy in size which limits the potential of holding a large stock. As such, it would not be feasible to fabricate the components prior to receiving the request (Hsu et al. 2018).

In order to mitigate the aforementioned challenges of the OSC supply chain, several tools and methods have been leveraged including building information modeling, artificial intelligence, game theory, lifecycle assessment, optimization, simulation, and hybrid methods (Hussein 2021). More specifically, simulation-based approaches are considered among the most utilized techniques given their ability to model and simulate the complexities and uncertainties associated with the different stages of OSC supply chain (Hussein 2021). Discrete event simulation (DES) illustrates how a certain system evolves over time (Law et al. 2007) and has been recognized as a sound decision-making tool by many (Martinez 2010). Agent-based modeling (ABM), on the other hand, considers the interactions of the individual agents in the system (Siebers et al. 2010). The combination of these two simulation approaches makes use of the simplicity of DES modeling alongside the capabilities of the ABM modeling (Borshchev 2013). In fact, simulation tools have been leveraged in several studies to model one (or more) of the OSC supply chain stages, including the production (Liu and Lu 2020), logistics (Hussein et al. 2022), and onsite installation stages (Taiwo et al. 2022). For instance, Mohamed (2020) developed a simulation model using DES and system dynamics to plan the installation of the prefabricated modules. Their model considered external factors, such as weather conditions, that affected the productivity of the installation process. Similarly, Taiwo et al. (2022) developed a DES model to assess the installation of modules on site, considering external factors, such as topography, and management factors, such as workers' training. Moghadam et al. (2012) attempted to enhance the manufacturing stage of offsite construction through lean principles and tested the impacts through DES models. Furthermore, Hussein et al. (2022) considered the logistics and installation of the OSC projects. Their model integrated the ABM and DES techniques to enhance the implementation of OSC projects by evaluating a set of decision variables. Similarly, Hussein et al. (2023) developed an ABM-DES model to model the logistics of OSC projects that considered a number of key performance indicators (KPIs), such as logistics cost and truck emissions, and evaluated a set of decision variables. Their approach was able to reflect the successful integration of simulation and optimization tools to provide stakeholders with a sound decision making tool when analyzing the tradeoffs between different potential scenarios.

In spite of the many contributions provided in the literature review on this topic, several gaps were identified. The association between the ABM and DES in modeling the supply chain of OSC projects is absent, except for Hussein et al. (2022) and Hussein et al. (2023) who did not consider the manufacturing stage of the OSC projects. Further, none of the previous studies has considered modular construction bridges. Modular bridges include manufacturing heavy steel (or reinforced concrete) modules in the factory (Lechner et al. 2021), as well as manufacturing precast slabs to be placed on top of the manufactured modules (Xiangmin and Dewei 2021). The complexity of the supply chain in modular bridge construction is argued to be more significant compared to residential structures, which form the focus of most of the previous studies. Modular bridge complexity also rises when integrating cable-stayed techniques, which include the tension of these modules from tall structures (pylons) using cables (Xiangmin and Dewei 2021). Moreover, although some of previous studies considered KPIs, such as cost and time, minimum research attention has been given to sustainability indicators, such as the reduction of CO_2 emissions.

In light of these limitations, many research questions are yet to be answered: How to count for the possible interactions between different resources (agents) considering all of the OSC supply chain stages? How to model processes included in modular bridges in manufacturing, transportation, and onsite stages? How to develop a decision support system to evaluate different solutions and scenarios in modular bridge construction? Therefore, this research aims to answer these questions by providing a hybrid simulation-optimization approach that counts for all of the stages in OSC construction projects. The study contributes to the body of knowledge by the following: 1) provide a hybrid simulation model that integrates ABM and DES simulation techniques in modeling the dynamic behavior of agents in modular bridge construction; 2) provide an optimization model that evaluates different generated solutions based on several KPIs, including time, cost, and CO_2 emissions; 3) introduce a case study of a modular cable-stayed bridge to validate the proposed approach.

2 METHODOLOGY

The methodology of this research work is divided into four stages: data collection, KPIs development, DES-ABM modeling, and model optimization. Figure 1 provides an overview of the adopted methodology.

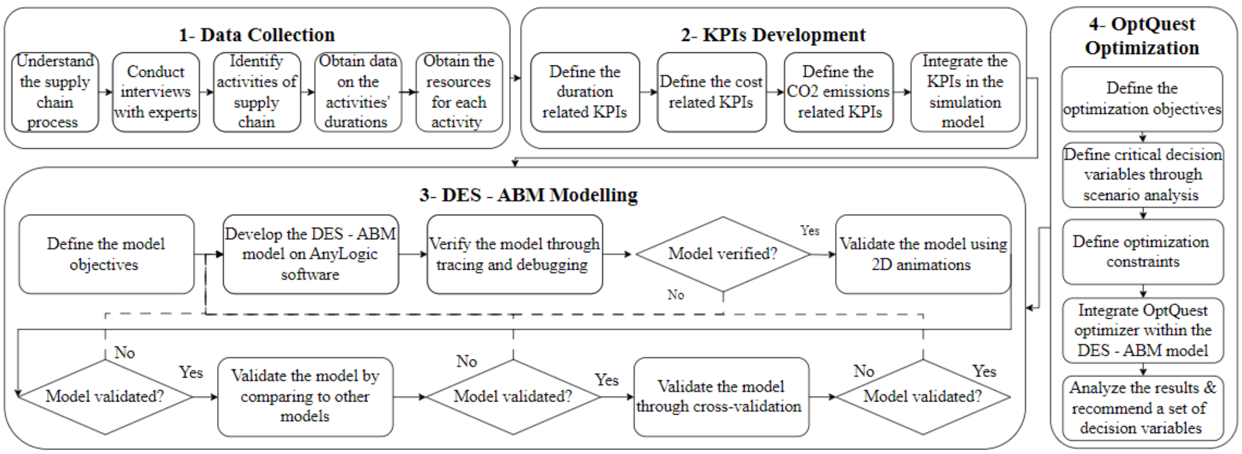


Figure 1: The overall methodology.

In the first stage of the methodology, data was collected from a cable-stayed bridge construction project by conducting interviews with construction personnel on the project. The interviews provided the authors with a clear understanding of the process and the corresponding sequencing of the activities taking place. The data included the different activities that constitute the supply chain process. For each activity, the duration and the corresponding resources were also obtained.

As for the second stage of the methodology, a set of KPIs was developed to assess the performance of the supply chain of the bridge construction in terms of duration, cost, and CO_2 emissions. These KPIs were integrated within the simulation model to allow for monitoring at any stage of the simulation runs. The list of KPIs, along with their description and equations, is described below (Hussein et al. 2023).

2.1 Duration-Related KPIs Included

Total Project Duration *(TPD)* is the total time required to complete the installation of the modules. The Total Girders Fabrication Duration *(TGFD)* is the total time required to fabricate the girders for the modules. Further, the total Onsite Works Duration *(TOD)* is the total time required to complete the module installation works on site.

2.2 Cost-Related KPIs Included

The developed cost-related KPIs are described as follows:

- Total Supply Chain Costs *(TSCC):* Cost of the entire supply chain, including both logistics and construction costs represented by $TSCC = TLC + TCC$
- Total Logistics Costs *(TLC):* Cost of the total logistics of the supply chain, including both road and maritime logistic costs represented by $TLC = MLC + RLC$

- Maritime Logistics Costs *(MLC):* Cost of maritime logistics as the total cost of renting ships represented by $MLC = \sum(ShT * ShR)$ where ShT is the time spent by ship shipping, and ShR is the cost rate.
- Road Logistics Costs *(RLC):* Cost of road logistics described as the cost of renting the trucks represented as $RLC = \sum(TT * TR)$ where TT is time spent by truck shipping and TR is the cost rate.
- Total Construction Costs *(TCC):* Cost of direct construction and indirect construction represented as $TCC = DC + IC$
- Direct Construction Costs *(DC):* Cost of direct construction works, including both labor and equipment represented as $DC = LDC + EDC$
- Labor Direct Construction Costs *(LDC):* Cost of the direct construction for all crews represented as $LDC = \sum(Tc * Cc)$ where Tc is the time spent by a crew working and Cc is the cost rate.
- Equipment Construction Costs *(EDC):* Cost of the direct construction works for all equipment represented as $EDC = \sum(Tc * Ce)$ where Tc is the time spent by working and Ce is the cost rate.
- Indirect Construction Costs *(IC):* The indirect construction cost represented as $IC = TPD * ICR$ where *ICR* is the indirect cost rate.

2.3 CO_2 Emission-Related KPIs Included

The developed emission-related KPIs are described as follows:

- Total Supply Chain CO_2 Emissions *(TSCE):* The total carbon emissions of the supply chain, including those related to logistics and those related to the construction site represented as $TSCE = TLE + TCE$
- Total Logistics Emissions *(TLE):* The total carbon emissions of the logistics part, including road and maritime represented as $TLE = RLE + MLE$
- Road Logistic Emissions *(RLE):* The carbon emissions related to road logistics are based on the corresponding emissions rate represented as $RLE = \sum(Dt * et)$ where Dt is the total distance traveled by truck, and et is the CO_2 emission rate of the truck.
- Maritime Logistic Emissions *(MLE):* The carbon emissions related to maritime logistics based on the ship's fuel consumption rate and the emissions factor represented as $MLE = \sum(FC * ShT * es)$ where FC is the fuel consumption rate, ShT is the time spent by a ship moving, and es is the emission rate.
- Total Construction Emissions *(TCE):* The total carbon emissions produced by each equipment, including both the busy time and the idle time represented as $TCE = \sum(eq\,(IT * IP + BT * BP))$ where eq is the emission rate, IT is the idle time spent by an equipment, IP is the power rating during idle time, BT is busy time spent by an equipment, and BP is the power rating during busy time.

In the third stage of the methodology, a DES-ABM simulation model was developed using the software AnyLogic to represent the overall supply chain activities of installing the modules of the selected cable-stayed bridge construction case study. This integration allows to model the interactions between entities of interest given the complexity of modeling the supply chain process. The objective of the model was to identify the values of certain parameters in order to enhance the project's KPIs. The developed model was then validated and verified with different approaches to ensure its usage as a sound decision-making tool.

Finally, the last part of the methodology involves the use of optimization to enhance the supply chain performance. The objective of the optimization problem is to minimize the set of KPIs related to time, cost, and CO_2 emissions. The decision variables are represented by the different parameters that impact the KPIs. In order to determine which parameters will be used as the decision variables, scenario-based analysis was conducted to study the sensitivity of the parameters on the KPIs. As for the optimization problem constraints, these were also identified based on the selected case study's limitations. The OptQuest optimization engine developed in the AnyLogic simulation tool (Shahi and Pulkki 2015) was adopted (Hussein et al. 2022). It combines both metaheuristics and neural networks (Hussein et al. 2022). Although it is capable of providing near-optimum solutions in less computation time, it is designed as a black box that only permits the users to identify the stopping criteria (Hussein et al. 2022). Finally, to evaluate the discovered solution provided by OptQuest and provide a more comprehensive visual representation of the best solutions. A normalization approach is followed where the top solutions are identified for each KPI. Then, for each solution, each KPI is compared to the best solution corresponding to the same KPI and a performance score (Ps) ranging from one to two is given, where one is the worst solution and two is the best one.

$$Ps_{i\,j} = 1 + \frac{j_i - Min\ j}{Max\ j - Min\ j} \tag{1}$$

Where i is the number of possible solutions and j is the corresponding KPI.

3 RESULTS AND DISCUSSION

3.1 Data Collection and Case Study Description

A case study is presented in this section to validate the proposed framework. The case study is located in Giza, Egypt. It represents the construction of a cable-stayed bridge. The bridge comprises the fabrication of 40 steel modules that are manufactured offsite and shipped to the site to be installed and assembled. Further, the length of the bridge is 540 meters, including a 300-meter main span (the focus of this study) and 240-meter side spans. This bridge has a Guinness World Record for being the widest cable-stayed bridge in the world. The width of this bridge is 67.3 meters. Two shared pylons, spaced 300 meters apart, were developed in the bridge to hold two separate decks that share the inner pylons' legs.

3.2 DES-ABM Model Development

As mentioned above, the developed model integrated ABM and DES approaches. The ABM method mainly considers the vehicles' interactions with each other and with the system. Four main agents are identified in the system: trucks that carry the steel girders from the steel factory to the yard, trucks that carry the precast slabs from the precast factory to the bridge, the barge that carries the modules from the yard to the bridge, and a traffic agent that affects the trucks traveling duration. Figure 2 shows the behavior of each agent in the developed model. The behavior of each agent is represented by a statechart. Statecharts are sets of transitions and states that define the behavior of a particular agent (Borshchev 2013). The states represent the different changes that happen to the agent. On the other hand, transitions are the conditions by which the agent moves from one state to the other (Hussein et al. 2022).

The precast truck agent is discussed in detail in this section. The initial state of the precast truck is in the parking lot. The truck remains in the parking lot until it receives a message from the DES simulation model. This message is "GoToPfactory" and is sent when a particular stage in the DES simulation has been reached. When this message is sent, the truck moves to the precast factory, spending some time according to the traveling distance. The truck then spends some time at the factory until it is called by the DES model when the loading of the precast slabs is done. It then receives a "GoToBridge" message from the DES model. The state of the truck changes from "AtFactory" to "AtBridge" after spending some time, depending on the traveling distance. Again, the agent is sent to the DES model to unload the precast slabs on the bridge. Once finished, the DES sends a message "Return" to the agent to return it to the parking lot until called again. It is worth mentioning that the precast truck can only carry a maximum of four slabs at once, meaning that the truck will have to go back and forth until it finishes the slabs needed for one module. Furthermore, the truck goes through regular maintenance once it travels 1000 kilometers or more. This is represented in the truck maintenance state that is controlled by a condition of total traveling truck distance.

As mentioned above, these agents interact with an overall DES system. The DES system comprises all stages of constructing the cable-stayed bridges. Overall, there are four main processes: manufacturing of the steel girders, manufacturing of the steel modules, assembly of the steel modules on the bridge, and onsite works. Figure 3 shows the main processes included in the DES model.

First, the steel girders are manufactured in a factory located away from the project. Eight main stations are included in the factory, including manufacturing flanges and webs and assembling the girders. All of the stations are represented as resources, and the number of workers is specified for each station. It is worth mentioning that the factory processes are built per the instructions given by Liu and Lu (2020).

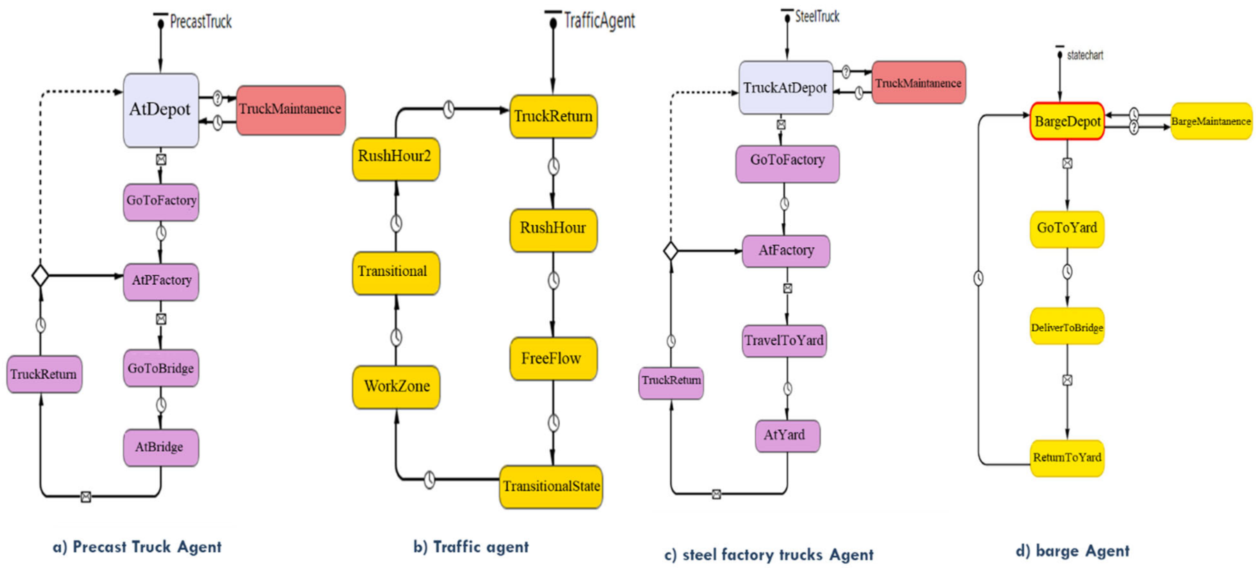


Figure 2: The included agents in the ABM model.

The second main process in the DES model is the assembly of the steel modules. In a yard with a limited number of spaces, five activities are included in manufacturing one steel module. Once the steel girders arrive at the yard, they are handled by the mobile cranes and yard workers to establish the steel modules, as shown in Figure 3(c). The process in the yard is held when the maximum number of manufactured steel modules is reached. The following process is injected once a steel module is manufactured.

The next process is the steel modules installation. When it is the turn for the steel module to move to the bridge, it is handled by a heavy crane, which places it on top of a barge. The barge is pushed by a ship to its specified place on the bridge. The derrick crane handles the module to its location on the bridge. This is followed by leveling and splice connection with the previous module. The anchor connection is then established, and the module is tensioned for the first time by a mono strand by the upper part of the pylon.

The last main process includes the onsite works that start with placing the precast slabs on top of the steel modules. This process includes two types of cranes: mobile cranes and floating cranes. The stitches between the slabs are poured with concrete after the shear connectors are placed. Finally, the strands of the cables go through a second tension from the upper part of the pylon using the mono strand.

3.3 Model Verification and Validation

Once the simulation model was developed, it was necessary to test its accuracy through verification and validation to ensure that it could be used as a sound decision-making tool (AbouRizk 2016).

The verification of the model included checking its integrity (AbouRizk 2016) using both static and dynamic approaches (Sargent 2010). The static approach was conducted through debugging and tracing to ensure that the code was free from errors (Sargent 2010). Certain portions of the code were debugged while tracing certain information of interest to ensure that the code was working as expected (Hussein et al. 2022). As for the dynamic approach, it was conducted by investigating certain input-output relationships by testing out different scenarios. For example, increasing the number of trucks changes the outputs of the model as expected. These effects are discussed in detail in the results section.

Once the model was verified, it was necessary to ensure that it represented the real system by validating it (AbouRizk 2016). Adopted validation techniques were validation by animations and cross-validation.

The validation by animation technique aims to display the process graphically throughout the simulation time based on the developed model (Sargent 2010). It was selected given its capacity to identify errors present in the simulation model as well as to verify the assumptions taken by the authors and compare them with the real-world model. It also allows us to fully capture the properties of the simulated processes to ensure process understanding and error detection, agent behavior and environment visualization, model correction, and fine-tuning. Regarding process understanding and error detection, each manufacturing/ construction process was analyzed, and logical task transition was ensured. Next, each agent's behavior was visualized through an interactive GIS map highlighting their behavior for each scenario, as seen in figure 4, where the delivery trucks and barge are using distances extracted from a GIS map and using them in distance estimation. The environment, on the other hand, was visualized using the Anylogic general interface, where the logistics network and the traveling distances are extracted with high accuracy from the GIS map. Finally, a set of parameters and variables were used and altered throughout the simulation time to ensure the model behavior was realistic and all the main features of the manufacturing and construction processes were captured.

Finally, cross-validation was adopted to compare the developed model to similar validated models that exist in the literature (Rand and Rust 2011). Specifically, the resulting behavior was compared to that presented in a study developed by Hussein et al. (2022) since a similar approach to developing the DES-ABM model was adopted for modeling a similar supply chain process. The overall effects of increasing or decreasing different resource variables, such as trucks shipping the steel girders and slabs or the number of workers at the fabrication shop, were compared against the overall results of the KPIs of the model. With the change in the number of resources, certain KPIs were affected, following the same trend as those reported in similar models. For example, with an increase in the number of trucks for the transportation of steel girders and concrete slabs, the total simulation time decreased by 23 %, the cost by 17 %, and the CO_2 emissions by 20 %. These results follow the overall trends presented by Hussein et al. (2022).

3.4 Analysis and Discussion

This section illustrates the results and discussion of the presented model. The results are presented in three main steps. First, a sensitivity analysis of the parameters is discussed to discover the potential ones that impact the KPIs. Second, the optimization model is used to minimize each KPI considering the identified parameters as the decision variables. Finally, the identified solutions are evaluated, and the main KPIs, time, cost, and emissions, are estimated.

Test cases of the model have revealed that the potential parameters are the following: 1) the number of workers in the factory, 2) the number of steel trucks moving from the steel factory to the yard, 3) the number of precast trucks moving from the precast factory to the yard, 4) the yard capacity, 5) the adoption of just-in-time technique, 6) the number of cranes onsite, 7) the number of production lines. A sensitivity analysis of these parameters is tested considering the KPIs. Figure 5 shows some of the sensitivity analysis results.

For instance, the results show that increasing the number of factory and precast trucks positively impacts logistics emissions while shortening the project's overall duration. On the other hand, the number of factory workers appears to be a critical parameter in the process. Increasing the number of factory workers shortens the factory manufacturing time significantly. Yard capacity indicates how many modules can be stored in the yard. A value will be added to the overall cost when the yard capacity increases. The figure shows a fluctuating behavior of the modules' manufacturing total time and costs when the value of the yard capacity changes. Hence, the impact of this parameter will be better discussed in the optimization section. Moreover, the number of available onsite mobile cranes negatively impacts the total onsite cost and the total onsite emissions. Hence, this conflict needs a more integrated approach that evaluates multiple parameters simultaneously. This approach is presented in the following section by introducing the optimization model. Besides, applying just-in-time (JiT) in the project can greatly influence the overall process. The results presented in the figure show that the application of JiT negatively influences the KPIs when considering the overall process. This result aligns with the results presented by (Hussein et al. 2022).

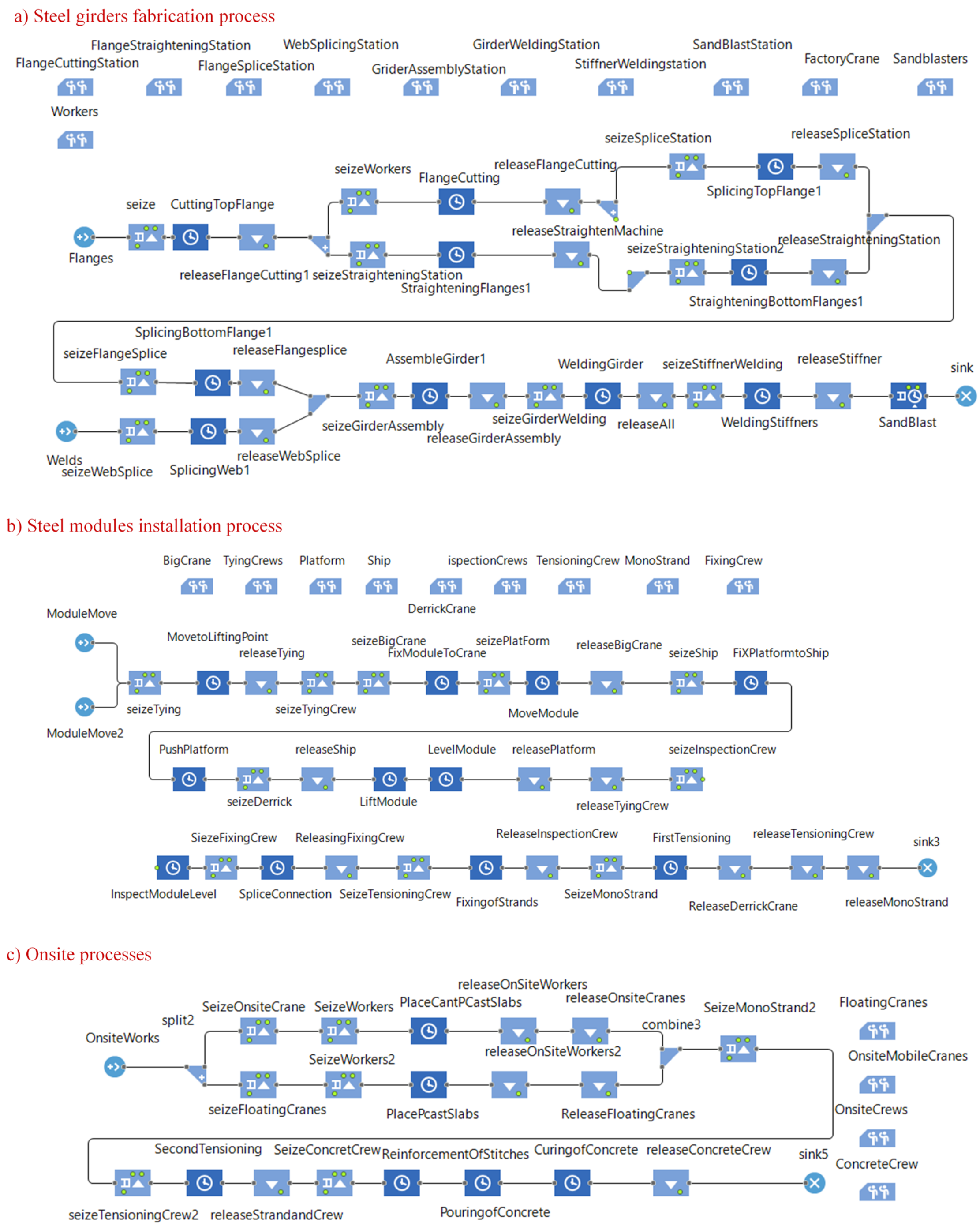
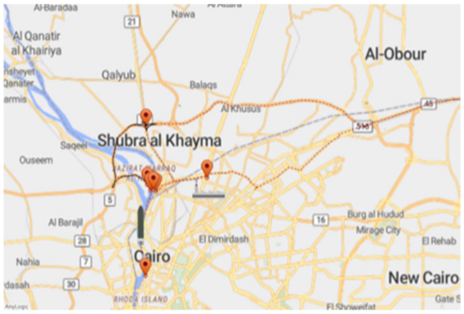


Figure 3: The overall DES process.



a) Steel factory and precast truck agents

b) The barge agent

Figure 4: Agent and environment visualization using an interactive GIS map.

3.4.1 Analysis of the Optimization Model

This section presents the results of the optimization model. As mentioned above, the optimization experiments are developed on the OptQuest engine of the Anylogic tool. For each of the identified decision variables, the simulation is run to minimize all of the discussed KPIs (project duration, total project cost, and total project emissions). The model's objective function is set to minimize one of the mentioned KPIs. A solution (consisting of a set of decision variables) is retrieved for each objective function. By the end of this experiment, a set of 14 possible solutions are discovered and evaluated against the 3 main KPIs.

In every run of the optimization model, a set of constraints based on the user's preference, is identified. In this study, these constraints are related to budget and sustainability considerations. For instance, the user can indicate a specific budget that must not be exceeded in any of the algorithm's iterations. If exceeded, the solution turns to infeasible solutions. Each run of the optimization algorithm is set to a thousand iterations; this stopping criterion is selected to cover all possible combinations of the decision variables.

Table 1 shows the 14 possible decisions discovered in the optimization problem. These solutions are identified based on running the optimization algorithm to optimize each of the KPIs individually. As one can observe, each optimized objective resulted in a different set of variables. For instance, increasing the number of trucks can enhance the factory's total time but negatively impact logistics costs. Similarly, minimizing the total duration needs an increase in the production lines, which hurts the project's total cost. Thus, a more integrated approach is needed to provide insights into the main KPIs. The following section will examine each of the provided solutions in Table 1 and test them against the main KPIs.

Figure 6 shows the results of evaluating the solutions according to the project duration in days, project cost in $ millions, and total project emissions in million kg CO_2 and their corresponding performance scores. Although there is no existence of a perfect solution that satisfies all of the KPIs, the figure provides many insights into enhancing the process. Many solutions that have high value in all KPIs, such as solutions 7 and 11, can be excluded. In addition, solutions such as 6 and 12 show a minimization of two KPIs, while a having a high value of the third one. Solutions, such as 2 and 13, show a potential to enhance the process and almost satisfy all KPIs. So, the best KPIs for the time, cost, and emissions are 301 days, 10.48 million $, and 1.586 million kg CO_2.

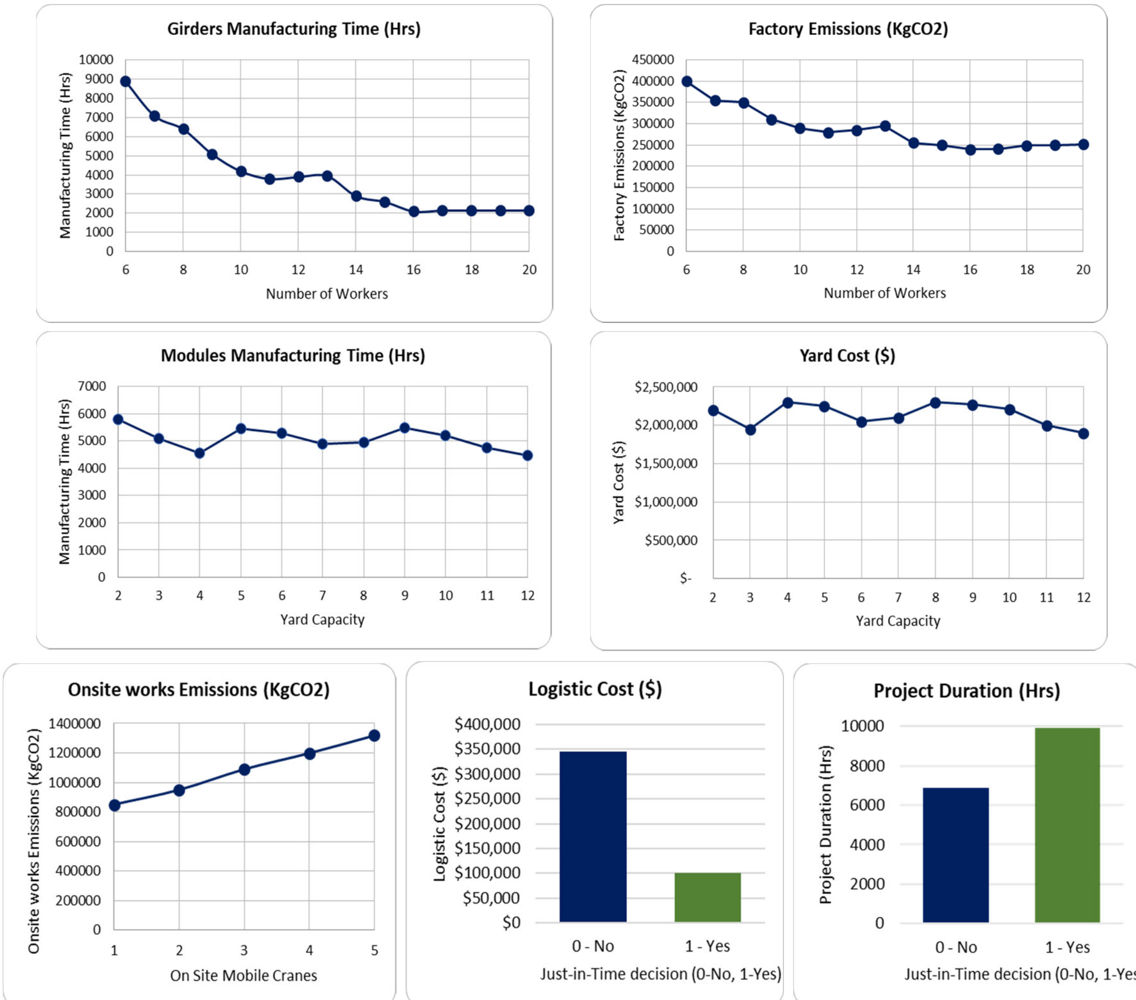


Figure 5: The main influential parameters of the model.

Table 1: The considered solutions and objective functions.

Solution	Objective function (minimize)	value	Decision Variables						
			Yard capacity	**No. Factory workers**	**No. Precast Trucks**	**No. girders Trucks**	**No. of onsite cranes**	**JiT**	**No. of production lines**
1	Total factory time	2452 (Hrs)	8	19	3	3	1	No	2
2	Total factory cost	3.5 (Mn $)	2	17	6	3	4	No	1
3	Total onsite cost	2.2 (Mn $)	4	15	6	1	2	No	2
4	Total onsite time	4137 (Hrs)	2	13	6	1	4	No	1
5	Yard total cost	1.24 (Mn $)	10	13	6	3	4	No	1
6	Yard total time	3036 (Hrs)	10	18	6	2	4	No	3
7	Logistics cost	0.091 (Mn $)	3	20	1	2	3	Yes	3
8	Logistics Emissions	0.168 (Mn KgCos2)	8	18	6	3	3	No	3
9	Onsite Emissions	0.623 (Mn KgCos2)	6	14	6	3	1	No	2
10	Yard Emissions	0.076 (Mn KgCos2)	10	13	6	2	4	No	1
11	Factory Emissions	0.228 (Mn KgCos2)	7	16	5	1	2	Yes	1
12	Total durations	301 days	5	15	6	3	4	No	3
13	Total cost	10.48 (Mn $)	2	20	6	2	4	No	1
14	Total Emissions	1.586 (Mn $)	8	14	6	3	2	No	1

4 CONCLUSION AND RECOMMENDATIONS

This study is motivated by the lack of research on efficient techniques used to enhance the adoption of offsite construction projects while considering all project phases. The study presented an optimized hybrid simulation model based on DES and ABM to tackle the challenges in offsite construction projects. The ABM model considers the interactions of the agents, such as the trucks, traffic, and barges, with the DES process and between one another. Further, the DES model considers the processes found in each phase of the offsite project, such as manufacturing, assembly, installation, onsite works, and logistics. A case study of a cable-stayed project was introduced to implement the proposed methodology. An optimization algorithm (OptQuest) was used to determine near-optimum solutions considering several identified KPIs, including total cost, total project duration, and total CO_2 emissions.

A sensitivity analysis of the parameters was conducted to identify the main influencing ones. These parameters were fed into the optimization model and used to optimize each identified KPIs. A total of 14 solutions were then evaluated according to the main KPIs. The study contributes in both theoretical and practical ways. Theoretically, the study provides efficient modeling of all the stages of offsite construction projects. Practically, the study can assist practitioners in making suitable decisions that can enhance the implementation of offsite construction projects.

Despite the contributions of the current study, it still contains some limitations. The discussed agents do not change their behavior throughout the process. Furthermore, a more comprehensive method to identify the possible solutions in multi-objective optimization can be implemented. Hence, future research may focus on integrating machine learning algorithms to develop more intelligent agents while further trade-off analysis can be implemented by revealing the Pareto frontier and obtaining the Pareto optimal set to identify the best possible solutions. Further, the study relies on historical observations and interviews in the data collection. Hence, real-time data can be added to promote the current study. In addition, many other factors, such as weather and penalties for late delivery, can be added to make the model more realistic.

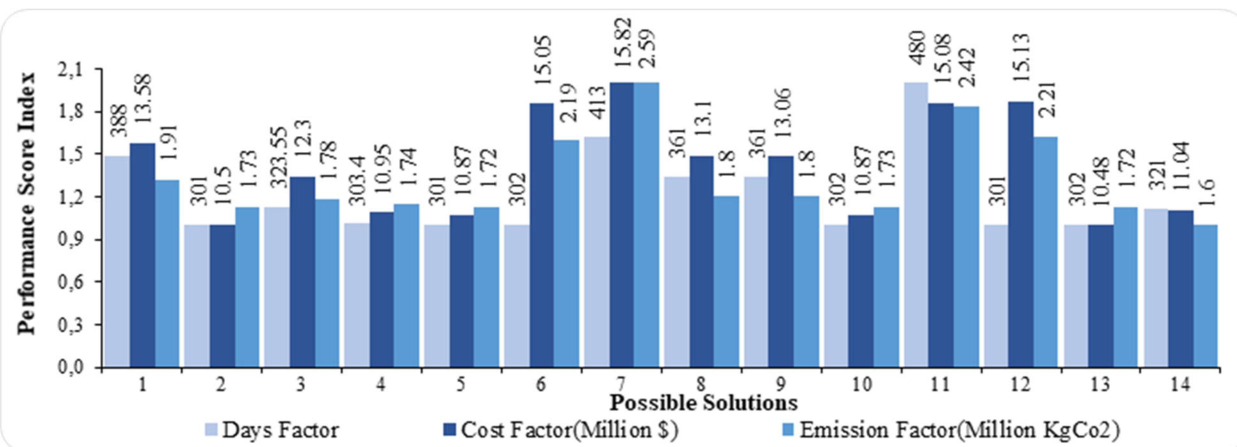


Figure 6: Evaluation of the discovered solutions.

REFERENCES

AbouRizk, S., S. Hague, and R. Ekyalimpa. 2016. *Construction Simulation: An Introduction Using Simphony*. Edmonton: University of Alberta.

Mohamed, S.M.A. 2020. Optimal Tower Crane Operation for Modular Integrated Construction Using Hybrid Simulation. PhD thesis, The Hong Kong Polytechnic University. https://theses.lib.polyu.edu.hk/handle/200/10753, accessed 5th June 2023.

Assaf, M., M. Hussein, S. Abdelkhalek, and T. Zayed. 2023. "A Multi-Criteria Decision-Making Model for Selecting the Best Project Delivery Systems for Offsite Construction Projects". *Buildings* 13(2):571.

Borshchev, A. 2013. "The Big Book of Simulation Modeling: Multimethod Modeling with AnyLogic 6". *AnyLogic North America.*

Gerth, R., A. Boqvist, M. Bjelkemyr, and B. Lindberg. 2013. "Design for Construction: Utilizing Production Experiences in Development". *Construction Management and Economics* 31(2):135–150.

Hsu, P. Y., P. Angeloudis, and M. Aurisicchio. 2018. "Optimal Logistics Planning for Modular Construction Using Two-Stage Stochastic Programming". *Automation in Construction* 94(1):47–61.
Hussein, M., A. E. Eltoukhy, A. Karam, I. A. Shaban, and T. Zayed. 2021. "Modelling in Off-Site Construction Supply Chain Management: A Review and Future Directions for Sustainable Modular Integrated Construction". *Journal of Cleaner Production* 310:127503.
Hussein, M., A. Darko, A. Eltoukhy, and T. Zayed. 2022. "Sustainable Logistics Planning in Modular Integrated Construction Using Multimethod Simulation and Taguchi Approach". *Journal of Construction Engineering and Management* 04022022-1.
Hussein, M., A. Karam, A. E. E. Eltoukhy, A. Darko, and T. Zayed. 2023."Optimized Multimodal Logistics Planning of Modular Integrated Construction Using Hybrid Multi-Agent and Metamodeling". *Automation in Construction* 145:104637.
Jin, R., S. Gao, A. Cheshmehzangi, and E. Aboagye-Nimo. 2018. "A Holistic Review of Off-Site Construction Literature Published Between 2008 and 2018". *Journal of Cleaner Production* 202:1202–1219.
Kamali, M., and K. Hewage. 2016. "Life Cycle Performance of Modular Buildings: A Critical Review". *Renewable and Sustainable Energy Reviews* 62(1): 1171–1183.
Law, A. M., W. D. Kelton, and W. D. Kelton. 2007. *Simulation Modeling And Analysis*. Vol. 3. New York: McGraw-Hill, Inc.
Lechner, T., V. Schmitt, O. Fischer, and J. Kempf. 2021. "Modulbauweisen im Verbundbrückenbau: Modular Construction Methods in Composite Bridge Construction – Review and Current Developments for Bridges with Small and Medium Spans". Stahlbau 90:116-127.
Liu, J., and M. Lu. 2020. "Synchronized Optimization of Various Management-Function Schedules in a Multiproject Environment: Case Study of Planning Steel Girder Fabrication Projects in Bridge Construction". *Journal of Construction Engineering and Management* 146(5):05020002.
Martinez, J. C. 2010. "Methodology for Conducting Discrete-Event Simulation Studies in Construction Engineering and Management". *Journal of Construction Engineering and Management* 136(1):3–16.
Moghadam, M., A. Alwisy, and M. Al-Hussein. 2012. "Integrated BIM/Lean Base Production Line Schedule Model for Modular Construction Manufacturing". In *Proceedings of the 2012 Construction Research Congress*. May 21st–23rd, West Lafayette, Indiana, 1271–1280.
Rand, W. and R. T. Rust. 2011. "Agent-Based Modeling in Marketing: Guidelines for Rigor". *International Journal of Research in Marketing* 28(3):181–193.
Sargent, R.G. 2010. "Verification and Validation of Simulation Models". *In Proceedings of the 2010 Winter Simulation Conference,* edited by B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yucesan, 166–183. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.
Shahi, S., and R. Pulkki. 2015. "A Simulation-Based Optimization Approach to Integrated Inventory Management of a Sawlog Supply Chain with Demand Uncertainty". *Canadian Journal of Forest Research* 45(10):1313–1326.
Siebers, P. O., C. M. Macal, J. Garnett, D. Buxton, and M. Pidd. 2010. "Discrete-Event Simulation Is Dead, Long Live Agent-Based Simulation!". *Journal of Simulation* 4(3):204–210.
Taiwo, R., M. Hussein, and T. Zayed. 2022. "An Integrated Approach of Simulation and Regression Analysis for Assessing Productivity in Modular Integrated Construction Projects". *Buildings* 12(11):2018.
Wang, Z., H. Hu, J. Gong, X. Ma, and W. Xiong. 2019. "Precast Supply Chain Management In Off-Site Construction: A Critical Literature Review". *Journal of Cleaner Production* 232(1):1204–1217.
Wei, Y., D. F. Wang, J.Y. Liu, C. L. Yu, T. Cheng, T., and D. G. Zhang, D. G. 2014. "Modularization Technology Development Prospects". *Applied Mechanics and Materials* 509(1):92–95.
Xiangmin, Y., C. Dewei. 2021. "Design and Construction of the Tahya Misr Cable-Stayed Bridge in Cairo, Egypt". *Civil Engineering* 174(2):79–88.

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