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AGENT-BASED MODELLING AND SIMULATION OF CONSTRUCTION CREW PERFORMANCE

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ABSTRACT

The construction industry suffers from chronic problems in project delays, crew ineffectiveness, and productivity loss. One of the root causes of such problems is improper planning and control. Project control requires not only sufficient experience, but also proactive decision-making and awareness. In order to ensure proactivity and problem awareness, simulation coupled with Lean Construction principles are used to inform the analysis of workers' performance and conditions on site, facilitate production control, and detect possible future shortcomings or delays. This paper presents an Agent-Based and Discrete-Event model that allows project controllers to simulate current or future project states within the Weekly Work Plan (WWP) of the Last Planner® System (LPS) in order to orient the project activities and performance as desired. This model can be used to help generate more realistic planned production rates considering LPS metrics for crew capacity and performance. Factors resulting in the non-completion of tasks are taken from data of a real project over the course of 94 weeks. The simulation model is applied to an example project to explain the goals behind the proposed model. Results indicate that the proposed model is useful as a basis for a decision support system for project planners to evaluate the reliability of their planned production rates.

KEYWORDS

Agent-based modelling and simulation (ABMS), discrete-event simulation (DES), lean construction, project control, Last Planner® System (LPS)

INTRODUCTION

Delays in construction are considered a common problem described as the time overrun beyond the specified completion date (Assaf and Al-Hejji 2006). Productivity has also been declining in the construction industry for the past several years (Aziz and Hafez 2013). To add fuel to the fire, the construction industry suffers from high levels of uncertainty. Throughout the lifetime of a project, planners will face uncertainties on a regular basis (Howell et al. 1993). Around 56% of the projects suffer from uncertainties

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in both project objectives and means at the beginning of the project (Howell et al. 1993). Uncertainties in projects are not restricted to project objectives and means, but can appear in different types. Production systems can be affected by uncertainty in workflow and resource availability (Ballard and Howell 1998).

Therefore, there is no question of construction projects' need for improvement, and planning and control happen to be the core of the construction management process (Alarcón and Calderón 2003). Project progress control is steered by the team's ability to identify and remove constraints, and constraint identification sheds light on the importance of proactivity for early problems detection (Mitropoulos 2005). Moreover, constraint identification and removal reduce workflow uncertainties (Chua et al. 1999; Hamzeh et al. 2012). The Last Planner System for Production control is used to reduce variation and minimize uncertainties in construction projects (Hamzeh et al. 2012). The WWP of the LPS contains the work planned to be executed in the upcoming week. As the reliability of the WWP (which is represented by the percent plan complete metric) increases, the overall performance of the project schedule increases (Hamzeh et al. 2012). Thus, it is important that project planning not only covers the scheduling phase, but also extends to monitoring and control during execution (adaptive real time tracking). For the purpose of monitoring and control, several metrics have been developed within the LPS in order to assess project progress and performance at the level of the WWP (El Samad et al. 2017).

However, metrics are effective in assessing the performance of the WWP, but do not present proactive measures during execution. To overcome this issue, the authors have previously presented a tool that integrates proactivity with project monitoring and control. The tool uses mathematical singularity functions that were introduced to construction management by Gunnar Lucko (Lucko 2007), to calculate resource allocation and improvements in production rates proactively. This tool also forecasts metrics such as PPC before the end of the week of execution. While the aforementioned tool presents a promising step forward in the development of monitoring and control, there is still no way to ensure that the calculated improvements can actually be implemented by crews. Moreover, uncertainties and constraints are not directly linked to the tool (Ezzeddine et al. 2019; Shehab et al. 2019).

In some situations, the team is unaware of the constraints in the project, or their attention is drawn to the goals rather than the means to reach them (Lau and Kong 2006). In such cases, which are quite common, simulation comes into play. Agent-Based simulation is a relatively new approach for experimenting and simulating systems with autonomous agents (Chan et al. 2010). As we live in the world of machine learning and artificial intelligence, computer simulation tools have become highly capable of studying, designing, and improving construction processes (AbouRizk 2010). Simulation is the process of developing a surrogate model of the process at hand in an attempt to understand, analyse, and improve the process in a risk-free environment (Shannon 1975).

Previous researches have linked simulation models to scheduling, where they were able to generate project schedules using discrete-event simulation. Chris Hendrickson presented a construction planning expert system named "Construction Planex", which uses artificial intelligence to generate activity networks, durations, and project schedules automatically (Hendrickson et al. 1987). Another research developed a framework to schedule modular construction in assembly yards (AbouRizk 2010). The developed system was able to generate CPM networks and resource allocation and levelling. Moreover, Lingguan Song developed an adaptive real time tracking and simulation framework for heavy construction operations in order to enhance lookahead planning. The author used real time tracking to develop an adaptive simulation model for producing more efficient lookahead schedules (Song and Eldin 2012).

While all proposed frameworks focus on the link between simulation or AI and scheduling, none have developed a framework for the sole purpose of schedule monitor and control. Furthermore, none of the models was linked to location-based schedules, even though some of the proposed frameworks addressed issues related to spatial constraints. Moreover, these models and the LPS are still not strongly linked, as LPS metrics are not present in any input or output of the proposed frameworks.

The purpose of this paper is to introduce a simulation model that can be used as a basis for developing a decision support system for project planners. The proposed model takes input which describes the crew's performance, reliability, and the effect of unremoved constraints in order to make their planned production rate more reliable and realistic (Improved Production Rate). The model is tested on an example project in order to show how this model can help in producing more reliable planned production rates.

LITERATURE REVIEW

SIMULATION

The use of simulation in construction was first introduced by Teiholz in 1963 at the University of Stanford (AbouRizk et al. 2011). Simulation using computers is defined as the creation of a model that is a surrogate representation of the real world and performing certain experiments with the model (Pritsker 1986). The purpose of using simulation in construction is to study, analyse, understand, and improve the system or process. Simulation models can positively impact construction projects by providing better understanding of the processes, lowering costs, and optimizing schedules, all in a risk-free environment (AbouRizk 2010).

Since 1970, several simulation systems have been developed for construction. The systems developed are categorized under general purpose tools since they can be used to model any process (Martinez and Ioannou 1999). Activity cycle diagrams (ACD) are networks of different shapes which represent activities and resources (Martinez 2001). Cyclone and STROBOSCOPE are general simulation tools that use ACD to represent construction operations (Martinez and Ioannou 1999). The first simulation tool designed for construction is CYCLONE (Halpin 1977). EZSTROBE is also a general-purpose simulation system that was built to be a simple modelling tool, which can represent simple to moderately complex problems (Martinez 2001).

The first type of simulation used in construction is called Discrete-Event Simulation (DES). Construction projects are considered to be dynamic since time is an important factor, and stochastic since uncertainties are always being tackled (Song and Eldin 2012). The models developed using DES are considered to be surrogate of the real world, where changes happen at discrete instances in time (Abou-Ibrahim et al. 2019). For example, when modelling a bank queue, the research is interested in changes happening once a customer enters or leaves the queue, and not changes happening each second. DES is considered process-centric, where the system is represented through a chain of activities and resources linked together. Another type of simulation is Agent Based Modelling Simulation (ABMS). The advantage of ABMS is the use of agents and their social interactions between each other and the environment they live in (Taylor 2014). The strength of ABMS is its ability to model systems that have high complexities and interdependencies and that require some sort of social interaction between resources (Taylor 2014). Before going into the aspects of ABM, we must first address the question “what is an agent?” Though there is no universal definition of an agent, most researchers describe agents as being any independent entity in a system, where it has its own behaviour that can range from simple to complex (Taylor 2014). Examples of agents in construction can be crews or trucks, and at the crew level, each worker can represent a different agent. Agents are considered to be decision makers, and can execute several different behaviours depending on the situation they face (Bonabeau 2002). As for the aspects of ABMS, the first would be the identification of the agents present in the system. Each agent has a defined attribute that governs its behaviour and responses in the system. The second aspect is the agent relationships, which represent the interaction between all agents present in a system, or between the agents and their surroundings. The third aspect is the agent environment, which defines where the agents live. Thus, a system in ABM is the combination of all three aspects in order to generate desired outputs (Taylor 2014).

LAST PLANNER® SYSTEM

The “Last Planner” refers to the person who produces assignments required to be done (Ballard 2000). LPS promotes planning in greater detail as we get close to performing the work, producing the work plan with people who will perform the work, revealing and removing constraints early on, practicing reliable promising, and learning from planning breakdowns by searching for root causes of failure (Ballard et al. 2009).

LPS combines four main planning processes: master scheduling, phase scheduling, lookahead planning, and weekly work planning. During the WWP, planners plan the weekly work and practice reliable promising by studying the quality of the assignments and matching their promises to their ability to fulfil them. They also measure percent plan complete (PPC) that tracks their performance of reliable promising, and they act on reasons of plan failure, all while learning from the breakdowns throughout the plan. During the WWP, tasks that were expected to be possible to be performed (can) are transformed into “Will” tasks, and then “Did” tasks after they are successfully executed (Tommelein and Ballard 1997). LPS works best when all four phases are developed in sync (Hamzeh 2009).

In the master and phase schedules, deliberative planning is practiced through performing actions of a premediated nature like setting milestones. However, in the lookahead and weekly work plans, the planning is described as situated, for planners must take into consideration the surroundings or “situations” that might impact the tasks (Senior 2007; Suchman 1987). One thing to take into consideration is the fact that while planning, planners must consider the capacity of the crew performing the work. The inability to match the load to capacity comes from the planners’ inability to predict first the exact amount of work that a certain crew can perform and second the amount of unconstrained activities at the time of execution (Abou-Ibrahim et al. 2019). Therefore, when the load and capacity are mismatched, crews are expected to alter either the load by postponing/accelerating the workflow or the capacity by reallocating workers and resources (Abou-Ibrahim et al. 2019).

Several metrics are being developed for the LPS to enhance project performance, monitoring and control. In this paper, four metrics are being used to generate a more realistic forecast progress. The first metric is the PPC which measures the reliability of planning on the WWP level of the LPS (El Samad et al. 2017). The second metric is the Percent Reliability Index (PRI), which shows the reliability of planning at activity level.

PRI is the ratio of actual to planned progress, and it gives an indication to planning effectiveness (Gonzalez et al. 2008). The third metric used is the Capacity to Load Ratio (CLR), which is the ratio of activities done at the end of the WWP, to all those planned on the WWP. CLR shows the ability of teams to efficiently use their resources and balance between their resources and load (Rizk et al. 2017). The fourth and last metric used in the Percent Improved Complete (PIC), which is obtained by dividing the number of activities that required improvement in their production rates during the WWP and were able to implement this improvement, over the total number of activities that required improvement. PIC shows the reliability and commitment of teams at the WWP level to implement required improvements (Ezzeddine et al. 2019; Shehab et al. 2019). Table 1 summarizes the aforementioned metrics, their formulae, and their usages.

Table 1: Metrics, their formulae, and their usages

Metric	Formula	Usage
Percent Plan Complete (PPC)	Activities completed / activities planned to be completed	Reliability of planning at the WWP level of the LPS
Percent Reliability Index (PRI)	Actual progress / planned progress	Reliability of planning at activity level (planning effectiveness)
Capacity to Load Ratio (CLR)	Activities done at the end of the WWP / all activities planned on the WWP	Ability of teams to efficiently use their resources and balance between their resources and load
Percent Improved Complete (PIC)	Improved activities during WWP / total number of activities that required improvement	Reliability and commitment of teams at the WWP level to implement required improvements

METHODOLOGY

Simulation is the research method used in this paper. Activities are modelled using Discrete-Event modelling and simulation (DES), as DES represents a process in which input is transformed into output through a chain of services and resources linked together. As for Agent-Based modelling and simulation (ABMS), it is used for modelling crews as agents of different states and properties.

The purpose of this paper is to modify planned production rates and to generate a more realistic production rate named Improved Production Rate (IPR). The planned production rate is inserted into the model and recalculated based on agent simulation, current site data, and LPS metrics obtained from the company's historical data. The model takes the congestion and the time remaining for improvement, in addition to minimum, mode, and maximum values for PIC, PRI, PPC, and CLR. Inside the model, this input is analysed using DES and ABM. The time remaining for improvement can be either the total duration of the activity if the activity has not started yet, or the remaining duration if the crew has already started its execution. ABM is used to represent the factors affecting the state of the crews in terms of being idle or working. These factors are called Reasons for Non-Completion (RNC), and they are taken from data of a real project which was monitored for 94 weeks. The output of the simulation model is all possible values of the activity's duration. These durations are used to calculate the IPR which allows the user to find the "most likely" production rate. This value allows for better forecasting of the possible improvement in crew performance. In this paper, a sample project is simulated with theoretical data for verification.

DATA SORTING AND ANALYSIS

Data is obtained from a pharmaceutical construction project where PPC values and reasons for non-completion were monitored over 94 weeks. Seventeen reasons were recorded from the project, however only eight were used in this study. Nine factors were excluded because they had missing data points in several weeks making them unsuitable to be used. The frequency of the occurrence is calculated for each reason. Table 2 below represents the reasons along with their descriptions and frequencies of occurrence and Figure 1 shows the percentage of the occurrence of each reason for non-completion with respect to the total number of reasons.

Table 2: Reasons for Non-Completion, Their Descriptions, and Frequencies

Reason	Description	Frequency over 94 weeks
Arch/Eng/Design RFI	Information on design drawings from architects and engineers	452
Prerequisite Work - Others	Prerequisite work from other subcontractors is not ready	573
Prerequisite Work - Self	Prerequisite work from the main contractors is not ready	250
Materials/Suppliers Availability	Materials are not available from suppliers	231
Weather	Unforeseen weather conditions	388
Client-Driven Changes / Delays	Changes or delays from the client	134
Qualified Staff Availability	Unavailable human resources	771
Safety non-conformance	Inadequate safety measures and conditions	235
Total		3034

Figure 1 shows the percentage of the occurrence of each reason for non-completion with respect to the total number of reasons.

Figure 1: Percentages of Reasons for Non-Completion Occurrence

AGENT BASED AND DISCRETE-EVENT MODELLING AND SIMULATION OF CREW PERFORMANCE

The model was developed using Anylogic. The discrete-event process is used to represent the execution of the activity and its duration, and it consists of a simple combination of a source, service (Activity) with a crew resource pool, and sink in addition to timeMeasureStart and timeMeasureEnd for duration measurements as shown in Figure 2.

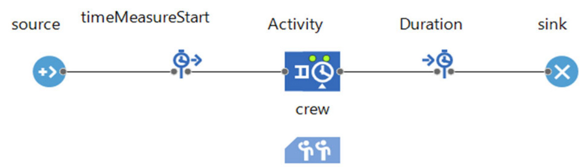

Figure 2: Discrete-Event Process

In the model, the users can insert the minimum, maximum, and mode values of PIC, PPC, PRI, and CLR. These values can be obtained from the company's historical data and they usually range from 0.1 to 1.0. The users can also insert the time remaining for improvement which can either be the full activity duration or the remaining duration if the crew has started execution. The congestion ratio can be also inserted which can be obtained by dividing the number of workers at a certain location by the working area. The value of the stops must range between 0 and 0.99 and is obtained from the team's historical data as well. The dashboard where the user inserts the mentioned inputs is shown in Figure 3.

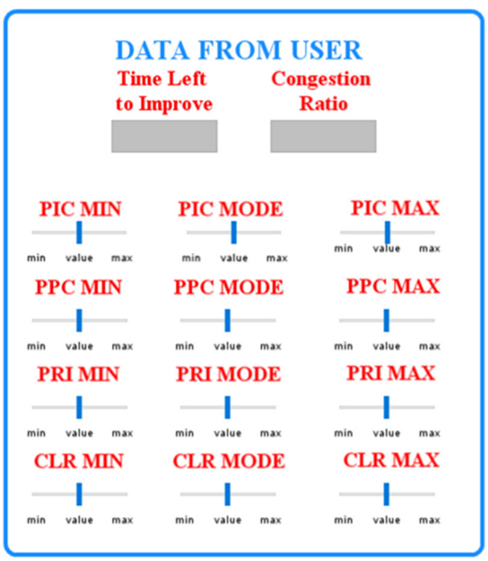

Figure 3: User Dashboard

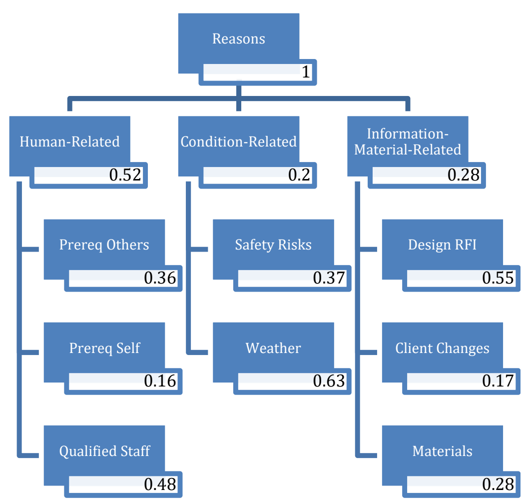

Figure 4: Reasons Probability Chart

For the Agent-Based Modelling, the crew agent includes a statechart where it moves from originally being "Working" to idle due to eight aforementioned different reasons of non-completion. The model only considers workers to be either working on their activity or idle, and it does not include them working on backlog activities or unplanned work. The eight idle states are reached through branches, and each state has a specified probability of occurrence calculated below from the obtained project data shown in Figure 4 below.

The crew moves from working to idle at a specified rate (thrice per week) and from idle to working after a specified time which depends on each reason. The crew statechart is shown in Figure 5.

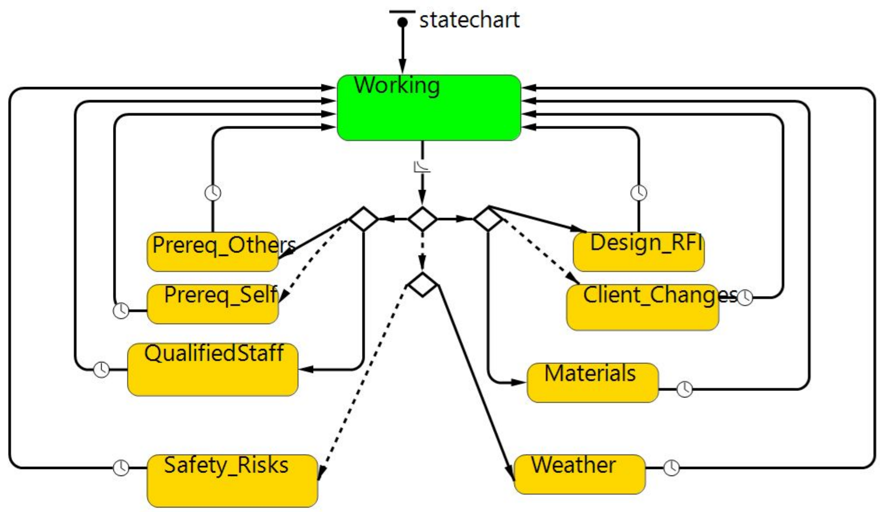

Figure 5: Crew Statechart

When the crew is idle due to any of the three situations, the duration of the activity increases based on the value of the congestion inserted by the user and the value of the idleness due to rework, lack of info, or lack of materials. The duration is calculated based on a PERT distribution including the idleness of the crew agent and the inputs inserted by the user, which are the LPS metrics (PIC, CLR, PPC, and PRI) and the congestion.

The model uses a developed code to calculate the duration of activities based on the aforementioned metrics and inputs. The code first checks if the crew is working or idle. If the crew is idle, then only the LPS metrics are taken into consideration for the calculation of the duration. If the crew is working, then in addition to the metrics, the level of congestion and the unforeseen working conditions are also taken into consideration.

After running the model, the datasets log including a distribution of durations is exported to an external file. The excel tool then transforms the durations distribution into a distribution of Improved Production Rates (IPR), after the user inserts the number of units of work required to be executed. The production rate obtained is called "Improved" because it is the rate at which the crew must operate in order to execute the required work during the time remaining. The "most-likely" IPR is then automatically calculated through the simulation model. The IPR gives the project controllers a realistic approximation of the rate that the crew will most probably work at to execute the work required, by considering congestion, idleness, and the LPS metrics.

ANALYSIS AND RESULTS

In order to verify if the model is correct, three different scenarios of crew performances were simulated by changing the inputs: good, average, and bad (shown in table 3). All scenarios had one day for improvement. High metric values and a low congestion ratio were input for the crew with good performance. Contrarily, low metric values and a high congestion value were input for the crew with bad performance. Simulation results of the distribution of durations and the most likely IPRs are shown in Table 3 below. The simulation of crews with good performance showed a higher IPR result than that of the crew with bad performance. Although this is an expected result, the power of using such a method is the ability to quantify this result as a practical value which planners can rely on.

The table shows the effectiveness of the proposed tool to generate improved production rates based on each crew's performance. Hence, this tool integrates crew performance metrics into the calculation of durations and production rates. It is logical to give each crew a duration and production rate based on their metrics and performance. Moreover, this method makes production rates more realistic because they are integrated with the project and crew's metrics. The graphical form of the IPR distribution for the crew with an average performance is shown in Figure 6.

Table 3 - Simulation Results of Mean Durations and Most Likely IPR Values among Different Crew Performances

Experiment	Min. Metrics	Mode Metrics	Max. Metrics	Congestion	Mean Duration	Most Likely IPR
Good performance	0.7	0.9	1	0.2	**1.7**	**6.7**
Average performance	0.4	0.6	0.8	0.5	**3.91**	**3.74**
Bad performance	0.1	0.4	0.5	0.9	**28.05**	**1.1**

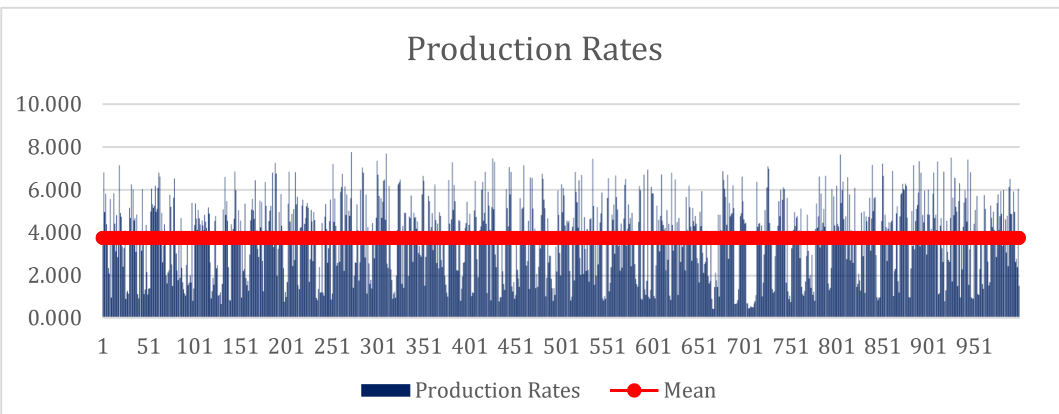

Figure 6: IPR Distribution for Crew with Average Performance

It is important to note that even if a crew's performance was ideal (i.e. metrics = 1 and congestion = 0), the mean duration will still be greater than the inserted one. This difference is due to the unforeseen issues that the model takes into consideration. This ideal case was simulated for model verification.

CONCLUSION AND FUTURE WORK

This paper presents a step forward in the use of simulation and LPS metrics to modify planned production rates to enhance project monitoring and control in the LPS. Previous work linked mathematical models to linear schedules to better monitor and control project progress. The model presented in this research adds to these mathematical models a simulation model that uses both DES and ABM simulations. The proposed model proved useful in project monitoring and control by allowing planners to obtain a more realistic planned production rate in the attempt to produce more reliable plans. Data was obtained from a pharmaceutical construction project where PPC and reasons for non-completion were recorded over 94 weeks.

The tool takes as input the time left to improve during the WWP and crew performance metrics. The LPS metrics used in the simulation model are PPC, PRI, PIC, and CLR which can be obtained from data from previous projects. Moreover, the level of congestion during task execution is also inserted into the model. Furthermore, ABM is used to consider unforeseen delays in execution obtained from the mentioned project data. The model was tested by using three crew performance scenarios; bad, average, and good. The generated production rates are proportional to the performances of the three scenarios and their metrics as the model helped in quantifying the performance of the crews.

The proposed study is considered a step forward and thus has several limitations which the authors plan to address in future work. The main goal in the future is to test the model on a live case study project to verify its effectiveness. Moreover, the authors suggest getting more accurate coefficient values for the variables that affect the duration such as PIC, CLR, PPC, PRI, and congestion. Such coefficient values may be obtained from previous research studying the effects of the mentioned metrics on the durations and consequently the crews' production rates. Finally, future work will focus on automating this framework to develop a practical and user-friendly tool.

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