Quantified Productivity Evaluation of Autonomous Excavation Systems using a Simulation Approach

Xiaoyu Bai[1], Beiji Li[1], Yong Zhi Koh[1,2], Soungho Chae[3], Meera C.S.[4] and Justin K.W. Yeoh[1]

[1]Department of Civil and Environmental Engineering, National University of Singapore, Singapore
[2]Koh Kock Leong Enterprise Pte Ltd, Singapore
[3]Kajima Technical Research Institute Singapore (KaTRIS), Singapore
[4]Advanced Remanufacturing & Technology Centre (ARTC), Agency for Science, Technology and Research (A*STAR), Singapore

xiaoyu.b@nus.edu.sg, lbj@nus.edu.sg, yzkoh@kkle.com.sg, s.chae@kajima.com.sg, chitra_sunil_meera@artc.a-star.edu.sg, justinyeoh@nus.edu.sg

Abstract -
Autonomous excavation systems are currently being developed to help address issues of poor productivity, by automating the excavation process and reducing manpower onsite. However, the impact of automation on the productivity of the excavation process remains to be determined. This paper uses a simulation approach to study this question. A typical excavation operation scenario is modeled and subsequently modified to account for the impact of automation. A comparative study between the typical and modified scenarios demonstrates the impact of automation on productivity. Three modes of automation are modeled in the excavation process: autonomous excavation, autonomous navigation of excavators, and autonomous lorry fleets. The models are validated using actual site data, and results suggest the impact of automation on the excavation process is severely limited.

Keywords -
Autonomous Excavation Systems; Simulation; Productivity Impact

1 Introduction

With the rapid advancement of technology, automation in civil engineering has brought about great benefits with regard to safety, cost, and productivity, as noted in several studies [1]. Excavators, one of the most commonly found heavy equipment on construction sites, are a prime example of where automation can improve operations [2]. Unmanned autonomous excavators are a trending research direction and have significant commercial interest [3].

Presently, construction companies all over the world that use traditional excavators are facing engineering problems, such as high labor intensity, low efficiency, and high safety risks [4, 5, 6]. Critical shortage of skilled operators for large machinery, and the dangerous working environment of some excavators may result in safety and health issues for on-site operators [6].

In response to some of the abovementioned issues, autonomous excavation systems hold some promise in mitigating productivity problems. Autonomous excavation systems encompass both autonomous (robotic) excavators and autonomous dump trucks (lorries). Development of these systems involves various areas of robotics research, including autonomous navigation, robotic path-planning, localization, and integration of digital terrain with survey data [7]. Robotic excavation also involves trenching, leveling, and slope cutting via remote teleoperation to achieve maximum work efficiency, precision, profitability, and safety.

The industry has several examples of commercially available or near commercialization autonomous excavators. Komatsu developed the PC210LCi-10 in 2013, which is based on the iMC (Intelligent Machine Control) technology, equipped with GNSS antenna, inertial measurement unit, stroke sensing cylinder, and controller. In 2021, an intelligent excavator developed by the Aviation Industry Control Institute and Sany Heavy Industry Co., Ltd., realized automatic planning and remote control, automatic moving, automatic trenching, and 5G remote control. FJ DYNAMICS has also developed a complete set of unmanned and digital solutions that include 3D spatial sensing integrated with guidance and control systems. These excavators are equipped with an excavation guidance system with 3D images that display the movement of the machine in real-time, and high-precision construction can be carried out at any time, even in low visibility and restricted access conditions.

However, despite the potential benefits of autonomous excavators, further development in several areas is required. A recent study found that remote operation of excavators may not be as effective as initially thought [8]. Current teleoperated systems may suffer from control delays compared to manual controls and may encounter difficulties in acquiring and understanding surrounding information such as soil, machines, nearby human workers, and other obstacles [4]. Full automation of every process on the job site remains challenging, given the uncertainties of the dynamic and complex excavation tasks onsite [5]. Thus, analyzing the impact of autonomous excavators on productivity is necessary to help justify whether there is a return on investment for autonomous excavators.

In this paper, a simulation model is used to study the excavation process. The model is validated using real-world data, and different modes of automation are modeled and studied. Finally, conclusions are drawn regarding the efficacies of automation on productivity and its practical implications discussed.

2 Literature Review

2.1 Autonomous excavator system

Automatic excavator systems are an emerging field of research that combines civil engineering and robotics. In recent years, there has been significant progress in the development of autonomous excavator systems that can operate continuously for extended periods without human intervention, such as the system developed by researchers from Baidu Robotics, Research Robotics and Auto-Driving Lab (RAL), and the University of Maryland, College Park, in 2021 [9]. The system is equipped with sensors that can perceive the 3D environment and identify materials, which significantly enhances productivity. An overview is provided in Figure 1.

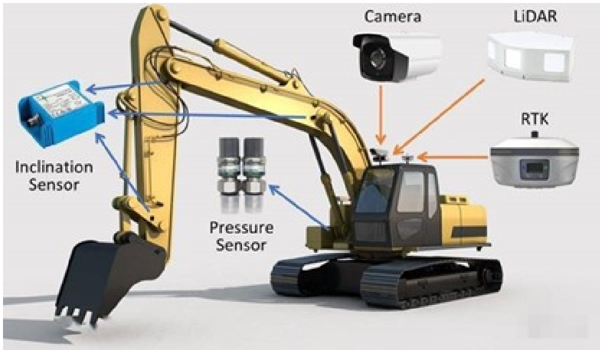

Figure 1. Autonomous excavator system from Baidu Robotics and Research Robotics and Auto-Driving Lab (RAL) and the University of Maryland, College Park (Zhang et al., 2021)

Navigation planning is a crucial aspect of autonomous excavator systems. The combination of point-to-point (PTP) and complete coverage path planning (CCPP) methods is one solution that has been proposed to achieve this. PTP is a technique that uses an algorithm such as the $A*$ algorithm, which relies on a heuristic function $h(n)$ to estimate the lowest-cost path from the start node to the goal node $g(n)$ [10]. CCPP algorithms are designed to split the workspace into square cells and use a cost function to optimize the path planning, taking into account various parameters such as water flow, travel distance, elevation, accessibility, and environmental constraints [6]. An algorithm proposed by Kim et al. in [11] provides an example of a CCPP algorithm that considers earthwork and environmental constraints as an optimization problem. The algorithm's cost function additionally takes into account the accessibility of the lorries and the external conditions of the work environment, such as the distance between cells, distance from the entrance, and isolation. These parameters are critical in determining the cost of excavation and the overall efficiency of the system [6].

2.2 Earthwork Simulations

Simulation systems play a crucial role in civil engineering and construction management by helping professionals understand and predict complex engineering problems, with the objective of potentially increasing work productivity. AbouRizk [12] showed that simulation plays an integral role in construction engineering and management by summarizing the key factors of deploying simulation models and key attributes of construction problems that make them more amenable for simulation modeling than other methods. In addition, simulation models are capable of capturing complex variables, analyzing the impact on the productivity of tunneling construction projects, and carrying out further sensitivity analysis[13].

One benefit of simulation systems is its ability to provide integrated simulation and optimization approaches to reduce CO2 emissions from the on-site construction process. For example, Li et al. [14] used a discrete-event simulation (DES) approach to model the construction process in cold regions, quantifying the amount of CO2 emissions, and optimizing on-site labor allocation using a genetic algorithm. This reduced the carbon footprint of construction activities in cold regions.

Another benefit is its ability to create simulation models for earthwork operations to enhance productivity. Simphony.Net, a simulation environment developed by AbouRizk et al. [15], provides construction simulation solutions that can handle both discrete event and continuous simulations. One important feature of this simulation environment is its extensibility and flexibility, which allows it to create special-purpose simulations for specific construction systems such as earth-moving, paving, etc.

In conclusion, simulation systems have become an essential tool for civil engineers and construction professionals. They provide a way to better understand complex engineering problems, optimize construction activities, and enhance productivity.

2.3 Gap in Current Studies

In recent years, there has been a rapid development of autonomous excavator technology. The potential for this technology in the civil engineering industry is immense. Autonomous excavation systems combine various technologies such as 3D vision, machine learning, and other artificial intelligence techniques to achieve fully autonomous operations. Earthwork operations analysis using simulation is also gaining popularity as it is proven to enhance the productivity of infrastructure projects.

However, the current application of autonomous excavators in the civil engineering industry is still in its experimental phase. Due to the uncertainties of dynamic and complex excavation tasks in the workplace [5], it is necessary to investigate and verify whether autonomous excavation systems can improve overall productivity. Therefore, it is essential to develop a baseline productivity measure to test the usability of autonomous excavators.

This paper identifies different strategies of autonomy for automated excavation systems, but there have been few studies on the impact of automation on the productivity of autonomous excavation systems, considering these different strategies. Therefore, it is important to measure productivity and compare it accordingly [16]. Therefore, the objective of this study is to define these strategies of automation for autonomous excavation systems and quantify their impact accordingly. Both of the objectives are realized by simulating the excavation process in Simphony.Net. By doing so, the study aims to provide a better understanding of the potential for autonomous excavation systems in the civil engineering industry.

3 Proposed Research Method

3.1 Overall simulation methodology

The overall methodology of this research is presented in Figure 2. It consists of four main sections, namely Data preparation, Simulation model building, Output analysis, and Discussion. Each of these sections can be further broken down into several sub-steps. The following paragraphs will introduce the activities in each sub-step in more detail.

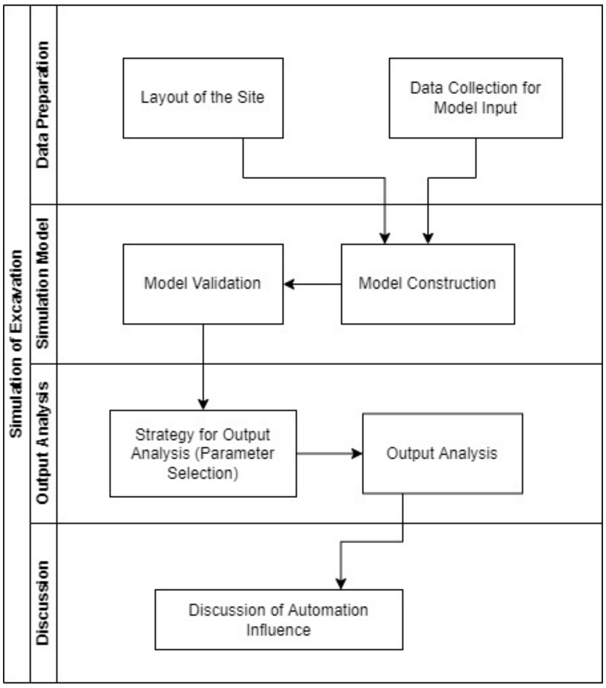

Figure 2. Research Method of the Research

To realistically simulate the excavation activity, data from an actual construction site is used. In the first step of data preparation, the layout of the site is analyzed, and project information is collected. The information gathered is then used to design the simulation model.

In the next step, the simulation model is built. The model is made up of several sub-cycles, including Excavators, Lorries, and Personnel. The earthwork is transferred as units flowing through different nodes. Once the simulation model has been constructed, input data is used to fit the simulation model.

To ensure the accuracy of the input data, a statistical t-test is conducted to establish a baseline model. This helps to validate the data input, as well as to identify any inconsistencies or errors that may have occurred during data preparation.

Finally, various automation strategies are formulated and tested on the simulation model. Metrics for assessment are selected, and a sensitivity analysis is carried out to investigate the results further. The results obtained from the simulation model are analyzed and discussed, with a focus on the impact of automation on the productivity of autonomous excavation systems. In conclusion, the overall methodology of this research is designed to provide a systematic and rigorous approach to investigating the impact of automation on the productivity of autonomous excavation systems.

3.2 Site Information: Layout of Site and Data Collection

To simulate the excavation process at a construction site, an open-cut bulk excavation project is selected here as a reference project to build the simulation model. The layout of the site is presented in Figure 3, which shows that the site has been divided into two zones, with each zone serviced by an individual gate. Lorries enter and exit the site from either Gates 1 or 2. There are no intermediate storage areas for excavated earth. The average travel distances of the excavators and lorries are estimated to be similar for both zones, and the size of each zone is about $350m^2$.

The overall objective of the excavation operation is to excavate 1000 cubic meters of soil from the construction site and move it to the dump site situated externally from the site. The excavators carry out two different activities: Some excavators carry out excavation and slope grading when not excavating, while others are tasked to load the excavated soil material onto the lorries. Other project machinery such as lorries and personnel including banksman, operators, supervisors, etc., are also incorporated into the simulation. These elements make up the fundamental components of the project, with further details listed below in Table 1.

Table 1. Fundamental Elements of Simulation

Element	Description	Units
Excavator	Bucket Capacity: $1.5m^3$	1
Lorry	Capacity: $8m^3$	15
Banksman	-	3
Safety Personnel	-	3
Operator	-	9
Supervisor	-	3
Traffic	-	3

Manpower is divided into three groups: those in charge of excavation, loading, and dumping, respectively. Lorries enter and exit the site via the two major gates at an average interval of 7 minutes due to the dumping activity. Excavators, lorries, and manpower are assumed to operate continuously over the working period. This assumption allows the simulation to operate at a steady state, thus allowing for more consistent results to be obtained.

Overall, the comprehensive simulation model created closely mirrors the excavation process at a real construction site. By incorporating all the key elements of the excavation project, including personnel, machinery, and different operational activities, the simulation model provides a realistic and accurate representation of the excavation process. This model will enable the impact of different automation strategies on excavation productivity and efficiency to be evaluated.

4 Simulation Model

4.1 Model Construction in Simphony.NET

The model is constructed within Simphony.NET, a modeling environment composed of simulation services and a

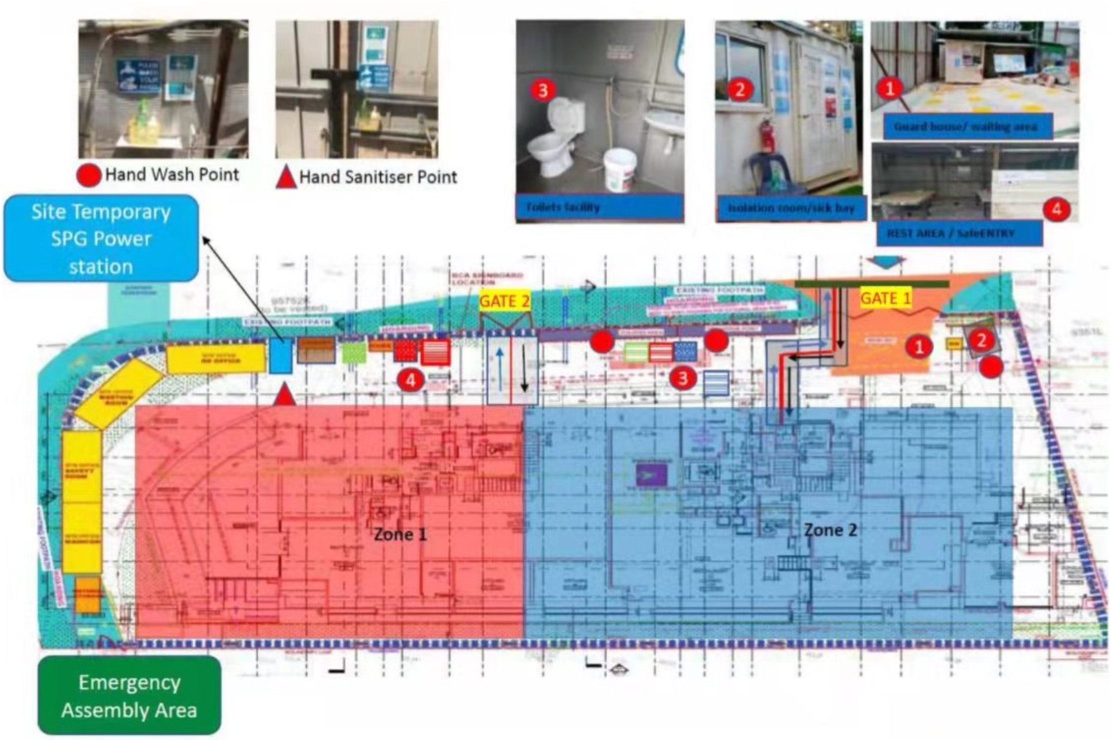

Figure 3. Layout of Test Site

modeling user interface that provides a visual representation of the excavation process. The overall excavation process is simulated in Simphony.NET as shown in Figure 4. The model is designed to simulate the sub-cycles within the excavation process, which mainly include the excavation sub-cycle, the loading sub-cycle, and the lorry cycle. These sub-cycles are connected to the soil sub-cycle, which depicts the transfer of earth from its original state to its excavated state, and finally to its dumping site.

By adjusting and tuning the parameters of the model and running simulations, output analysis can be conducted to determine how these parameters impact the total operation time and production rate. This output analysis refers to the evaluation of strategies and is used to evaluate the effect of different classes of autonomous excavation systems.

In Figure 4, green nodes depict major resource units utilized by the simulation. Deep yellow nodes represent processes whose duration follows an estimated statistical distribution from historical data. Light yellow nodes indicate activities where the time durations are estimated from video data collected onsite, and used to tune the model.

To integrate the simulation model, data is required, including the duration of processes and unit quantities. Table 2 lists the data required for the simulation.

Cycle times for normal excavation, excavator maneuver, and loading are estimated based on video recordings of the site excavation works. The time spent on internal travel and external travel of lorries is estimated using a statistical distribution, with lognormal distribution assumed for the two durations. Examples of such data are often recorded in site lorry logs. Table 3 provides the complete data input set for the simulation.

4.2 Model Validation

Validation of simulation models is a crucial step in the modeling process to ensure the model accurately reflects the actual situation of the construction site. In this case, the simulation model is validated using data records of lorries coming in and out of the site, and durations of internal and external travel are used as a metric. Internal travel refers to the time lapse between the entry and exit of a specific lorry from the site, and the mean and standard deviation of these durations are computed. T-tests are then conducted to determine if there is a statistical difference between the simulation results and the observed data. The computed p-values of the two durations indicate a high probability that the observed data is not significantly different from the simulated results. Therefore, the model structure is deemed acceptable, and the simulated model is representative of the actual situation on-site.

With the validated simulation model, two modes were further developed, each with the same structure and node layout. The first mode, “Real Situation” depicts the scenario where the validated model was used as-is. The second mode, “Optimized Situation” shows the scenario where further resource balancing was carried out on the validated model to optimize the resources. In this “Optimized Situation”, the resources of manpower, excavators, and lorries were analyzed and balanced to match the interaction of the different cycles. By doing so, the resources are adjusted to match the needs of the excavation, loading, and lorry cycles. The optimization process ensures the re-

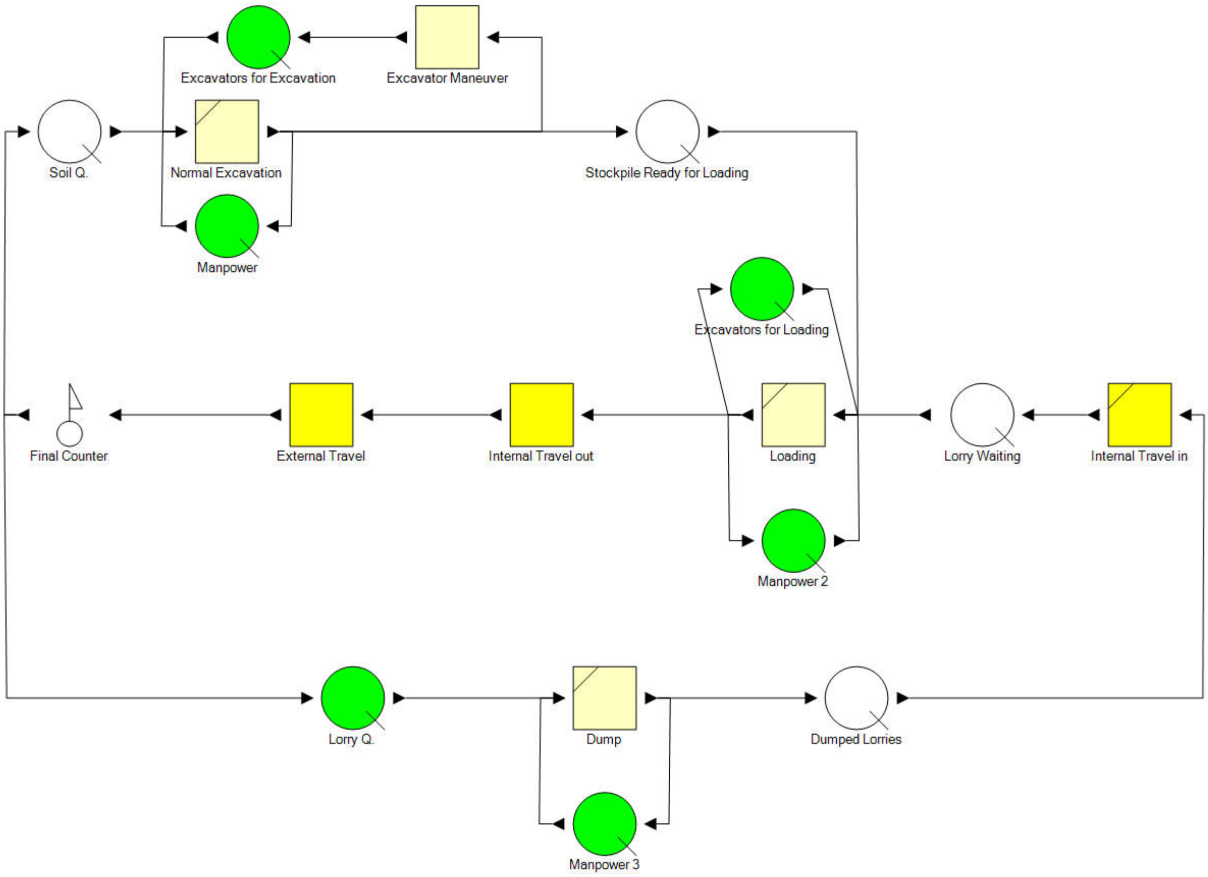

Figure 4. Overall Simphony.NET Model

Table 2. Data Requirements for Simulation Model

Data Requirements	Description
Capacity of Excavator Bucket and Lorries	Capacity is used for unit balancing
Number of Excavators, Lorries, and Manpower	The major resources used for maintaining the cycles
Soil Amount	The target amount of soil that needs to be transported outside the site
Internal Travel	Duration of lorries traveling in the site
Loading	Duration for excavator loading the lorries
External Travel	Duration when lorries are traveling outside the site
Normal Excavation	Duration of one excavator finishing a single excavation cycle
Excavator Maneuver	Duration of excavator maneuvering to excavation point

Table 3. Data Input Values used in Model

Parameter	Value
Internal Travelling Time	$\sim LN(1.996, 0.272)$
External Travelling Time	$\sim LN(4.705, 0.160)$
Normal Excavation Duration	0.25 minutes
Number of Excavators	3
Number of Lorries	30
Loading Duration	1.5 minutes
Excavator Bucket Capacity	$1.5m^3$
Lorry Capacity	$9m^3$
Number of Manpower	6
Excavator Maneuver Duration	0.5 minutes
Soil Amount	$1000m^3$

sources are utilized to their full potential, thus reducing the overall operation time and increasing the production rate. The rationale of comparing the results from the two modes is to isolate the effect of automation from the impact of resource optimization. This allows a more accurate evaluation of the effect of automation on the excavation process.

5 Output Analysis

5.1 Strategies for Autonomous Excavation systems

This paper identifies three modes or strategies of automation that will improve excavation: autonomous excavation, autonomous navigation and automated lorry fleet.

Autonomous excavation is achieved through the use of bucket sensors and posture detection techniques. Bucket sensors enable the excavator to detect the location and depth of the earth being excavated, while posture detection ensures the excavator maintains the correct posture while performing the excavation. These techniques work together during the excavation process to ensure greater accuracy and speed than a human operator.

Autonomous navigation is another key area where robotics can help improve excavation processes. By using real-time data to identify the boundaries of excavation activity, autonomous navigation can help to allocate dynamic zones of excavator operation and reduce conflicts inside the site. This can significantly reduce the duration for maneuvering and control of the excavator, resulting in increased efficiency and productivity.

Automating the fleet of lorries is also a potential strategy that can help to reduce the amount of travel within the site. By using autonomous navigation techniques to optimize the routes taken by lorries, it is possible to reduce the time and fuel consumption required for transportation.

To simulate these three strategies in the Simphony.NET model, the effects of these strategies are modeled by decreasing the expected durations of their associated activities, as shown in Table 4. In the simulation, each strategy is modeled as a simulation scenario, wherein a different level of automation is depicted. Additional simulation scenarios are also defined where the different strategies are combined. The effects of the strategies are obtained from expert judgment found in Li et al. [16].

Table 4. Strategies for Automation of Excavation Process

Strategies	Associated Nodes	Change
Autonomous Excavation (Strategy 1)	Normal Excavation	-30 %
Autonomous Navigation (Strategy 2)	Excavator Maneuver	-30 %
Automated Lorry Fleet (Strategy 3)	Internal Travel Time	-30 %

As each of the above strategies may be used in conjunction, this research further identifies the following scenarios. This creates a total of seven possible strategies, arising from the possible combinations of the above three strategies.

- Strategy 1&2: Autonomous Excavation with Autonomous Navigation
- Strategy 1&3: Autonomous Excavation with Autonomous Lorry Fleet
- Strategy 2&3: Autonomous Navigation with Autonomous Lorry Fleet
- Strategy 1&2&3: Autonomous Excavation with Autonomous Navigation and Autonomous Lorry Fleet

Several metrics are defined that are used as indicators of the overall productivity of the excavation process:

- Metric 1: The “Last Arrival Time” is the total time taken within the simulation to excavate $1000m^3$ of earth.
- Metric 2: The “Average waiting times” of excavators for loading activities.
- Metric 3: The “Average waiting times” of excavators for excavation activities.

This paper uses three metrics to evaluate the impact of automation on the excavation process. The first metric, Metric 1, is used to measure the overall productivity of the entire excavation process. This metric is commonly used by earthwork contractors to assess their productivity, making it a valuable tool to assess the effectiveness of the different automation strategies. Metrics 2 and 3 are used to track the utilization of the equipment. This information can be used to identify any inefficiencies or idling of the equipment, which may occur as a result of automation.

The study focuses on measuring the change in the numerical values of these metrics, as different automation strategies are implemented. The objective is to identify any negative effects, such as excessive idling of the equipment, and develop strategies to mitigate them. By monitoring these metrics, insights can be gained into the effectiveness of the different automation strategies and their impact on the excavation process.

5.2 Results and Discussion

The aforementioned 7 simulation scenarios refer to the possible combinations of the automation strategies; these scenarios were then applied to both the “Real Situation” and “Optimized Situation” modes respectively. The purpose was to determine if there was a significant difference in the mean values of the simulation results obtained from applying the strategies compared to the base cases from either the ”Real Situation” or the ”Optimized Situation.” To determine this, a t-test was performed. The results of these hypothesis tests are presented in Table 5 for the “Real Situation” and Table 7 for the “Optimized Situation”. In both tables, $m1$ represents the mean value of the metric used obtained from applying the strategy, and $m2$ represents the mean value of the same metric obtained from the base scenario. The results in bold indicate significant differences between the two mean values.

Table 5 presents the quantitative results of the three metrics tracked in the study. The table shows that only ‘Strategy 3’, ‘Strategy 1&3’, ‘Strategy 2&3’, and ‘Strategy 1&2&3’ have a significant difference in productivity (Metric 1). The corresponding improvements in the “Real Situation” were measured and compared against the base results from the same situation, as well as the ”Optimized Situation” results. Table 6 shows these results, with the actual mean values obtained for each set of simulations presented in parentheses. Negative percentage values indicate a percentage decrease in the metric measured, and values in parenthesis indicate the absolute mean values obtained for each set of simulations. Values in parentheses within the header of the table indicate the mean value of the base ’Real Situation” scenario.

Table 7 and Table 8 refer to the hypothesis tests and their corresponding quantitative results in the “Optimized Situation”. The table shows that only ‘Strategy 1&3’ and ‘Strategy 1&2&3’ have statistically significant results in the optimized scenario.

In the “Real Situation”, the unbalanced number of resources means that there are not enough lorries to support the excavation and loading operations. As a result, the

Table 5. Results of Hypothesis Testing of Strategies in Real Situation

	Metric 1	Metric 2	Metric 3
Strategy 1	$m_1 = m_2$	$m_1 = m_2$	$m_1 < m_2$
Strategy 2	$m_1 = m_2$	$m_1 = m_2$	$m_1 < m_2$
Strategy 3	$\mathbf{m_1 > m_2}$	$m_1 > m_2$	$m_1 > m_2$
Strategy 1&2	$m_1 = m_2$	$m_1 = m_2$	$m_1 < m_2$
Strategy 1&3	$\mathbf{m_1 > m_2}$	$m_1 > m_2$	$m_1 < m_2$
Strategy 2&3	$\mathbf{m_1 > m_2}$	$m_1 > m_2$	$m_1 < m_2$
Strategy 1&2&3	$\mathbf{m_1 > m_2}$	$m_1 > m_2$	$m_1 < m_2$

Table 6. Quantitative Metrics for "Real Situation"

	Metric 1 (1097.13)	Metric 2 (7.35)	Metric 3 (2.93)
Optimized Situation	-18.08% (878.78)	-24.56% (5.54)	106.85% (6.05)
Strategy 1	0.17% (1099.05)	0.27% (7.37)	15.85% (3.39)
Strategy 2	0.11% (1098.32)	0.21% (7.36)	5.45% (3.09)
Strategy 3	**-1.84% (1076.98)**	-2.19% (7.19)	-2.66% (2.85)
Strategies 1&2	-0.00% (1097.18)	-0.03% (7.35)	20.49% (3.53)
Strategies 1&3	**-1.85% (1076.84)**	-2.13% (7.19)	12.41% (3.29)
Strategies 2&3	**-1.68% (1078.69)**	-1.9% (7.21)	2.46% (3.00)
Strategies 1&2&3	**-2.00% (1075.24)**	-2.19% (7.18)	17.48% (3.44)

Table 7. Results of Hypothesis Testing of Strategies in Optimized Situation

	Metric 1	Metric 2	Metric 3
Strategy 1	$m_1 = m_2$	$m_1 = m_2$	$m_1 < m_2$
Strategy 2	$m_1 = m_2$	$m_1 = m_2$	$m_1 < m_2$
Strategy 3	$m_1 = m_2$	$m_1 = m_2$	$m_1 = m_2$
Strategy 1&2	$m_1 = m_2$	$m_1 = m_2$	$m_1 < m_2$
Strategy 1&3	$\mathbf{m_1 > m_2}$	$m_1 = m_2$	$m_1 < m_2$
Strategy 2&3	$m_1 = m_2$	$m_1 = m_2$	$m_1 < m_2$
Strategy 1&2&3	$\mathbf{m_1 > m_2}$	$m_1 > m_2$	$m_1 < m_2$

Table 8. Quantitative Metrics for "Optimized Situation"

	Metric 1 (898.78)	Metric 2 (5.54)	Metric 3 (6.05)
Strategy 1	0.19% (900.51)	0.11% (5.55)	7.54% (6.51)
Strategy 2	-0.08% (898.02)	-0.13% (5.54)	2.27% (6.19)
Strategy 3	-0.26% (896.48)	-0.09% (5.54)	-0.37% (6.03)
Strategies 1&2	-0.03% (898.50)	-0.02% (5.54)	9.75% (6.65)
Strategy 1&3	**-0.28% (896.27)**	0.02% (5.54)	7.08% (6.49)
Strategy 2&3	-0.12% (897.71)	0.15% (5.55)	2.34% (6.20)
Strategy 1&2&3	**-0.18% (897.14)**	-0.03% (5.54)	9.47% (6.63)

excavators used for excavating have to wait for longer periods of time, which reduces the efficiency of the operation. The waiting time for loading excavators, on the other hand, does not show much variation in different scenarios, indicating that automation does not have a significant impact on the utilization of loading excavators.

The quantitative results presented in Table 6 show that the Last Arrival Time (Metric 1) decreases from 1.68% to 2% in the statistically significant scenarios from Table 5. The average waiting time for loading (Metric 2) shows little variation in different scenarios. This indicates that automation does not affect the utilization of loading excavators significantly. However, the waiting time for excavators used for excavating increases significantly by up to 17.5%. This increase in waiting time is due to the lack of enough lorries to support the operation. When the excavating machinery finishes the work faster, but the subsequent loading is not fast enough, significant delays may occur during excavation, hence reducing the overall efficiency of the operation.

For "Optimized Situation", where resources are balanced, the overall production time drops by about 20% when compared to the "Real Situation". This reduction in production time is due to the smoother and more efficient operation arising from balanced resources. However, the effect of automation on total productivity is not as significant as one might expect. The decrease in last arrival time (Metric 1) and loading excavator waiting time (Metric 2) in the "Optimized Situation" is almost trivial, ranging from -0.18% to -0.28%. The waiting time for excavators used for excavating (Metric 3) is also longer than that of the 'Real Situation" although the increase in waiting time is not as significant, ranging from 7% to 9%.

In conclusion, resource constraints (the lack of lorries to balance production) is inferred to dominate productivity, despite the availability of automation. From both Real and Optimized Situations, the impact of automation on productivity is observed to be minimal.

6 Conclusion

Simulations are valuable tools for modeling complex processes and predicting their potential outcomes. In this study, an excavation simulation model was created using real-world site data. The model aimed to represent the standard workflow of an open-cut excavation project, which includes excavating, maneuvering, and loading. The simulation model was built using Simphony.NET, a powerful software tool for creating dynamic simulations of industrial processes. The required data for the simulation model was gathered from actual site data or estimated from secondary sources. The model was then validated using various techniques to ensure that it accurately represented the real processes.

Once the simulation model was set up successfully, an output analysis was conducted to determine the potential impact of automation on the overall excavation productivity and equipment utilization. The analysis revealed that the changes to the metrics were not significant within the simulation model. This may be due to the shortage of lorries which limits the effect of automatic excavators.

Although automatic excavators help reduce the time for excavation, maneuvering, and loading, the changes made to the overall productivity (Last Arrival Time) and utilization (average waiting time for excavators) are minimal. The study showed that the lack of lorries constrains the effect of automatic excavators on productivity. This suggests that the effect of automation may not be as significant as expected, especially if there is a shortage of resources.

As future work, the simulation study can be significantly improved by comparing the results to the reported performance of autonomous excavator systems. This verification may be obtained in the future through collaboration with developers of autonomous excavator systems. Such collaboration can help to further validate the simulation model and enhance its accuracy, which can in turn provide valuable insights for optimizing excavation processes.

7 Acknowledgements

This project is supported by Building Construction Authority (BCA) Singapore and National Robotics Programme (NRP) under its Built Environment Robotics R&D programme W2122d0153. Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not reflect the views of BCA or NRP.

References

[1] Behrokh Khoshnevis. Automated construction by contour crafting—related robotics and information technologies. *Automation in Construction*, 13(1):5–19, 2004. ISSN 0926-5805. doi:10.1016/j.autcon.2003.08.012.

[2] Masakazu Haga, Watanabe Hiroshi, and Kazuo Fujishima. Digging control system for hydraulic excavator. *Mechatronics*, 11(6):665–676, 2001. ISSN 0957-4158. doi:10.1016/S0957-4158(00)00043-X.

[3] Kwangmin Kim, Minji Kim, Dongmok Kim, and Dongjun Lee. Modeling and velocity-field control of autonomous excavator with main control valve. *Automatica*, 104:67–81, 2019. ISSN 0005-1098. doi:10.1016/j.automatica.2019.02.041.

[4] Masaru Ito, Chiaki Raima, Seiji Saiki, Yoichiro Yamazaki, and Yuichi Kurita. Effects of Machine Instability Feedback on Safety During Digging Operation in Teleoperated Excavators. *IEEE Access*, 9:28987–28998, 2021. ISSN 2169-3536. doi:10.1109/ACCESS.2021.3059710.

[5] Dominic Jud, Simon Kerscher, Martin Wermelinger, Edo Jelavic, Pascal Egli, Philipp Leemann, Gabriel Hottiger, and Marco Hutter. HEAP - The autonomous walking excavator. *Automation in Construction*, 129:103783, 2021. ISSN 0926-5805. doi:10.1016/j.autcon.2021.103783.

[6] Jeonghwan Kim, Dong-eun Lee, and Jongwon Seo. Task planning strategy and path similarity analysis for an autonomous excavator. *Automation in Construction*, 112:103108, 2020. ISSN 0926-5805. doi:10.1016/j.autcon.2020.103108.

[7] Jin Sol Lee, Youngjib Ham, Hangue Park, and Jeonghee Kim. Challenges, tasks, and opportunities in teleoperation of excavator toward human-in-the-loop construction automation. *Automation in Construction*, 135:104119. ISSN 0926-5805. doi:10.1016/j.autcon.2021.104119.

[8] Hikaru Nagano, Hideto Takenouchi, Nan Cao, Masashi Konyo, and Satoshi Tadokoro. Tactile feedback system of high-frequency vibration signals for supporting delicate teleoperation of construction robots. *Advanced Robotics*, 34(11):730–743, 2020. ISSN 0169-1864. doi:10.1080/01691864.2020.1769725.

[9] Liangjun Zhang, Jinxin Zhao, Pinxin Long, Liyang Wang, Lingfeng Qian, Feixiang Lu, Xibin Song, and Dinesh Manocha. An autonomous excavator system for material loading tasks. *Science Robotics*, 6(55), 2021. doi:10.1126/scirobotics.abc3164.

[10] A. R. Soltani, H. Tawfik, J. Y. Goulermas, and T. Fernando. Path planning in construction sites: Performance evaluation of the Dijkstra, A*, and GA search algorithms. *Advanced Engineering Informatics*, 16(4):291–303, 2002. ISSN 1474-0346. doi:10.1016/S1474-0346(03)00018-1.

[11] Sung-Keun Kim, Jeffrey S. Russell, and Kyo-Jin Koo. Construction Robot Path-Planning for Earthwork Operations. *Journal of Computing in Civil Engineering*, 17(2):97–104, 2003. ISSN 0887-3801. doi:10.1061/(ASCE)0887-3801(2003)17:2(97).

[12] Simaan AbouRizk. Role of Simulation in Construction Engineering and Management. *Journal of Construction Engineering and Management*, 136(10): 1140–1153, 2010. ISSN 0733-9364, 1943-7862. doi:10.1061/(ASCE)CO.1943-7862.0000220.

[13] Yasser Ebrahimy, Simaan M. AbouRizk, Siri Fernando, and Yasser Mohamed. Simulation modeling and sensitivity analysis of a tunneling construction project's supply chain. *Engineering, Construction and Architectural Management*, 18(5):462–480, 2011. ISSN 0969-9988. doi:10.1108/09699981011074600.

[14] Hong Xian Li, Limao Zhang, Don Mah, and Haitao Yu. An integrated simulation and optimization approach for reducing CO2 emissions from on-site construction process in cold regions. *Energy and Buildings*, 138:666–675, 2017. ISSN 0378-7788. doi:10.1016/j.enbuild.2016.12.030.

[15] S AbouRizk, S Hague, R Ekyalimpa, and S Newstead. Simphony: A next generation simulation modelling environment for the construction domain. *Journal of Simulation*, 10(3):207–215, 2016. ISSN 1747-7778. doi:10.1057/jos.2014.33.

[16] Beiji Li, Xiaoyu Bai, and Justin K.W. Yeoh. Review and Classification of Autonomous Excavation Systems. In *Proceedings of the 22nd International Conference on Construction Applications of Virtual Reality (CONVR 2022)*, Seoul, South Korea, 2022.