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A SIMULATION-BASED DECISION-SUPPORT SYSTEM FOR REDUCING DURATION, COST, AND ENVIRONMENTAL IMPACTS OF EARTHMOVING OPERATIONS

Elyar Pourrahimian
Malak Al Hattab
Rana Ead
Ramzi Roy Labban
Simaan AbouRizk

Hole School of Construction Engineering
University of Alberta
5-080 Markin/CNRL Natural Resources Engineering Facility
Edmonton, AB T6G 2W2, CANADA

ABSTRACT

Earthmoving operations are equipment-intensive processes that rely heavily on the proper selection of the equipment fleet and proper scheduling of associated tasks. Early equipment planning decisions have direct implications on schedules, costs, and more importantly, the environmental performance of such operations. While traditional planning of earthmoving works is ad-hoc and based on planners' experiences, ensuring favorable performance requires advanced analytical techniques that consider multiple variables and competing objectives. Accordingly, this study develops a discrete-event simulation-based decision-support system (DES-DSS) for selecting the optimal equipment fleet, while considering the trade-offs between time, cost, and environmental impacts. The model's results from a case study reveal how different fleet mixes and sizes can considerably impact associated emissions, durations, and costs. The DES-DSS can aid planners in making informed decisions during early planning stages and be used as a control feedback mechanism to continuously enhance operations in real-time while reducing emissions.

1 INTRODUCTION

The Architecture, Engineering, and Construction (AEC) industry has traditionally been founded on three main pillars: time, cost, and quality. With the increasing worldwide demand for more sustainable industries, the construction sector has been set to deliver projects under stricter environmental considerations, bringing the sustainability pillar into play. Despite the notion of green buildings being around for decades, the AEC is still one of the largest energy consumers and waste emitting sectors (Wong and Zhou 2015). Buildings and construction together produce 39% of energy-related carbon dioxide (CO_2) emissions, while the construction and demolition phases generate roughly 40% of all solid waste (Abergel et al. 2017). Given the current technologies available for the built environment area, better utilization and orientation of such tools toward more sustainable operations are vital to the industry's future.

Among the most equipment-intensive processes in construction are earthmoving operations, where hundreds of heavy equipment, such as trucks, excavators, loaders, and dozers, are required to excavate, grade, and haul large quantities of earth material (Zhang 2008). The efficiency of such equipment impacts schedule durations and budget constraints, and is also associated with high levels of greenhouse gas (GHG) emissions that contribute to global warming and climate change. When comparing different processes within the construction industry, a study by Ahn et al. (2009) concluded that construction equipment is a key contributor to environmental impacts, producing more than 50% of the sector's GHG emissions.

Although extensive research has been conducted on optimizing equipment fleet size to minimize costs or maximize productivity, studies on the environmental impacts of earthmoving equipment operations remain limited. Assessing these impacts during the early planning stages of these operations can play a crucial role in improving the overall sustainability of the construction industry. Therefore, this study extends existing research on construction sustainability and utilizes the power of simulation to provide a practical framework that integrates time, cost, and environmental considerations when optimizing construction operations.

2 LITERATURE REVIEW

Sustainability research in the AEC sector has been focused on sustainable building design where the selection of different building materials and engineering systems directly impacts building energy performance over a building's entire life cycle (Azhar et al. 2011). On the other hand, the importance of "greenifying" construction operations lies in the fact that, depending on project size and complexity, the construction phase can last anywhere between one and five years, where the highest amounts of consumed energy, materials, and generated waste occur over a limited period (Wong and Zhou 2015). Although research for design and operations is abundant, research on the environmental performance of the construction stage is still limited in comparison.

The high reliance of earthmoving operations on heavy equipment is linked with significant amounts of generated emissions. This necessitates the optimization of these processes to reduce associated adverse environmental effects. These operations are highly uncertain due to risks of equipment breakdown and productivity, severe weather, and unexpected site conditions (Marzouk and Moselhi 2004; Zhang 2008). Modeling via computer-based simulation is an effective approach to predict the potential uncertainty in earthmoving operation and their impacts (AbouRizk and Hajjar 1998; Marzouk et al. 2000; Marzouk and Moselhi 2004).

Optimizing earth work operations has been mainly concerned with time/cost reduction and productivity improvement. For instance, a simulation framework, SimEarth, was developed for determining earthmoving equipment availability and analyzing time-cost tradeoff where the simulation model automatically stores and processes cost-related components to help users determine different fleet configurations (Marzouk and Moselhi 2004). However, this research is unable to select a combination of different equipment types for each fleet. In addition, this framework cannot differentiate between performance from the stochastic nature and input variances (Zhang 2008). In response to this issue, Zhang (2008) solved the differentiation problem using statistical methods, such as two-stage ranking and selection. Similarly, Jabri and Zayed (2017) developed an agent-based simulator for earthmoving operations (ABSEMO) to simulate a riverbed excavation in a dam project. Their model results and the actual project earthmoving operation had only 0.42% difference that was due to using statistical input data. Another study for modeling earthmoving operations involved the use of 2D and 3D sensory data from earthmoving equipment tracking technologies to capture the details of operating trucks and excavators (Vahdatikhaki and Hammad 2014). However, none of the frameworks in these studies considered reducing the environmental impacts of earthmoving operations.

Research in construction operations has since been evolving to integrate the environmental component in the optimization of construction activities. Resource consumption, reflected by equipment use in earthmoving operations, is a central point to consider when analyzing relationships between time, cost, and environmental performance. Accordingly, a system dynamics simulation approach has been developed to select optimal resource utilization plans for a highway bridge construction to reduce environmental emissions while optimizing time and cost (Ozcan-Deniz and Zhu 2012). Other optimization-based models such as multi-objective genetic algorithms have been developed for enhancing construction schedules and costs to reduce GHG emissions (Ozcan-Deniz et al. 2012; Ozcan-Deniz and Zhu 2017; Li and Chen 2017). Moreover, some efforts addressed the quantification of CO_2 emissions during a house construction process using BIM (Mah et al. 2011), and others focused on minimizing material wastes on construction projects (Porwal and Hewage 2011; Jiao et al. 2013). Although all these studies provide important contributions towards reducing associated environmental impacts of construction activities, they remain limited in their ability to accurately depict equipment operations, consider several variables along with environmental aspects, and provide real-time feedback from actual site data.

This research, therefore, aims to overcome some of the limitations of previous studies on earthmoving operations by developing a discrete-event simulation-based decision-support system (DES-DSS) in *Simphony.NET* that enables modeling different equipment fleet combinations and sizes while simultaneously considering time, cost, and environmental implications. In addition, the DES-DSS is extended to determine the updated fleet configurations in response to actual real-time data based on work progress feedback. The contribution of this DES-DSS is its ability to aid planners in making informed decisions during early planning stages, and as the project progresses, by reflecting the impacts of each fleet configuration to ensure operations are sustainable, as well as time and cost effective.

3 METHODOLOGY

To better demonstrate the impacts of informed decision making in planning equipment-intensive operations, an earthmoving project is simulated with actual construction data using *Simphony.NET*. In this process, the total volume of dirt to be moved is 1,000,000 m^3 of loose material. A working day consists of two shifts, a day and a night shift, with 10 working hours each. Three scenarios are simulated, the first two use equipment fleets comprised of trucks and excavators; the third scenario replaces excavators with dozers and loaders. The performance of the fleets is examined under each scenario by varying the number of trucks, excavators, dozers and loaders. The fleet mixes and sizes are selected that most strictly satisfy the three main objectives of minimizing emissions, cost and time.

For each scenario described above, the simulation is divided into two phases as shown in Figure 1. The first phase, used in the planning stage, aids project managers in selecting the best fleet combination that satisfies the baseline objectives and constraints of the project. According to the types and models of earthmoving equipment available to the contractor and the existing project site information, the input parameters to the simulation are modified. The simulation is run, and the fleet size and combination are selected that meet the objectives and constraints. If the selected fleet size and combination are approved by the project stakeholders, they are used for planning and scheduling; otherwise, the process is repeated until the optimal scenario that meets the objectives is reached.

The second phase of the simulation is used during the execution stage. During project execution, actual progress on the construction site often deviates from planned performance. These deviations can be in the form of higher costs and/or lower productivity, leading to longer durations and higher emissions. If deviations from planned performance are detected early, it is the easier and less costly to reduce their impact on project goals. Accordingly, real-time construction performance data is fed into the simulation model to forecast the expected cost, time, and emissions at completion. If deviations from baseline objectives are found, the equipment fleet size can be modified to recover performance. Once a new fleet size is approved by project managers, the originally selected fleet size can be altered accordingly.

The proposed methodology illustrates the importance of early planning for earthmoving operations. It demonstrates that two decision factors – the type of equipment and size of equipment fleet – have a direct impact on the sustainability, cost, and duration of a project. By simulating these factors, project managers can use this information before and during the execution of the project to enhance the overall performance while reducing environmental impacts.

3.1 Emissions

This study focuses on five types of GHG and criteria air pollutants (CAP) that are emitted by different equipment operated during earthwork operations: nitrogen oxides (NO_x), carbon monoxide (CO), carbon dioxide (CO_2), hydrocarbons (HC), and particulate matter (PM). All five are key contributors to the greenhouse effect and, subsequently, climate change (US EPA 1999). Construction operations can result in the emission of considerable amounts of GHG and CAP. According to a report published in 2009 by the

US Environmental Protection Agency (US EPA), the construction industry is among the top three industrial sectors with high GHG emissions (US EPA 2009). Thus, it is crucial for managers of construction projects to quantify emissions to mitigate their environmental impact.

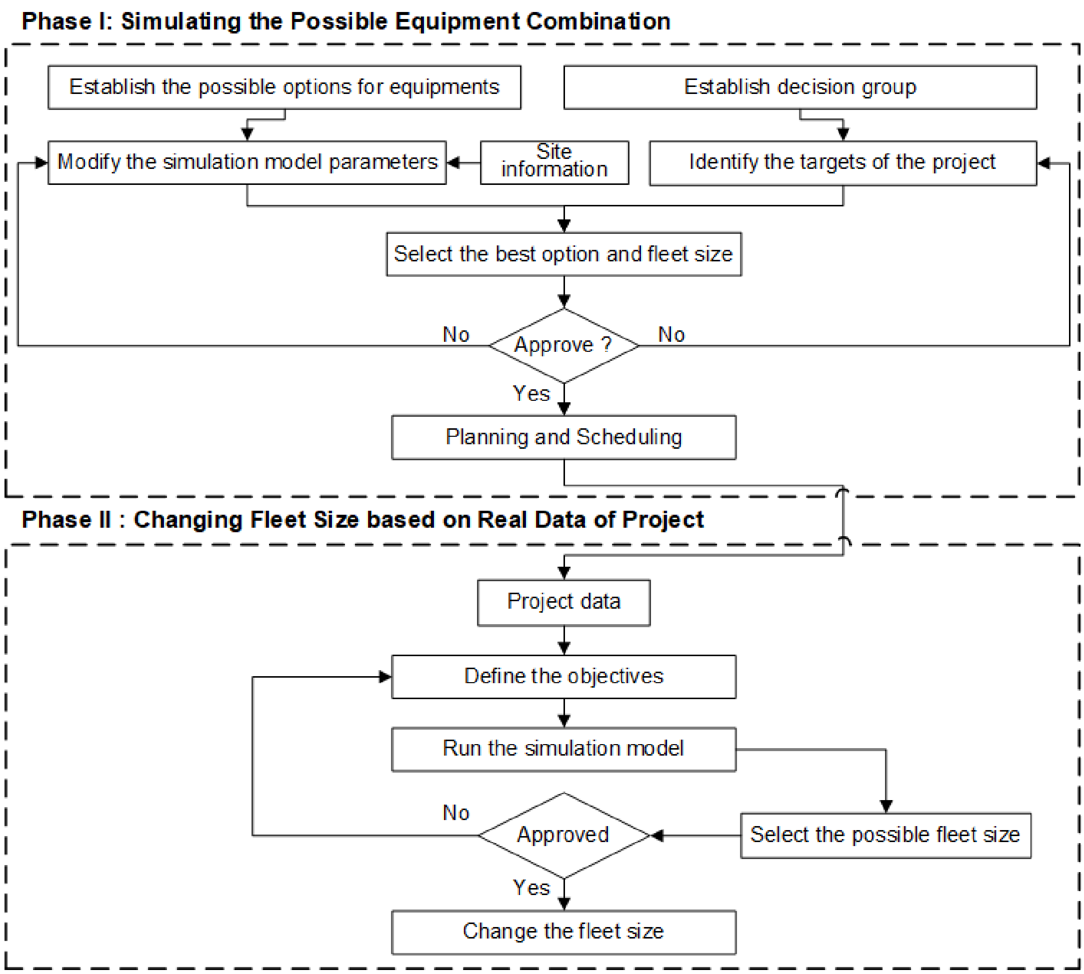

Figure 1: Proposed decision support system (DSS).

The literature on the life cycle assessment (LCA) technique consists of several models to estimate emissions for different equipment. In these models, emissions are calculated by multiplying the amount of fuel consumed by the fuel-to-fuel conversion coefficient. The conversion coefficient is not specific to each piece of equipment, rather it is a factor of the operating hours of that equipment. Another model for estimating the amount of emissions is known as the NONROAD model (US EPA 2004). As shown in Equation (1), the quantity of emissions is a product of the engine power (hp), the number of operating hours, emission factors, and load factors.

$$\text{Emission (g/h)} = \text{Engine Power (hp)} \times \text{Operating hours (h)} \times \text{Emission Factor (g/hp-h)} \times \text{Load Factor} \quad (1)$$

Engine power is a specification of the equipment's engine; operating hours are the total duration in which the equipment is operational; and load factor is used to account for the idle time as well as transient operation. Although the emission factor for CO_2 is determined based on the brake-specific fuel consumption (BSFC), the emission factors for CO, HC, NO_x, and PM is based on the steady-state emission, transient adjustment, and deterioration factors (US EPA 2004). The steady-state emission factor is derived from the model year and horsepower of the equipment. The transient adjustment factor is used to correct the difference between the actual and steady-state test environment. Finally, the deterioration factor adjusts the amount of emissions by accounting for the age of the engine (Ahn et al. 2010). Emission factors and load factors can be determined from the dataset of the emission inventory model. This research relies on the NONROAD model to estimate the amount of emissions for the different equipment used.

3.2 Case Study

This research uses a case study of an earthmoving project. The scope of the project is to haul away 1,000,000 m^3 of excavated loose material. According to the baseline plan, the time available to complete the project is 6 months. A 6-day working week is assumed with 20 working hours per day, divided equally over two shifts. For all equipment, the time efficiency for the day and night shifts are 50 and 40 minutes/hour, respectively.

Figure 2 shows the hauling route for trucks carrying the excavated material. Trucks haul the material from the construction site through the industrial city until they reach a port where the material is dumped. The route is approximately 14 km long and consists of five traffic lights, a roundabout, and a security gate at the entrance to the port. The speed of each truck is modeled as a uniform distribution with the parameters being the minimum and maximum possible speeds. (The maximum speeds are shown in red circles in Figure 2.) Furthermore, the times allocated for passing a traffic light, a roundabout, or crossing the security gates, as well as for loading the trucks, are also represented by statistical distributions, as shown in Figure 2.

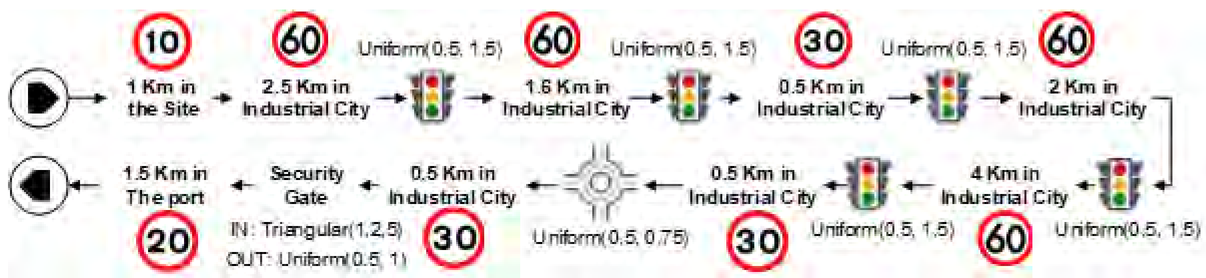

Figure 2: Hauling route for trucks.

Table 1 contains information about the specifications, weight, horsepower, and capital costs of the equipment used in the project. In the first two scenarios, combinations of trucks and excavators are used. The excavator unearths loose material and then unloads it from the bucket into a truck. In the third scenario, a combination of trucks, loaders, and dozers is used, where the loaders and dozers replace the excavator. The roads are in a remote area and site layout is large enough to accommodate the amount of equipment required.

Table 1: Equipment specifications.

Equipment Description	Weight (kg)	Horsepower (hp)	Purchase Price ($)
Loader (4.2 cu yd bucket, 10 ft dump height)	28,985	275	562,600
Dozer (10.9 ft blade width)	23,696	215	456,900
Excavator (5 cu yd bucket size, 26.4 ft digging depth, 24.8 ft dump height)	53,297	396	616,000
Truck (19.6 cu yd capacity, 8ft 11in empty loading height)	23,040	316	445,700

The capital recovery, overhead, and operating costs of each type of equipment, shown in Table 2, are used to calculate the total hourly cost of utilizing the equipment. Capital recovery cost represents the hourly ownership cost; it is derived based on the purchase price of the equipment, the lifetime, and the salvage value at the end of the lifetime. Overhead costs include accounting fees, insurance costs, tax, etc. Operating costs encompass all costs of operating the equipment including the cost of overhauls, maintenance, fuel, lube, tires, and wear parts.

Table 2: Costs of equipment.

Cost Component		**Loader**	**Dozer**	**Excavator**	**Truck**
Capital Recovery ($)		56.26	30.46	44.00	11.89
Overhead ($)		1.97	1.07	1.54	0.42
Overhaul ($)	Parts	9.92	3.13	4.97	1.57
	Labor	7.31	3.69	5.12	2.09
Maintenance ($)	Parts	18.43	4.70	7.45	2.92
	Labor	13.58	5.54	7.69	3.87
Fuel ($)		26.16	17.76	28.62	13.17
Lube ($)		5.25	4.20	6.45	4.89
Tires ($)		0	0	0	2.80
Spare Parts ($)		2.80	9.98	2.95	0
Total ($)		141.69	80.53	108.79	43.62

The emissions for the equipment are calculated using Equation 1 shown above. Table 3 shows the emission factors for each type of equipment.

Table 3: Emissions factors for different equipment.

Emissions	**Loader**	**Dozer**	**Excavator**	**Truck**	**Idle (All Equipment)**
NO_x (g/h)	1,135.64	887.86	2,312.95	1,241.27	105.96
CO (g/h)	365.33	285.62	864.84	422.82	36.00
CO_2 (g/h)	147.34	115.19	212.12	160.09	6.72
HC (g/h)	48.69	30.45	86.99	54.09	18.34
PM (g/h)	45.08	35.24	132.01	64.19	0.67

A simulation model was developed to mimic the earthmoving operation discussed above. Based on the probabilistic nature of the model, a Monte Carlo (MC) simulation with 200 runs is performed for each fleet size in each scenario. Using the statistical distributions, a set of random numbers, each corresponding to the value of one input parameter (i.e. truck speed, duration at different road sections, and loading time), is generated. The input values are fed into the simulation model to provide a set of output variables corresponding to the duration, operation cost, and emissions of the project. The process is repeated with a newly generated set of random numbers until the specified runs of the simulation are completed. Finally, the collected sample of output variables are statistically analyzed. The MC simulation process provides more confidence in the results. The following section discusses and analyzes the results of the simulation.

4 SIMULATION RESULTS, ANALYSIS, AND DISCUSSION

The simulation model tested different equipment fleet mixes and sizes. Accordingly, three scenarios were tested. Scenario 1 includes one excavator with a varying number of trucks, Scenario 2 includes two excavators and a varying number of trucks, and Scenario 3 involves a mix of one dozer, one loader, and a varying number of trucks. Under each scenario, 200 iterations were simulated each time while varying the number of trucks from 65 to 100. The resulting duration, cost, and emission outputs were analyzed for each fleet mix and size. The most likely values of duration, cost, and emission outputs (obtained from the histograms of the 200 iterations for each fleet size and mix) are used in the following analyses.

4.1 Project Duration Analysis

Figure 3 depicts the varying changes in project durations under each scenario when varying the number of trucks in each fleet. Observing Scenario 1 where one excavator is used, the project duration gradually decreases from 179 to 119 days (–33.5%). However, the simulation model reveals that upon increasing the number of trucks from 80 to 100, the queue length of trucks waiting for the excavator increases from one to 10 trucks; thus, the excavator's production rate controls the production rate of the entire process. Thus, idling trucks are considered wasteful and non-productive to the process.

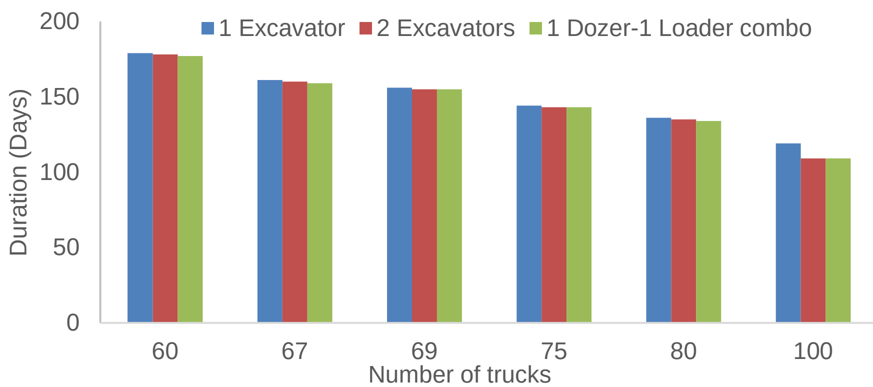

Figure 3: Most likely occurring project durations for each scenario.

Accordingly, Scenario 2 simulated earthmoving operations with the addition of a second excavator. Similar to the trend with one excavator, the project duration decreased from 178 to 109 days (–38.8%). This reflects a 5% further reduction in project duration upon adding a second excavator. Moreover, the queue length of idle trucks remained zero, indicating that two excavators are sufficient to supply up to 100 trucks.

To further determine which equipment fleet mix is better for the project duration, excavators were substituted by a combination of one dozer and one loader. The duration trends resulting from Scenario 3 and shown in Figure 3, revealed a similar duration reduction to Scenario 2 when increasing the number of trucks from 60 to 100: a 38.4% reduction from 177 to 109 days and a truck queue length of 0.3 (~ 0). Based on these findings, the fleet mix and sizes for Scenarios 2 and 3 are both equally favored for reducing project durations. Since the decision of fleet size and mix depends other factors in addition to duration, equipment cost and emissions are analyzed in the following sections.

To determine whether using 200 MC runs provides statistically significant results, the standard error was calculated for each scenario. The standard error measures how far the sample mean is from the true population mean. As the number of samples increases, the standard error decreases. For the duration parameter, the average standard error was approximately 0% indicating that the number of MC runs are sufficient.

4.2 Equipment Cost Analysis

Figure 4 shows the histogram of equipment cost for a fleet scenario composed of 69 trucks and one excavator. The histogram shows that 85% of equipment cost falls between \$9,739,333 and \$9,745,667, with a mean of $9,742,621 and standard deviation of $3,000 USD. Costs lower and higher than these ranges are only 6.5% and 8% likely to occur, respectively.

Figure 5 illustrates the equipment cost trends for each scenario upon varying the number of trucks in each fleet. The equipment cost trend for Scenario 1 indicates that as the number of trucks increase, the associated equipment costs increased from $9.74M to $10.66M (+9.5%). The cost increased considerably beyond 80 trucks, due to having 10 trucks queued in line and idle, hence contributing to capital costs of employing more trucks that are not productive on site. Additionally, since these trucks are queued and not contributing towards the reduction in duration, there are no operational cost savings that could result from enhancing production with more trucks. Given that the production rate of the excavator in this scenario is controlling the production rate of the process, adding more trucks will increase associated equipment costs.

For Scenario 2 where a second excavator is added, the costs decreased by $77,672, from $10.1M to $9.99M. These cost savings are a result of enhanced production upon adding another excavator, as well as the associated decrease in duration that decreases the operational costs of equipment. Therefore, adding more trucks and a second excavator provides financial savings. Similarly, the costs of using a combination of one dozer and one loader also showed a cost reduction of $71,863 when increasing the number of trucks, to reach slightly lower costs than Scenario 2 with 100 trucks. The lower capital and operational costs, as well as the efficiency of using loaders and dozers instead of excavators, contributed to overall lower equipment costs compared to Scenarios 1 and 2. Considering the economic feasibility of selecting the best fleet size and mix, using one excavator with 80 trucks provides the lowest costs. However, upon increasing the number of trucks, it becomes more feasible to substitute the excavator with a combination of one loader and one dozer. In addition, the average standard error for the different combinations of each scenario is less than 0.002%, indicating that the simulation results are statistically significant.

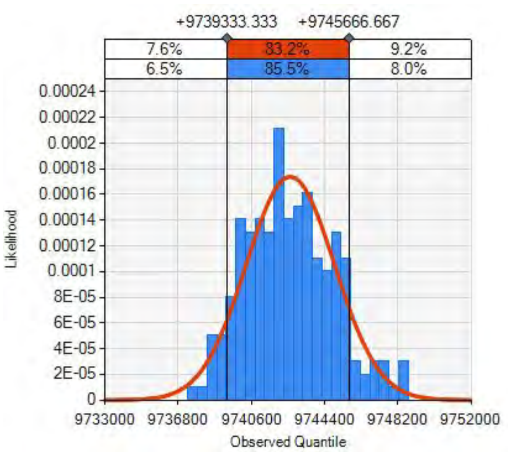

Figure 4: Histogram of equipment cost.

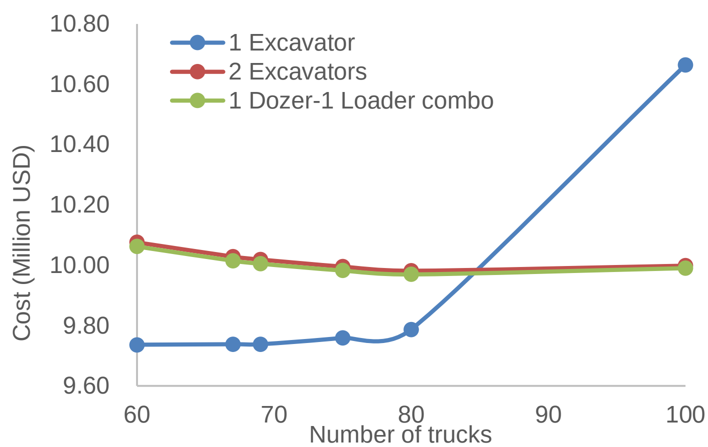

Figure 5: Most likely incurred costs for each scenario.

4.3 Emissions Output Analysis

The third output that this study focuses on is the resulting emissions from different fleet combinations and sizes. To achieve sustainable earthmoving operations, planners should select the scenario that provides the lowest associated emissions while considering the different time and cost trade-offs. The outputs for CO, CO_2, HC, NO_X, and PM emissions for some scenarios are summarized in Table 4. The resulting trends of the aggregated emissions are depicted in Figure 6.

Comparing the values in Table 4 and the aggregated results in Figure 6, it is evident that the combination of trucks and one dozer-one loader provides the lowest emissions. For each of the scenarios, the resulting emissions increased by ~ 2% when increasing the number of trucks from 60 to 100. When comparing Scenario 3 with Scenario 2, the amount of emissions consistently increased by about 2,000 kgs when using two excavators instead of a loader-dozer combination. Relative to Scenario 1, the overall emissions of Scenario 3 decreased by about 1,300 kgs when using 60 trucks and the difference slowly decreased to about 200kgs when using more than 80 trucks. This indicates that Scenario 2, where two excavators are used, starts to improve on the overall emissions being generated when using more than 80 trucks. However, the combination of loaders and dozers remains to be the most sustainable option for fleet size and mix. Similar to the duration and cost parameters, the standard error was calculated for the emission parameter. The average standard error for the scenarios is less than 0.01%, with a minimum of 0.006% and a maximum of 0.012%, indicating that 200 runs provides statistically significant results.

4.4 Time, Cost, and Emissions Trade-Offs

Determining the optimal equipment fleet mix and size depends on which of the three objectives (lower cost, lower duration, and lower emissions) is considered a priority for the project at different times. Table 5 summarizes the most optimal scenario for each objective that planners can decide upon. Intuitively, the lowest duration is achieved by increasing the number of trucks and either excavators or loaders/dozers combination. Achieving lowest costs or emissions is possible when using the least amount of equipment, in this case, lowest number of trucks and one excavator or one dozer-one loader combination, respectively. According to these results, the objectives are competing and therefore a trade-off is necessary and dependent upon project requirements. Providing scenario-based results and data can aid planners in making informed and evidence-based decisions by understanding the implications on emissions, cost, and time of different equipment fleet mixes and sizes.

Table 4: Most likely values for each type of emissions (in kg).

No. of Trucks	Excavator or Loader-Dozer	CO Emissions	CO_2 Emissions	HC Emissions	NO_x Emissions	PM Emissions
80	1 Excavator	90,833	34,377	11,640	266,571	13,769
60	2 Excavators	90,188	34,154	11,515	264,677	13,689
100	1 Loader-1 Dozer	91,883	34,792	11,741	269,654	13,942

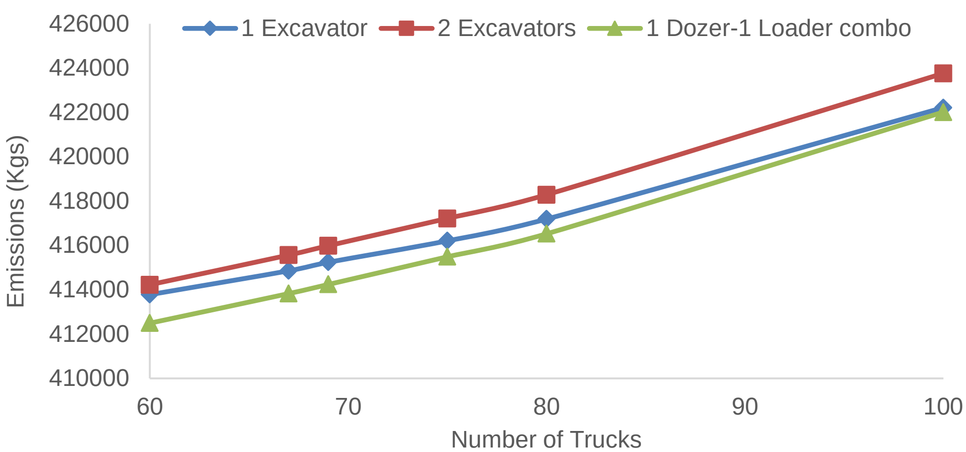

Figure 6: Most likely aggregated emission values for each scenario.

Table 5: Optimal cases for each objective.

Objectives	No. of Trucks	Excavator/ Loader-Dozer	Duration (days)	Cost ($)	Total Emissions (kg)
Lowest Durations	100	2 Excavators	109	9,998,718	423,759
Lowest Costs	60	1 Excavator	179	9,736,459	413,780
Lowest Emissions	60	1 Loader-1 Dozer	177	10,062,740	412,494

4.5 Updating Model Based on Actual Site Data

The proposed model was run during the implementation phase of the project to re-determine the optimal fleet mixes and sizes based on actual progress feedback data collected from site. As an example, the actual amount of hauled material after two months is 200,000 m^3 instead of the planned 333,333 m^3. Also, assuming that project managers need to complete the excavation and hauling of the remaining 800,000 m^3 in the next 4 months, the model is updated to reflect actual data and determine the optimal fleet sizes and mixes capable of achieving this target. The associated durations, costs, and aggregated emissions are summarized in Table 6.

Table 6: Updated optimal fleet mix and size results.

Fleet mix and size	Duration (days)	Cost ($)	Total emissions (kg)
83 Truck - 1 Loader - 1 Dozer	104	7,972,522	334,115
84 Trucks - 1 Excavator	104	7,854,746	334,935
83 Trucks - 2 Excavator	104	7,993,110	335,721

Based on these results, the optimal scenario that achieves the set duration and decreases emissions is 83 trucks with the one loader-one dozer combination. Depending on whether cost is a determining factor, using 84 trucks with one excavator becomes the more economic choice with the second lowest emission value. As discussed earlier, depending on project constraints and progress, the model aims to support planners and managers in selecting optimal decisions that are backed by data-driven analytical methods.

5 VALIDATION AND VERIFICATION

Model verification can be performed using several techniques. A sensitivity analysis was carried out on the proposed simulation model. In this technique, the values of the input parameters are changed to see the model's behavior and compare the relations with the real system (Sargent 2007). To achieve this, 55 trucks and 2 excavators, with the same specifications as discussed in the case study, are assumed. By varying the amount of loose material to be moved, the outputs of the model are expected to vary as well. In other words, when the amount of loose material decreases, the project duration, cost and emissions are expected to decrease as well, and vice versa, where an increase in loose material results in an increase in duration, cost, and emissions. Table 7 shows the results of the sensitivity analysis, thereby demonstrating verification of the model.

The validity of the model is checked by using face validation technique. Face validation is described by Sargent (2007) as asking individuals with knowledge about the system whether the model and its output are acceptable. The results of the simulation were reviewed and approved by two industry experts.

Table 7: Sensitivity analysis results.

Loose material (m^3)	**Duration (days)**	**Cost (\$)**	**CO (kg)**	**CO_2 (kg)**	**HC (kg)**	**NO_x (kg)**	**PM (kg)**
100,000	21	1,017,305	8,984	3,399	1,147	26,359	1,368
500,000	106	5,093,208	45,008	17,029	5,748	132,059	6,854
1,000,000	212	10,185,717	90,017	34,059	11,495	264,124	13,708

6 CONCLUSION

This paper proposed a discrete-event simulation-based decision support system that allows planners to make informed decisions during early planning stages on which equipment fleet size and mix can best achieve desired time, cost, and environmental considerations. Additionally, this system allows for continuously optimizing operations in real-time and updating equipment fleet assemblies as needed to re-direct progress.

The simulation was applied on a case study project of earthmoving operations to demonstrate the impacts of different fleet sizes and mixes on environmental emissions, project duration, costs. Several scenarios were simulated, and the results reveal how varying equipment types and numbers can significantly impact the associated emissions, as well as durations and costs. Depending on the objectives, different fleet configurations are deemed optimal for either achieving lowest emissions, costs, or durations. Moreover, the results of updating the model based on actual site data showcases how the fleet mix needs to be altered throughout the project implementation phase to re-align operations with the plan, while understanding the resulting implications on project objectives. Therefore, modeling different scenarios and measuring their impacts aids planners in deciding which fleet combination to assign to a project and how it needs to be modified based on project progress and objectives.

One of the challenges of this approach is gathering actual progress data to select the best fleet size and combination. The future research will tackle this challenge by providing a framework to use Building Information Model (BIM) as the source of the parameters needed for the simulation.

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AUTHOR BIOGRAPHIES

ELYAR POURRAHIMIAN is a PhD student at the University of Alberta studying Construction Engineering and Management. He received his MSc in Project Management (2015) and BSc in Industrial Engineering (2013) from the University of Tehran. His Email address is elyar@ualberta.ca.

MALAK AL HATTAB is a Postdoctoral Fellow at the University of Alberta. She researches how the adoption of Building Information Modeling (BIM), simulation, and lean techniques can help improve design workflows, optimize construction planning and operations, and enhance the sustainable performance of projects and the industry. Her email address is elhattab@ualberta.ca.

RANA EAD is an MSc student at the University of Alberta studying Construction Engineering and Management. She received her BSc in Construction Engineering from the American University in Cairo in 2018. Her email address is rsead@ualberta.ca.

RAMZI ROY LABBAN is a Postdoctoral Fellow at the University of Alberta. He has more than 20 years of experience in the construction industry with focus on modeling and simulation, as well as machine learning for construction. His email address is labban@ualberta.ca.

SIMAAN ABOURIZK is a Distinguished University Professor and Canada Research Chair in Operations Simulation at the University of Alberta. His research is focused on developing an improved framework for the planning and control of construction projects through advancements in simulation. His email address is abourizk@ualberta.ca.