Discrete Event Simulation to Predict Construction Equipment Emissions on a Digital Twin Platform

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Abstract

Emissions from machinery that is primarily fueled by Diesel represent a significant environmental concern in the construction sector. Traditional monitoring methods, including both Simplified and Portable Emissions Measurement Systems (SEMS and PEMS, respectively) encounter practical and financial constraints when deployed extensively across the diverse machinery types. This paper introduces a novel approach on predicting emissions and fuel consumption by leveraging a priori recorded emissions data from non-road mobile machinery (NRMM) in a Discrete Event Simulation (DES) as part of a Digital Twin Platform (DTP). Focusing on three types of construction machines (drilling rig, loading excavator, and hauling dump truck) the DES models their basic operations on a DTP purposed for earthwork and foundation activities for a high-rise building project in Denmark. With the input of different configurations (e.g., machine quantity and type, location,), DES allows for the prediction of emissions and work output. Verification of the approach occurred in a field-realistic outdoor construction laboratory setting while the validation was demonstrated on a construction site. The results provide an efficient and economical avenue for monitoring emissions related to construction equipment operations. Beyond the environmental benefits, the proposed method generates knowledge that can supply construction managers with critical insights into performing proper resource leveling.

Keywords –

Construction equipment emissions, Digital Twin, Discrete Event Simulation, Site layout optimization, Non-road Mobile Machinery, Portable Emission Measurement System, Prediction and avoidance.

1 Introduction

Construction machinery is mainly powered by diesel fuel and contribute substantially to Greenhouse Gases (GHG) and thus, global warming [1]. Heavy construction machinery, often referred to NRMM, accounts for about half of all CO_2 (Carbon Dioxide) emissions produced by the construction industry in Denmark in 2004 [2]. Besides CO_2, NRMM produces Nitrogen Oxides (NO_x), Carbon Monoxide (CO), Particulate Matter (PM), and Hydrocarbon (HC) pollutants that are dangerous to human health and the environment. Specifically, off-road diesel equipment is identified as the third largest contributor to NO_x emissions (14.5%) and the second largest contributor to PM emissions (24.3%) among mobile vehicles [2].

The European Union (EU) applies regulations for threshold levels of emissions from NRMM and to that end, various sensor technologies are set up to measure emission levels during the construction phase [3]. At a national level, the Danish Government has set a target for the green transformation of the built environment. It aims to achieve the goal of carbon neutrality by 2050 [4].

This is where Digital Twin (DT) concepts come into play that integrate, among other data, Building Information Modeling (BIM), construction schedule (4D component), Internet of Things (IoT, incl. data from sensors communicated wirelessly to a DTP and being processed for further analysis), and user interfaces (i.e., UI dashboards). Yet, a challenge of DTs in construction seems to be the reliable gathering of accurate field data and connecting the different data from the various sources for further reasoning in knowledge-based representations, for example, as part of high-fidelity information that is already available in 4D BIM models.

In essence, the further purpose of a DT is “a virtual representation of an object or system that spans its lifecycle, is updated from real-time data, and uses simulation, machine learning, and reasoning to help decision-making” [5]. While the virtual models of DTs can monitor real-time data from SEMS [6] and PEMS [7], DTs may also access data recorded in the past that assist in generating further insights from the data-driven simulations [8]. In construction simulations newly created knowledge benefit decision making, for example, reducing fuel consumption in construction logistics [9].

However, an open research question is: *How can these individual components (4D BIM, IoT/sensors, DTP* *incl. UI) be applied together in a meaningful way that can demonstrate the environment benefits of reducing construction equipment emissions while increasing output?*

The following sections explain the background, the methodology, and preliminary findings how data from heavy construction equipment involved in creating foundation piles, loading and hauling the excavated earth material off site are used in predictive simulations for construction site operations emissions assessment.

2 Background

This section is subdivided in a few very brief reviews of some of the relevant topics an interested reader might want to be familiar with, for example, the key alternatives to (a) gather live construction equipment emissions data (2.1-2.3) and (b) conduct basic construction equipment emissions simulations (2.4).

2.1 Portable Emission Measurement Systems

Portable Emissions Measurement Systems (PEMS) have been used for several decades, gaining significant traction in the late 1990s and early 2000s. These systems are designed to measure and analyze emissions from various sources like road vehicles and NRMM. There is a diverse range of PEMS available in the market. Therefore, they vary in measurement capabilities, features, and compatibility with different machines or equipment. PEMS systems consist of sensors, analyzers, and data acquisition systems that can be transported and installed for on-site measurements. The adoption of this technology grew as researchers recognized the importance of obtaining accurate emissions data. They sought data from real-world field experiments, with machines working in their operational settings, going beyond traditional laboratory testing. PEMS find applications in research, emissions monitoring, and other activities related to emissions control and environmental studies [7, 9, 10]. Noteworthy, PEMS is supported by both the U.S. Environmental Protection Agency (EPA) and the European Environment Agency (EEA) for measuring emissions.

2.2 Telematics

Telematics provides an advanced monitoring method widely employed in the automotive industry to track assets like cars, trucks, and construction equipment. It utilizes Onboard Diagnostics (OBD), often in combination with Global Navigation Satellite Systems (GNSS) technology to record and map a vehicle's movement, providing valuable data for fleet tracking and management. End-user access to telematics data, if granted, further enables efficient monitoring of various vehicle aspects, such as speed, idling, fuel consumption, tire pressure, etc. This is feasible through a sophisticated onboard computer in the vehicle, capable of capturing comprehensive information [11].

2.3 Simplified Emission Measurement Systems

Compared to PEMS, a Simplified Emission Measurement System (SEMS), as used in [2] and [6], comes at a much lower expense (a few thousand Euros). SEMS is a portable emission meter and can be applied to several means of transportation, including NRMM [12]. Due to its small size and the less time-consuming installation, usually less than 15 minutes, it is suitable for simplified measurements when equipment operations are not to be interrupted for a long time or inspections, for example, by regulatory authorities. Due to the lower complexity, fewer experts are required to mount the system than PEMS, simplifying its installation process and use overall [13]. Yet, [2, 6] pointed out that the latest released emission standards from the EEA for NRMM make it difficult if not impossible for some of the relatively inexpensive sensor components in SEMS to record the ever-smaller emission levels very accurately.

2.4 Discrete Event Simulations

Discrete Event Simulation (DES) involves modeling systems where the state variable undergoes changes at specific time points [14]. It has found widespread adoption as an effective technique for comprehending system behaviors and assessing different operational strategies. Since the inception of the CYCLic Operations Network (CYCLONE) [15] has been instrumental in crafting computer-based simulation models for construction projects, aimed at analyzing and optimizing their performance [16]. Following CYCLONE's introduction, a multitude of construction simulation systems emerged, including STROBOSCOPE [17] and RiSim [18], and SDESA [19]. DES was also implemented for estimating construction emissions by investigating load factors and based on various equipment activities [20]. Besides other tools, SimPy emerged as an open-source library that includes components enabling DES workflows efficiently [21]. These simulation systems offer valuable tools for project managers to replicate the dynamic interactions between resources and activities, facilitating comprehensive performance evaluation and the generation of insights.

3 Research Method

The employed Digital Twin Platform (DTP) plays a pivotal role in gathering and streaming the raw machinery data via IoT-sensors (Internet of Things) to an accessible cloud storage space. There, a pre-processing module filters the data first for erroneous elements and then processes it online for emissions reasoning by applying simplified mathematical formulas. Finally, the resulting information is transformed as input values into a DES simulation model. This model finds out how environmental and economical the construction operations process can be. Subsequently, a User Interface (UI) presents the results to the end user in a visual and accessible dashboard format in commercially available web browsers. As shown in Figure 1, the designed technical components in this workflow seamlessly incorporate some manual user input, fostering a collaborative and interactive working environment for easily refining the required parameters to run the DES, which predicts previously not available outcomes.

Multiple steps are involved in the workflow of data recording, communication, processing and visualizing: (1) Recording raw equipment emissions and location data (latter, if available), (2) wireless communication to cloud storage space via mobile networks, (3) processing raw data streams online by applying simplified mathematical conversions, (4) reasoning by applying basic thresholds to detect emission breaches that violate regulations, (5) linking the results to parameters of already existing elements of 4D BIM models, (6) taking this automatically generated information and further manual input as values to run the DES, (7) visualizing the results as part of a dashboard in the DTP.

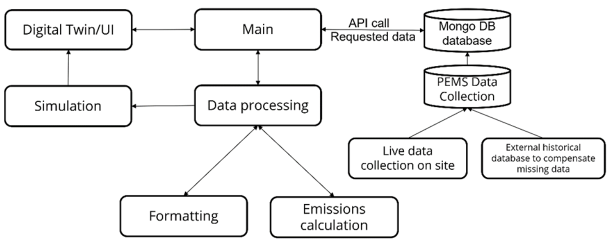

Figure 1. Workflow of acquiring, communicating, processing, and populating emission information to the Digital Twin Platform (DTP).

For demonstration, the method is applied to a realistic but highly simplified use case involving two alternative construction plans of up to two drilling rigs purposed to create reinforced concrete piles for a foundation wall, one excavator loading the excavated earth material from the drilled piles into at least one dump truck that hauls the material off the building site.

4 Implementation

4.1 Live and online emission datasets gathering

Emissions data for 3 different NRMM were collected. The drilling rig, Bauer BG55, collects the emissions data via PEMS on the (final demonstration) high-rise building construction site for 1 full workday (7 effective work hours). Mobilization of PEMS took several hours. Due to several unknown false data readings of NOx emissions, the dataset was manually filtered and cleaned before used in the further analysis. More information on the recording of emissions data of the drilling rig (2 hrs.) is here [3].

For the excavator, Caterpillar 325F, a structured experiment took place at another location, a realistic outdoor construction laboratory setting. This was necessary since only one PEMS was available for testing at the final demonstrator site. However, the same PEMS device (AVL492) was utilized for recording 1.5 effective working hours of the excavator's emissions, like NO_x and CO_2. The excavator operated in different working modes including loading and idling, during cold and hot starts.

All machines operated on Diesel fuel. The utilized PEMS in all tests (drill rig and excavator) logged data at high frequency (1 Hz) via the CAN-bus system. Such data can also easily be exported as CSV (Comma Separated Values) file for potential other post processing.

Since no dump truck was readily available at either location in Denmark, the PEMS data used for a dump truck came from an online data repository. Chosen was a 10-ton dump truck, Isuzu FTR850 AMT. The PEMS device in the study that collected the emission data [22] was a SEMTECH®DS unit recording multiple trips on urban routes in South Africa at a rate of 1 Hz. While some risk is potentially involved in procuring data over the internet for our research purposes, the data set was previously published in a peer-reviewed academic outlet and although the recording location was not identical to the climate in Denmark, still deemed trustworthy.

4.2 Datasets processing into averaging heat maps

After dataset gathering, we proceeded with assessing the impact of engine speed and engine load on the emissions within the context of the machine being in several modes, incl. direct work, supporting work, and other works, including idling.

First, we removed data points where the engine speed was below 800 rpm, as it is unlikely for engines to be working at such speeds in practical scenarios. Based on observation and preliminary analysis by checking the distribution of engine speed value when the machine is idling, we defined the idling mode as when engine speed is between 800 rpm and 900 rpm. We calculated the average value for the emission rate (g/s) of CO_2 and NO_x and the consumption rate (g/s) of fuel at the idling mode, which is then used in DES for simulating the emission and consumption of idling machine as shown in Table 1.

For other working modes, the observation heat map of engine speed and engine load is created. The approach focused on creating informative heatmaps for detecting the machine's operating mode automatically based on, specifically, its engine speed, engine load, and emissions values. The first step included extracting the relevant data from the dataset and then dividing its engine speed and engine load into sections to construct a more detailed grid for the heat map. The process proceeded otherwise with calculating the average NO_x emissions within each grid element by applying certain filtering conditions to the dataset. The same process was used for the CO_2-values and for the fuel consumption. Additionally, we visualized the resulting information data as a heat map, using a color scheme to represent average emissions, and included annotations for clarity. Axis labels and a title provide context, and a color bar assists in the interpretation. Given the space restrictions in this paper, Figure 2 presents the calculated heat maps for the drill rig only. Figure 2 (a) shows the percentage of engine load and speed of the drilling rig when it is working in drilling mode. Figure 2 (b-d) shows the CO_2 and NO_x emission rate as well as Fuel consumption rate when the drilling rig is working at different sections of engine load and speed. Figure 2 (b-d) is created from the observation on all working modes and reflects the correlation between emissions and engine speed and load, which are thus also used for the simulation of other working modes.

Table 1. Average NO_x and CO_2 emission and FUEL consumption for idling equipment.

Equipment	NO_x (10^{-3} g/s)	CO_2 (g/s)	Fuel (g/s)
Drilling rig Bauer BG 355G	13.80	5.38	1.71
Excavator CAT 325F	3.77	2.20	0.50
Truck Isuzu FTR850 AMT	0.87	1.21	0.38

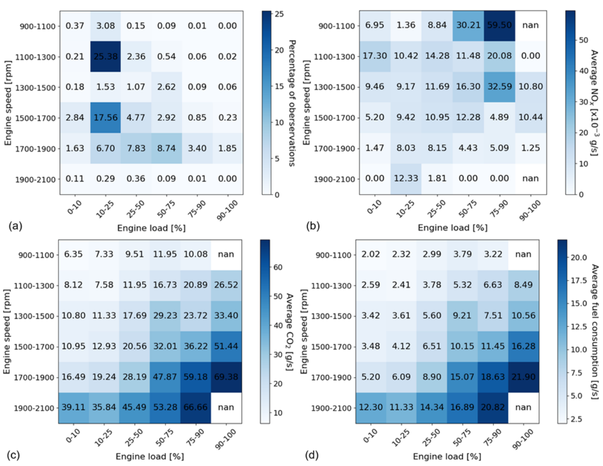

Figure 2. Heat maps for Bauer 355G drilling rig when it is in the drilling mode for 3 hours of observed work.

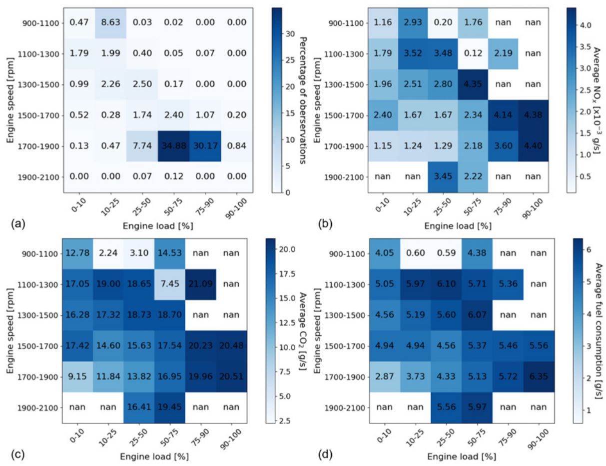

Figure 3. Heat maps for CAT 325F excavator when it is in the loading mode for 3 hours of observed work.

Overall, few deviations in the engine load and the speed are observed, and therefore, the emissions can be associated automatically when engine parameters fall within operating modes as outlined above. Likewise, it is a useful source of input data for building a simplified DES for equipment emissions (explained later).

For the loading activity as shown in Figure 3, the excavator operates in higher engine load for the majority of the time (50%-90%) and between 1700 to 1900 rpm. It is a more intensive activity and it is logical to observe the differentiation in engine load and engine speed between the loading and idling activity. In the same manner the rate of fuel consumption and CO_2 emission are much higher than in the idling activity, whereas the NO_x emission shows a significant monotonic correlation with engine speed and engine load. This is explained due to the catalyst existing in the machine which activates when it reaches temperatures above 120 °C.

4.3 Emissions calculating from simulation

Based on the live recorded PEMS emissions data two arrays are generated: a probability array and a value array. The probability array encapsulates the likelihood of engine speed and load of the machine when the machine is in different working mode. Simultaneously, the value array associates real average values with each combination of engine speed and load. The core of our method involves the calculation of cumulative probabilities. After flattening the probability array, we calculated the cumulative probabilities of that array. The next step is the generation of random numbers distributed uniformly between 0 and 1. Subsequently, our approach identified the corresponding combination of engine load and speed for each randomly generated number. From the simulation we receive the time of each machine's operation in the unit of seconds. For each second, we estimate the emission and consumption calculation on the basis of the specified probabilities and associated values . The final result is a sum of emission and consumption values sampled from the distribution.

4.4 Simulation engine, logic and parameters

We used the SimPy simulation engine to perform the DES. SimPy is an open-source process-based discrete-event simulation framework for Python. It provides the necessary components for modeling and simulating complex systems with discrete events, such as the advancement of time and interactions between different entities in the simulation (Table 2). The simulation (Figure 3) starts with a human user entering numerous input parameters it needs to run (see Table 3).

Here, the vehicle agents of the excavator and trucks are modeled as resources (Figure 4). Conditional activities represent a task that starts when the resources are available in the queues. For instance, the loading operation starts when an excavator and a dump truck are available. A normal activity starts whenever an instance of any preceding activity ends. Therefore, the transportation operation takes place when the loading is finished. The queue nodes represent events that can occur in line ups, for example, when any of the machines turn to idling state. Additional information regarding the aforementioned terminology can be found in [19].

Figure 4 shows dump truck/s stationed at an idling stage, forming a queue until an available loading spot becomes vacant for filling. The number of available loading spaces mirrors the count of excavators on site [1]. Upon reaching a loading spot, a truck awaits while the assigned excavator commences the filling operation, subsequently returning to the idling stage. The filling operation relates to the filling time. Once a dump truck is loaded, it departs from the construction site to haul the excavated soil to a temporary dump location. In cases where another truck awaits its turn, it promptly occupies the newly vacated loading space, ensuring seamless loader utilization. Conversely, should all loading spots be temporarily occupied, the excavator transitions into an idling mode until its services are requested. The loading process adheres to predefined parameters, specifically the truck's capacity, the excavator's bucket size, considering bank and loose states, which collectively determine the filling efficiency. Notably, the drilling rig operates independently from the excavator-dump truck system. It executes drilling operations and can enter very short idling modes when encountering major changes in soil type classifications, with the duration governed by distribution patterns, all are more detailed in Table 3. This structured approach intends to optimize construction site efficiency, ensuring resource allocation aligns with operational demands.

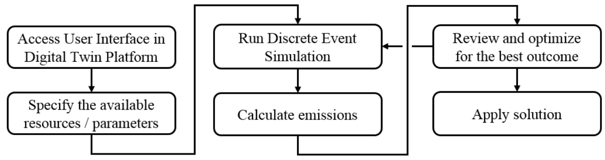

Figure 3. Simulation logic to retrieve desired solution.

Table 2. Time distributions of activities for construction machines used in the DES.

Equipment	Working modes	Time distributions
Drilling rig	Drilling	Uniform (10,14) [min]
	Idling	Normal (30,10) [sec]
Excavator	Loading Idling	Normal (25,5) [sec]
Truck	Driving Idling	Uniform (5,8) [min]

Table 3. Simulation parameters and preselected units.

Parameter	Explanation	Units
Simulation time	The corresponding work time the simulation runs	min [480 min = 1 workday]
Excavator	Loading material on dump truck, idling at times	No. [1]
Dump truck/s	Hauling off material, idling at times	No. [1..n]
Drilling rig/s	Boring piles in uncertain soil conditions, unloading material, idling at times	No. [1-2]
Distance to travel	Hauling distance from construction to dump site	km [1..30]
Initial soil amount	The amount of soil left over from previous drills	m^3 [1..n]
Soil type variations	Possibility of slightly varying excavated soil	Factor [1-3]
Excavator bucket size	Volume for one swing of the excavator arm	m^3
Truck capacity	Truck bed size, incl. bank and loose states	m^3 [5-10]

4.5 Realistic simulation scenario

The logic explained above was applied to simulate activities, inspired by a real-life construction operation (a high-rise building in Aarhus, Denmark). On this project, a drilling rig produced foundation walls and, in the process, an excavator loaded the bored soil material on a dump truck that hauled it away to a nearby temporary storage location (Figure 5). A site manager interested in the construction equipment emissions and fuel consumption values provided the simulation parameters according to Table 3. The simulation was run 100 times to improve the confidence level of the results. Mean values were returned to the user for review (Table 4).

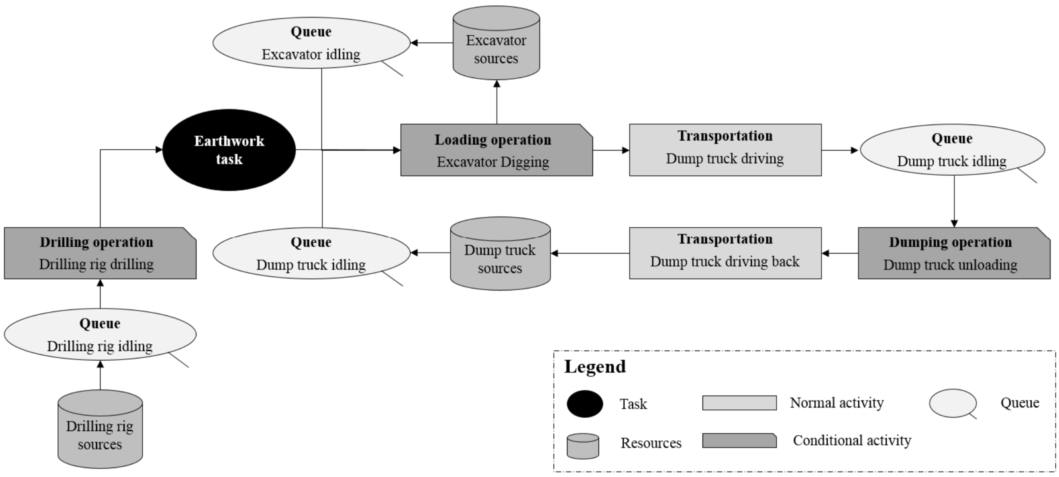

Figure 4. Discrete Event Simulation (DES) flowchart of the construction site operation.

The simulated activities replicate a real high-rise building construction site in Aarhus, Denmark. A drilling rig produced foundation walls and the excavator loaded a dump truck to haul excessive earth material away to a nearby temporary dumping location (Figure 5).

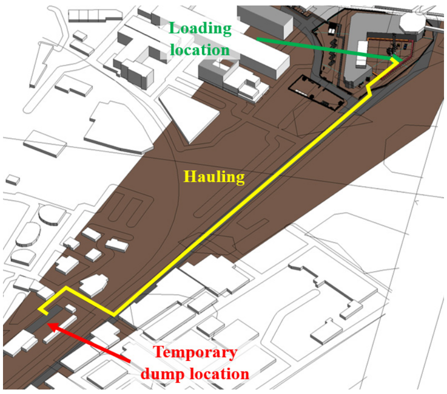

Figure 5. BIM-based construction site layout visible in the online user interface on the Digital Twin Platform

Our DTP contains a BIM-based construction site layout plan that is linked via the Autodesk Platform Services (APS) to our DES. This is accessible online in a user interface in a web browser. The simulated scenarios allow to change any of the parameters given in Table 2, for example, the hauling distance can change from the nearby site (1 km) to further away (30 km) increasing the transportation time, creating more emissions and higher idling times for the truck, unless the end user (a project manager) decides to run the DES to optimize the system for both environmental and economic goals. Detailed results from the simulation can be visualized in the dashboard of the DTP (note: not shown) and are accessible in a .CSV-file for further processing using tools construction site practitioners are more familiar with (e.g., Excel).

5 Results and Discussion

For demonstration, we simulated two construction alternatives based on the realistic scenario. One serves as a baseline scenario (Alternative A) where one drilling rig, one truck and one loader are employed for soil digging and hauling for one full day. Alternative B employs one additional drilling rig of identical machine parameters.

In the comparison between the two alternative construction plans (Table 4: A and B), it is evident that the utilization of two drilling rigs instead of using one is more productive. In the same work time Alternative B dug out nearly twice (199.04%) the amount of soil as Alternative A (158.12 m^3 vs. 79.44 m^3, respectfully, using the same number of trucks and loaders). The trucks also moved twice the amount of soil (153.33 m^3 vs. 76.07 m^3, respectfully). However, the sum of all equivalent emission values (NO_x and CO_2) and the total fuel consumption of all machines increased by only 57.65%, 70.05%, and 74.39%, respectfully.

The system's productivity of the two drill rigs, excavator and truck doubled compared to the scenario with only one drilling rig. From the decomposition of emission and fuel consumption, one can see that two drill rigs create nearly twice as much the amount of emissions. However, since the utilization rate of both loader and truck increased (note: less idle times), emissions drop sharply by using Alternative B instead of A. Moreover, the excavator loading the excavated material emits more CO_2 emissions and consumes more fuel in Alternative B as it idles less and performs more loading cycles.

Another key finding is that the alternative construction plan B doubled the amount of soil transferal in the same work time, resulting in higher productivity and less emissions per unit of work output as shown in Table 4. As anticipated, the drilling rig consumes a substantial amount of Diesel fuel, resulting in higher emissions. The loader follows as the second-largest emitter, trailed by the dump truck.

In brief, CO_2 emissions exhibit a strong correlation with fuel consumption across all the machines. These and more insights can offer a comprehensive overview of emissions across the machinery fleet that is used in construction projects, aiding eventually in environmentally conscious decision-making and optimization efforts.

Table 4. Results to a simplified Discrete Event Simulation (DES) comparing two alternative systems (A and B, while B consists of one additional drilling rig) (note: the choice of selecting alternative construction plans depends on the environmental and economic targets of the construction project and might be site and situational dependent).

Machine		Time [mins]		NO_x [g]		CO_2 [kg]		Fuel [kg]		Soil moved [m^3]	
Alternative		A	B	A	B	A	B	A	B	A	B
Drilling rig 1		477.48	475.86	149.21	148.80	191.82	191.15	60.79	60.58		
	Drilling	398.30	396.80	83.64	83.33	166.28	165.65	52.66	52.46		
	Idling	79.18	79.06	65.56	65.46	25.54	25.50	8.13	8.12	79.44	158.12
Drilling rig 2			475.98		148.79		191.21		60.59		
	Drilling		396.90		83.31		165.70		52.48		
	Idling		79.08		65.48		25.51		8.12		
Loader		460.59	469.49	102.78	103.26	67.99	76.68	16.25	18.91		
	Idling	446.30	440.67	101.07	99.79	58.81	58.06	13.48	13.31		
	Loading	14.29	28.82	1.71	3.46	9.19	18.61	2.77	5.60		
Truck		477.37	477.11	7.25	7.84	25.03	25.34	7.84	7.94		
	Idling	395.03	381.46	2.96	2.86	19.04	18.38	5.97	5.76		
	Loading	33.76	32.79	1.76	1.71	2.46	2.39	0.77	0.75		
	Hauling	15.24	30.73	0.79	1.60	1.11	2.24	0.35	0.70	76.07	153.33
	Unloading	33.34	32.13	1.74	1.67	2.43	2.34	0.76	0.73		
Soil left [m^3]										3.38	4.78
Sum		480	480	259.24	408.69	284.84	484.38	84.88	148.02		
Savings according to Sum (2*A-B)/A [%]				42.35%		29.95%		25.61%			
Rates for emission or fuel consumption by work output (def. as soil moved by truck)				3.41 g/m^3	2.67 g/m^3	3.71 kg/m^3	3.15 kg/m^3	1.16 kg/m^3	0.97 kg/m^3		

6 Conclusion and Outlook

This paper presented a novel approach where a Digital Twin Platform came into play to integrate, among other important construction data, a BIM-based construction site layout model, emissions from heavy equipment coming from IoT-sensors and being further processed, and a DES. While the simulation presented one noteworthy case of comparing alternative construction plans (resources and schedules), initial value was generated when assessing for environmental vs. economic project objectives.

While the overall workflow and method have proven to work successfully, further work is necessary exploring more complex construction scenarios. This includes some statistical analysis of the results and the implications on environmental policies. Future work can also explore agent-based (simulation) modeling (ABM). Existing ABM primarily replicate how individuals within an organization or across various organizations interact in a synthetic environment, where agents make decisions and engage in communication [23]. Yet, several studies have explored the use of ABM to enhance efficiency in construction operations. With respect to their work, ABM has proven valuable particularly in earthmoving operations, due to its ability to accommodate diverse equipment specifications and provide more accurate time and cost estimates compared to simulation methods like Discrete Event Simulation (DES) [24]. Aside from researchers employing ABM to simulate earthmoving operations by equipping equipment agents with state charts and static and dynamic properties, ABM can be utilized to evaluate how off-site congestion and traffic flow of equipment agents impact the earthmoving efficiency [25]. Future work can also concentrate on the coordination between the earthmoving equipment agents at the project level and the provided safety measures to prevent collisions [26] and noise emissions [27].

Acknowledgements

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