Modeling Earthmoving Operations in Real Time Using Hybrid Fuzzy Simulation

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Abstract

Predicting and optimizing performance in earthmoving operations is critical, because they are essential to many construction projects. The complexity of modeling earthmoving operations remains challenging, even with several modeling techniques available, including simulation. This paper advances the state-of-the-art of modeling earthmoving operations by introducing a hybrid fuzzy system dynamics–discrete event simulation framework with the capacity to: capture the dynamism of performance in earthmoving operations; capture subjective uncertainty of several factors affecting them; model their sequential nature and resource constraints; and determine actual travel time, in real time, using online navigation systems. Findings from this research confirm the proposed framework (1) extends the application of simulation techniques for modeling construction processes involving dynamic input variables and subjective uncertainty, through its ability to capture the non-probabilistic uncertainty of construction systems, and (2) when combined

with the use of online navigation systems to assess trucks' travel time, improves the accuracy of earthmoving operation models.

Keywords: Construction modeling, hybrid simulation, system dynamics, discrete event simulation, fuzzy logic

1. Introduction

Due to the increasing complexity of construction systems (e.g., construction activities, operations, and projects), numerous managerial techniques have been developed or adapted from other engineering disciplines in order to model and predict the behaviour of these systems. These techniques also support practitioners in improving the performance of construction systems. Simulation techniques are among these managerial techniques and were originally developed for use in operational research (OR) and computer science to model different aspects of real-world systems (Brailsford et al. 2019). Simulation techniques are naturally designed to improve understanding about the structure of real-world systems and facilitate their management (Heermann 1990). Though variations in simulation techniques exist across different disciplines, there is consensus about the four simulation techniques best suited to the context of construction engineering and management: Monte Carlo simulation (MCS), discrete event simulation (DES), system dynamics (SD), and agent-based modeling (ABM) (Raoufi et al. 2018). Each of the aforementioned simulation techniques suits specific types of construction problems, depending on the characteristics of the problem being modeled (Raoufi et al. 2016; Brailsford et al. 2019).

The MCS technique is suitable for capturing the probabilistic uncertainty observed in real-world systems but ignores the time dependency of system behavior. The DES technique is best suited to modeling construction processes, where a sequence of construction tasks are repeated to complete the process (Raoufi et al. 2016; Brailsford et al. 2009). In addition, the DES technique can predict the total time and cost of construction processes and determine performance indicators for resources, including utilization and idle time (Sadeghi et al. 2015; 2016). SD is another simulation technique suitable for modeling the complex structure of real-world systems, where the behaviour of the system is dynamically changing over time and under the effect of numerous interacting elements (i.e., system variables) (Nojedehi and Nasirzadeh 2017; Gerami Seresht and Fayek 2018; Rasoulkhani et al. 2019). Finally, ABM is a more recently developed simulation technique compared to the other three techniques. ABM has the capacity to capture the behaviour of individual agents within the system in order to derive overall system behaviour (Raoufi and Fayek 2018).

While each simulation technique has strengths in modeling specific types of real-world systems, the selection of an appropriate simulation technique is a crucial step for simulation modeling (Bokor et al. 2019; Brailsford et al. 2019). Although the aforementioned simulation techniques provide powerful platforms for modeling construction systems, none of them fully address all the complexities of several processes in construction projects. One such complex construction process is earthmoving operations, which is included in the majority of construction projects, ranging from residential and commercial building projects to industrial and civil megaprojects. Accordingly, developing accurate simulation models for predicting and optimizing the performance of earthmoving operations can benefit a wide range of construction projects. In this paper, a hybrid simulation model using SD and DES techniques is developed to address the several complexities associated with the modeling of earthmoving operations.

In recent years, an increasing number of applications for hybrid simulation techniques in the OR community have been developed, where two or more simulation techniques are integrated in a modeling framework. The hybridization of simulation techniques capitalizes on the strengths of individual techniques to overcome their limitations, resulting in more capable and comprehensive techniques for modeling construction systems (Moradi et al. 2015). Numerous efforts have been made to optimize earthmoving operations in different construction contexts (Yi and Lu 2019; Salem and Moselhi 2020). While the reliability of optimization results relies extensively on the accurate definition of the decision space — performance of earthmoving operations in different settings, in this case — a lack of research still exists regarding how to develop accurate models for predicting the performance of earthmoving operations, owing to a number of challenges. The first challenge is choosing an appropriate technique for modeling earthmoving operations. Neither SD nor DES alone can simulate the process of earthmoving operations effectively. SD is best suited for modeling the production rate of activities, such as excavation and loading, which are constantly changing under the effects of multiple interacting factors. In contrast, when predicting the total duration of earthmoving operations, the sequence of different activities involved needs to be carefully modeled and is best accomplished by DES. The second challenge is the different types of uncertainty exhibited by variables affecting earthmoving operations. Many factors that affect the performance of earthmoving operations exhibit non-probabilistic (i.e., subjective) uncertainty, but simulation techniques are not equipped to handle this type of uncertainty. The third challenge is predicting the duration of hauling activities in earthmoving operations, especially for those projects executed in urban areas. The duration of hauling activities is affected by multiple factors (e.g., geographical setting and traffic data), and it is best predicted by online mapping platforms.

In this paper, the three aforementioned challenges (i.e., selection of an appropriate simulation technique, capturing non-probabilistic uncertainties, and predicting the duration of hauling activities) have been addressed by developing an FSD-DES model of earthmoving operations, integrated with geographical information system (GIS) and Google Maps®. In the proposed FSD-

DES model, the FSD component captures dynamic changes in the production rate of excavation and loading, and it addresses the non-probabilistic uncertainty exhibited by different variables that affect this operation. The DES component determines the total duration of the operation, based on the sequence of the activities involved, and finally, the GIS and Google Maps® component predicts the hauling duration using online traffic data. The contributions of this paper are threefold. First, integrating fuzzy logic with hybrid simulation techniques will advance the state of the art of hybrid simulation techniques in construction by capturing the non-probabilistic uncertainties in construction variables. Second, integrating the FSD-DES model with Google Maps® provides realistic predictions of hauling duration by considering online traffic data. Third, the FSD-DES model proposed in this paper will improve the planning and management of earthmoving operations by predicting the performance of these operations, while accounting for their complex and dynamic nature.

The remainder of this paper is organized as follows. The second section presents a review of the literature on hybrid simulation techniques and on predictive modeling of earthmoving operations. The third section presents the research methodology used to develop the hybrid FSD-DES model of earthmoving operations, and the fourth section presents a construction case study to illustrate a real-world application for the proposed FSD-DES model. Finally, the fifth section discusses conclusions and future areas for research on this topic.

2. Literature Review

2.1. Hybrid Simulation Techniques

Jackson and Keys (1984) first introduced the idea of hybridizing simulation techniques and suggested combining two or more OR techniques in order to overcome their limitations and capitalize on their strengths for modeling complex, real-world systems. In recent years, applications for hybrid simulation techniques (i.e., integration of two or more of MCS, DES, SD, and ABM techniques) in solving OR problems have increased (Brailsford et al. 2019). There are four types of hybrid simulation techniques, which can be distinguished based on their architecture (i.e., how the two simulation techniques are connected) and their interactions (i.e., the flow of information between the two techniques) (Brailsford et al. 2019; Morgan et al. 2017):

- Enriching models, in which one of the two simulation techniques is dominant. The non-dominant technique is used to enrich specific aspects of the dominant technique.
- Sequential models, in which two (or more) simulation techniques work in sequence. The first technique simulates specific aspects of the system, and its outputs are delivered to the next simulation technique to model another aspect of the system. In sequential models, the flow of information occurs in one direction only (e.g., from the first technique in the sequence to the second).
- Interactive models, in which the two simulation techniques are constantly connected, and the outputs or intermediate outputs of the two techniques are constantly exchanged. In interactive models, the flow of information occurs in both directions and continuously during the simulation run.
- Integrated models, in which the two simulation techniques are completely integrated and work seamless and inseparably. The different modeling elements of the two simulation techniques are integrated to an extent that their boundaries are indistinguishable.

The FSD-DES hybrid simulation model introduced in this paper is interactive, where the FSD and DES components are continuously interacting during the simulation run time.

Despite their popularity in other disciplines and the demonstrated superiority of hybrid models, hybrid simulation techniques have received less attention in construction research. The results of a literature search in the Scopus search engine revealed that out of a total of 484 articles published in the area of hybrid simulation, only 19 articles were related to construction. Moreover, the majority of articles in this group of 19 focused on construction labor productivity and construction safety. Accordingly, introducing new applications for hybrid simulation techniques in construction contexts, such as the earthmoving operations model introduced in this paper, will help to advance the state of the art in construction modeling.

Despite the fact that fuzzy simulation techniques have proven to be more effective than conventional simulation in modeling real-world construction systems (Raoufi et al. 2016), there is no hybrid simulation model in the literature that incorporates fuzzy logic. This paper addresses this research gap by hybridizing FSD with DES, where FSD provides a fuzzy simulation technique with the capacity to capture the non-probabilistic uncertainties involved in real-world construction systems.

2.2. Predictive Modeling of Earthmoving Operations

Various techniques have been used for modeling earthmoving operations, each focusing on specific performance measures such as time, cost, safety, or environmental impacts of the operation. Artificial intelligence (AI) and simulation are two of the most commonly used techniques for modeling earthmoving operations. Although AI techniques have the capacity to mimic the reasoning process of humans and allow for the development of accurate predictive models, they are commonly static in nature and cannot represent the dynamism of earthmoving operations. Moreover, AI techniques cannot capture the logical sequence between different activities involved in the operation. In contrast, simulation techniques have the capacity to address these limitations by predicting changes that occur in the performance of earthmoving operations over time, while considering the logical sequence of activities as well as the impact of multiple factors affecting the operation. Among the available simulation techniques, DES has been most commonly used in the context of earthmoving operations, because of its strength in modeling the repetitive nature of this kind of operation. However, one challenge associated with modeling earthmoving operations using DES is in defining the duration of activities included in the operation (e.g., loading and hauling activities), since the duration of such activities constantly change under the impact of multiple factors.

To address this limitation, Peña-Mora et al. (2008) and Alzraiee et al. (2015) proposed hybrid SD-DES frameworks for modeling earthmoving operations, in which the SD component captures the dynamic behaviour of the operation and predicts the duration of activities dynamically, and the DES component captures the sequential nature of the operation. While the capability of SD for modeling the performance measures of earthmoving operations is proven in previous research (Goh and Askar Ali 2016; Gerami Seresht and Fayek 2018), the hybrid SD-DES models (Peña-Mora et al. 2008; Alzraiee et al. 2015) improve the accuracy of modeling earthmoving operations compared to simulation models developed by the DES technique only. However, the two hybrid simulation models proposed by Peña-Mora et al. (2008) and Alzraiee et al. (2015) have two limitations. First, both studies lack the capacity to capture the non-probabilistic uncertainty of factors affecting earthmoving operations; and second, these models predict the duration of hauling activities without considering the geographical settings of the operation, nor the road and traffic conditions. Recent studies by Alshibani (2018) and Montaser and Moselhi (2014) reveal that the duration of hauling activities in urban areas, where multiple routes are available for trucks to travel through, is best assessed by considering the geographical setting of the project site using global positioning system (GPS) and GIS. The existing limitations of SD-DES frameworks for earthmoving operations (Peña-Mora et al. 2008; Alzraiee et al. 2015) are addressed in this paper by integrating the proposed framework with fuzzy logic to address the non-probabilistic uncertainties of the factors that affect this operation and using Google Maps® to retrieve online traffic data for predicting the duration of hauling activity. The use of Google Maps® in the proposed FSD-DES model can improve its accuracy compared to the GIS- and/or GPS-based models, since Google Maps® combines the geographical systems' data with online traffic information to predict trucks' travel time.

3. Methodology for FSD-DES Modeling of Earthmoving Operations

The methodology for developing the FSD-DES model for earthmoving operations involved two major steps, which are discussed in greater depth in the following sub-sections. First, an FSD model is developed to predict the production rate of the excavation and loading activities. Second, a DES model is developed to model the resource constraints and sequence of activities involved in the earthmoving operation (i.e., excavation and loading, hauling, dumping, and returning) to determine the total duration of the operation. The two components of the proposed model (i.e., the FSD and DES components) interact throughout the simulation run, where the duration of the excavation and loading activities are dynamically predicted by the FSD component and transferred to the DES component. The flowchart presented in Figure 1 provides additional details about these two steps.

As shown in Figure 1, the methodology for developing the proposed FSD-DES model consists of two major steps, which each focus on development of the two simulation components (FSD and DES) and connect the two components in the final step. Further details regarding the two steps are discussed in the following sub-sections.

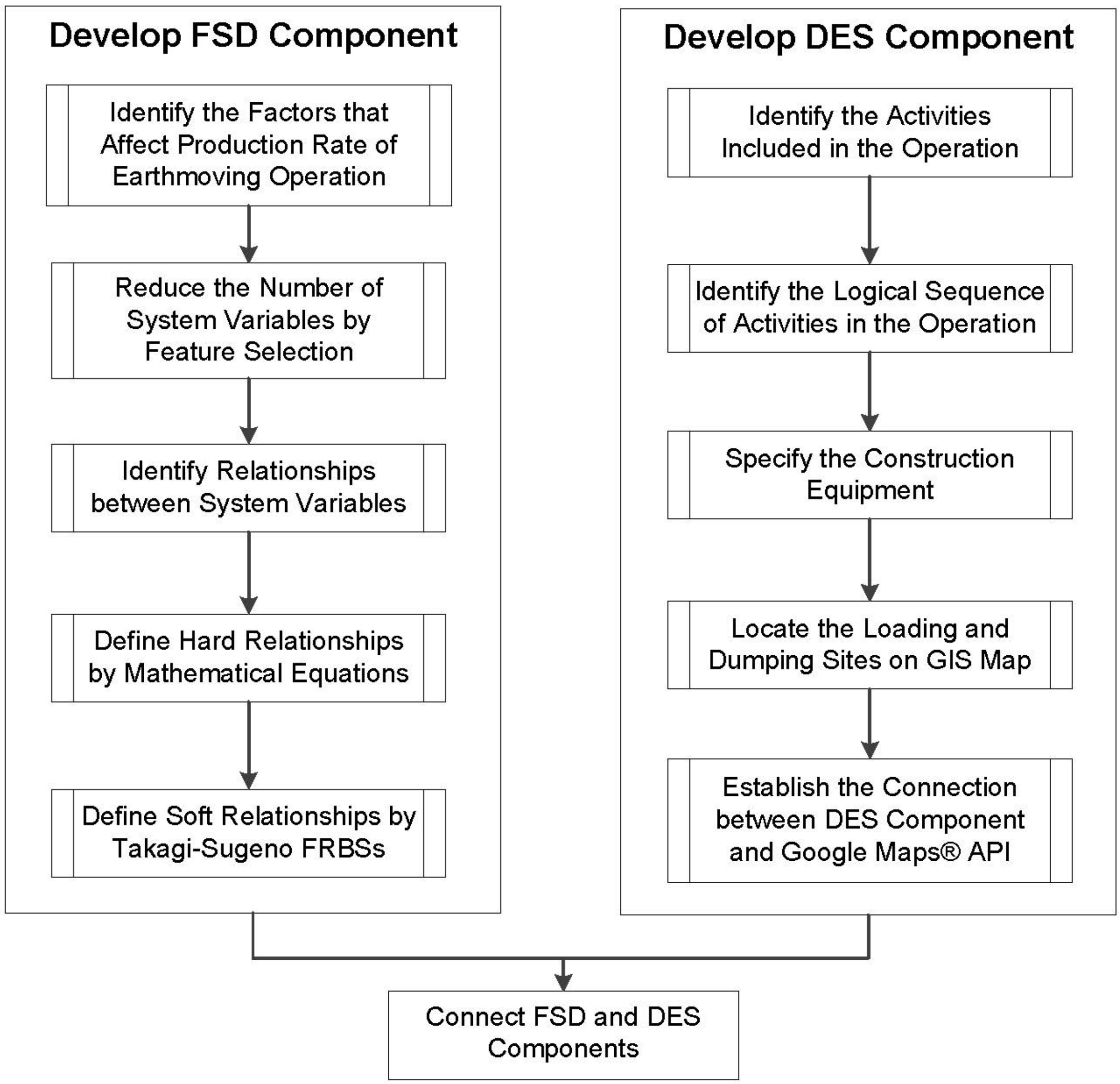


Figure 1. Methodology for developing the FSD-DES model of earthmoving operations.

3.1. Modeling Production Rate of Excavation and Loading Activities Using FSD

In order to model the production rate of earthmoving operations using the FSD technique, the factors affecting the production rate (hereafter referred to as *system variables*) first needed to be identified. System variables were derived from previous research conducted by Gerami Seresht and Fayek (2019), which identified a total of 201 factors affecting the multi-factor productivity of equipment-intensive activities. Moreover, because of the large number of factors affecting the performance of earthmoving operations, the number of input variables was reduced by feature selection in order to improve the accuracy of the FSD model. In predictive modeling problems, the choice of feature selection method depends on the modeling technique used for mapping input variables to the outputs. In the case of FSD modeling, relationships between different system variables need to be qualitatively identified and then numerically defined using a predictive modeling technique. In the present research, these relationships were defined using fuzzy rule-based systems (FRBS). In addition, the wrapper method of feature selection was used to reduce the dimensionality of the data, as recommended by Ahmad and Pedrycz (2011).

There are two types of relationships between system variables: hard relationships with a known mathematical form, and soft relationships with an unknown mathematical form. While hard relationships are naturally defined using mathematical equations, soft relationships need to be defined using a predictive modeling technique, such as statistical regression or FRBS (Nasirzadeh et al. 2018; Gerami Seresht and Fayek 2018). Because of the higher accuracy of FRBSs compared to linear regression (the most common statistical method used for SD and FSD modeling) and their higher computational efficiency for processing fuzzy numbers as input variables, soft relationships between system variables were defined using FRBSs. FRBSs can be developed using empirical data (i.e., data-driven methods) or expert knowledge (i.e., expert-driven methods). In highly dimensional problems where a large number of input variables are mapped to the outputs, data-driven methods are superior to expert-driven methods. According to Zadeh's (1975) principle of incompatibility, the dimensionality of a system has an inverse relationship with experts' understanding of the system structure. Soft relationships in the FSD model were defined using data-driven Takagi-Sugeno FRBSs, developed using a subtractive clustering method and empirical data. Takagi-Sugeno FRBSs use a set of crisp functions for inputs (i.e., state functions) to predict the output of the system, so that the FRBS outputs are crisp values. The use of Takagi-Sugeno FRBSs in the proposed methodology enables the representation of subjective system variables (e.g., site restrictions, crew motivation) using fuzzy numbers rather than the use of lookup functions as practiced in conventional SD modeling (Nasirzadeh et al. 2019; Gerami Seresht and Fayek 2020). Representing subjective system variables with fuzzy numbers can improve the accuracy and applicability of the FSD model by allowing the modeler to use linguistic terms for evaluating the subjective system variables and transforming the linguistic terms into numerical values rather than nominal values as used in lookup functions (Khanzadi et al. 2012). Additional information about the different techniques for defining soft relationships in FSD models is available in Gerami Seresht and Fayek (2018) and Nasirzadeh et al. (2013).

3.2. Modeling the Process of Earthmoving Operation Using the DES Technique

The process of earthmoving operations consists of four main activities: loading, hauling, dumping, and returning (Marzouk and Moselhi 2004). Although calculating the total duration of the operation by considering the sequence of activities is simple for one or two cycles, once the number of cycles and the number of pieces of equipment increase, the complexity of the problem increases substantially. The DES technique is appropriate for addressing such complexity and determining the total duration of operations. Numerous studies have explored modeling of earthmoving operations using DES, all of which address the four main activities (loading, hauling, dumping, and returning) (Marzouk and Moselhi 2004; Jassim et al. 2019; Krantz et al. 2019). Loading and hauling activities can be executed with different types of equipment, such as loaders and excavators for loading, and scrapers, dump trucks, or haul trucks for hauling, depending on the characteristics of the operation. Accordingly, the choice of equipment used for earthmoving operations can affect the production rate and the duration of the operation. In the present research, it was assumed that the loading activity was executed by excavators and the hauling activity was accomplished by dump trucks, which are both commonly used in different types of construction projects.

While the accuracy of the DES model relies on accurate prediction of the duration of the four activities, predicting the duration of loading activities is challenging, since it is affected by multiple factors (e.g., weather conditions, soil conditions) and changes over time. The duration of loading activities has traditionally been determined as a probabilistic distribution using historical data (Rodrigues et al. 2018; Krantz et al. 2019). However, using this approach, the effects of the different factors influencing the duration of this activity are not explicitly accounted for but are instead implicit in the probabilistic distributions. In order to address this challenge in the present work, at each cycle of the operation, the duration of loading activity was determined based on the dynamic prediction of the production rate, which was identified by the FSD component. In addition, the impact of all influencing factors was explicitly considered.

The next challenge is associated with predicting the accurate duration of hauling and returning activities, since the duration of these activities depend on multiple factors, including project location, hauling distance, road conditions, maximum allowable speed, and equipment specification. Hauling and returning activities can be also decomposed into more detailed activities in order predict their durations more accurately. For example, in the DES model developed by Krantz et al. (2019) for earthmoving operations in road construction projects, hauling activities are further decomposed into “hauling on roads” and “hauling on bridges” because of different speed limits and safety requirements. Although including such additional activities can improve the accuracy of the simulation model, it limits the application of the model to the specific context for which the model was developed. To address this limitation, the durations of hauling and returning activities were determined using GIS data and online information retrieved from Google Maps®. Using an online connection with Google Maps® enables the model to predict the duration of hauling and returning activities accurately without sacrificing the universality of the model. The GIS map included in the simulation model allows the modeler to locate the loading and dumping sites on an interactive map (shown in Section 4). At each simulation time step, the model sends information regarding the simulation time and location of loading and dumping sites to Google Maps® and then requests the travel time between the two locations. Since the traffic data is collected from Google Maps® in real time, the proposed model can simulate the process of loading/dumping from and to multiple sites (i.e., geographical locations). For this purpose, the location of loading and dumping sites can be changed before each entity (i.e., loaded truck) enters the hauling activity manually or else automatically using Java algorithms if the changes are mathematically predictable. The connection between the simulation model and Google Maps® was established using MATLAB® and Java programming languages. The methodology proposed in this paper for predicting the durations of hauling and returning activities allows the model to accurately simulate earthmoving operations in various contexts, ranging from building projects in busy urban areas to industrial energy projects in remote areas.

4. Hybrid FSD-DES Model of Earthmoving Operations

The hybrid FSD-DES for earthmoving operations introduced in this paper is an interactive hybrid simulation model, which means that during the simulation run, the FSD and DES components are connected and constantly exchanging information. Additionally, ongoing interaction occurs between the DES component, the GIS map, and Google Maps® during the simulation run. Figure 2 presents the architecture of the model and the flow of information during the interactions between the different model components.

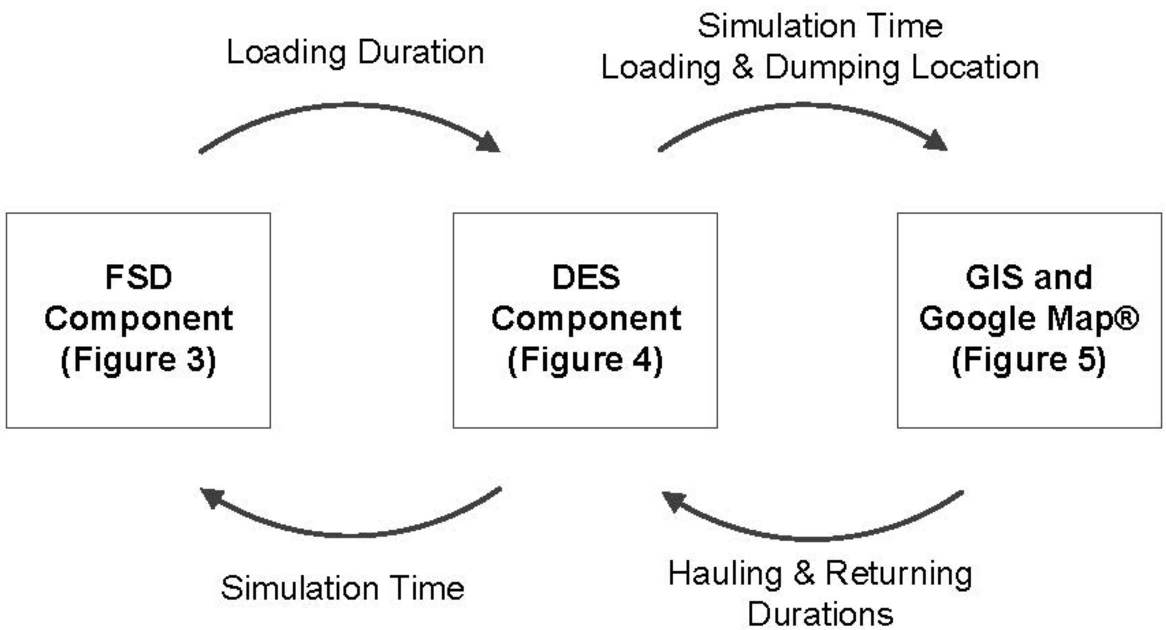


Figure 2. The architecture of the hybrid simulation model.

As shown in Figure 2, the three components of the model are constantly interacting with one another during the simulation run. The three components of the model are further discussed in this section, and the interactions between each are illustrated. The FSD component of the model is presented in Figure 3, which dynamically predicts the production rate of excavation and loading activities in earthmoving operations, assuming excavators are used for excavating and loading the hauling trucks. The 18 factors selected for modelling the production rate of excavation and loading activities were extracted from an earlier study by Gerami Seresht and Fayek (2018; 2019). Gerami Seresht and Fayek (2019) identified a total of 201 factors that affect earthmoving operations; using statistical methods and artificial techniques for feature selection, the number of activities were reduced to 18 factors (Gerami Seresht and Fayek 2018; 2020). Furthermore, feature selection and development of the FSD model were based on the empirical data collected from a construction case study in a pipeline maintenance project in Alberta, Canada. This project included 79 work packages (i.e., digs), each of which included the following activities: excavation, sandblasting, welding, coating, and backfilling. The data utilized in this paper are collected from the excavation activity only.

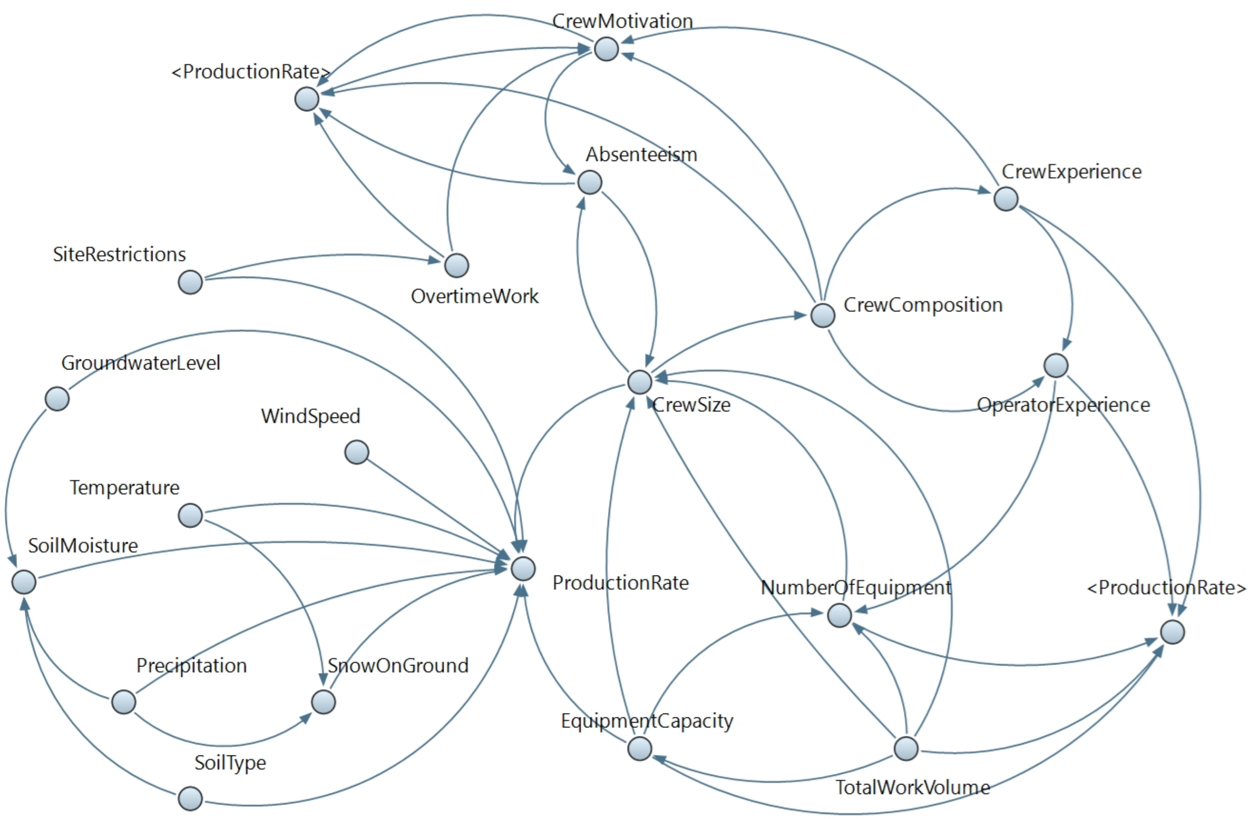


Figure 3. The FSD component for predicting the production rate of loading activity dynamically.

The FSD component dynamically predicts the production rate of excavation and loading activities based on the value of the 18 system variables shown in Figure 3 and sends the information to the DES component. The relationships between the system variables of the FSD component are defined by Takagi-Sugeno FRBSs, which were developed using subtractive clustering of empirical data collected from a case study of earthmoving operations in Alberta, Canada (Gerami Seresht and Fayek 2018). Each soft relationship of the system is defined by one Takagi-Sugeno FRBS, in which the inputs are mapped to the output using a set of linear state functions. The inclusion of fuzzy logic in the FSD component allows the model to capture the non-probabilistic (i.e., subjective) uncertainty exhibited by the different factors affecting earthmoving operations, including crew motivation and site restrictions. Each subjective system variable is measured by a number of linguistic terms, each of which is represented by a fuzzy membership function. In the proposed model, shown in Figure 3, crew motivation and site restrictions are represented by five and three fuzzy membership functions, respectively, as shown in Figure 4.

Figure 4(a) shows the five fuzzy membership functions used to represent crew motivation, and Figure 4(b) shows the three membership functions used for representing site restrictions. The number of fuzzy membership functions representing each subjective system variable depends on the parameters used for subtractive clustering (Gerami Seresht and Fayek 2020).

The output of the FSD component at each time step is the production rate, which is measured in cubic meters of dirt loaded per hour (i.e., $\frac{m^3}{hr}$). The FSD component of the proposed hybrid FSD-DES model only includes a cause-and-effect diagram and no stock-and-flow diagram, since the FSD model does not track the accumulation of any variables in the system, such as total produced output or total operation time. In the hybrid FSD-DES model proposed in this paper, the DES component tracks the operation progress (i.e., total produced outputs) and operation time. The DES component uses Equation 1 to determine the duration of loading activities in minutes.

$$LoadingDuration\ (min) = \frac{Truck\_Capacity}{PR_{loading}} \times 60 \qquad 1$$

where $PR_{loading}$ stands for the production rate of a loading activity predicted by the FSD component. Truck capacity is provided by the modeler, based on the equipment specifications. Next, the duration of the loading activity is used by the DES component to continue the simulation run. Figure 5 presents the sequence of the activities within the DES component.

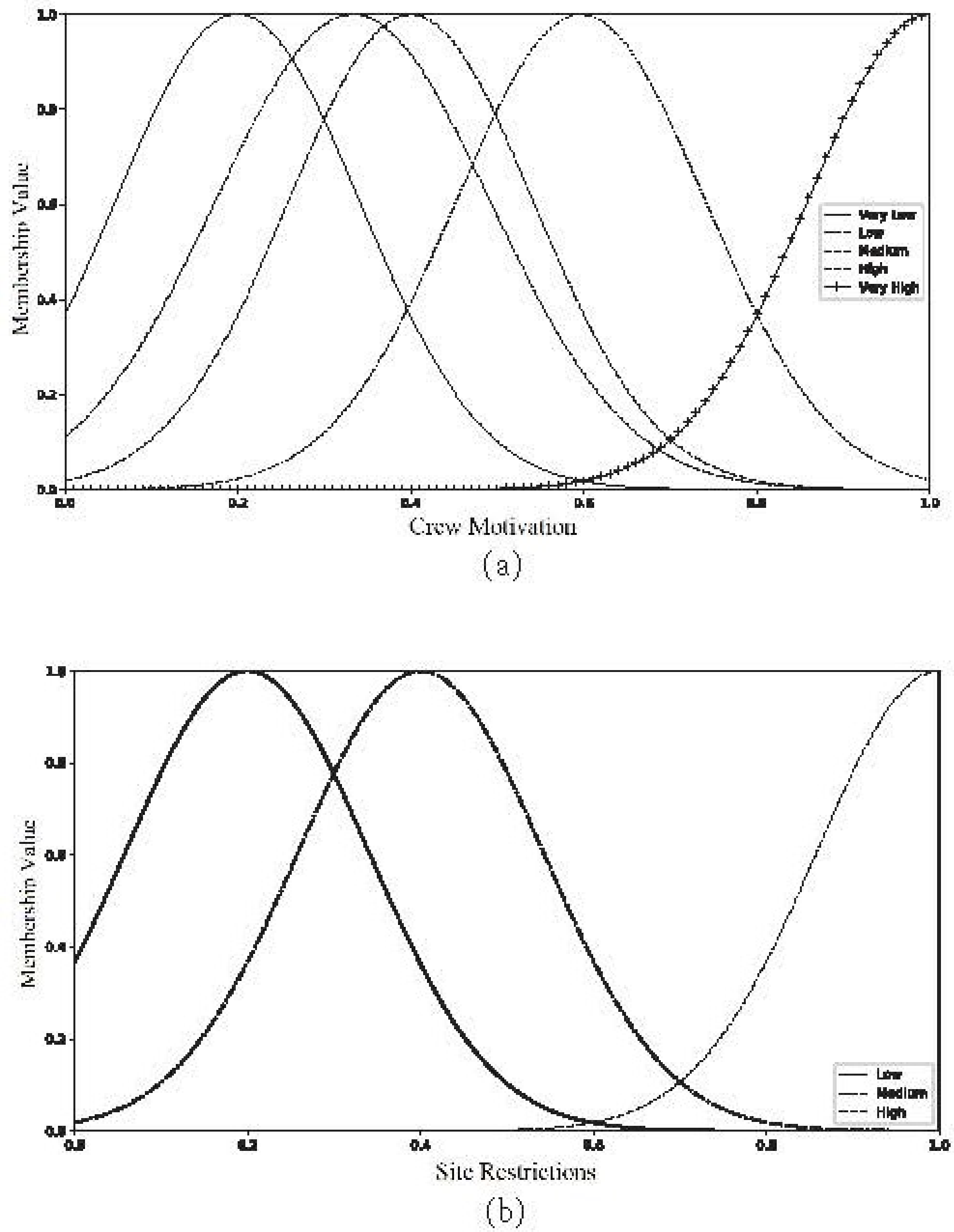


Figure 4. Fuzzy membership functions used for representing subjective system variables.

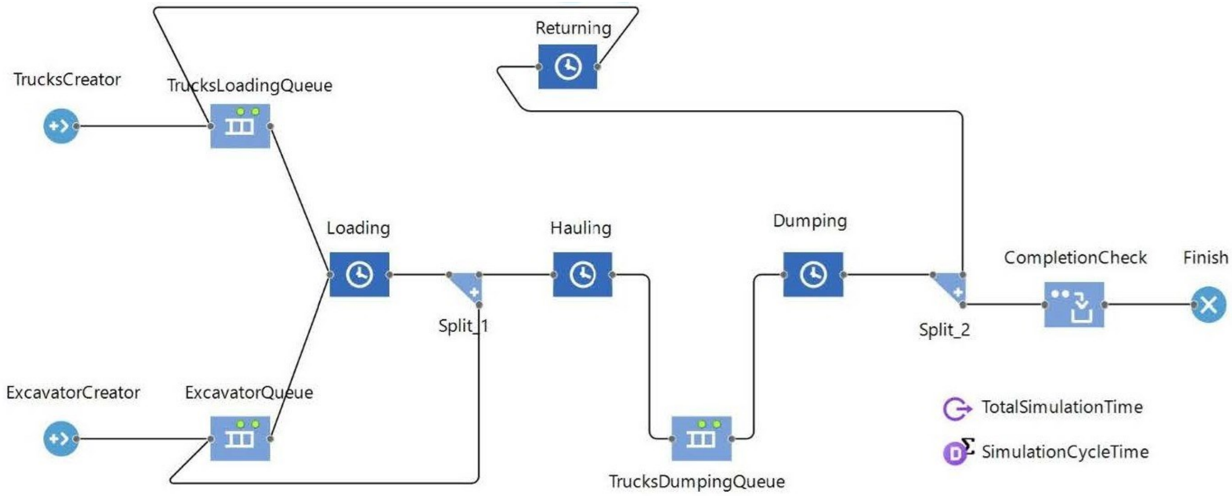
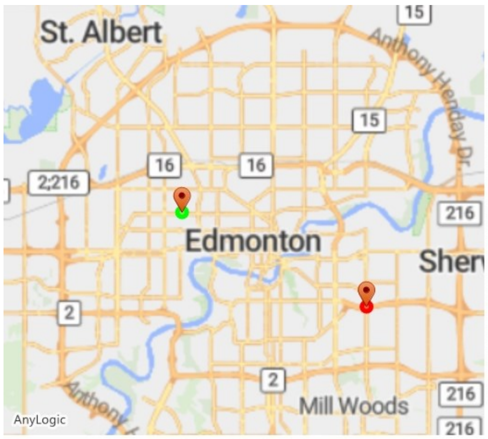


Figure 5. The DES component for determining the total duration of the operation.

As presented in Figure 5, in each cycle of an earthmoving operation, once the loading activity is completed, the excavator returns to the queue to load the next truck, and the loaded truck starts the hauling activity. In order to determine the duration of the hauling activity, the DES component receives the location of the loading and dumping sites from the GIS map using the latitude and longitude of the two locations. Next, the DES component sends the current simulation time and the two locations to Google Maps® to determine the duration of hauling and returning activities.

Figure 6(a) shows an example of GIS information for the proposed simulation model, in which both the loading and dump sites are located within the city of Edmonton, Alberta, Canada. The loading and dump sites need to be located on the GIS map of the proposed model using the longitude and latitude of the exact geographical location. Figure 6(b) presents the pseudo code that established the connection to Google Maps® and determines the duration of hauling activity. Google Maps® assumes that the maximum speed of travel is determined by the set speed limits of roads, which might not hold true when commuting with dump or haul trucks. To ensure the accuracy of the duration predicted by the pseudo code presented in Figure 6(b), the average speed of travel must not exceed the top speed of the equipment. The FSD-DES model provides three outputs after the simulation run: the duration of each cycle of the operation; the total duration of the operation; and the production rate of the operation, which is calculated using Equation 2.

$$PR_{Earthmoving} = \frac{Total\_Volume(m^3)}{Total\_Duration(hrs)} \quad (2)$$




```
HaulingDuration(Load,Dump,SimTime,TopSpeed):

# Create a new Google direction object to determine the hauling duration.
DirectionObject=New GoogleDirection();

# Write a search query using the locations of load and dump sites and time.
request="direction from" + Load + "to" + Dump + "departure =" + SimTime;
DirectionObject.load(request);

# Determine two durations: (1) the duration returned by Google; and
# (2) determined based on the distnance returned by Google and
#     Truck's top speed.
Duration_1=DirectionObject.Duration();
Duration_2=DirectionObject.Distance()/TopSpeed;

Return max(Duration_1,Duration_2);
```

(a) (b)

Figure 6. GIS map (by AnyLogic®) and pseudo code to collect traffic data from Google Maps®.

5. Construction Case Study

A case study was conducted to test the practicality of the proposed FSD-DES technique for modeling earthmoving operations on construction projects. In this case study, empirical data were collected for the loading activity from earthmoving operations on a pipeline maintenance project in Alberta, Canada. To illustrate the practicality of the model in handling real-world cases, it was assumed that a John Deere® 290 G LC was used for loading and MACK Granite® trucks were used for hauling. The lifting capacity of a John Deere® 290 G LC is 9,777 kg, and the total loaded weight of MACK Granite® trucks is 42,000 kg. Further details regarding the specifications of these construction vehicles are provided in their specification sheets (Deere 2021; MACK 2021). Furthermore, the top speed for the loaded truck is 120 km/hr, the top speed for the empty truck is

150 km/hr, and the maximum allowable hauling speed is determined by Google Maps using the pseudo code presented in Figure 6(b). The location of the project was assumed to be in the city of Edmonton, Alberta, Canada, as shown in Figure 6(a). As mentioned above, the empirical data used for developing the proposed hybrid FSD-DES model were collected from a pipeline maintenance project in Alberta, Canada. Accordingly, the only hypothetical component of the presented construction case study is the location of the loading and dump sites. Further discussions regarding the accuracy of the FSD component for predicting the production rate of excavation and loading activities are provided in Gerami Seresht and Fayek (2018). Unlike the actual pipeline maintenance project, the location of loading and dump sites were moved within the city of Edmonton (in urban area with variable traffic conditions throughout the day) to illustrate the benefits of real-time connection with Google Maps for collecting traffic data. The simulation model was run for 100 cycles. Results are presented in Table 1.

The results show that in each simulation cycle, a number of factors caused changes in the durations of loading, hauling, and returning activities. By using the FSD component and Google Maps®, the model explicitly accounts for all factors affecting the duration of each activity. This capability can help the user analyze different scenarios for execution of the operation in order to improve its performance. The simulation results shown in Table 1 reveal that the duration of each cycle reached its maximum value between 8:00 AM and 9:00 AM and between 4:00 PM and 6:00 PM, which are rush hour times in the city of Edmonton. Moreover, the production rate of the

Table 1. Simulation results for the FSD-DES model of earthmoving operation.

			Cycle Duration (min)		Production Rate $\left(\frac{m3}{hr}\right)$	
From	To:	Number of Data Points	Average Cycle Duration	Standard Deviation	Average Production Rate	Standard Deviation
8:00:00 AM	9:00:00 AM	11	144.02	47.22	13.81	4.21
9:00:00 AM	10:00:00 AM	10	118.52	37.60	16.78	5.26
10:00:00 AM	11:00:00 AM	10	123.96	43.02	15.96	4.47
11:00:00 AM	12:00:00 PM	10	122.62	24.54	15.39	3.75
12:00:00 PM	1:00:00 PM	12	120.40	37.99	16.79	5.94
1:00:00 PM	2:00:00 PM	7	105.69	21.44	17.84	4.01
2:00:00 PM	3:00:00 PM	9	142.78	34.89	13.69	4.65
3:00:00 PM	4:00:00 PM	12	128.48	34.97	15.33	5.01
4:00:00 PM	5:00:00 PM	7	145.85	46.31	13.67	4.38
5:00:00 PM	6:00:00 PM	12	147.36	40.80	13.34	4.41
Total		100	129.97	40.10	15.26	4.92

operation was variable throughout the day. This phenomenon results from factors affecting the duration of loading activities (refer to Figure 3) as well as changes in traffic conditions throughout the day. The standard deviation for the cycle duration and production rate also varied for different time periods throughout the day, and the variability of simulation results (i.e., measured as the standard deviation of cycle duration and production rate) reached its maximum value during rush hours. The ability of the model to retrieve actual traffic data from Google Maps® provides a realistic prediction of the operation's duration and allows the user to optimize the operation by selecting the best time and route for hauling activities. Moreover, the FSD component captures the effect of multiple factors influencing excavation and loading. It also provides dynamic and realistic predictions for the duration of loading activities in different scenarios. As a result, the FSD component can be used to test multiple scenarios by changing the system variables (e.g., crew size, crew composition, equipment specification, and overtime work) to improve the performance of the operation. Traditionally, DES models of earthmoving operations have supported planners for making decisions regarding type and amount of equipment. The FSD-DES model proposed in this paper has two additional capabilities. First, the integration of the simulation model with Google Maps® supports decision-making about the timing of the operation. Second, the FSD component models the complex and dynamic aspects of earthmoving operations, predicting the duration of excavation and loading, which is affected by multiple system variables (refer to Figure 3). The proposed FSD-DES model accounts for all of these system variables and allows construction planners to test multiple scenarios by changing their values.

6. Conclusions and Future Work

Over the past few decades, substantial research has been devoted to the modeling of earthmoving operations, since these operations are a part of many different types of construction projects. Traditionally, simulation techniques, and specifically the DES technique, have been used in this context, because of the repetitive nature of the operation. In the present research, an FSD-DES model of earthmoving operations was developed by combining three components: an FSD component, which dynamically models the production rate of excavation and loading activities; a DES component, which models the logical sequence of different activities in the operation; and a

GIS and Google Maps® component, which predicts the duration of hauling and returning activities using geographical information and online traffic data. The inclusion of the FSD component enables the model to explicitly account for the impact of multiple factors affecting the operation (i.e., system variables) and dynamically track changes in its production rate. Moreover, the inclusion of fuzzy logic allows the model to capture the non-probabilistic (i.e., subjective) uncertainty exhibited by different factors affecting earthmoving operations, such as crew motivation or site restrictions. The GIS map and Google Maps® component enables the model to realistically predict the duration of hauling and returning activities, since they account for the distance between loading and dumping sites, online traffic data, and the top speed of trucks.

The contributions of this paper are threefold. First, this paper advances the state of the art of hybrid simulation modeling in construction by integrating the SD-DES framework introduced by Peña-Mora et al. (2008) with fuzzy logic to create the FSD-DES model, in order to capture the non-probabilistic uncertainty of construction systems. The inclusion of fuzzy logic in the developed FSD-DES model allows the modeler to assess the value of subjective system variables with linguistic terms (e.g., “high crew motivation”) rather than numerical values. Second, the FSD-DES model presented in this paper facilitates the management and planning of earthmoving operations by providing realistic performance predictions. The developed model explicitly accounts for the impact of multiple factors affecting earthmoving operations and allows practitioners to simulate different scenarios for project planning purposes. Finally, the integration of the model with the GIS map and Google Maps® improves the reliability of simulation results, especially for those projects that are executed in urban areas with varying traffic and road conditions.

Although traffic data are associated with several probabilistic uncertainties, the proposed model is limited in terms of capturing the probabilistic uncertainties. In future research, the FSD-DES model will be integrated with the MCS technique to capture the probabilistic uncertainty of earthmoving operations, thus enabling the model to process probabilistic distributions as the inputs of the FSD and DES components. Although the model proposed in this paper is limited to modeling earthmoving operations, the FSD-DES modeling framework can be utilized to simulate a variety of construction operations, such as modular construction and pavement operations, that have multiple complex and dynamic aspects and are repetitive in nature. In future research, this hybrid framework will be used for modeling these other types of construction operations.

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8. Competing Interests Statement

The authors declare there are no competing interests.

9. Contributors' Statement

Nima Gerami Seresht: Conceptualization, Methodology, Formal analysis, Software, Validation, Data curation, Investigation, Writing - original draft, Writing - review & editing.

Aminah Robinson Fayek: Conceptualization, Investigation, Writing - review & editing, Supervision, Project administration, Funding acquisition.

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11. Data Availability Statement

All data generated or used during the study appear in the submitted article.

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