DESIGN REQUIREMENTS OF AN AUTOMATED DATA-DRIVEN SIMULATION MODEL GENERATOR FOR CONSTRUCTION OPERATIONS

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Abstract: Most construction projects take place in uncertain operational settings where formulating resource interactions and jobsite complexities prior to commencing the project is not a trivial task. As a result, simulation modeling has a great potential to streamline the decision-making process by providing a convenient means to examine different operational scenarios, perform sensitivity analysis, and determine best combinations of resources to finish a project on time and within the specified budget. However, existing construction simulation systems are mostly suitable for early planning stages as they rely on historical data and human expert judgments to create conceptual simulation models. Such systems often fail to properly link real project data and uncertainty characteristics at the execution phase to key simulation parameters and design variables. As such, the resulting simulation models rapidly become obsolete as they cannot keep up with the real world events evolving over the course of the project. Generating simulation models at the operations level with the goal of providing reliable and timely decision support to project engineers and field personnel requires that process data describing the dynamics and uncertainties of field activities be meticulously captured and integrated into the simulation modeling process. To this end, this paper presents the latest finding of an ongoing research which aims at designing and testing an integrated data-driven simulation framework by collecting and fusing multi-modal process data from construction resources involved in various field activities. A reasoning process comprising of data mining, clustering, and fusion techniques are used to analyze raw data, form metadata structures that reveal spatiotemporal patterns hidden within the data, and generate a computer interpretable layout of the jobsite that can be readily used for simulation modeling. Currently, the authors are validating key data mining and knowledge extraction algorithms using several operational scenarios that include multiple types of construction resources interacting in various simulated settings.

Keywords: construction, data mining, heavy equipment, knowledge discovery, data-driven simulation, optimization.

1. INTRODUCTION

Computer simulation models provide means and methods to study and predict the performance of an engineering system under various conditions that could be otherwise difficult, expensive, or time-consuming to be evaluated in a real world setting. Construction operations fall within the scope of this definition considering the complex, uncertain, and dynamic environment under which projects are performed. Computer simulation facilitates the decision making process by enabling sensitivity analysis of project time, cost, and quality performance metrics using different operational scenarios and various resource combinations.

Although modeling such dynamic settings is a viable approach to obtain information about the future of an operation, the simulation output is only as reliable as the quality of its input. In other words, a simulation model is a true representative of the real system only if the input parameters encompass the uncertainties and evolving nature of the real system. To this end, most conventional construction simulation systems that are designed to accept manual input from a human users, expert judgments, or data from past projects fail to provide a reliable and generalizable output (Akhavian & Behzadan, 2011). Given the limited data from the actual project during the early planning stages, existing simulation methods are to some extents suitable for long term scheduling and performance prediction, while they often fail to add any value to short term decision making and look-ahead scheduling during project execution. Particularly, projects that require extensive use of heavy equipment, involve many crews performing different tasks, and take place in an uncertain environment, are among those that are harder to model with high accuracy. The dynamic nature of such projects coupled with unrealistic input modeling is known to be one of the major impediments that prohibit the widespread use of simulation models within the construction industry (AbouRizk, 2010; Chang & Hoque, 1989).

Hence, the lack of a systematic methodology to provide simulation models with realistic input data and update such models as the project makes progress is a major gap in knowledge in construction simulation. The research presented in this paper is motivated by the need to address this challenge by introducing the design of a data-driven construction simulation framework developed by the authors. The developed system captures multi-modal process data from construction equipment using data collection instrumentations and employs data mining and process reasoning methods to transform raw data into meaningful knowledge necessary for data-driven simulation modeling. The ultimate goal of this ongoing research is to create a construction simulation model generator that uses real time operational data streams from an active construction jobsite to automatically generate and constantly update a realistic simulation model corresponding to the ongoing operations. If successful, such system will eliminate the burden of manual model creation and help make a stronger case to the construction industry about the real added value of simulation modeling. The rest of this paper provides some background information about the current state of construction simulation and recent efforts in other disciplines to create data-driven simulation models. Next, main building blocks and the system architecture will be described, and finally results of validation experiments conducted using the developed algorithms will be provided.

2. LITERATURE REVIEW

2.1 Simulation in Construction

Computer simulation tools customized for construction operations have been in use for almost three decades since the introduction of CYCLONE by Halpin (1977). Several other simulation tools such as UM-CYCLONE (Ioannou, 1989) and Micro-CYCLONE (Halpin, 1990) were designed based on CYCLONE. Later on, a new generation of computer simulation software came into life that provided object-oriented capabilities. STROBOSCOPE (Martinez, 1996) and Simphony (Hajjar & AbouRizk, 1999) are two examples of such modeling environments that are widely used by other researchers due to their extensibility and added capabilities.

2.2 Real Time Simulation

Many previous attempts have been made in areas other than civil and construction engineering to develop real time data-driven simulation models. Among those, examples of Dynamic Data-driven Application Simulation (DDDAS) used in emergency management, contaminant tracking, enhanced chemical progress design, and dynamic traffic signal control (Darema, 2005; Douglas & Efendiev, 2006; Douglas et al., 2004; Lin et al., 2010) can be highlighted. In a recent study, a railway simulation system was developed that employed a dynamic data-driven approach using real time measures (Huang & Verbraeck, 2009). Tannock et al. (2007) used the concept of data-driven simulation to develop models for supply change in aerospace engineering.

However, a review of the literature within the domain of construction engineering revealed a dearth of research in simulation modeling paradigms that can accept input data from the ongoing project. A real time simulation framework was proposed by Hammad & Zhang (2011) to improve productivity and enhance safety considering the required spatio-temporal localization resolution. Song & Eldin (2012) suggested real time tracking of construction equipment to update a dynamic simulation model for look-ahead scheduling. Although both work provided more realistic input data for simulation models compared to the traditional techniques that use static input data, they only considered equipment location information to determine activity durations, which can potentially result in limited accuracy of simulation input modeling due to the existence of cases where data other than positional information may be necessary to describe an operation. Akhavian & Behzadan (2012a) investigated the applicability of data-driven simulation models and visualization techniques for short term construction decision making by calculating activity cycle durations from captured equipment motion data. In the presented paper, the authors used multiple modes of process data to provide not only durations of activities, but also other elements necessary to build a simulation model such as resource allocations, precedence logics, and service priorities (operations logic). The presented study differs with previously attempted work in the manner that it uses project data in real time to fine-tune, update, and ultimately construct a simulation model from scratch.

2.3 Automated Simulation Model Generation

In manufacturing and industrial engineering, there are a number of recent applications in real time simulation. Examples include a discrete event simulation (DES) system for fabrication, machine set-up, assembly, and part transportation (Yuan et al., 1993), as well as an automated simulation model generator for real time shop floor control by (Son & Wysk, 2001). However, as stated earlier, there is limited (if any) amount of previous work in real time simulation within the construction engineering domain. As a matter of fact, to the authors' best knowledge there has been no systematic effort in this domain to develop an inclusive data-driven simulation model generator.

3. MEHODOLOGY

In this research, an integrated framework was developed that is capable of collecting raw data from construction resources (i.e. equipment) using a distributed network of sensors. Next, a reasoning process is applied to the raw data. The reasoning process also accepts minimum input from users regarding basic project information (e.g. project type, number of work areas), and outputs contextual knowledge required for creating a simulation model corresponding to the real system. The generated simulation model is continuously updated using new knowledge extracted from constantly incoming data streams. The system architecture is shown in Figure 1.

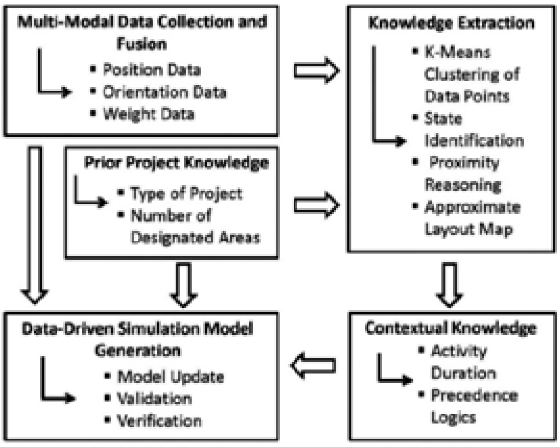

Figure 1. System architecture of the developed framework

3.1 Automated Multi-Modal Data Collection and Fusion

Manual data collection is proven to be a daunting task considering the complexity and diversity of resource interactions in construction and thus, automated data collection strategies are considered great assets in reducing uncertainty and improving data accuracy (Akhavian & Behzadan, 2012b; Martinez, 2009). In the particular case of this study, this becomes even more important since here, multiple modes of data need to be collected from various classes of construction equipment. Capturing different data modes using sensors mounted on construction fleet provides information valuable in determining the basic state of each piece of equipment (i.e. idle, busy), and the nature of interaction(s) it has with other equipment, as discussed in the next Subsection.

In the developed framework, three modes of data are collected to provide contextual knowledge necessary to describe the operations in a computer-interpretable format necessary to build a simulation model. In particular, positional data is sensed using ultra-wide band (UWB) tags and receivers (for indoor applications such as the validation experiments presented in this paper) or global positioning system (GPS) (for outdoor use) to determine the location of the target equipment at any given time. In addition to position, the orientation of the articulated segments of equipment body is a valuable supplement in order to distinguish between several equipment states that may occur with no change in position. For instance, an excavator may not move from one point to the next, but it can still turn its arm and lower or raise it bucket. To this end, attitude and heading reference system (AHRS) sensors are used as orientation trackers in this research. The third mode of data is weight. This data is in essence useful for instance, to determine the amount of material loaded into or transported by dump trucks. Zegbee-enabled load cells are mounted on dump trucks' beds to detect events that trigger start and end of activities that involve weight change (e.g. loading and dumping). All these three modes contribute to the process of extracting required contextual knowledge about the state of equipment at any given time, according to the methodology described in the next Subsection. The manufacturer specifications of the employed sensors are shown in Table 1.

Table 1. Specifications of data acquisiotn sensors

Sensor Type	Measured Quantity	Key Specifications	
Load Cell	Weight	Capacity	5, 10, or 20 Kgs
		Accuracy	± 0.02 %
		Resolution	24 bit
		Update Rate	16 Hz
UWB	Position	Accuracy	15 cm in 3D real time
		Update Rate	0.00225Hz up to 33.75Hz
		Radio Frequencies	Ultra-wideband 6GHz – 8GHz
AHRS	Orientation	Roll/Pitch Accuracy	0.8° RMS
		Heading Accuracy	0.5° RMS
		Resolution	< 0.5°

3.2 Knowledge Extraction and Reasoning Process

The simplest form of taxonomy to describe the state of construction equipment is a binary classification of idle or busy. In order to extract meaningful (contextual) knowledge necessary to automatically generate or refine a simulation model that reflects the latest conditions of a real dynamic system, proper detection of such states with sufficient level of detail is of essence. For example, if it is known that loading a dump truck is completed at time t_1 and dumping of soil at a different location starts at time t_2, the duration of haul activity which connects loading and dumping activities can be calculated by subtracting t_1 from t_2. As such, it is first necessary to precisely detect loading and dumping states and their corresponding time stamps. Sometimes, the binary state classification may not provide the proper level of detail. For instance, knowing that "a dump truck is idle (not moving)" one may intuitively infer that the truck is out of service (e.g. has a flat tire) and needs mechanical maintenance, whereas another logical conclusion could be that the truck is being loaded by an excavator and thus, is not moving. Figure 2 shows a typical hierarchical taxonomy of construction resources involved in a typical earthmoving operation. According to this Figure, if certain types of physical motion (e.g. change in position, change in body configuration, or both) are observed in a dump truck or a loader, the state of the resource can be categorized as busy. The reasoning algorithm observes the trends of individual data modes and combinations of these modes that correspond to each resource state and relates this information to the knowledge required to describe project activities.

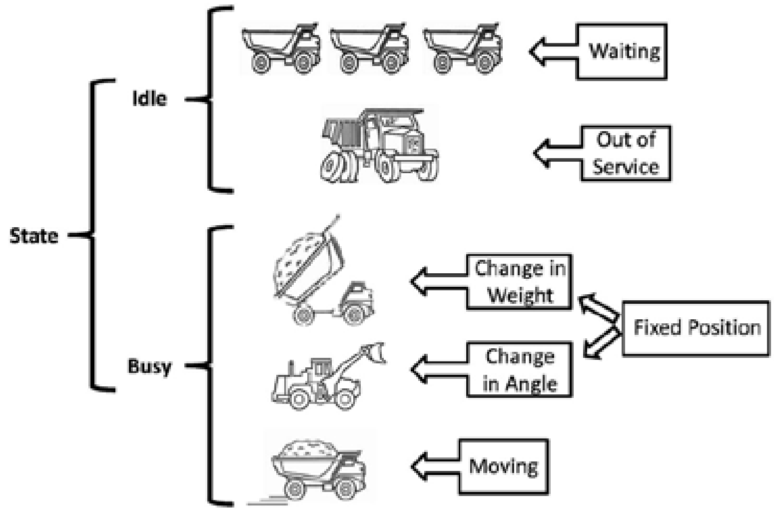

Figure 2. Taxonomy-based state classification of earthmoving fleet

State identification is not the only contribution of the collected data to building a precise simulation model. One of the other inputs that simulation models accept as an important attribute of a server (herein a construction resource such as a loader loading a dump truck) that serves a client (herein a construction resource such as a dump truck that is being loaded) is the operational logic. In a real engineering system, there may be instances where multiple types of resources (e.g. small and big dump trucks) are available to start an activity. However, one resource type (e.g. big dump truck) may normally receive a higher priority based on existing constraints, demands, or resource allocation requirements (Martinez, 1996). This might be due to different reasons, for example, the fact that big dump trucks are of higher rental price with more productivity and thus, a site manager decides that when both small and big dump trucks (clients) are waiting to be loaded by an excavator (server), big dump trucks should be loaded first, so the job can be completed faster. As such, developing methods to extract this knowledge and identify any potential precedence logic is another step in developing a data-driven simulation model. Other than the priorities based on the attributes of resources (e.g. size), there are a number of other precedence logics based on arrival orders such as first in first out (FIFO), last in first out (LIFO), or random pattern.

In addition to activity cycle durations and precedence logic, the layout of the site and the arrangement of resources at any given time can be also identified using collected multi-modal data. To this end, marking the position of construction equipment in an XY diagram over time may reveal clusters of high intensity data points in various locations of the jobsite. Work areas designated to specific tasks (e.g. loading, dumping) or waiting queues, in particular, have higher intensity of positional data points, since the presence of equipment over time is the most in such locations. Thus, clustering algorithms applied to such locally intense data points help detect borders of designated work areas and waiting queues. One such clustering algorithms is k-means which is known to be the most popular scatter point clustering method due to its simplicity, computational efficiency, and speed (Berkhin, 2006). Knowing the number of clusters ahead of time, k-means run an iterative two-step process. First, each data point in the n-dimensional space is assigned to an arbitrary point in space representing the centroid of one cluster. In the second step, the goal is to minimize the squared error within each cluster. Then, new centroids are calculated to match the means to which part of the data points were assigned. These two steps repeat for several times until readjusting means and assigning data points do not significantly change cluster centroids. The k-means method can be applied to data points in n-dimensional space. In this research, it is applied to data points in a 3D XYW space containing positional (i.e. XY) and weight (i.e. W) data. A more intense cluster of positional data points represents a more congested area. Weight data as the third dimension of each positional data point helps distinguish between different work areas. For example, although the loading queue and loading area are adjacent to each other, in the former, the weight data shows constant close-to-zero values, while in the latter, weight is more than zero and constantly increasing due to the dump truck being loaded.

In a simplified scenario of an earthmoving operation when a front-end loader is tasked with loading a dump truck, k is equal to 2 as it is already known that in 2 locations (i.e. loading and dumping areas) the intensity of points should be higher than anywhere else. Then, considering the trend of W data as the third dimension, it would be possible to distinguish between these two areas as this trend is increasing in a loading area and decreasing in a dumping area. It is also possible to have other areas with high-intensity data points such as a service area for periodic or random maintenance. Such complexities and other likely scenarios that involve different numbers and combinations of resources (i.e. equipment) require that a robust and inclusive data mining methodology is designed and used.

3.3 Automated Simulation Model Generation and Refinement

As discussed earlier, generating a simulation model from scratch has been explored in disciplines other than construction engineering. According to Mathewson (1984) a simulation model generator is a tool for translating the real system logic into the simulation language, thus enabling computer to represent the behavior of the model. In order to automatically generate or refine a simulation model, all model components such as resources, activities, variables, and their associated attributes should be either known upfront or properly linked to operational data such that their values can be computed in real time. Most such data are static characteristics that can be manually plugged in to the model. For example, the overall area and coordinates of the jobsite in which a project is taking place and locations of facilities or buildings to be constructed are typically known ahead of time and are not significantly altered during the course of a project. All other input data, that are either subject to regular (predictable) changes while the project is making progress, or cannot be estimated with enough accuracy ahead of time (i.e. uncertainties), need to be dynamically captured in real time.

Within the context of this research, and in order to facilitate the automated generation and refinement of self-adaptive simulation models, data collected from sensors mounted on construction fleet is fused and mined to extract information and discover operational knowledge corresponding to activity durations, precedence logics, and layout of queues and working areas. Currently, the developed simulation framework is capable of refining pre-generated simulation models describing a real engineering system. However, as an extension to the developed framework, this simulation model generator will be modified in the future such that as input datasets are populated, it will automatically search a library of activity cycle diagrams (ACDs) that contains preassembled networks of common fleet operations and gradually generate a simulation model from scratch. If a close match is found inside the ACD library that best fits the observed trends in the collected data and extracted operational knowledge, it will be used to generate the simulation network. If, however, the search returns no valid results, a new network will be automatically created, used for simulation model generation, and then added to the ACD library for future use.

4. PRELIMINARY EXPERIMENTS AND RESULTS

In order to demonstrate the applicability of using real time streams of process data in providing a data-driven simulation model with the latest operational knowledge, several laboratory-scale experiments were conducted in the Decision Support, Information Management, and Automation Laboratory (DESIMAL) at the University of Central Florida (UCF). The test setup consisted of a 12 m^2 model jobsite and remotely controlled (RC) construction equipment. Positional data of dump trucks were captured using a network of UWB receivers and tags, while loader boom motions were sensed by an AHRS tracker. Zigbee-enabled weight sensors were also used to track the amount of material transported by each dump truck. The goal of these experiments was to test the ability of the developed data mining and reasoning algorithms to extract activity cycle durations and potential precedence logic patterns. The following Subsections describe the details and results of two such experiments.

4.1 Experiment 1: Extracting Activity Durations

In this experiment, one front-end loader was tasked with loading multiple dump trucks. In addition to the loading area, dumping area, and loading and dumping queues, a designated service area was added to the site layout to test if the developed methodology could properly distinguish queues from this service area with no prior information about the location of the service area. Therefore, the prior knowledge for the k-means algorithm was that the number of clusters (i.e. k = 5) representing loading area, dumping area, loading queue, dumping queue, and service area. The layout of the experiment is shown in Figure 3. Also the plots of collected positional and weight data in 2D (XY) and 3D (XYW) spaces is shown in Figure 4.

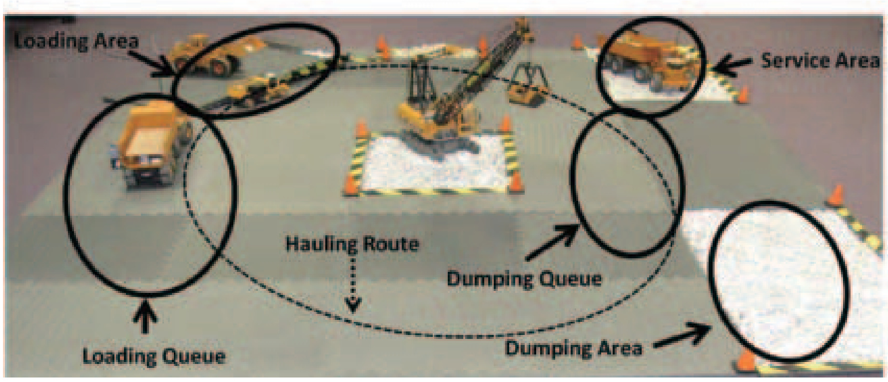

Figure 3. Layout of the model construction jobsite used in proof-of-concept experiments

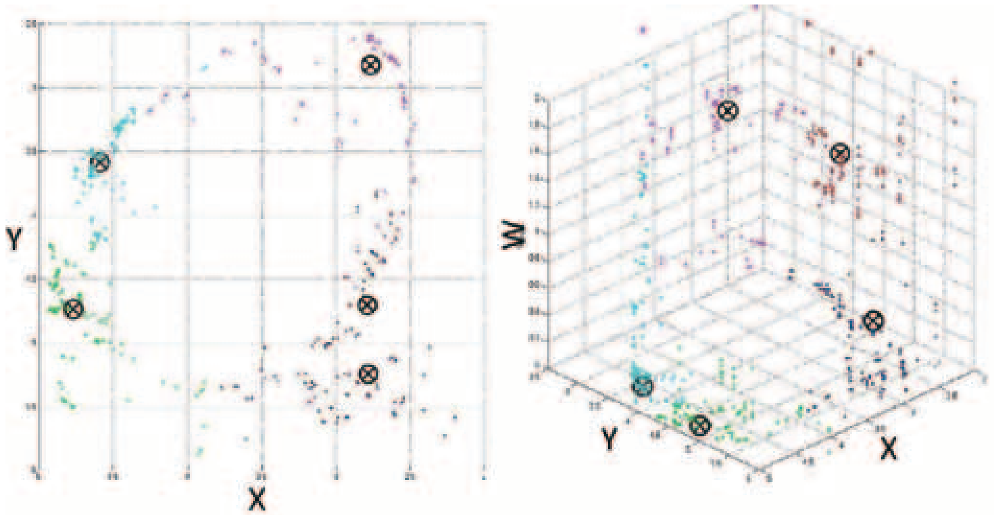

Figure 4. Results of k-means clustering algorithm applied to the positional and weight data in 2D (XY) and 3D (XYW) spaces

Taking into account the discussions in Subsection 3.2, the state of each equipment at any given time was then identified. Next, activity durations were calculated using the time-stamped positional and weight data. Further statistical analysis on pools of activity durations provided means and standard deviations corresponding to the duration of each activity. Table 2 compares the observed mean and standard deviation of activity durations (by analyzing the videotape of the experiment) with durations that were approximated based on the overall site layout and resource specifications (e.g. distances of hauling and return routes, equipment speeds), and the extracted mean and standard deviation (calculated using the developed reasoning process and statistical analysis). As presented in Tables 2, the extracted durations were very close to the real observed values, while the approximated (expected) durations were significantly different from observed values. This highlights the advantage of using the developed framework in providing more realistic input data for simulation models.

Table 2. Observed vs. extracted activity duration means and standard deviations for experiment 1

Activity	Observed Duration (Seconds)		Approximated Duration (Seconds)		Extracted Duration (Seconds)	
	Mean	SD	Mean	SD	Mean	SD
Load	22.3	10.5	10.0	00.0	25.7	11.5
Haul	30.9	8.9	25.0	00.0	34.7	6.3
Dump	10.1	4.8	5.00	00.0	8.1	2.5
Return	28.2	3.6	20.0	00.0	35.0	12.2

4.2 Experiment 2: Discovering Client-Server Precedence Logic

The potential of the developed methodology in detecting the precedence logic patterns was evaluated in this experiment. Again, one front-end loader was tasked with putting soil in multiple big and small dump trucks. However, the operator of the front-end loader was asked to load small dump trucks first when both small and big dump trucks were available for loading. In other words, the precedence logic of the front-end loader operator in the real system was set to be "*small dump trucks get higher priority for loading*". Figure 5 shows a chronological representation of the service pattern extracted from time-stamped positional data streams.

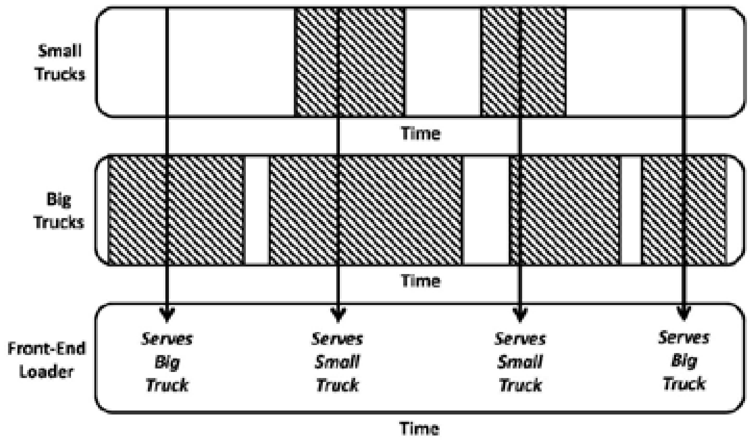

Figure 5. Loading precedence based on the availability of each dump truck type in the loading area

As shown in this Figure, the algorithm used collected positional data from each dump truck to generate two time sequences corresponding to the presence/absence of small and big dump trucks (clients) in the vicinity of the loading area. Then, a third time sequence was generated to show which dump truck (client) was picked by the front-end loader operator (server) when both small and big dump trucks were available. This important piece of knowledge can be discovered by observing the trends of data streaming from the front-end loader (positional data) and dump trucks (weight data). In particular, when the front-end loader starts the loading process, there will be only one weight sensor (mounted on a dump truck) that transmits constantly increasing weight values. The dump truck corresponding to this weight sensor (that can be either small or big) is the client that is being served by the server. If in fact, there is a pattern in the way clients with different attribute (e.g. size) are served, this trend can be revealed through observing several cycles of the operation. Results obtained from constantly streaming data in experiment 2 indicated that out of the 24 loading cycles during which both small and big dump trucks were available in the loading area, in 21 instances small dump trucks received a higher priority and were loaded first while in the remaining 3 instances, big dump trucks received a higher priority. From the video of the experiment, it was already known that in the real system, small dump trucks received higher loading priority in all 24 loading cycles. Therefore, the reliability of the precedence logic detection algorithm in this experiment was about 87.5% with 12.5% false detections. Hence, it was concluded with 87.5% confidence that the underlying precedence logic of the front-end loader operator was "*small dump trucks get higher priority for loading*". This critical piece of knowledge was then used inside the simulation model to yield more accurate results when forecasting the future project performance.

5. CONCLUSIONS AND FUTURE WORK

Construction simulation models are conventionally used for long term planning and decision making prior to the start of a project. Due to reliability and adaptability issues, most such models cannot be used for execution-phase planning and short term decision making purposes. A simulation model that is intended to provide insights about the future performance of an ongoing project needs to incorporate real time data and be updated based upon the latest conditions under which real field operations are taking place. This, as opposed to using historical input data, makes the results of the simulation more realistic and facilitates the process of model validation by the industry practitioners. To this end, this paper described the design requirements for developing a data-driven simulation system. An integrated framework was developed that used real time multi-modal operational data from construction equipment and data mining algorithms to translate data into meaningful contextual knowledge. Such knowledge, in the current stage of this research, included major input requirements of a simulation model such as activity cycle durations, site layout, and precedence logics. The future work in this research will include minimizing the amount of collected data so data is collected and transmitted only when a meaningful change in the real system occurs, and enabling automated generation of construction simulation models from scratch using the extracted knowledge about key model parameters and precedence logic.

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