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IDENTIFICATION OF INFORMATION REQUIREMENTS USING SIMULATION FOR SUPPORITING CONSTRUCTION PRODUCTIVITY ASSESSMENT

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ABSTRACT

Project managers need to assess how well construction crews are performing in terms of productivity. This paper presents the preliminary results of an effort carried out by the authors to develop a simulation based framework to support the identification of the information requirements for assessing productivity performance. A prototype to test the proposed framework for the identification of information requirements by studying the assessment of earthmoving productivity is introduced. Based on literature regarding the factors that can affect earthmoving productivity, several scenarios, representing different factors that affect earthmoving productivity, have been created and studied. These scenarios have been simulated to help to identify the information items required for assessing earthmoving productivity, such as hauling distance and loading time. Several potential data capture technologies, such as GPS, RFID and On-Board Instrument can help in acquiring the information items identified in this paper.

1 INTRODUCTION

Project managers need to assess how well construction crews are performing in terms of productivity. A prototype to test the preliminary simulation based framework for the identification of information requirements for assessing earthmoving productivity is introduced in this paper. This prototype consists of different earthmoving scenarios which were designed and simulated to test the framework. In order to assess earthmoving productivity and to investigate the effect of different factors on earthmoving productivity, first, we need to measure productivity. Section 2 presents a metric used in this paper to measure productivity and the required information items for measuring it.

In order to assess earthmoving productivity in a construction jobsite, the required information items related to the factors which affect the productivity should also be collected. To identify these required information items, we developed some earthmoving scenarios based on known factors that affect earthmoving productivity. We conducted a literature review and did scenario simulation to identify the corresponding required information items to assess productivity of the earth moving operation in each scenario. Section 3 discusses the scenarios and the required information items to assess earthmoving productivity in those scenarios.

Different data capture technologies can be used to collect the required information for measuring and assessing earthmoving productivity from the jobsite. The potential data capture technologies and the potential generic data sources for providing the required information items for measuring and assessing earthmoving productivity are discussed at the end of Section 2 and 3, respectively.. Generic data sources such as soil databases and RS Means (2007) are not specific to the project under study.

2 REQUIRED INFORMATION ITEMS AND POTENTIAL DATA CAPTURE TECHNOLOGIES FOR MEASURING EARTHMOVING PRODUCTIVITY

Recently, ASTM published a standard practice (ASTM E2691-09) for Job Productivity Measurement (JPM). This standard provides a metric for measuring productivity differential. Productivity differential for a cost code is presented in (1) (ASTM E2691-09).

$$\mathrm{Pr}\,oductivity\ Differential = \frac{(LPRP - Current\ \mathrm{Pr}\,oductivity)}{LPRP} \tag{1}$$

Labor Productivity Reference Point (LPRP) can be calculated based on Baseline Labor Hour Budget. The data required to create a baseline labor hour budget can be drawn from company's past practice or industry standards such as RS Means (ASTM E2691-09). Current productivity can be calculated based on observed percent complete and expended labor hours which should be collected on the jobsite.

JPM measures productivity changes, trends and anomalies and it can be considered as an early warning signal for construction productivity (ASTM E2691-09) problems. Five signals are proposed in the standard to represent anomalies and deviations from the reference point: Trends, shifts in the mean, extreme points, saw tooth pattern and missing data. For instance, if 6 or more consecutive points (productivity differentials) show an increasing or decreasing trend, the signal is representing "Trends" (ASTM E2691-09).

The required information items to measure earthmoving productivity based on JPM is represented in Table 1. The standard practice for job productivity measurement (ASTM E2691-09) is used to identify the required information items. Table 1 also presents some potential data capture technologies and data sources to measure productivity differential.

Table 1: Required information items and potential data capture technologies to measure earthmoving productivity

Required information items to measure construction productivity	Potential data capture technologies and data sources	Relevant literature to the application of data sources
Observed Percent Complete	GPS (on excavator) and project models; Laser scanner; Camera (Images);	Navon et al (2004) El-Omari and Moselhi (2008) Chae, S. and Naruo, K. (2007) El-Omari and Moselhi (2009)
Expended Labor Hours	RFID	El-Omari and Moselhi (2009)
Baseline Labor Hour Budget (BLHB) for each task	Industry Standards; Profile of company past projects	RS Means (2007) ASTM E2691-09

3 REQUIRED INFORMATION ITEMS AND POTENTIAL DATA CAPTURE TECHNOLOGIES FOR ASSESSING EARTHMOVING PRODUCTIVITY IN DIFFERENT SCENARIOS

In order to assess earthmoving productivity at the jobsite, the required information items related to the factors which affect the productivity should also be collected. In order to identify these required information items, we designed several earthmoving scenarios based on the factors which affect earthmoving productivity. We reviewed relevant literature and simulated the scenarios in order to identify the required information items. EZStrobe (Martinez 2001) was used for simulating earthmoving operation.

EZStrobe is an easy to learn and simple simulation system and meanwhile it is "capable of modeling moderately complex problems" (Martinez 2001). It is a general-purpose simulation system that is based on Activity Cycle Diagrams (Martinez 2001). EZStrobe can be used to simulate earthmoving operations discretely. We created a stochastic model to simulate the earthmoving operation. The stochastic parameters were represented using appropriate distributions. For instance, we used PERT distribution to represent cycle times.

Three excavators (Backhoe, hydraulic, crawler mtd., 1.5 C.Y. Cap) and 30 trucks (12 C.Y. dump truck, 16 ton) were supposed to remove 100,000 cubic yards of soil in 45 days of operation. The soil type was assumed to be sandy clay (Average fill factor=105%, average bank weight=1.325 ton/cubic yards and average percent swell=25%) in the base case. We simulated 45 days of earthmoving operations for each scenario. The base case is designed based on the information extracted from RS Means (2007), Peurifoy and Schexnayder (2002) and Caterpillar (2002). Sections 3.1 through 3.4 elaborate on the four scenarios that were created. Section 3.5 summarizes the scenarios, the required information items and the potential data capture technologies to acquire the required information items.

3.1 Scenario 1: Adverse earthmoving site and access road condition

A project manager needs to make sure that the access road and earthmoving site are in good condition. Rutted and soft roads that have higher rolling resistance may affect the hauling duration (Kannan 1999). Truck speeds can be affected by different rolling resistance. For instance, the performance figures of a 777F off-highway truck show that the maximum speed of truck is lower when moving in roads with higher resistance (Caterpillar 2006 a). Furthermore, uneven surfaces can impact the hauling time (Kannan 1999).

We designed a scenario that represents adverse site and access road condition. During the first 10 days of operation, the jobsite and access road are in good condition and truck operators do not need to reduce speed when they are moving in the construction site and its access road. For the remained 35 days, the jobsite and access road are not in good condition and truck operators need to reduce the speed by 20 percent. Figure 1 represents the productivity differential in percentage for 45 days of operation.

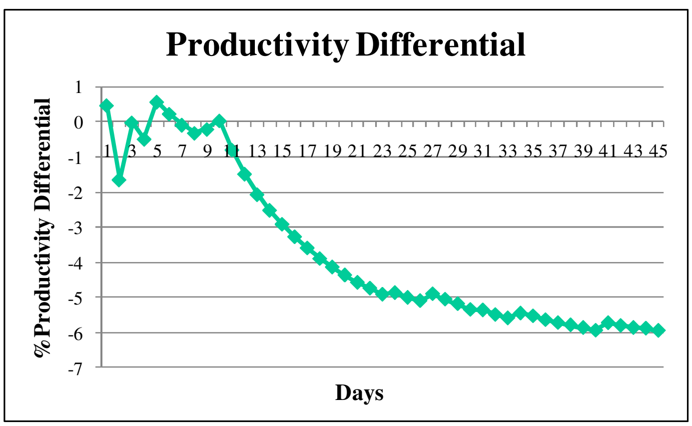


Figure 1: Productivity differential in percentage for 45 days of operation in which access road and site are not in good condition after 10 days

Previous research has shown that control information is generated irregularly (Akinci et al 2004) and the information is not acquired in a timely manner (Navon 2007). These limitations show that the required information is not always available at the right time. Figure 2 represents the potential ability of the project manager to improve earthmoving productivity in this scenario if he or she improves the site and its access road condition on day 17.

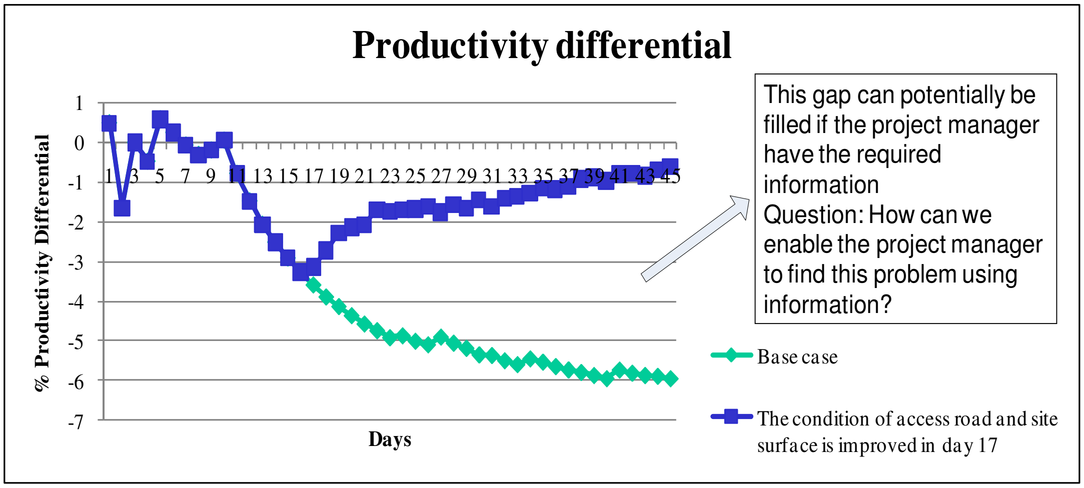


Figure 2: Potential ability of the project manager to improve productivity if s/he is provided with the right information at the right time

Figure 1 does not show the reason behind the reduction in the productivity. In order to investigate this scenario further, we divided the area in which the haulers and excavators move into three sections. Figure 3 represents schematically the earthmoving site and its access road, the main road (highway), and the dumping area and its access road.

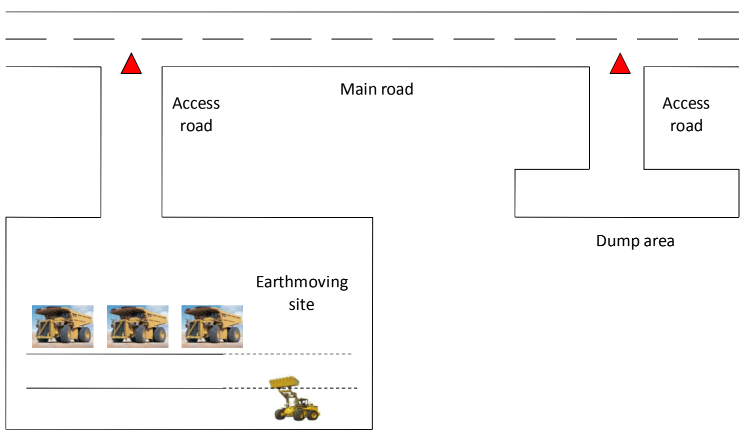


Figure 3: Schematic representation of earthmoving site, main road, dump area and access roads

Figure 4 represents the average durations that a hauler spent in the earthmoving site and its access road, the highway and the dumping area and its access road. As shown, there is a shift in the figure which represents the average time that a hauler spent in the site and access road in each cycle. This shift is not recognizable in the other figures. So, it shows that something happened in the site. But it still can be due to other factors, such as soil change or loading problems.

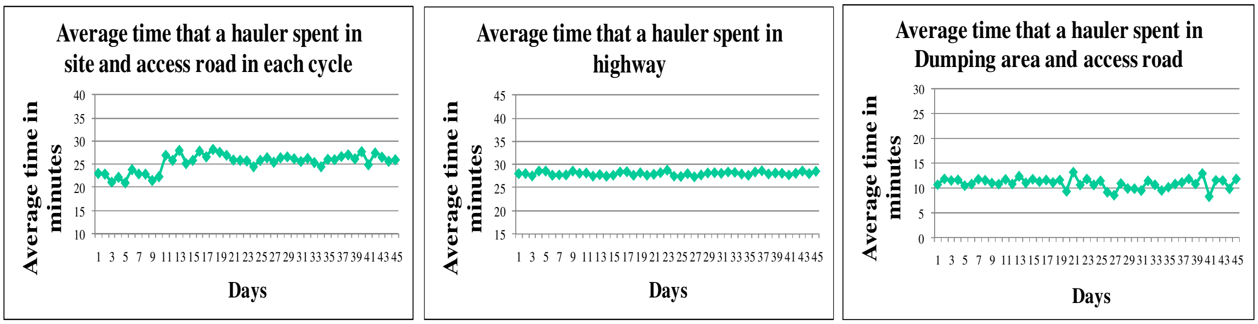


Figure 4: Average time that a hauler spent in access road and site, highway and dumping area and its access road

Figure 5 represents the average time that a hauler spent at the earthmoving site and its access road, excluding the loading and waiting times. A shift is apparent in this figure. This shift is due to the factors that affect truck speed in the earthmoving site and its access road when the truck is moving. This data cannot be collected only with On-Board Instrument (OBI , which is usually installed on trucks and is composed of different sensors, such as inertial sensor, pressure sensor and temperature sensor, for collecting vehicle performance data), since OBI does not distinguish the time that a hauler enters the access road or the job site. However, OBI provides information about the waiting and loading times, which are required. GPS can be used to identify the time that a truck spends in the earthmoving site and its access road. A combination of OBI and GPS could potentially be used to collect the required information item in situations like the ones highlighted by this scenario.

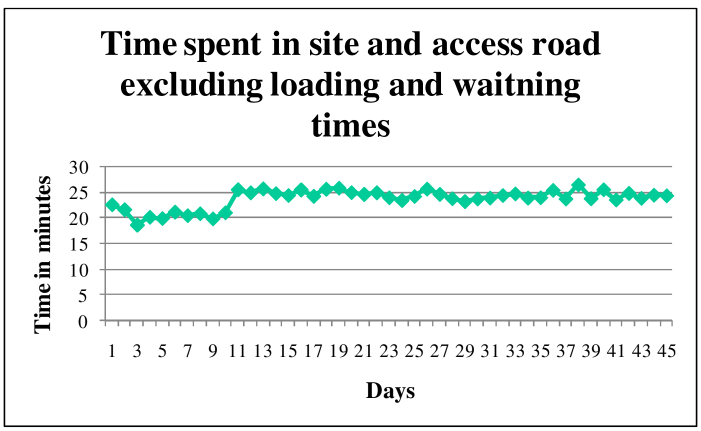


Figure 5: The average duration that a hauler spent in site and access road excluding the loading and waiting time per cycle

Although this scenario models adverse conditions for an earthmoving site and its access road, the results can be applied for adverse conditions for a dumping area and its access road. It can also be applied for adverse highway conditions. The combination of data acquired from GPS and OBI can help us to identify the section of the road that is not in good condition.

3.2 Scenario 2: Changes in Soil type

In this scenario, the soil type changes after 10 days of operation. In the first 10 days of operation, the soil type is sandy clay with an average density, average percent swell and average load factor of 1.325 tons per cubic yard, 25%, and 1.05, respectively. Load factor can be defined as the ratio of average load to the maximum load for a given period of time (Peurifoy and Schexnayder (2002). After 10 days of operation, the soil type changes to clay with an average density, average percent swell, and average load factor of 1.47 tons per cubic yard, 40%, and 0.85, respectively. Figure 6 represents the productivity differential for 45 days of operation in which soil type has changed after 10 days of operation.

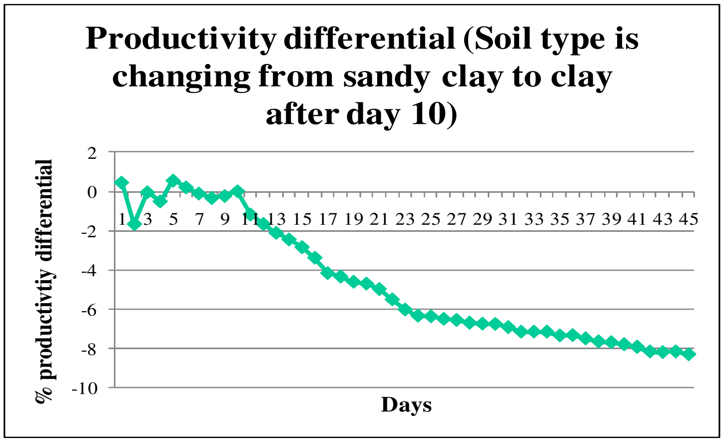


Figure 6: Productivity differential in percentage for 45 days of operation in case that soil type has changed after 10 days of operation

Figure 6 does not show the reasons behind the decreasing trend in differential productivity after 10 days of operation. Figure 7 represents the average loading time per cycle of hauling when the soil type has changed after 10 days of operation. Although the load factor changes from 1.05 to 0.85 after 10 days of operations there is not a significant increase in average loading time per cycle of hauling after 10 days of operation. The reason is that the swell percent is also increased after 10 days of operation and the haulers are filled earlier. So, it is difficult to assess this scenario just with data about the loading time.

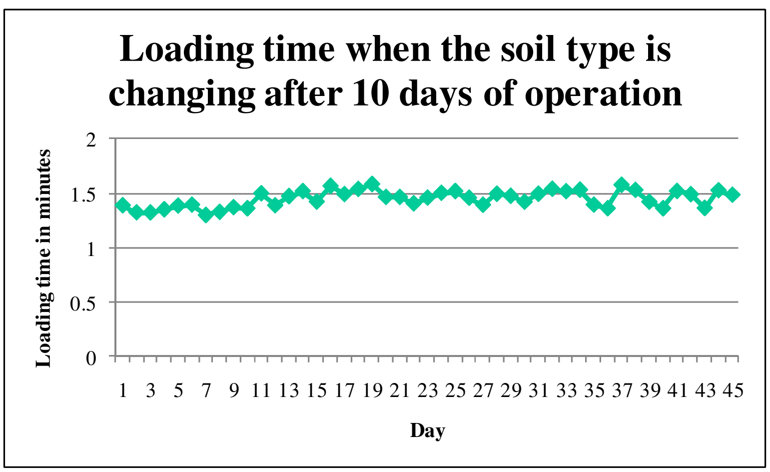


Figure 7: Average loading time per cycle of hauling when the soil type has changed after 10 days of operation

Figure 8 shows the soil density and percent swell of soil for the 45 days of operations. As shown, there is a shift in soil density and percent swell. If this data is provided for the project manager, he would be able to assess the earthmoving productivity loss presented in this scenario.

If the volume of removed soil and the payload are available for each day, the average density of the soil could be estimated. For instance, OBI could be used to find payload and GPS data along with earthmoving plans could be used to identify the volume of removed soil. Although OBI could be used to collect the payload data, it is not free of noise. So, further field study should be performed to examine the effectiveness of using OBI to collect payload data for this scenario. Navon et al. (2004) developed a model to convert measured locations to progress information which is the amount of removed soil in our case. As an alternative, the volume of removed soil can be determined by laser scanner.

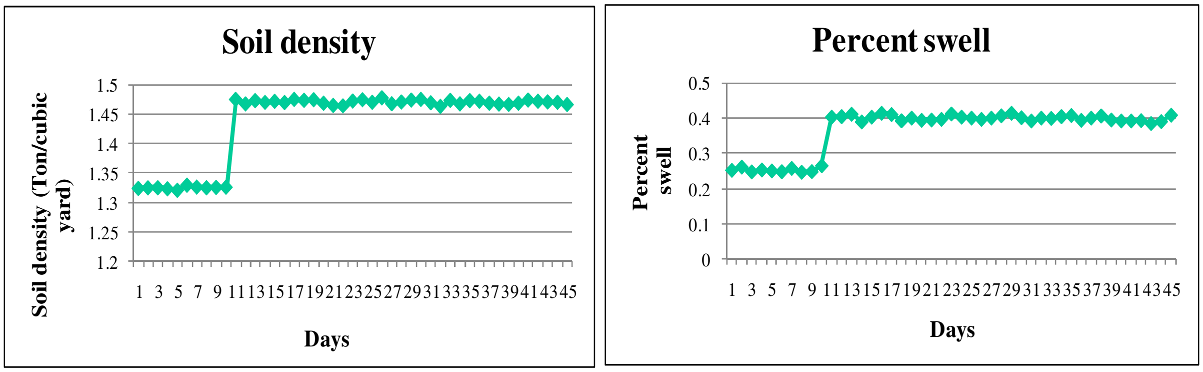


Figure 8: Soil density and percent swell for 45 days of operation

3.3 Scenario 3: Excavator breakdown

This scenario represents the case in which one or two excavators are not involved in the excavation process after 10 days of operation. Figure 9 represents the productivity differential for 45 days of operation in the case that one or two excavators breakdown and are not involved in the excavation process after 10 days of operation.

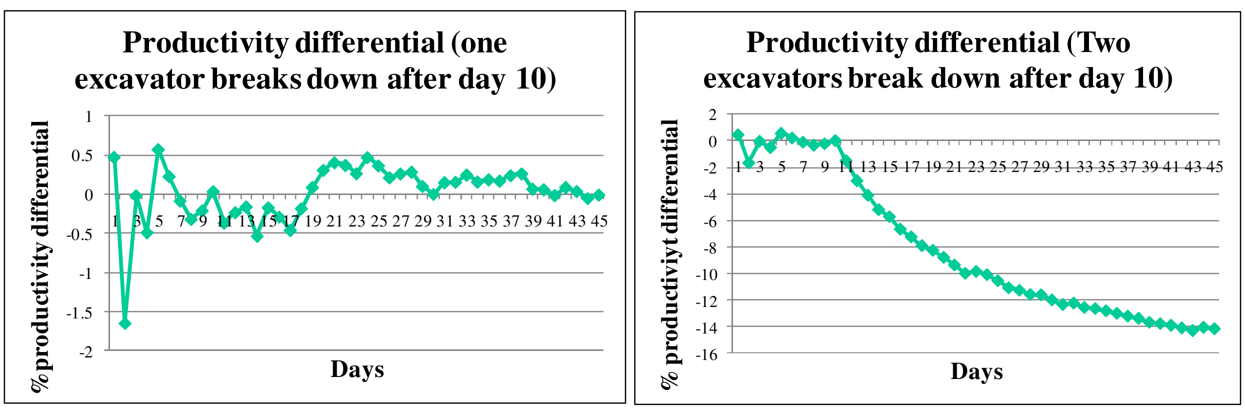
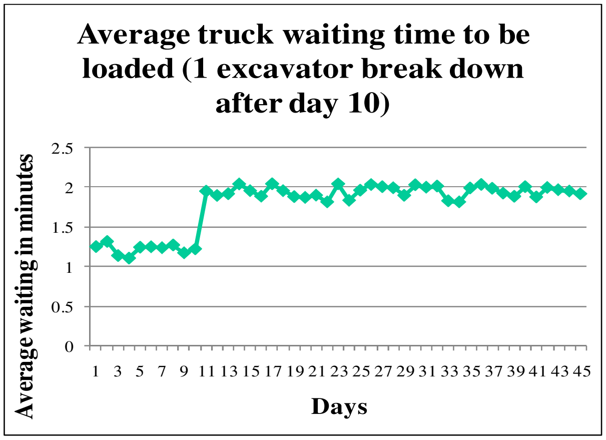


Figure 9: Productivity differential for 45 days of operation in cases that one or two excavators break down after 10 days of operation

As it is shown in Figure 9, the effect of removing one excavator from the excavation process is not noticeable by using productivity differential. It might be because that the number of excavators has been overdesigned in the first place. Figure 9 shows that if two excavators are removed from the process of excavation, the productivity differential is highly affected. Figure 9 does not show the reason behind the decreasing trend when two excavators are removed from service after 10 days.

Figure 10 represents the average waiting times for a truck to be loaded when one or two excavators are not involved in the excavation process after 10 days of operation. A shift in average truck waiting time per cycle is noticeable in Figure 10, which can be used as an indicator to show that excavators are not working efficiently or some of them are removed from the excavation process.



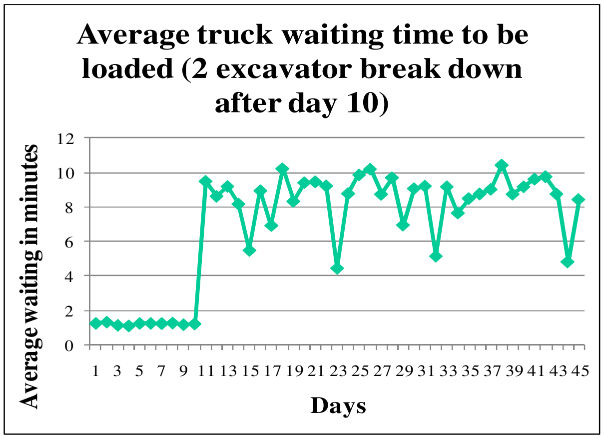


Figure 10: Average waiting times for a truck to be loaded in cases in which one or two excavators are not involved in the process of excavation after 10 days of operation

3.4 Scenario 4: Changes in depth of cut

It is sometimes difficult for an equipment operator to fill the bucket of the excavator in one pass when the depth of cut increases beyond certain depths (Kannan 1999). In this scenario, we assumed that depth of cut increases after 10 days of operation. We also assumed that the impact of this increase is that the operator can fill 60% of the bucket on average in each pass. Figure 11 represents the productivity differential in case that depth of cut increases after the first 10 days of operation.

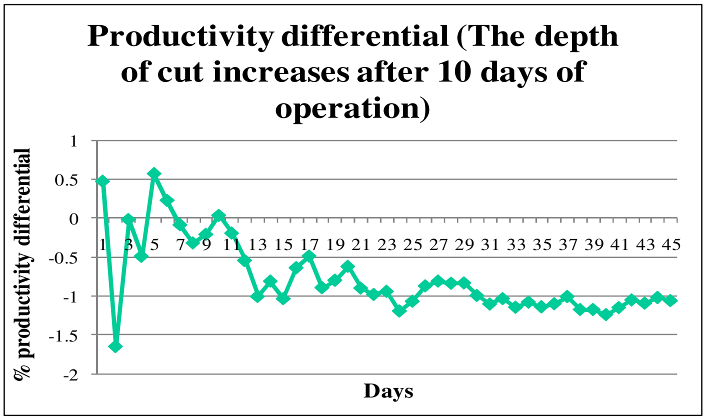


Figure 11: Productivity differential when depth of cut increases after 10 days of operation

Figure 12 represents the number of passes that the operators of excavators try to fill the buckets when depth of cut increases after 10 days of operation. The number of passes in Figure 12 is the total number of passes per day. As it is shown in the figure, the number of passes can be used as an indicator to show that the depth of cut has been increased. A combination of GPS and OBI can potentially be used to identify the number of passes. The start and end times of loading in each cycle can be retrieved from OBI. GPS can be used to detect the movement pattern of trucks and the specified loading time. Here, we assumed that the range of excavator moves in each cycle is more than the accuracy of the GPS.

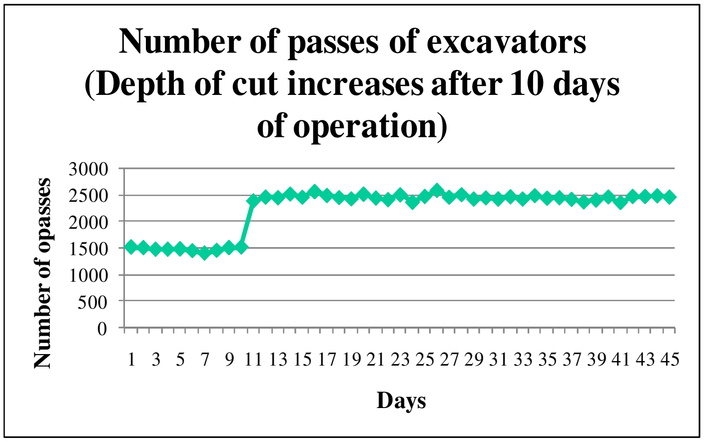


Figure 12: Number of passes that the excavator operator tries to fill the bucket per day when depth of cut increases after 10 days of operation

Several systems have also been proposed to check the depth of cut. These systems can potentially be used to collect the required information for this scenario. For instance, Caterpillar <www.caterpillar.com> introduced "AccuGrade Laser Reference System" (Caterpillar 2006 b) to check grade and depth of cut. This system includes several sensors such as inclinometer, cylinder position sensors, swing sensors, and laser transmitter and receiver.

3.5 Required information items and potential data capture technologies to assess earthmoving productivity in the presented scenarios

Table 2 represents the required information items to allow earthmoving productivity assessment for the different scenarios presented above. Different data capture technologies are proposed to collect the identified required information items for assessment of earthmoving productivity. The potential data capture technologies which are introduced in this paper can help to acquire the identified required information items in one of the following ways:

- The data capture technology can potentially provide adequate data to measure the required information items. For instance, a laser scanner can be used to measure the volume of removed soil.
- The data capture technology can potentially provide data which can be fused with the other sources to measure the required information items. For instance, the data acquired from GPS and OBI should be fused to satisfy the information requirements in scenario 1.

4 CONCLUSION AND FUTURE WORK

In order to identify the required information items for supporting earthmoving productivity assessment, several different earthmoving scenarios have been created and studied. These scenarios were created based on the factors that affect earthmoving productivity. These scenarios have been simulated and the required information items have been identified. Some potential data capture technologies have also been proposed. The results of the prototype to test the preliminary framework for the identification of information requirements for assessing earthmoving productivity were introduced. The results of the prototype shows that the simulation based framework can be developed to support the identification of information requirements for assessing productivity performance. The prototype results showed that designing and simulating different scenarios based on different factors that affect earthmoving productivity can support the identification of the relevant information requirements for assessing earthmoving productivity. The applied simulation environment could satisfactorily support the generation of the required data for analyzing the scenarios.

Table 2: The required information items to assess earthmoving productivity for different scenarios and potential data capture technologies (These required information items in each scenario should be collected along with the required information items in Table 1)

Scenario	Scenario-specific required information items to assess earthmoving productivity	Relevant literature to scenarios	Potential data capture technologies	References for the application of data capture technologies
Adverse site and access road condition	The average duration that a truck spends in the earthmoving site and its access road excluding the waiting times and loading times The images of jobsite and access road	Kannan (1999) Caterpillar (2006 a) Caterpillar (2002) RS Means (2007)	OBI and GPS RFID Camera	Navon et al (2004) El-Omari and Moselhi (2008) Chae, S. and Naruo, K. (2007) El-Omari and Moselhi (2009)
Soil type is changing	Soil percent swell Soil Density Loading time	Peurifoy and Schexnayder (2002) Caterpillar (2002) RS Means (2007)	OBI and GPS (along with earthmoving plan) OBI and Laser scanner	Navon et al (2004) El-Omari and Moselhi (2009)
Excavator breakdown	Average time that a hauler waits to be loaded in each cycle	RS Means (2007)	OBI	Kannan (1999)
Depth of cut is changing	Number of passes to fill the bucket Number of passes to fill the truck Loading time	Kannan (1999) RS Means (2007)	GPS (on excavator) and OBI	Navon et al (2004) Kannan (1999)
Over time	Labor hours related to workers who work overtime Labor hours related to workers who do not work overtime	Hanna et al (2005) Business Roundtable (1980) RS Means (2007)	RFID	El-Omari and Moselhi (2009)
Day and night shift	Day-shift expended labor hours Night-shift expended labor hours Day-shift percent complete Night-shift percent complete	Pradhan (2009) Kannan (1999) RS Means (2007)*	RFID	El-Omari and Moselhi (2009)
One-way hauling road	Duration that a hauler waits to enter the hauling road	Martinez (2001) RS Means (2007)	GPS	Navon et al (2004)
Heavy traffic in hauling road	Duration that a hauler spends in hauling road	RS Means (2007)	GPS	Navon et al (2004)
Changing dumping location	Hauling distance	RS Means (2007)	OBI GPS	Kannan (1999)

Designing more earthmoving scenarios and identifying the information requirements for assessing earthmoving productivity in these scenarios are among the future work of this research. Real case studies will be used to evaluate the effectiveness of the identified information requirements for assessing earthmoving productivity in different situations in construction job site.

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