Automated Monitoring and Assessment of Productivity in Earthmoving Projects

<table>
<thead>
<tr>
<th>Journal:</th>
<th>Canadian Journal of Civil Engineering</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manuscript ID</td>
<td>cjce-2018-0183.R1</td>
</tr>
<tr>
<td>Manuscript Type:</td>
<td>Article</td>
</tr>
<tr>
<td>Date Submitted by the Author:</td>
<td>29-May-2018</td>
</tr>
<tr>
<td>Complete List of Authors:</td>
<td>Salem, Ashraf; Concordia University, Department of Building, Civil and Environmental Engineering  Moselhi, Osama; Concordia University, Department of Building, Civil &amp; Environmental Engineering</td>
</tr>
<tr>
<td>Keyword:</td>
<td>Automated data acquisition, Earthmoving operations, Road conditions analysis, GPS, Productivity measurement</td>
</tr>
<tr>
<td>Is the invited manuscript for consideration in a Special Issue?</td>
<td>Not applicable (regular submission)</td>
</tr>
</tbody>
</table>
Automated Monitoring and Assessment of Productivity in Earthmoving Projects

Authors:

Ashraf Salem, PhD Candidate, Department of Building, Civil & Environmental Engineering, Concordia University, Montreal, Canada H3G 1M8.

Osama Moselhi, Professor, Department of Building, Civil & Environmental Engineering, Concordia University, Montreal, Canada H3G 1M8.

Corresponding Author:

Ashraf Salem
Concordia University
Department of Building, Civil & Environmental Engineering
Montreal, Canada H3G 1M8
Phone: 1(514)848-2424 – Ext. 7091
Email: as_salem@encs.concordia.ca
Automated Monitoring and Assessment of Productivity in
Earthmoving Projects

Abstract

Continuous monitoring of productivity and assessment of its variations are crucial processes that
significantly contribute to success of earthmoving projects. Numerous factors may lead to
productivity variations. However, these factors are subjectively identified using manual
knowledge-based expert judgment. Such manual recognition process is not only subject to errors
but also time-consuming. There is a lack of research work that focuses on near real-time
assessment of productivity variation and its effect on cost, schedule and effective utilization of
resources in earthmoving projects. This paper presents a customized multi-source automated data
acquisition model that acquires data from a variety of wireless sensing technologies. The
acquired multi-sensor data are transmitted to a central MySQL database. Then a newly
developed data fusion algorithm is applied for truck state recognition, and hence the duration of
each earthmoving state. Multi-sensor data fusion facilitates measurement of actual productivity,
and consequently the assessment of productivity ratios that support continuous monitoring of
productivity variation in earthmoving operations. The developed tracking and monitoring model
generates an early warning that supports proactive decisions to avoid schedule delays, cost
overruns, and inefficient depletion of resources. A case study is used to reveal the applicability
of proposed model in monitoring and assessing actual productivity and its deviations from
planned productivity. Finally, results are discussed and conclusions are drawn highlighting the
features of proposed model.
Keywords: Automated data acquisition, Earthmoving operations, Productivity measurement, GPS, Road conditions analysis.

1. Introduction

Earthmoving operations are usually encountered in most construction projects. In average it represents about 20% of overall cost of construction projects (Kang et al. 2009). Consequently, productivity and performance of earthmoving operations need to be regularly monitored since it can impact success and failure of this class construction projects. Productivity variation as well is crucial, where it indicates trends in performance of e projects. Productivity variation may lead to adverse impact on schedule, cost and efficient utilization of resources. Low productivity results in schedule delay, and inefficient utilization of resources. However, high productivity may lead to cost overruns and over deplete in resources. Therefore, monitoring productivity in earthmoving operations is crucial to avoid undesirable consequences that may damage one or more of the project objectives. Performance level in earthmoving operations is interrelated to the productivity rates which in turn depend on various operational, environmental, technical and managerial factors. Therefore, assessment of productivity rates is fundamental for evaluating performance of these projects. Over the last few decades, automation technology market witnessed a remarkable advancements both hardware and software. Data acquisition systems have been promoted as a direct consequence of this advancement. These data acquisition systems are inevitable to be automated with less or no human intervention to avoid subjectivity and to boost accuracy and reliability of the acquired data. Available research work commonly utilized off-the-shelf technologies, which provide expensive solutions in a black box format that makes it difficult for users to modify and/or adapt to suit project requirements. In other words, the available research work lacks cost efficiency and flexibility to outfit specific needs of the project.
at hand. Also, Limited research has been conducted to study and develop a customized design of automated data acquisition systems to overcome the limitations of off-the-shelf technologies. This paper introduces a novel automated model for near real-time monitoring and productivity assessment of earthmoving operations. The developed model consists of four modules; (1) automated data acquisition module, (2) planned productivity module, (3) automated measurement of actual productivity module, and (4) driving and road condition analysis module. A set of sensors, smart board, and a microcontroller used in the development of a customized data acquisition module. Sensor data fusion algorithm is developed for accurate productivity measurement. Detailed illustration of the research methodology, different modules, and applied algorithms are revealed in the proposed model section.

2. Background

In earthmoving operations, productivity is defined as the total output from the entire fleet per unit of time. However, only examining productivity is not enough for assessing the performance of an operation (Fu 2013). Earthmoving projects usually involve cyclic routine operations. These operations in most of earthmoving projects are loading, hauling, dumping and travel back to loading area to repeat that cycle of work. The problem of accurate estimation of earthmoving productivity has attracted many researchers for decades; however, a model that predicts the output of such operations with a satisfactory degree of confidence under different conditions is not available (Smith 1999; Shahandashti et al. 2010). The researchers’ endeavors towards assessing and predicting the productivity of earthmoving operations followed deterministic or stochastic procedure. Experience-based models have been commonly used for earthmoving productivity forecasting. These heuristic methods are based on rules of thumb and engineering
knowledge. Several mathematical models have also been established for estimating productivity such as queuing theory and fuzzy logic (Fu 2013).

Tracking and monitoring of onsite construction operations received considerable attention in the domain of automation in construction. Individual or multi-sensing technologies were used for that purpose, e.g., Brilakis et al. (2011); Montaser et al. (2012); Brilakis et al. (2011); Ibrahim and Moselhi (2014). In earthmoving operations; standalone GPS played an important role throughout the last decades. Despite its vital role, various studies have proved that use of standalone GPS does not satisfy all the needs for appropriate tracking. This drawback motivated researchers to augment GPS by another technologies.

Monitoring of earthmoving operations obtains substantial interest from many researchers (Ibrahim & Moselhi 2014). The majority of existing research work focused on assessing the productivity of earthmoving operations (Montaser et al. 2012; Ibrahim & Moselhi 2014; Montaser & Moselhi 2014) Using conventional methods that involve human intervention (i.e. manual or semi-automated methods) or fully automated methods using a variety of sensing technologies including; RFID (Montaser & Moselhi 2014), GPS (Brilakis et al. 2011; Montaser et al. 2012), computer vision-based (Rezazadeh et al. 2012), or grouping two or more of these sensing technologies (Brilakis et al. 2011; Ibrahim & Moselhi 2014). Identifying factors that lead to low productivity has attracted the attention of other researchers with respect to equipment utilization (Glopvarvar-Fard et al. 2013; Azar 2015; Alshibani & Moselhi 2016) labor productivity (El-Gohary & Aziz 2013; Azar 2015), and improvement of specific process (Tsehayae & Robinson Fayek 2014) to raise productivity and hence to improve the performance in earthmoving operations (Chi & Caldas 2012).
Rueda & Javier (2011) presented a method to obtain and present historical productivities of key equipment using different data processing methods to extract useful information from the acquired historical data, to provide a tool to aid estimating and generate reference information to support decision making. Montaser et al. (2014) presented a model for stochastic forecasting of productivity of earthmoving operations considering uncertainty. Their model integrates GPS/GIS technology for automated site data acquisition and DES (Discrete Event Simulation) for estimating activity’s future performance.

Ibrahim & Moselhi (2014) presented an automated model for actual productivity assessment of earthmoving operations in near real-time. Their model includes hardware and software development. The hardware consists of: microcontroller, GPS and different types of sensors (strain gauges, 3-Axis accelerometer, and barometric pressure sensor). Bluetooth wireless communication was used for data streaming and proximity detection. Vahdatikhaki & Hammad (2014) presented a model that uses spatiotemporal data sets retrieved from GPS and UWB on an excavator and dump truck to analyze the operational states of the truck and excavator and therefore creating near real-time simulation. Akhavian & Behzadan (2015) classified features from a variety of data sets captured using a smartphone fixed on a front-end loader. This data comprised GPS, gyroscope, and accelerometer. The model estimated the operational cycle durations; then it utilized these durations to simulate the monitored earthmoving operations.

Regardless of limitations associated with these methods, they offer improvement for the assessment process of productivity in earthmoving operations. These methods, however, are not able to investigate undesirable variations of productivity that could affect schedule, cost, and efficient utilization of resources. Productivity assessment solely doesn’t grant any indication about likely incidence of undesirable consequences, therefore, analyzing productivity vitiations
is recommended where, and productivity deviation indices can be used for identifying bottlenecks and provides better forecasting of project cost and duration or for prospect estimates. Delivering this kind of productivity analysis in a timely manner guarantees proactive interference to keep project with its planned track. The advancement of sensing technologies and data processing techniques, provided a great opportunity for timely collection, transfer and analysis of data in near real-time. The majority of available technologies are off-the-shelf, expensive and in the form of a black box, such as On-Board Instrumentation Systems (OBIS). Also, the users of black box format have not the capability to access the relevant algorithms and modify it as they see fit. Also, the stored data is often difficult to be accessed without using the seller specific software. Limited research has been conducted to study and develop a customized design of automated data acquisition systems to overcome the limitations of off-the-shelf technologies. Open source technologies allocate a minute portion in data acquisition systems' marketplace. Also, studies of automated progress tracking and reporting lacked the integration of circumstantial data that could affect productivity such as driving behavior and road conditions. This type of data impacts realistic productivity assessment and analysis. The aforementioned background proves gaps and limitations that demonstrate the need for a near real-time open source automated model for monitoring and assessing the actual productivity of earthmoving operations.

3. Developed Model

The developed model introduces an automated model for tracking and monitoring productivity of earthmoving operations. The model automatically measures productivity of hauling equipment (dump trucks) and hence the productivity of earthmoving fleet. The developed model has the role of (1) collecting necessary data required for calculating actual productivity, (2) analyzing drivers’ behavior of hauling equipment, and (3) analyzing access and travelled road conditions.
Figure 1 shows the developed model flow chart, where different sensor data acquired in an automated manner. Then, this data is transmitted to the model’s relational database to be processed. Finally, achieving the model’s outputs as follow: truck state recognition, each state start and end time, hence each state duration, soil weight and volume in addition to the water content in the loaded soil. This output data is then used to calculate the actual productivity of each truck in the fleet. Automated determination of actual productivity allows for near-real-time recognition of productivity variations when compared to those planned. Furthermore, the model is capable of monitoring road conditions and drivers’ behavior.

**Insert Figure 1**

The model utilizes (1) a customized configured open source hardware (Waspmote®™) which was using Arduino®™ open source platform, (2) OBD (On-Board Diagnostic scanner). This hardware consists of a smart sensing board associated with a microcontroller as shown in Figure 2, where a variety of sensors are associated with the hardware for collecting data of weigh, acceleration, GPS coordinates and soil water content. The microcontroller and the smart board have a lightweight of 40 grams for both of them.

**Insert Figure 2**

Although the utilized smart boards, sensors and microcontrollers have a comprehensive application; construction activities are not a part of these applications. The smart board is dedicated to bundle a selected variety of sensors that satisfy the specific requirements of each project. This customization has been done through questionnaire-base, where the experts’ responses were analyzed to determine the most needed sensors in a ranked manner (Salem et al. 2017; Salem et al. 2018). The selected sensors undertake capturing of data required in calculating actual productivity. The microcontroller is a small computer, where it contains a limited capacity.
data processor, memory and in and out programmable peripherals. It drives all the associated
sensors by uploading special programming code syntaxes which control both the amounts and
acquisition intervals of the captured data.

3.1 Data Acquisition Module

a. Module description

Earthmoving operations are cyclic activities in which spatiotemporal data is a part and particular
of data needed for productivity measurement and analysis. The developed Data acquisition
system incorporates a GPS receiver module with the utilized microcontroller. The
microcontroller has integrated RTC (Real Time Clock) and a sensitive 3D accelerometer. The
RTC permits unified timestamps for all the collected sensor data to the timestamp of the GPS. It
sets its time and date by getting the data from the GPS, where time and date are identified by the
values returned by the GPS using a specific programming function.

A soil moisture content sensor and a load cell sensor are hosted by the smart board for collecting
water content naturally incorporated in the excavated soil and soil weight respectively. The
utilized soil moisture content sensor is an electrical resistance sensor for assessing soil water
tension which is also known as soil water suction. This sensor comprises a permeable body in
which a pair of electrodes is embedded. The sensor may be laid to rest at any desired depth in the
excavated soil which has been loaded in the truck. A two-wire lead from the sensor is connected
to the smart board mounted on the microcontroller. Such sensors actually measure the fluctuated
frequency of an electronic circuit or changes in this frequency (Evett 2008). Soil water content is
very dependent on soil type thus there is no direct way to achieve it from Soil water tension
without heading off to the laboratory (Evett 2008). Equation (1) depicts the relationship between
water tension and the sensor frequency reading according to the sensor’s data sheet (Libelium website 2018).

\[
TA = \frac{150940 + 19.74 \ F}{2.8875 \ F - 137.5} \quad \text{Equation (1)}
\]

Where:

- \(TA\) is water tension in Kpa
- \(F\) is frequency in Hz

The relation between these two parameters has been determined for some soil types using the curves shown in Figure 3 (MEA 2018). Web-Plot- Digitizer® application has been used to digitize the chart’s image to determine the relationship between soil water tension and percentage of water content and its most fitting equation.

Insert Figure 3

The relationship has been determined for three different types of soil; sand, clay, and loam as follow: (1) digitize the image of the specific curve, e.g., for sand, a soil moisture tension of 10 Kpa corresponds to 20% of soil moisture content, (2) establish a graphical representation of the relationship using the obtained pairs of digits, (3) recognize the most fitting equation demonstrates each curve. Aforementioned three steps procedure permitted converting the soil water content acquired sensor data from the frequency in Hertz into a percentage of water content. The higher the frequency, the lower water tension, and vice versa the lower water tension, the higher water content. Therefore, the higher frequency, the higher water content. This multi-step conversion process has been coded thru series of queries in the developed MySQL database. Table 1 shows the developed equations (2), (3), and (4) for sand, clay, and clay loam soils respectively. Where \(TA\) is the water tension measured in Kpa or Cmb (Centibar) and \(WC\ %\)
is the percentage of water content. Since the water tension represented in logarithmic scale, a range of 1:300 Kpa has identified as effective range for developing this algorithm.

**Insert Table 1**

Figure 4 (a), (b), and (c) represent these relationships for the three types of soil; sand, clay and clay loam respectively. Figure 4 (d) shows the relationship between water tension in centibars (Kpa) and the frequency in Hertz according to the sensor’s data sheet (Libelium website 2018).

**Insert Figure 4**

Soil water content remarkably contributes to the achievement of the truck’s payload, as the presence of water increases the total weight of soil. Hence, the truck may unnoticeably reach its weight capacity before reaching the commonly in-practice utilized volumetric burden. The recognition of the amounts of water associated with loaded soils contributes to not only retaining the truck away of mechanical damage due to over loading, but also sidestepping from the traffic penalties due to excessive loads than those designated for roads and bridges.

The degree of compaction is a vital requirement in related activities which encountered earthmoving operations, e.g., highways and earth-dams construction. The compaction is directly impacted by soil water content. Determining the water content automatically using the developed model eliminates the need of conducting the time-consuming field tests. These tests are typically done for determining the water content after the delivery of soils to the fill areas. The existed water content is compulsory to be known to calculate the required amount of water to be added to reach the optimum water content corresponding to the maximum dry density to achieve the desired degree of compaction. Equation (5) depicts the relation between existing natural water content and the required amounts of water which needed to be added to satisfy the maximum dry
density as shown in Figure 5, where this curve shows that soil reaches the maximum dry density when it contains the optimum amount of water content.

\[
WC_{opt} = WC_{ext} + WC_{req} \quad \text{Equation (5)}
\]

Where;

- \(WC_{opt}\) is optimum water content
- \(WC_{ext}\) is existing water content
- \(WC_{req}\) is required water content to be added

Insert Figure 5

The developed model works mainly on the hauling equipment (dump truck) in typical earthmoving operations. Figure 6 shows the different components of the developed model, part A: customized data acquisition system for collecting a variety of datasets. Part B: OBD II (On-Board Diagnostic scanner); provides self-diagnostic and reporting capabilities of the status of various vehicle sensors and subsystems. While part C: is a MySQL relational database which forms the model’s processing and reporting unit. Finally, part D: is the model’s output. Table 2 shows the data sets include different data components collected by the sensors associated with parts A and B.

Insert Figure 6

Insert Table 2

The microcontroller integrated RTC permits unified timestamps for all data sets collected using different sensors, where these timestamps work as a principal connecting identifier for the various entities in the relational database. In other words, the data records captured at the same time are connecting to each other through their respective timestamp. The frequency of obtaining
data differs from a sensor to another, which means that the time intervals of acquiring data is
varied accordingly as shown in Table 3.

Insert Table 3

b. Model Implementation

The developed model has been implemented initially by fixing the Waspmote data acquisition
module on the truck dashboard close to the windshield to guarantee a robust GPS-satellite signal.
The orientation of the data acquisition module is crucial, where the microcontroller’s integrated
3D-Axis accelerometer readings are aligned to X, Y, and Z axis of the truck. X + axis is
horizontally pointing towards the front of the truck, Y + axis horizontally pointing to the truck’s
right-hand side, while Z + axis is vertically pointing towards the roof. Figure 7 shows the
implementation and orientation of the developed data acquisition module, the utilized OBD II
scanner, and its connecting slot, where the adequately oriented data acquisition module fixed on
the truck dashboard. The OBD II has a specific 16-pin slot underneath the truck’s steering wheel.
The load cell sensor is fixed underneath the truck bed and connected through its four wires
electric plexus to the smart board. The water content sensor is attached to the truck bed and
connected by two wires to the smart board. Load cell and soil water content sensors are designed
to have long wires for connecting them to boards which helps the protection of the data
acquisition system in harsh environments.

Insert Figure 7

In the beginning, the utilized microcontroller connected to a laptop computer via standard mini-
USB data cable to upload the designated code for capturing data according to the user
commands. The hardware is powered by a 6600mAh -3.7V (Li-Ion) Lithium-ion rechargeable
battery through a particular slot for the battery connection. The low power consumption extends
the battery life for up to 8 hours before the need for recharging. The model also utilizes another economic and practical power source thru 12V truck’s battery port. The hardware has data storage capabilities, where a maximum 2 GB micro SD card can be inserted into the data logger slot. The developed model stores the different collected sensor data on SD card in CSV format, which in turn is transmitted to the SQL database for applying different algorithms and procedures. Figure 8 shows a schematic architecture of the model’s inputs and the interim CSV output files.

Insert Figure 8

3.2 State Recognition

Earthmoving operations are cyclic and encounter repetitive tasks, in which each of the involved equipment has a specific state. The states of different equipment are directly related to each other, for example, a truck in a loading state means that at least one loader or excavator is doing that loading. The hauling equipment (dump truck) is considered a Common denominator in earthmoving operations, where the identification of the truck state is an essential step towards measuring its productivity and hence the productivity of the fleet. The developed data acquisition module collects multiple sources data, which are heterogeneous in nature, content, and format. Each set of the collected data may have some characteristic patterns and trends that could help in recognizing the state of the truck. The vast sums of collected data make the manual observation of these patterns and trends a very challenging task that consumes time and lacks accuracy. The developed model overcomes this problem, where the developed relational MySQL database navigates through all collected sensor data regardless of its source to recognize the truck state. The developed algorithm fuses different types of data by satisfying some specific predetermined conditions in each truck state.
The hauling equipment has six probable states of operation which are frequently repeated in earthmoving operations. These states usually happen in this order: wait for loading, loading, hauling (traveling), wait for dumping, dumping and returning back to the loading or cut zone. These six states form a complete earthmoving cycle. Another possible state is out of service in which the truck may become in idle mode regardless of its location. Two additional states are considered: exist loading zone and exist dumping zone, to differentiate the traveled distances in and out these zones. This differentiation is crucial in the assessment of access roads condition.

Data sampling process has been done to determine the prevalent ranges throughout each state. So, a number of experiments have been conducted to distinguish the different patterns and trends of each sensor data set in the course of each state. The purpose of these experiments is to determine the most probable lower and upper sensor readings, i.e., the maximum and minimum acceleration readings in the three directions for each state. Similarly, the lower and upper limits have been determined for soil water content.

Accordingly, a truck is considered in traveling state when (1) its previous state of operation was loading, (2) GPS data refers to a location within the access or travel road, (3) OBD II data records a speed higher than 0 Km/h, (4) load cell shows an electrical potential approximately equivalent to the truck payload capacity, and (5) soil water content and acceleration records fall within the predefined ranges.

### 3.3 Data fusion algorithm

The model fuses captured sensors data to recognize the truck state. Then the timestamps for the start and end of each state are used to determine the duration of each state. And accordingly determine the total duration of each earthmoving operations cycle. Figure 9 shows a tabulation of the prevalent sensor data patterns and trends which are utilized to develop data fusion algorithm.
3.4 Positioning trucks and correlation to soil properties

The database is programmed to run the algorithm shown in equation (6) to scan the GPS detected latitude and longitude recorded points to determine whether the truck is located within the loading, dumping zones or the hauling road. This algorithm is built on Jordan Curve Theorem, where; any continuous simple closed curve cuts the plane in exactly two pieces: the inside and the outside (Princeton University 2018). It checks if any line segment of the polygon intersects a ray from the GPS point of study. The polygons shaped by the coordinates of the different points of both loading and dumping zones were registered in the database as predefined givens. Hence this algorithm checks if the recorded truck’s coordinate lie in or out of this polygon. Figure 10 shows the change of soil properties within the same loading zone, where the loading zone is divided into 3 sub-zones G1G5G6, G1G2G5, and G2G3G4G5 respectively. This segmentation is based on the change in soil density from a sub-zone to another. The same procedure is applicable for a multi-cut and fill zones in case of highway construction, where soil properties are most probably changeable from a cut zone to another.

\[ Y_0 = \frac{Y_{i+1} - Y_i}{X_{i+1} - X_i} (X_0 - X_i) + Y_i \]  

Equation (6)

Where;

\[ X_i \leq X_0 \leq X_{i+1} \]
The readings of the load cell are interpreted from the electrical potential in Microvolts to weights in Kilograms using the proper conversion formula according to the load cell data sheet. Soil reports are always prepared prior commencement of projects, where these reports include soil density for different spots within the same site depending on its area. Consequently, for the same loading zone; may have a variety of soil densities. The captured GPS data during the loading state permits the stipulation of related soil density to the loaded soil. Hence the model determines the loaded soil volume using payload information from load cell and the specific soil density associated with exact area of the loading zone.

Figure 11 represents the flowchart of the productivity measurement algorithm. The model takes into consideration not only the change of soil types but also its water content. The productivity analysis module is responsible for comparing actual and planned productivity. It also associates any loss in productivity with operational and road condition.

**Insert Figure 11**

### 4. Driving and road condition analysis

Operational behavior of truck drivers and travelled road conditions impact productivity in earthmoving projects. Achieving targeted productivity usually leads equipment operators to stress the equipment beyond its upper limit capacity. As well the driver to achieve higher production rates may lead to harmful and abusive actions for hauling equipment (i.e., speeding, harsh acceleration, and braking). A 3D accelerometer is used for recognizing undesirable driver behavior of hauling equipment. The proposed accelerometer is build-in the microcontroller. The Wasp mote built-in accelerometer can make up to 2560 measurements per second from -6g to +6g on the three axis X, Y, and Z. The algorithm shown in Figure 12 depicts driving and road conditions analysis, where captured acceleration data is processed to realize any exceedance over
a particular limit to report driving or road condition problem. The application of this algorithm allows automated monitoring of hauling equipment drivers to detect and report any adverse behavior and travelled road deficiencies as well. Alerts are triggered by excessive speeding, harsh breaking, severe maneuvers and unsafe lane changes. Figure 13 shows a sample of the 3D accelerometer data representation and driving and detection of abnormal road conditions, where harsh brake and acceleration can be recognized by the data represented on X. Also, data shown on Y recognizes harsh maneuvers, while Z delivers graphical detection of ruts and bumps. The boundaries of safe and harsh accelerations and brakes are ±0.3g and ±0.5g respectively (Langle & Dantu 2009; Fazeen et al. 2012; Li et al. 2017).

**Insert Figure 12**

**Insert Figure 13**

The algorithm utilizes these acceleration boundaries to flag violent operational behavior. The microcontroller is coded using C++ syntax, where the acceleration thresholds are defined as triggers. The data collected by the integrated 3D accelerometer is processed in the central MySQL database, where acceleration data integrated with GPS data to recognize the driving triggered event time and location.

The utilized data acquisition module permits an opportunity to process this data in the microcontroller, which means in-sensing-node processing. This data processing procedure requires the utilization of GPRS module that can send alerts in the form of short text or recorded vocal messages. The procedure above permits data collection, aggregation, and analysis in near-real-time. Moreover, it allows exact momentous and rapid retrieval of the data analysis results.
5. Case study

The applicability of the developed model has been examined through a designed hybrid case study to evaluate and validate the model. This case study is divided into two integrated stages, where the first stage has been performed using a scaled loading and hauling equipment due to unavailability of real loading and hauling equipment. In this stage, a total of 100 buckets with different fill capacities were handled into the truck bed, while the data acquisition module was installed and appropriately oriented above the cabinet of the scaled truck. Acceleration data has been recorded in a high sampling rate (100 reading/second). Also, the load cell records, water content sensor readings have been filed in CSV format. All data sets have been recorded in the SD card. Therefore, the second stage started using a real vehicle, where the data acquisition module and the OBD II scanner have been appropriately attached to the car as explained in the developed model section. Then the vehicle has performed several trips between 2 designated locations which identified as loading and dumping zones. Figure 14 illustrates the case study field showing loading, dumping zones and hauling roads.

Insert Figure 14

In this stage, the vehicle has simulated different states as in real earthmoving operations. Duration of each state has been recorded using time laps. GPS, acceleration and OBD II data have been stored in the SD card in a CSV format. Thereafter, all the acquired data from the two executed stages have been transmitted to the central MySQL database. The designated procedure has been run invoking the application of the developed algorithms. Figure 15 shows model outputs of 2 trips in this case study, where every two adjacent columns with the same color are representing a specific state in which the first column shows the start and the second column indicates the end of this state. The figure also shows the developed procedure to calculate
productivity of a dump truck and hence the total productivity for a fleet of trucks. In this procedure, exact volumes of soil were calculated using the records of the load cell and the precise density of the excavated soil based on its location determined using the GPS module.

**6. Results and discussion**

The study demonstrated virtuous capabilities of the developed model including the recognition of the truck’s state of operation and the duration each state. Table 4 and Figure 16 show a comparison between the actual operational times for each state captured using a stopwatch and time laps and the calculated durations of the developed model. In this comparison, the calculated durations for exit loading and dump areas; were added to the hauling and return states respectively. The model demonstrates ability to recognize different states even for the ones which take few seconds as in the states of exit loading and dumping zones, where they have durations as little as 5 seconds.

**7. Conclusion**

This paper introduces a novel automated model for near real-time monitoring and assessment of productivity in earthmoving operations. The developed model consists of four modules; (1)
automated data acquisition module, (2) planned productivity module, (3) automated measurement of actual productivity module, and (4) driving and road condition analysis module. A variety of sensors, smart boards, and a microcontroller are utilized in the development of the customized data acquisition module. A sensor data fusion algorithm is developed for accurate productivity measurement. The model fuses data acquired by different sensing technologies to recognize the operational state of hauling trucks, start and finish times for each state of operation, hence the duration of each earthmoving cycle. The integrated load cell captures the loaded soil weight which is used to calculate its volume and hence truck and fleet productivity. The driving and road condition module is capable of detecting drivers’ offensive behavior such as aggressive acceleration and barking, also it can identify unsafe maneuvers and lane change. This module can automatically detect road anomalies and differentiate between potholes and bumps. The model is configured in a customized manner to serve the individual needs of earthmoving projects. This customization philosophy could be applied for other construction applications. The developed model has been validated using a scaled case study and was not applied to a real earthmoving project. The developed model demonstrated to measure actual productivity in an accurate manner, where a case study has been used to reveal the applicability and accuracy of proposed model in monitoring and assessing actual productivity. The recommended future work of this research is to develop a web-based application through which the near real time automated measured productivity could be retrieved remotely.

8. References


Fu, J., 2013. Logistics of earthmoving operations: simulation and optimization (Doctoral dissertation, KTH Royal Institute of Technology).


Princeton University, Department of computer science. 2018


I. Data Acquisition Module

- GPS
- Load Cell
- Accelerometer
- OBD II
- Soil Water Content Sensor

Collect Data

II. Data Transfer and Processing

- User Input
- Planned Productivity
  - Soil Density Polygon and Sub-polygons
  - Truck ID
  - Driver ID
  - Loader ID
  - Loader Operator ID
  - Excavator ID
  - Excavator Operator ID
  - Loader Bucket’s Capacity
  - Excavator Bucket’s Capacity
  - Spotter ID

- Loading and Dumping Zones Polygons

- Project Relational Database
  - Zone Polygons
  - Divide into Sub-polygons based on Soil Properties
  - Determine Latitude and Longitude

Data Fusion and Processing

III. Model Output

Output

- Truck’s State Recognition
  - States’ Duration
  - Productivity

- Soil Weigh

- Soil Volume

- Soil Water Content

- Road Conditions and Driver Behavior

- Water Required for Desired Degree of Compaction

- Fleet Productivity

- Actual VS Planned

- Productivity Analysis

Figure 1 Proposed model flow chart
Figure 2 Components of the customized data acquisition module
Figure 3 Typical relationship between soil water tension and soil water content (MEA, 2018)
Figure 4 (a), (b), and (c): WC % - TA relationship for sand, clay, and clay loam respectively. (d): Relationship between water tension and frequency (Libelium®, 2018)
Figure 5 Relationship between dry density and soil water content
Figure 6 Components of developed model
Figure 7 Data acquisition modules implementation and orientation
Figure 8 Schematic architecture of the model’s inputs and interim CSV output files
In this study and due to the space consideration, some values have been abbreviated as follow:

1. Acceleration in any of the 3 directions ≈ 0, means it is range -0.25g: +0.25g.
2. Ranges determined experimentally depend on hauling roads.
3. Load cell reading in microvolt ≤ 1.5 loader bucket’s capacity.
4. EPC: Equivalent Payload Capacity for truck.

**Figure 9 Prevalent sensor data patterns and trends utilized to develop the data fusion algorithm**
Figure 10 Change of soil properties within the same loading zone
Figure 11 Flowchart of the productivity measurement algorithm
Figure 12 Flowchart of driving and road condition analysis algorithm
Figure 13 3D accelerometer data representation, driving and road conditions recognition
Figure 14 Case study field: loading, dumping zones and hauling roads
### MySQL - Output

#### Truck States’ Start & End

<table>
<thead>
<tr>
<th>Trip_id</th>
<th>W4L_S</th>
<th>W4L_E</th>
<th>L_S</th>
<th>L_E</th>
<th>ELS</th>
<th>ELE</th>
<th>H_S</th>
<th>H_E</th>
<th>W4D_S</th>
<th>W4D_E</th>
<th>D_S</th>
<th>D_E</th>
<th>ED_S</th>
<th>ED_E</th>
<th>R_S</th>
<th>R_E</th>
</tr>
</thead>
</table>

#### Truck States’ Duration

<table>
<thead>
<tr>
<th></th>
<th>W4L_duration</th>
<th>W4L_duration</th>
<th>L_duration</th>
<th>L_duration</th>
<th>ELS_duration</th>
<th>ELE_duration</th>
<th>H_duration</th>
<th>H_duration</th>
<th>W4D_duration</th>
<th>W4D_duration</th>
<th>D_duration</th>
<th>D_duration</th>
<th>ED_duration</th>
<th>ED_duration</th>
<th>R_duration</th>
<th>R_duration</th>
<th>Total_duration</th>
<th>Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0:01:49</td>
<td>0:01:41</td>
<td>0:01:30</td>
<td>0:00:11</td>
<td>0:02:14</td>
<td>0:00:05</td>
<td>0:02:42</td>
<td>0:10:46</td>
<td>816.94</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0:01:36</td>
<td>0:01:39</td>
<td>0:00:51</td>
<td>0:00:22</td>
<td>0:03:34</td>
<td>0:00:07</td>
<td>0:01:59</td>
<td>0:10:42</td>
<td>766.298</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Truck productivity** \( m^3/\text{hr} \) = \( \frac{\text{Soil Volume (m}^3\text{)}}{\text{Cycle time (hr)}} \)

**Total Productivity** = \( \sum_{i=1}^{n} \text{Truck Productivity (i)} \)
Figure 16 Durations of different states of operations for the two trips
Table 1 Best fit equations represent the relationship between (WC) % and TA

<table>
<thead>
<tr>
<th>Soil Type</th>
<th>TA 1:300 Kpa (Effective range)</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sand</strong></td>
<td>(WC) % = - 4.036ln TA + 28.342</td>
<td>Equation (2)</td>
</tr>
<tr>
<td><strong>Clay</strong></td>
<td>(WC) % = 3 x 10^{-5} TA^2 - 0.0371 TA + 32.298</td>
<td>Equation (3)</td>
</tr>
<tr>
<td><strong>Clay Loam</strong></td>
<td>(WC) % = 0.0002 TA^2 - 0.1265 TA + 37.741</td>
<td>Equation (4)</td>
</tr>
</tbody>
</table>
### Table 2 Utilized sensor data and each dataset components

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Data Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPS</td>
<td>Timestamp, latitude, longitude, altitude, course, and speed</td>
</tr>
<tr>
<td>Accelerometer</td>
<td>Timestamp, acceleration in three direction X, Y, and Z (m / sec(^2))</td>
</tr>
<tr>
<td>Load cell</td>
<td>Timestamp, Electrical potential in Microvolt, which converted to weigh in Kg</td>
</tr>
<tr>
<td>Water content sensor</td>
<td>Timestamp, frequency in Hz, which converted to water tension that converted to % of water content</td>
</tr>
<tr>
<td>OBD II</td>
<td>Timestamp, Speed, and engine rpm (revolution per minute)</td>
</tr>
</tbody>
</table>
### Table 3 Data sampling rates for each of the utilized sensors

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Date record delay</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPS</td>
<td>3 Seconds (≈ record each 3 sec)</td>
</tr>
<tr>
<td>Accelerometer</td>
<td>0.01 Second (≈ 100 records / sec)</td>
</tr>
<tr>
<td>Load cell</td>
<td>10 Seconds</td>
</tr>
<tr>
<td>Water content sensor</td>
<td>10 Seconds</td>
</tr>
<tr>
<td>OBD II</td>
<td>0.2 Second (≈ 5 records / sec)</td>
</tr>
</tbody>
</table>
Table 4 Actual manual vs developed model’s calculated records

<table>
<thead>
<tr>
<th>Actual Dur. (Sec.)</th>
<th>Model Dur. (Sec.)</th>
<th>Difference (Sec.)</th>
<th>Error %</th>
<th>Total Dur. (Sec.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Trip 1</td>
<td>Trip 2</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Wait for Loading</td>
<td>Loading</td>
<td>Hauling</td>
<td>Wait for Dumping</td>
</tr>
<tr>
<td>103</td>
<td>97</td>
<td>147</td>
<td>96</td>
<td>38</td>
</tr>
<tr>
<td>109</td>
<td>90</td>
<td>145</td>
<td>101</td>
<td>34</td>
</tr>
<tr>
<td>6</td>
<td>-7</td>
<td>-2</td>
<td>5</td>
<td>-4</td>
</tr>
<tr>
<td>0.0583</td>
<td>-0.0722</td>
<td>-0.0136</td>
<td>0.0521</td>
<td>0.1053</td>
</tr>
</tbody>
</table>

(1) Based on manual observation using stopwatch.
(2) Calculated based on captured sensor data.