www.itcon.org - Journal of Information Technology in Construction - ISSN 1874-4753

AUTOMATED PRODUCTIVITY ASSESSMENT OF EARTHMOVING OPERATIONS

SUBMITTED: March 2014
REVISED: July 2014
PUBLISHED: July 2014
EDITOR: Žiga Turk

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SUMMARY: *This paper presents an automated system for actual productivity assessment of earthmoving operations in near real-time. Several research attempts had been made to calculate productivity, but a number limitations had been found in literature such as, assuming the hauling unit is loaded to its full capacity and the need for manual user entry of efficiency factors (For example: bucket fill factor). The proposed system addresses some of the limitations found in previous research. The system consists of hardware and software developments. The hardware consists of three main units: (1) Truck mounted unit, (2) Loader mounted unit and (3) Fixed unit at the construction site. The software development consists of three main algorithms: (1) Data processing algorithm, (2) Productivity calculation algorithm and (3) Operating conditions analysis. Using sensor-aided GPS, site data is collected, organized and saved in the system's database, which is housed on a central server. Equipment location is tracked using the GPS, while the hauling unit load weight is measured using strain gauges mounted on its suspension and wired to a micro-controller. The loading and dumping activities are monitored by a number of sensors mounted on both the loader and trucks. The site weather condition is recorded and correlated with measured productivity in each recorded interval for later use in future estimates. A simulated case study is presented to demonstrate the usage and capabilities of the system. The case study demonstrated how the proposed system can assist project managers in measuring actual projects.*

KEYWORDS: *Automated Productivity Assessment, Progress Tracking, Earthmoving Operations*

REFERENCE: *Magdy Ibrahim & Osama Moselhi (2014). Automated productivity assessment of earthmoving operations, Journal of Information Technology in Construction (ITcon), Vol. 19, pg. 169-184, http://www.itcon.org/2014/9*

1. INTRODUCTION

Earthmoving operations involve moving of massive quantities of soil or unformed rock. Earthmoving work package usually occupy around 20% of total amount of construction project cost (Kang et al 2009). Therefore, estimating onsite earthmoving productivity is always a main concern for project managers (Zhang et al., 2009). However, the key challenge in accurate productivity estimation is the collection and evaluation of a large amount of onsite data. Traditional manual methods for productivity estimation are not only expensive and subject to human error but also are delivered with a time lag. Field supervisory personnel on construction site spend between 30-50% of their time recording and analyzing field data (McCullouch 1997) and 2% of the work on construction sites is devoted to manual tracking and recording of progress data (Cheok et al. 2000). In addition, since most data items are not captured digitally, data transfer from a site to a field office requires additional time. When the required data is not captured accurately or completely, extra communication is needed between the site office and field personnel (Thorpe and Mead 2001).

The construction industry lags behind other industries in adopting innovative new technologies (Kulatunga et al. 2006). Reichstein et al, (2005) conducted a study using data from 'UK innovation survey' found out that less number of firms in construction sector are engaged in product and/or process innovation than other sectors. The need to accelerate the rate of technological adoption in the construction industry has been well documented in the literature (Mitropoulos and Tatum, 2000). The rapid advances in sensing technologies motivated researchers to study the feasibility of using such technologies to automate and integrate individual technologies for automated productivity estimation in the construction industry. With the development of site data acquisition technologies, a large amount of data can be collected on construction sites in semi-automatic and semi-continuous bases. However, processing and reducing data to meaningful conclusions and fusing the data from different sources remain as obstacles for achieving a practical automated progress tracking solution on construction sites. Soibelman et al. (2008) noted the problem of the increasing volume of the collected data on construction sites.

This paper presents an automated method for productivity assessment of earthmoving operations using sensor-aided GPS that not only facilitates data collection on site, but also evaluates the project performance in near real-time. The developed method includes hardware and software developments. The hardware development encompasses a microcontroller, set of sensors and GPS. Bluetooth wireless communication is utilized for data streaming and proximity detection. A localized data management scheme is implemented to maximize the collected data utilization. The software development includes three algorithms: (1) Data processing algorithm, (2) Productivity calculation algorithm and (3) Operating conditions analysis. The developed method was tested on eight experiments, with a total execution time of 124 hours. The results of these experiments indicated that the presented method provide better results than "traditional" GPS methods.

2. LITERATURE REVIEW

In earthmoving operations, measuring actual performance and forecasting project time and cost during its execution are crucial for successful project delivery. Problems associated with measuring actual performance have been widely recognized and are well documented (Bassioni et al. 2004). Effective performance measurement relies on accurate and timely data collection from construction sites. Measuring actual performance enables comparison with the as-planned progress. This comparison enables the determination of project status and assists in identification of selecting appropriate corrective actions. Traditionally, site data collection has been commonly based on manual methods, in which the collected data are recorded on paper by human observers. Manual methods are recognized to be costly and not necessarily accurate (Hildreth et al. 2005).

Earthmoving operations have received considerable attention from researchers and industry professional. Wide ranges of methods and technologies were used in tracking and control of these operations. For example, Global Positioning System (GPS) and radio frequency identification (RFID) technologies had been utilized for progress tracking (Hildreth et al. 2005; Navon and Shpatnisky 2005; Montaser and Moselhi 2012). Hildreth et al. (2005) proposed a method for data processing of earthmoving information using GPS technology located on-board vehicles to determine start and stop times of activities such as loading, hauling, dumping, and returning. Navon and Shpatnitsky (2005) used GPS technology to measure earthmoving performance automatically by identifying the locations of equipment at regular time intervals and converting the information into a project performance index. However, there are a number of shortcomings associated with standalone GPS. The acquired data is limited to time and location which sometimes makes it difficult to distinguish between productive and non-value-added movements. Also, these spatiotemporal records cannot help in the review process to find the events that caused abnormal cycles. Montaser and Moselhi (2012) utilized RFID to estimate the loading, hauling, and dumping times of the dump trucks. Fixed readers installed at entrance gates of loading and dumping sites record the entrance and exit of RFID tags attached to dump trucks. The time differences are considered as loading, traveling, and dumping cycle times. However, implementation of this system is cumbersome in linear projects such as road and highway construction. Further, it cannot confirm whether the truck is actually fully loaded.

Computer vision–based methods offer an alternative approach to monitoring and tracking of construction activities. In this respect, several researches used video processing including object tracking (Brilakis et al. 2011; Park et al. 2011) and object recognition (Azar Rezazadeh and McCabe 2011; Chi and Caldas 2011; Jog et al. 2011; Azar Rezazadeh and McCabe 2012). However, their proposed algorithms for object recognition, tracking, and segmentation can fail under certain conditions, particularly in the visually noisy images of a typical construction site. Kim et al (2011) developed a wireless real-time vision based productivity measurement system. In that he conducted two field experiments on asphalt paving project and a bridge reconstruction project. While the results of these experiments generated identical productivity measurements to those calculated using the stopwatch method, his method is limited to the use of one camera, which is not adequate to represent site conditions in a wide range of projects. As well, his method is not fully automated; requiring continuous human involvement to analyze the data. That human involvement not only results in delays but also is prone to errors due to human biases. Azar et al (2013) introduced a vision-based framework, which can recognize and estimate dirt loading cycles. The results showed that their system could recognize and measure 98.2% of the loading cycles with 95% accuracy in durations; however, their system is not only vulnerable to occluded equipment images but also is incapable of handling more than one operating excavator.

Despite the few commercially available solutions for tracking and control of earth moving equipment, most of them are semi-automated and require manual user input. For example, the "Haul Truck Assignment and Tracking System" developed by Topcon (2014), can track load/dump time and locations, but the operator must push a button when loading and dumping is performed on site. This system alone is not able to track real-times volumes being moved on site, another system such as SiteLink3D must be integrated to receive automated volume reports. The need of multiple systems to automate the process has a high cost impact on the contractor.

While progress tracking of road construction operations has been investigated using different emerging technologies (e.g., GPS, Radio Frequency Identification (RFID), Ultra Wideband (UWB), image based systems and video), GPS remains the most common current practice for semi automated on-site data acquisition on road construction projects. Perkinson et al (2010) conducted a survey to establish the state-of-practice of GPS data collection and utilization by heavy construction contractor companies in the United States. Survey responses collected from 155 companies showed that a majority of the contractors surveyed actively used GPS on their jobsites. However, these companies were not taking full advantage of the technology as approximately half of them did not record the data generated by GPS and a majority of the contractors that collected GPS data did not use it to its full extent or in a meaningful way. The survey identified the primary reasons why contractors were not collecting and using GPS data as (i) the lack of a suitable Information and Communication Technology (ICT) infrastructure, (ii) the lack of a clear understanding of the benefits, and (iii) the contractors' lack of knowledge of how to successfully collect and use GPS data for project management applications.

3. RESEARCH OBJECTIVES AND MOTIVATION

The above review identified the limitations and gaps in related research work. The literature revealed the need for enhanced on-site data acquisition and automated on-site productivity assessment, particularly customized tools that address this need. The latest advances in remote sensing technologies and the need for effective data management schemes were main motives behind this research.

The main objective of this research is to develop a method for near-real time productivity assessment of earthmoving operations and to support current practice in tracking and control of construction projects. The developed method encompasses innovations in hardware design and automated data processing algorithms. The hardware incorporates latest advances in sensing technologies. The software algorithms are designed to eliminate manual user intervention and provide fully automated near- real time productivity estimates and onsite progress reports. The developed method utilizes effective data management scheme that not only enhances data collection and processing but also maximizes the useful utilization of collected data.

4. DATA COLLECTION SCHEMES

Information communication technologies (ICT) can broadly be defined as technologies dedicated to information storage, processing and transmission. Also, it involves a combination of hardware, software and networks to transform raw data into useful information for speedy retrieval (Farag, 2009). Effective data collation, information transfer and information retrieval have been cited as important areas for improvement in construction (Bowden, 2005). By enhancing information flow between different site processes and teams, it becomes easier to monitor, control and assess project progress and hence integrate on-site processes effectively (Moniem, 2000). It is beneficial for contractors, subcontractors, owners and their construction management teams to monitor onsite productivity. However, with the deployment of advanced site data acquisition technologies, a large amount of data is collected. Effective processing of such huge volume of data remains a challenge; particularly for near-real time automated productivity assessment on construction sites. Ward et al. (2004) noted the need for customized and tailored data management schemes for different construction processes. He suggests that efforts should be made towards providing a standard set of interfaces which can enhance data collection and information extraction.

In automated site data acquisition methods such as those cited in the literature review above, data collection schemes commonly use sensors or readers to relay raw data to a mobile computing. Such raw data has little value in itself. Hence this data is processed to extract meaningful information. The data collection scheme adopted in these methods suffers from high volume of data traffic towards the sink node, which creates bottleneck and, hence results in long processing time (see Figure 1).

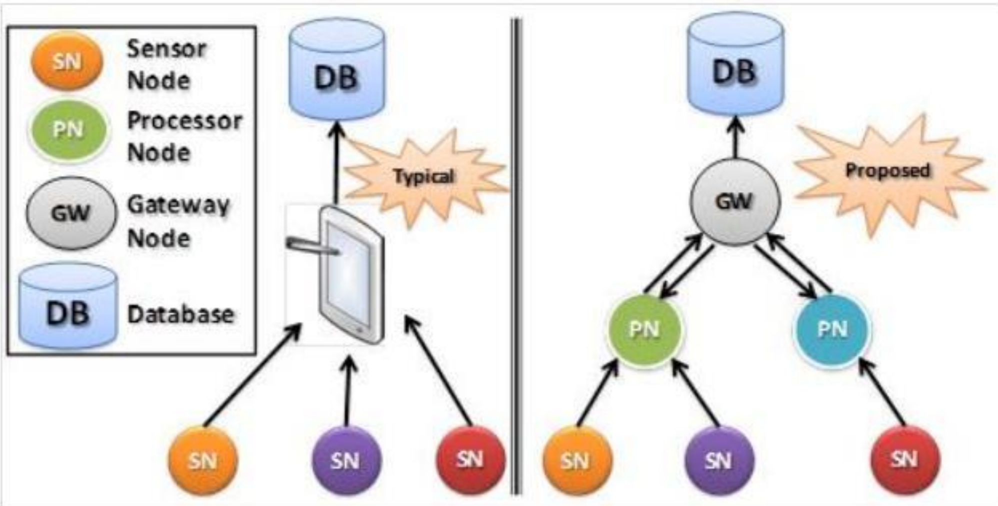


Figure 1: Data Collection Schemes

The proposed scheme supports localized cooperation of sensor nodes to perform complicated tasks and in-network data processing to transform raw data into high level useful and actionable information. Towards this direction, data aggregation and processing have to be done in a way that renders it valuable to large-scale real-life applications that receive near- real time data. Sensory data has to be collected, aggregated and interpreted at the sensor node level. This decreases post-processing time and user intervention required for analyzing processed data for project tracking and control. The proposed sensor network is built using a gateway node and one or more sensor nodes. The gateway node has sufficient computing power and no energy or memory restrictions. That acts as interface to the system. The sensor nodes are resource constrained devices, running on batteries and perform actual data acquisition. The sensor nodes are organized into a tree that routes data directly towards the gateway node as shown in Figure 1. Such tree configuration facilitates in-network aggregation and reduces the amount of data routing.

5. PROPOSED METHOD

The developed method consists of four modules; 4-D model generation module, activity recognition module, site operations module and project control module (see Figure 2). The 4-D model is generated by integrating the 3-D terrain model and the project schedule. The generated 4-D model defines equipment work zones in relation to scheduled activities. The defined work zone coordinates serve as boundaries for equipment tracking as described later on. A list of pending activities is generated based on their completed predecessors. Planned quantities for each pending activity are calculated from the 4-D model using trapezoidal rule based on longitudinal and cross-section profiles of road sections. Activities under execution are recognized by the activity recognition module which utilizes sensed equipment locations and cross match it with work zone boundaries of pending activities. Also crew formation is identified using RF proximity detection and cross checking of allocated resources. Once an activity is identified as being under execution, its actual progress (start, finish, duration and quantities) is estimated by the site operations module. Actual productivity is estimated based on measured time using the developed hardware, actual excavation quantities measured by strain gauges mounted on hauling trucks and actual materials delivered to the site. Data from accelerometers mounted on equipment and weather station on site is analyzed to flag any interruptions in work performed on site; which can be utilized for improved forecasting of project status. The project control module estimates actual progress based on actual productivity measured on site. Project total cost and duration at completion are forecasted based on actual progress, taking into account onsite operating conditions.

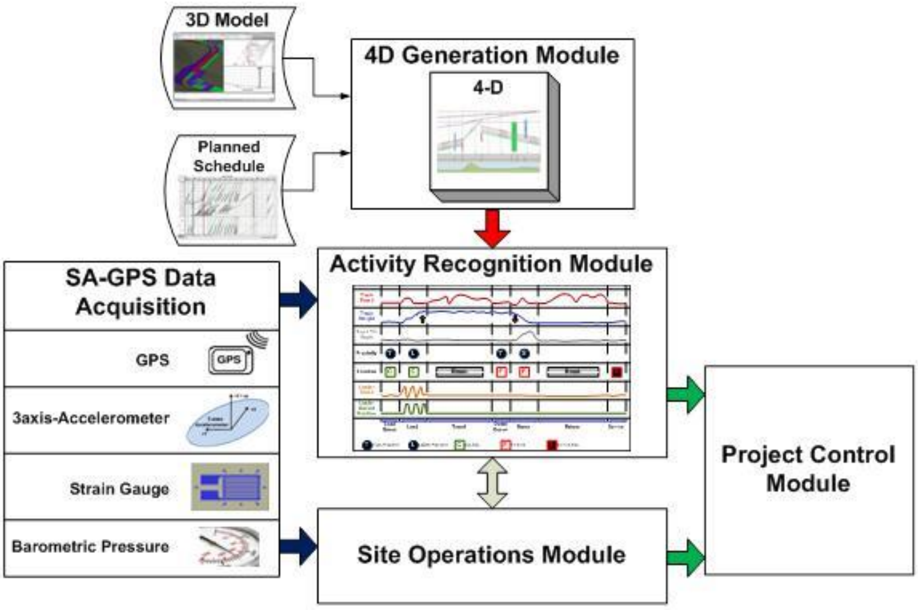


Figure 2: Proposed Productivity Assessment Method

5.1 Design Criteria

The main design criteria for the proposed method are:

a) Accuracy: The main performance measure in comparing the proposed method to traditional methods is the productivity measurement accuracy. The higher the accuracy, the better the system; however, there is often a tradeoff between accuracy and other characteristics such as cost. The accuracy is measured as the average error in the productivity assessment.
b) Latency: The system latency is attributed to hardware, computing, and human intervention/efforts during data transfer and processing. The proposed method is designed to measure the productivity in near real-time, which requires fast and efficient data processing with no human intervention.
c) Scalability: The proposed method is required to be applied to any project size without any need for further adjustment or development.

d) Robustness: The system robustness is defined by its ability to function normally even when some signals are not available. The proposed method is designed to have multiple data sources from different sensors and be able to function even if some sensor data is missing or corrupted.

e) Cost: The proposed method must be cost effective with respect to traditional methods.

5.2 Hardware Implementation

The hardware is designed to satisfy the above mentioned design criteria. The proposed hardware consists of mobile units and fixed units. The mobile units are mounted on all equipment of road construction fleet. The fixed units are installed in key points on the construction jobsite. The mobile unit consists of a basic configuration and a number of sensors. The sensors configuration is selected according to equipment type. The basic system configuration consists of a microcontroller with data logging capabilities, a RF module, GPS positioning module, and power supply. The Block diagram of the mobile unit is shown in Figure 3.

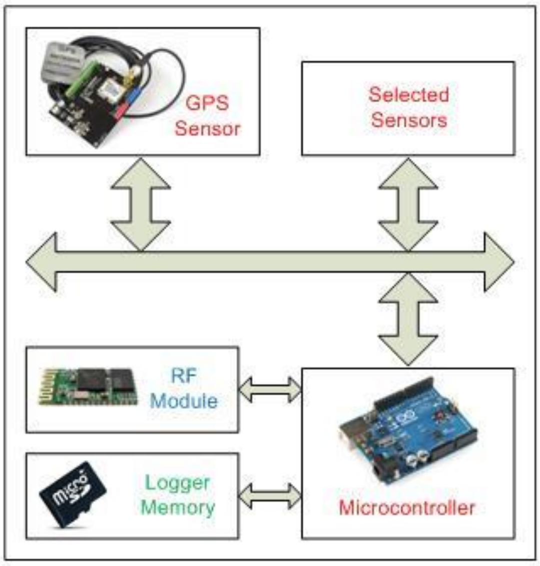


Figure 3: Mobile Unit Block Diagram

The characteristics of the selected sensors are presented in Table 1.

Table 1 Sensors Characteristics

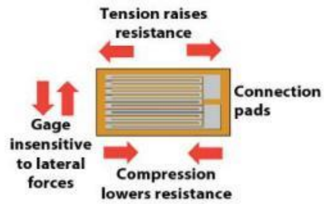
<table>
<tr>
<td>Strain gauge is a sensor whose resistance varies with applied force; It converts force, pressure, tension, weight, etc., into a change in electrical resistance which can then be measured as shown in Figure 4. Four strain gauges are mounted on hauling truck leaf springs. The payload is obtained by summing up measured loads in the four gauges.</td>
<td>

Figure 4: Strain Gauge Sensor</td>
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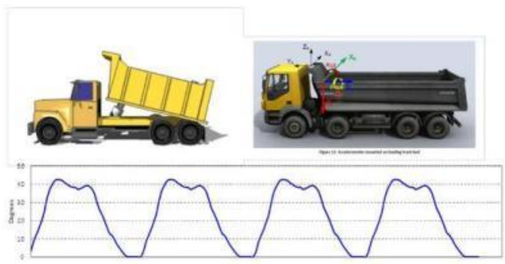
<td>3-Axis accelerometers are widely used for tilt sensing in industrial applications, such as automobile security alert systems. A full measurement scale of ±3 g is optimum for tilt sensing applications. The accelerometer is installed in a truck bed as shown in Figure 5. The tilt angle is calculated as:

$\alpha = \arcsin(a/g)$ Eq. (1)

Where: a is the measured acceleration and g is earth gravity vector.</td>
<td>
Figure 5– Accelerometer Mounted on Truck Bed</td>
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</table>

Barometric pressure sensor for elevation measurement. An altimeter does not actually measure altitude directly, but rather just atmospheric pressure. The barometric pressure sensor is attached to a loader bucket as shown in Figure 6. The bucket altitude is calculated as:

$$\text{Altitude} = 44330 \times \left(1 - (p/p_0)^{(1/5.255)}\right) \quad \text{Eq.(2)}$$

Where: p is the measured pressure and p0 is the pressure at sea level in (hPa).

Figure 6 –Pressure Sensor Attached to Loader Bucket

5.3 Hardware Configuration

The prototype was built using five main hardware modules described above in the integrated configuration shown in Figure 7. The description of each module is outlined below:

- Arduino Uno microcontroller, which is based on the ATmega328. This microcontroller has 14 digital input/outputs and 6 analog inputs. It is reasonably priced and development software is open-source.
- Roving Networks (RN-41) RF module. It is a Class 1 Bluetooth Module. Its Data transfer rate is up to 3-Mbps with a range up to 100 meters.
- SkyTraq (Venus638FLPx) GPS module. It is a high performance, low cost, single chip GPS receiver. It has low power consumption, high sensitivity, and low time-to-first-fix.
- Analog Devices (ADXL335) 3-axis accelerometer. It measures static acceleration of gravity in tilt-sensing applications, as well as dynamic acceleration resulting from motion, shock, or vibration.
- Adafruit Industries (DS1307) data logger. It has a real time clock (RTC) with backup battery for up to 7 years of timekeeping. It can fit any SD/MMC storage up to 32GB.

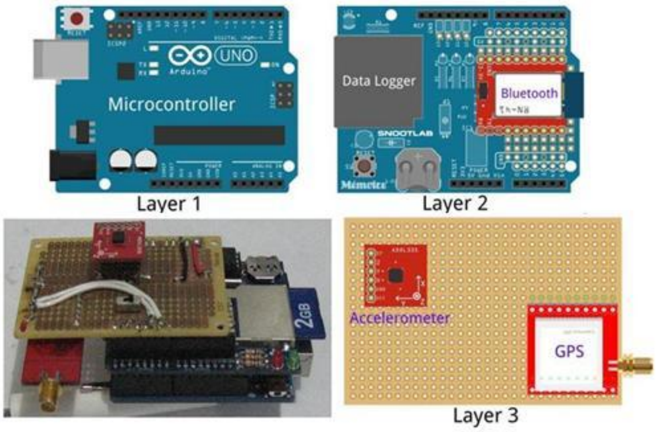

Figure 7: Developed Productivity Assessment Prototype

5.4 Software Implementation

The software development consists of three main algorithms: (1) Data processing algorithm, (2) Productivity calculation algorithm and (3) Operating conditions analysis.

5.4.1 Data Processing Algorithm

The raw sensor data is collected using the designed hardware as described above. The data processing takes place in the sensor node and the gateway node, where higher level of information is extracted representing the operation modes of the equipment and the volume of excavated soil. Two sub algorithms are developed, namely, the haul truck activity recognition algorithm and the hauling volume calculation algorithm. A detailed description of each sub algorithm is presented in the following section.

5.4.1.1 Haul Truck Activity Recognition Algorithm

The haul truck activity recognition algorithm aims to interpret the sensor (mounted on equipment) readings into understandable modes of operations. In this study seven states considered: queue loading, loading, travel, queue dumping, dumping, return and out of service. These states were selected because they are performed regularly by a truck in typical earthmoving operation. These states involve repetitive motions which make these states easier to recognize. Table 2 lists the seven selected states and the expected sensors readings during these states.

Table 2 Haul Truck States

Task	Location	Speed	Load Weight	Proximity	Tilt Angle	Previous Task
Load Queue	Loading Area	= 0	≈ 0	Trucks	= 0	Return
Load	Loading Area	= 0	++	Loader	= 0	Return or Queue Loading
Travel	Road	> 0	> 0	Non	= 0	Loading
Dump Queue	Dump Area	= 0	> 0	Trucks	= 0	Travel
Dump	Dump Area	= 0	--	Spoter	> 0	Travel or Queue Dump
Return	Road	> 0	≈ 0	Non	= 0	Dump
Service	Service Area	= 0	Any	Any	= 0	Any

Figure 8 plots the sensors data for a haul truck during a typical earthmoving operation. The periodic patterns for all the above mentioned seven states can be described in terms of the time between peaks and by the relative magnitudes of the sensors readings values. The location for the haul truck is identified based on the coordinate's boundaries of the cut, fill, hauling road and service areas. The proximity of other equipment is identified by continues scanning by the RF communication module to discover nearby equipment. The discovered equipment type is identified by cross checking their media access control (MAC) address against a pre-defined list stored on the microcontroller SD memory card.

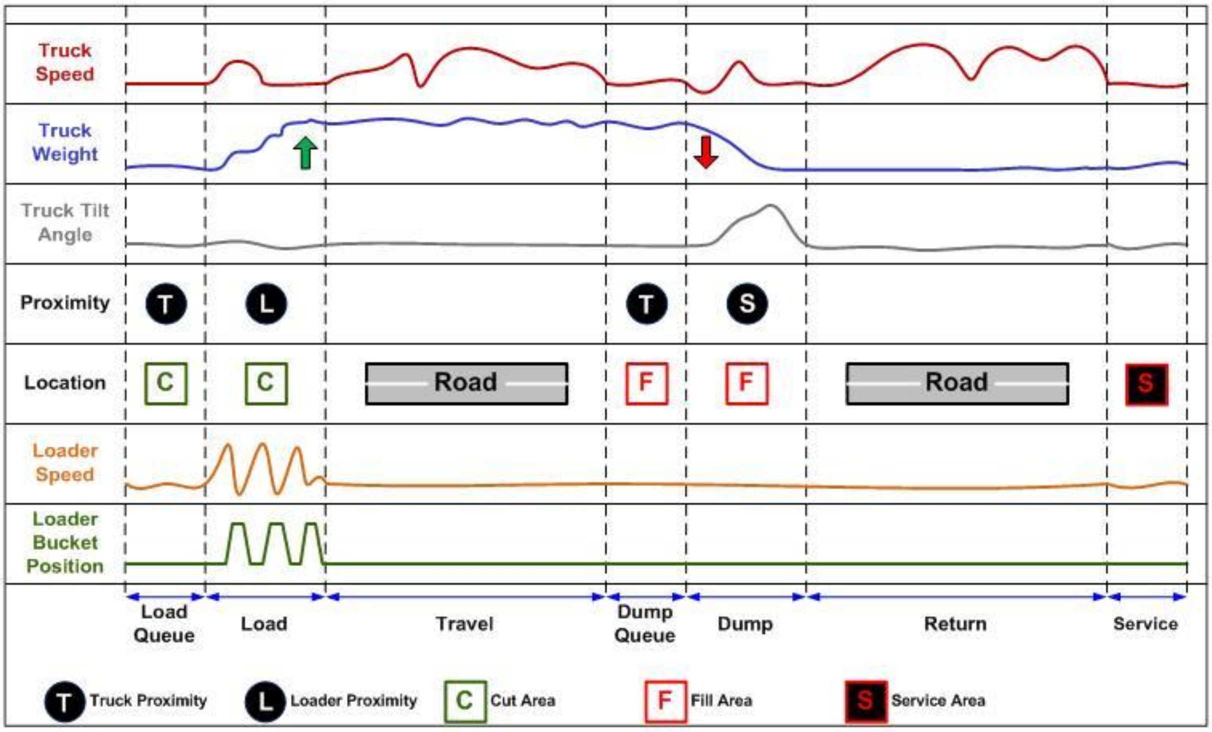

Figure 8: Sensor Data Patterns

The developed algorithm utilizes a logic-based approach, which views an activity as a knowledge model that can be formally specified using various logical formalisms. From this perspective, activity modeling is equivalent to knowledge modeling and representation. The algorithm is composed of a number of distinct states and a reasoning engine, which are responsible for aggregating and transforming sensor data into logical terms and formula. The logical representation of sensor data is passed onto the reasoning engine which performs logical reasoning against the pre-set states. The developed algorithm does not require pre-existing large-scale dataset, and activity modeling and recognition is semantically clear and elegant in computational reasoning. Its main drawback is its inability to represent uncertainty, but this can be elevated by integrating fuzzy logics into the logical approaches, which will be addressed in future research.

5.4.1.2 Hauling Volume Calculation Algorithm

For maximum efficiency of the hauling equipment, the trucks must be filled as close to their rated hauling capacity. The current practice in earthmoving operations, a truck is loaded them until its volumetric capacity is reached. However, overloading the truck will cause higher fuel consumption, reduced tire life, and increased mechanical failures. The developed method uses strain gages installed on truck's suspension leaf spring to estimate the payload weight and volume. This feature not only enables accurate tracking of excavated soil volume but also enables alarming the operator for any overloading conditions, and hence protects the contractor from possible extra costs for fuel, tires and mechanical failures.

The weight at each suspension is calculated based on voltage signals of strain gages. The total payload of the vehicle is obtained by summing load readings in all suspensions; but resultant errors vary in a wide range. To reduce the error, a Kalman filter is used to account for nonlinearity in measurement. Once the payload is measured the volume of the payload can be estimated based on the excavated soil properties.

Strain is the amount of deformation of a body due to an applied force. More specifically, strain (e) is defined as the fractional change in length. A strain gauge is a device whose electrical resistance varies in proportion to the amount of strain in the device which is shown in figure 4. The truck's suspensions are denoted as Left-Front (LF), Left-Rear (LR), Right-Front (RF), and Right-Rear (RR), respectively. In Fig. 9, the cross mark denotes the center of gravity of the payload with a value represented by W.

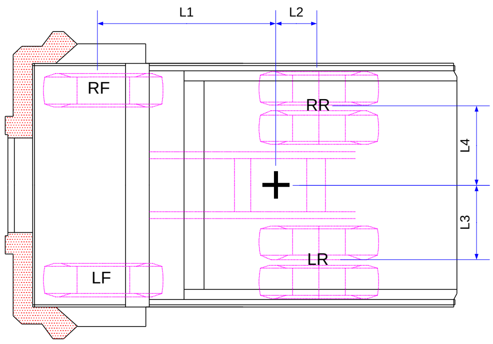

Figure 9: Schematics Diagram for Truck Payload Center of Gravity and Distances

For converting the measured strain gauges voltage to the payload, the load applied to each suspension must be calculated first. From Fig. 9, the following equations can be derived in accordance with force balance and torque balance:

$$P_{LF} + P_{RF} + P_{LR} + P_{RR} = W \qquad Eq.(3)$$

Where:

W is the gross payload weight in Kg.

P_{LF} , P_{RF}, P_{LR}, P_{RR} are the measured weight in Kg at the left front, right front, left rear and right rear truck suspensions respectively.

$$P_{LF} = W \times \frac{L_2}{L_1+L_2} \times \frac{L_4}{L_3+L_4} \qquad Eq.(4)$$

$$P_{RF} = W \times \frac{L_2}{L_1+L_2} \times \frac{L_3}{L_3+L_4} \qquad Eq.(5)$$

$$P_{LR} = W \times \frac{L_1}{L_1+L_2} \times \frac{L_4}{L_3+L_4} \qquad Eq.(6)$$

$$P_{RR} = W \times \frac{L_1}{L_1+L_2} \times \frac{L_3}{L_3+L_4} \qquad Eq.(7)$$

The Payload volume is calculated from the measured load weight as following:

$$V = (W_{gross} - W_{truck\ bed}) \times \rho_{soil} \times Swell\ factor \qquad Eq.(8)$$

Where:

W_{gross} is the gross payload weight in Kg.,

$W_{truck\ bed}$ is the weight of the truck bed in Kg., and

ρ_{soil} is the soil density in Kg/m^3.

After calculating the load volume, a Kalman filter is applied to the measurement to reduce the error in the measurement. The Kalman filter is modeled as following:

$$\hat{V}_k = K_k Z_k + (1 - K_k)\hat{V}_{k-1} \qquad Eq.(9)$$

Where:

$\hat{V}_k$ is the current volume measurement,

K_k is Kalman gain, and

$\hat{V}_{k-1}$ is the previous volume measurement.

5.4.2 Productivity Calculation Algorithm

The on-site productivity is calculated from the measured cycle times and the excavated volumes collected by the developed hardware and software algorithms described above. The overall operation productivity is calculated by summing the individual truck productivity using the following equation:

$$Overall\ Productivity = \sum_{i=1}^{n} Truck\ Productivity_i \qquad Eq.(10)$$

Where:

$Truck\ Productivity_i$ is truck i productivity in m^3/hr, and

n is the number of trucks.

The truck productivity is calculated using the following equation:

$$Truck\ Productivity = \frac{Soil\ Volume\ (m^3) \times load\ factor}{Total\ Cycle\ time\ (hr)} \qquad Eq.(11)$$

Where:

Total cycle time is equals the summation of loading, travel, dumping, returning and service time

Load factor is the factor for converting soil material to a compact state

5.4.3 Operating Condition Analysis Algorithm

The operating condition algorithm monitors the earthmoving operation and declares a set of alarms for potential bottle necks in the operation as following:

- Loss of productivity:

  The fleet production is normally controlled by the loading equipment production capacity. It is very crucial to keep loading equipment busy all the time. If there are not enough trucks, there will be loss in production. The number of trucks required to balance the fleet at maximum capacity is calculated using the following equation in the planning phase:

$$Number\ of\ trucks\ required = 1 + \frac{truck\ cycle\ time}{loader\ cycle\ time} \qquad Eq.(12)$$

At the project execution phase, the number of trucks required may vary because of changes in haul road conditions, reductions or increases in haul length, or changes in conditions at either the loading or dump areas. The loader and trucks queuing time is monitored at the loading area and the algorithm declare an alarm to the project management if deviation from the planned is identified. A higher loader queuing time means that there is a need to increase the number of trucks to keep the production at maximum capacity. A higher truck queuing time means that there is a need to decrease the number of trucks or to increase the number of loaders to keep the production cost at minimum. The truck travel and return time is monitored to alarm for possible traffic congestion and an alarm is declared if the time is greater than the planned in order to review possible usage of alternative routes.

- Adverse weather conditions:

The weather conditions are monitored using the developed method and co-related with the achieved productivity on site. This co-relation between the weather conditions and the productivity enables better productivity estimation on future jobs. The method also acquires a weather forecast from the weather channel website and alarm for possible adverse weather conditions, which enables project management to anticipate potential project delays and take suitable corrective actions.

- Operator behavior

Equipment operators are usually under a great deal of pressure to achieve target production rates. While the operator will push the equipment to the maximum to achieve the requested production, it is beneficial to the contractor to monitor the operator behavior for equipment abuse. Speeding is a huge factor in high fuel usage. Maintaining proper speeds can significantly reduce the fuel consumption. The developed method monitors the operator and equipment to flag and report any unwanted behavior. Alerts are triggered for excessive speeding, harsh breaking, excessive idling, engine start-up or shut-down during off-hours and unauthorized travel routes. A three axial accelerometer is used for detecting aggressive driver behavior such as sudden acceleration and breaking as shown in Figure 10.

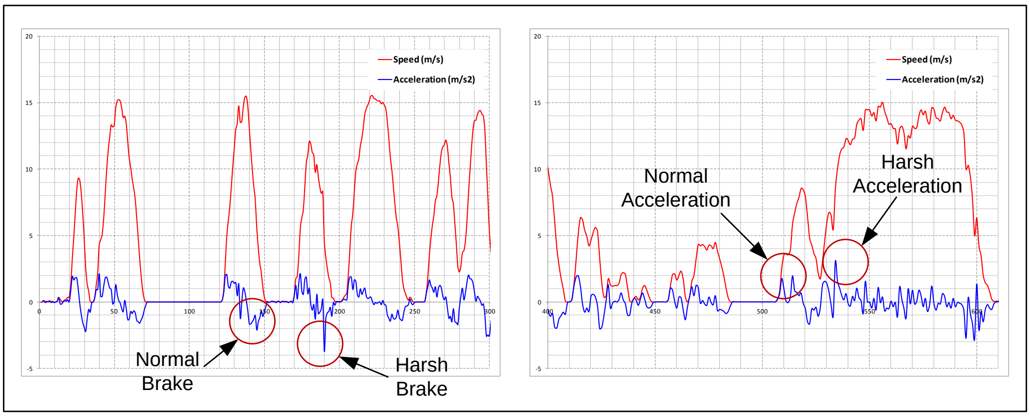

Figure 10: Truck Operator Behavior Monitoring Field Test

6. CASE STUDY

A simulated case study was conducted to test the functionality of the developed method and to demonstrate its applicability to earthmoving project. The developed prototype was mounted on scaled 1:50 equipment to test the operation in outdoor environments.

In order to validate the designed method, 8 experiments were conducted on a model jobsite and remotely controlled equipment models as shown in Figure 11. Equipment positions were captured by GPS, loader boom angle was sensed by 3-axis Accelerometer, and strain-gauge sensors tracked the weight of material transported by dump trucks. In these experiments, a simple case of earthmoving operation is considered. The operation involves excavation of 2.72 cubic meters of dry sandy soil. The equipment fleet consists of one wheeled loader and two hauling trucks. Table 3 represents the activity duration based on actual equipment performance and site layout. Table 4 represents equipment hourly rate.

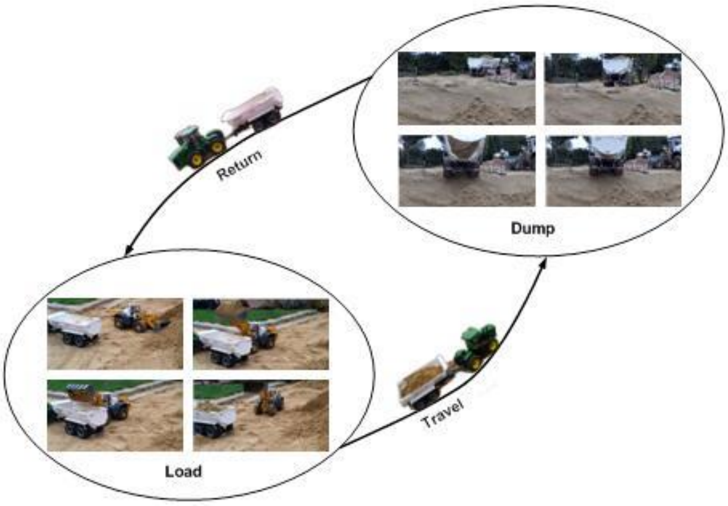

Figure 11: Site Layout for Earthmoving Operation Case Study

Table 3: Activity Duration

Activity	**Approximated duration (S)**	
	Mean	**Standard deviation**
Load	5	1.5
Haul	24	7
Dump	2	0.6
Return	19	5

Table 4: Equipment Hourly Rate

Equipment	**Type**	**Hourly Rate**
Truck	Highway 2 axles	$55.37
Loader	CAT 430E	$65.31

As presented in Figure 12, a discrete event simulation model is developed to calculate planned productivity, project duration and cost. The model takes into account soil quantity, calculated activates duration and equipment characteristics.

Four separate measurable quantities (namely, total project duration, total project cost, average productivity, and equipment utilization) were selected to assess the results generated by the simulation model (Table 5).

Table 5 Simulation Output

Measurement	**Value**
Total Project Duration	10.83 hrs
Total Project Cost	$1906.68
Average Crew Productivity	0.272 m3/hr
Loader Utilization	19.99%
Truck Utilization	99.38%

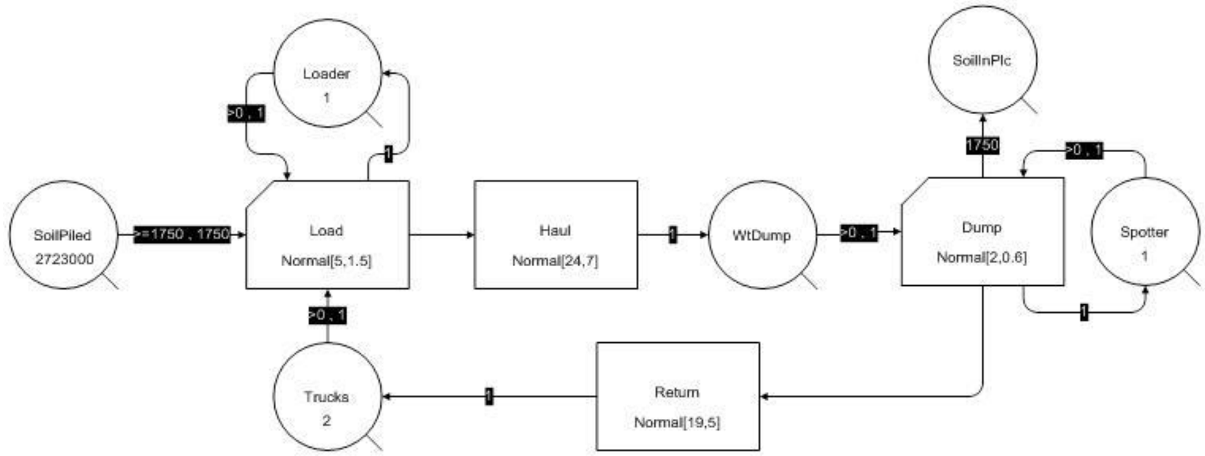

Figure 12: Discrete Event Simulation Model of the Case Study

7. ANALYSIS OF RESULTS

The site data was gathered using the developed hardware and conventional GPS tags in order to compare the performance of both technologies. The data included longitude, altitude, time, direction, travelled distance, load weight, truck-bed tilt angle, velocity, and equipment proximity. The progress was calculated using these two technologies and compared to the actual progress which was calculated manually as shown in Figure 13. A video camera was used to record the actual construction progress in order to measure the actual project duration. The project was completed in 13 hrs with a total cost of $2288.65. The actual total volume of soil in cut locations was 2.947 cubic meters.

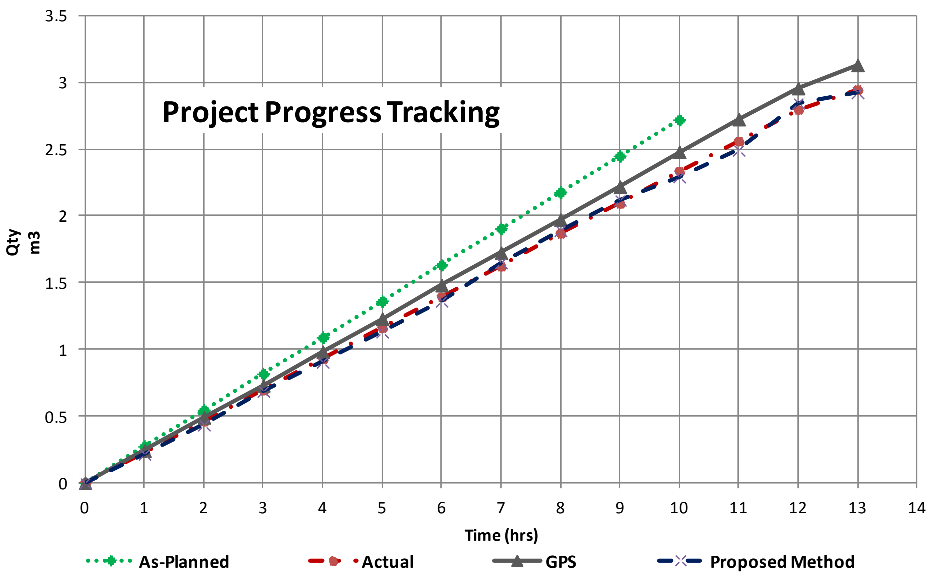

Figure 13: Project Progress Tracking Using Different Technologies

The comparison results (illustrated in Figure 14) show that conventional GPS estimated the productivity of the fleet with a mean absolute error of 6.05%. This deviation is attributed to the assumption that the hauling trucks are loaded to their maximum capacity, while the captured video showed that this assumption is not valid due to rocks and boulders in the excavated soil. The developed method measured the productivity with considerably less errors at 2.20%. The lower error is attributed to the utilization of real time volume and durations data. These results show that the SA-GPS outperformed the conventional GPS in measuring the earthmoving fleet productivity which was also resulted in more accurate forecasting of project cost and duration at completion.

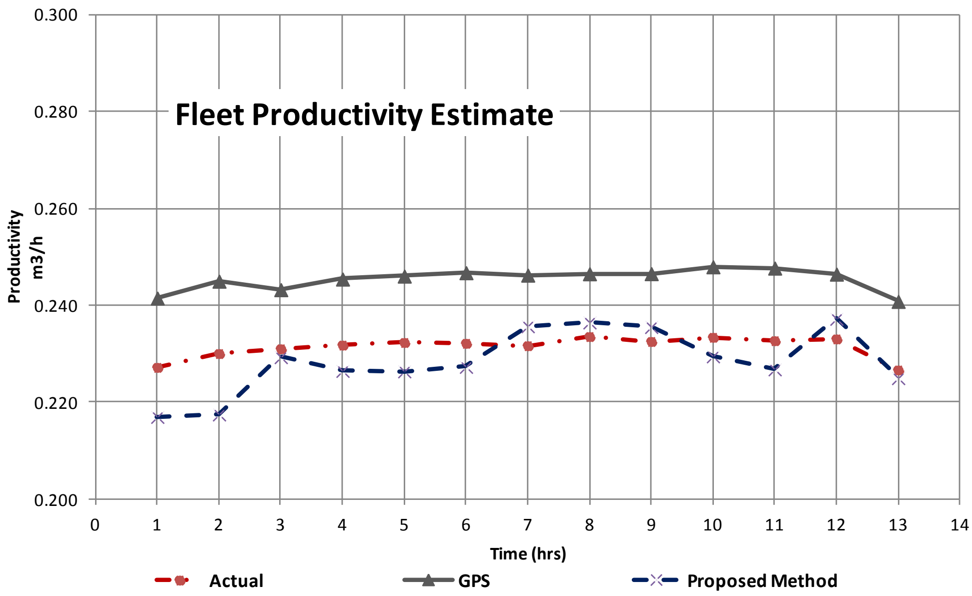

Figure 14: Fleet Hourly Productivity Estimate Comparison

8. CONCLUSION

The present study demonstrated the useful application of the developed SA-GPS method for productivity assessment of earthmoving operations. It presented a practical and easy to use framework for monitoring and tracking of earthmoving operations in near real-time, which facilitates early detection of discrepancies between actual and planned performances and supports project managers in taking timely corrective actions. The developed method was used to measure the productivity of earthmoving operations of a scaled project. The developed method was tested on eight experiments, with a total execution time of 124 hours.. The results of these experiments indicated that the developed method measured the productivity with 2.20% mean absolute error. The low estimation error can be attributed to the utilization of actual near real-time data captured by the developed hardware. It is expected that the accuracy of the developed hardware demonstrated in this paper can be achieved on large scale earthmoving projects. This is attributed to the fact that the developed method does not require any scalable developments on the hardware technology used nor it requires any additional computational developments beyond the software developed.

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