CSCE Annual Conference
Growing with youth – Croître avec les jeunes

Laval (Greater Montreal)
June 12 - 15, 2019

LOW-COST SMART PRODUCTIVITY TRACKING MODEL FOR EARTHMOVING OPERATIONS

Ashraf, Salem[1, 2] and Osama, Moselhi[1, 3]
[1] Construction Automation Lab., Department of Building, Civil and Environmental Engineering
Concordia University, Montreal, Quebec, Canada
[2] as_salem@encs.concordia.ca
[3] moselhi@encs.concordia.ca

Abstract: This paper introduces a model for automated monitoring and control of productivity in earthmoving operations. The model makes use of advancements in wireless sensing networks, Internet of Things (IoT), and artificial intelligence. It consists of two modules; the first is a low-cost open-source remote sensing data acquisition module for collecting data throughout earthmoving operations. The collected data is sent to a cloud-based MySQL database, in which the second module is designed to (1) measure actual productivity in near-real-time, (2) detecting the location and condition of hauling roads and (3) monitoring and reporting driving conditions over these roads via short email messages. The work encompassed field and scaled laboratory experiments in the development and validation processes of the developed model. The laboratory experiments 1:24 scaled loader and dumping truck to simulate loading, hauling and dumping operations. The truck was instrumented with the microcontroller equipped with accelerometer, GPS module, load cell and soil water content sensor. Fifteen simulated earthmoving cycles were conducted using the scaled equipment. The field work was carried out in the city of Saint-Laurent, Montreal, Canada using a passenger vehicle to mimic the hauling truck operational modes. Fifteen Field simulated earthmoving cycles were performed. The data collected from the lab experiments and field work was used as input for the developed model. The results will be presented, highlighting the accuracy of the developed model in recognition of the status of the hauling truck, traveled road condition and in the estimated duration of the simulated earthmoving cycles.

1 INTRODUCTION

Timely collection of data about resources and project status is essential for supporting management to lead a project successfully. In this process, a significant amount of data from construction sites is required to determine the project status, and hence corrective actions can be taken if needed (Shahi et al. 2013). Collecting, storing and processing construction job-site data are regularly manual and labor-intensive methods. The usual practice for progress tracking typically depends on foremen daily or weekly reports which entail rigorous manual data collection and involve frequent record or data entry mistakes (Song et al. 2006).

Over the last few decades, automation technology market witnessed a remarkable advancement in both hardware and software. Data acquisition systems were 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.

This paper introduces a novel automated model for near real-time measurement of productivity 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.

2 BACKGROUND

The construction industry has an emergent need for automated means of measuring construction progress, especially for approaches that employ remote-sensing technology, because the methods that are typically used to measure progress are labor intensive and therefore time-consuming (Abeid et al. 2003, Wu et al. 2009). Many efforts were made to replace data collection paper-based with project monitoring and control systems providing a project-wide scope of automated solution. Several researchers have presented integrating different automation technologies, e.g., RFID, bar coding, 3D laser scanner, and GPS. The research is persistent in that field to augment the efficiency and to reduce the cost of implementation. The last two decades have included several research endeavors to study and develop automated on-site data acquisition systems. These studies have utilized several technologies, and they have targeted a broad scope of applications in construction. Throughout these studies, the recent advancement in sensing technologies, computing techniques, and wireless communication have played a vital role to automate the process of on-site data acquisition not only on construction job sites but also on the constructed facilities (Li et al. 2016). These research studies have incorporated different technologies such as barcode, radio frequency identification system (RFID), GPS, image processing and Photogrammetry, laser scanners, remote and embedded sensors, wireless sensor networks (WSN), and mobile computing.

GPS technology was identified as an accurate and robust technology for automated data collection for controlling highway construction. However, there are inaccuracies associated with the collected GPS data which are caused by objects hindering communication between GPS receiver and satellites (Navon and Shpatnisky 2005). GPS technology was utilized in tracking, e.g., to track earthmoving operations and/or highway construction (Alshibani and Moselhi 2016, Montaser et al. 2012, Hildreth et al. 2005, Navon and Shpatnitsky 2005), also in tracking pipe spools position in a construction project (Caldas et al. 2006).

Many research studies used GPS as a standalone tool, while most of these studies concluded that standalone GPS could not usually satisfy the needed requirements to solve the research problems. In case of standalone GPS utilization, the obtained data are limited to time and location, which is sometimes hard to differentiate between productive and idle times. Furthermore, the acquired records do not present enough information that could be used to estimate the quantities of the excavated soil or confirm that the trucks are fully loaded (Ibrahim 2015). The productivity of earthmoving operations was substantially studied during the last decades. However, equipment as a part and particular of earthmoving operations play a vital role in the production, many other internal and external factors could influence productivity i.e., weather and road conditions (Salem et al. 2017). Research has introduced numerous analytical methods that used in the planning, measurement and analysis of earthmoving operations. However, some of these methods proved the efficiency and effectiveness; they still lack being fully automated in line with the current technological advancement. Moreover, most of automated models have depended on black-box and off-the-shelf technologies.

3 DEVELOPED MODEL

3.1 Automated Productivity Analysis Framework

The main objective of this research is the automation of productivity measurement and analysis to guarantee a near-real time detection of different factors influencing productivity of earthmoving operations. The developed framework of this research integrates data acquisition as well as productivity measurement and analysis in a near-real-time. Figure 1 shows a simplified overview of this framework.

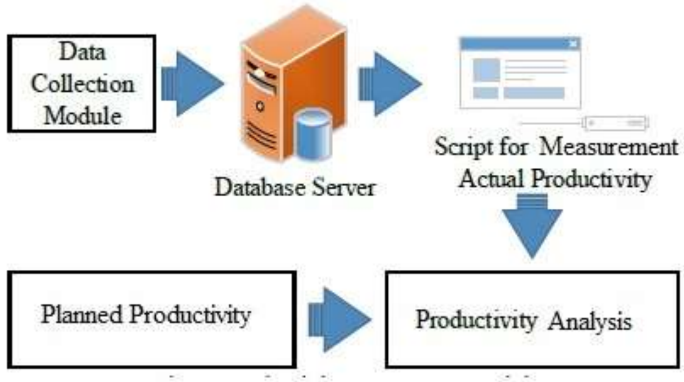


Figure 1: Simplified representation of the developed measurement and analysis framework

The developed automated models consist of two main modules; each module has one or more sub-modules. Figure 2 shows a schematic design of the proposed automated productivity analysis framework. The developed model has a variety of data communication protocols, such as 3G, GPRS, Bluetooth, Xbee and Wi-Fi. The data collected by different sensors as well as the weather station is tabulated in internal MySQL database. This internal database is built-in the communication gateway (Meshlium®). The gateway was developed by Libelium®™ and it has a capacity of up to 40 GB of data storage. In this research, GPRS and Wi-Fi are the utilized data communication protocols due to their low risk in data transmission. The internal MySQL database allows preprocessing of the collected data. The main purpose of this preprocessing is to filter the captured raw data with a focus on extracting and processing key data items before its final processing distention on the host server i.e. cloud.

Figure *3* shows a framework of the developed automated productivity analysis model. Figure 4 shows the architecture of the onsite automated data acquisition module. It was provided with sensors for air temperature and humidity, luminosity, wind speed and direction, rainfall. This board (Waspmote agriculture) allows up to fifteen sensors to be connected at the same time. As shown in Figure 4, the principal components of the data acquisition module are the microcontroller and the smart sensor board.

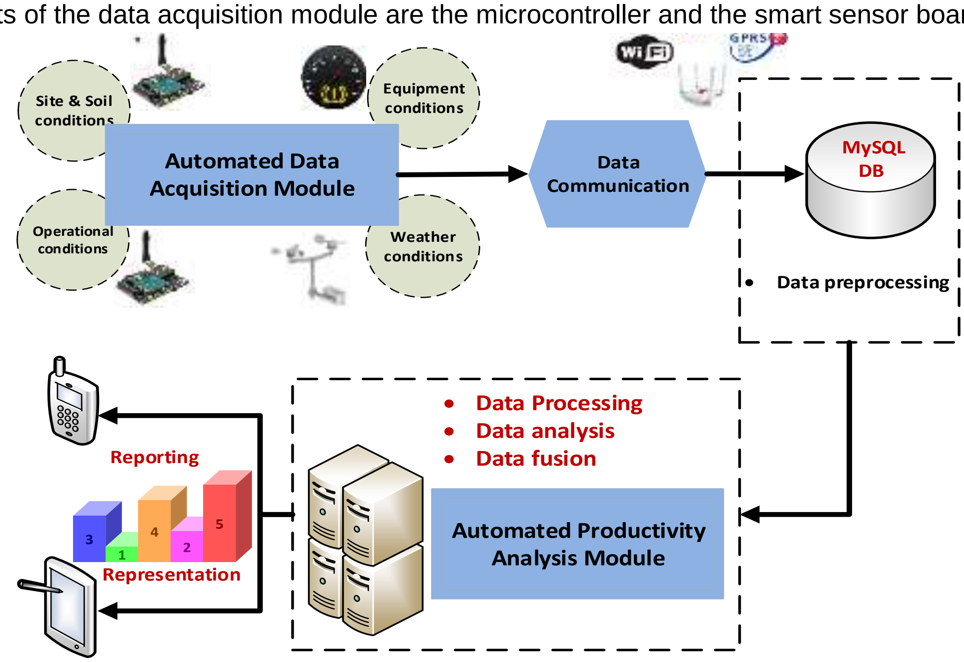


Figure 2: Schematic design of the developed automated productivity analysis framework

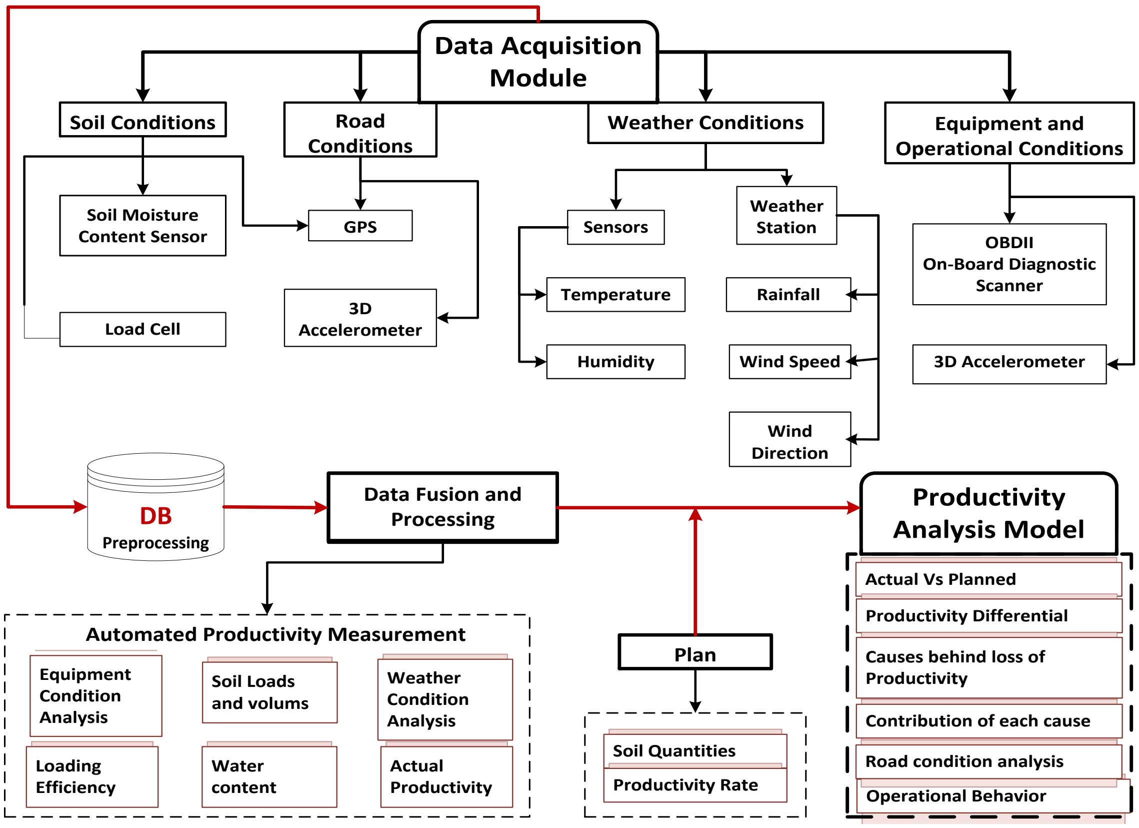


Figure 3: Framework of the developed automated productivity analysis model

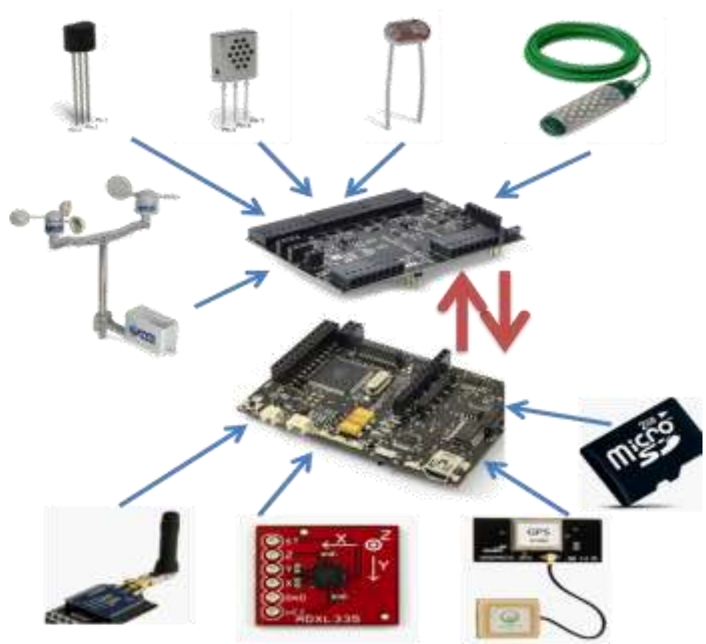


Figure 4: Onsite data acquisition module block diagram (Salem et al. 2018)

3.2 On-Site Data Acquisition Development

The data acquisition system consists of portable components installed on hauling equipment and fixed data storage and preprocessing gateway (Meshlium) on the excavation site, as shown in Figure 5. The customized multi-sensor data acquisition prototype and the on-board-diagnostic scanner OBDII are attached to all the hauling trucks in the earthmoving project, while the data receiver is installed near either the loading zone or the project gate.

Figure 5: Data acquisition module deployment

3.3 Productivity Measurement, Assessment and Analysis

Different algorithms are utilized to automate the measurement, assessment, and analysis of earthmoving operations using data mining, data fusion and machine learning techniques. The main goal of developing the productivity measurement, assessment, and analysis models in this research is to avoid the time consumed in conventional recognition of productivity variations. Also, to automate the identification of main reasons behind productivity variations. Productivity analysis model receives different data from the data acquisition module, where the collected data is pre-processed on the microcontroller units and the gateway's local database. Microcontrollers have the role of controlling not only data-captured delays and transmission intervals, but also it determines the appropriate data sets to communicate to the productivity analysis module. Waspmote™ smart boards and microcontrollers permit through its programming the application of efficient strategies and algorithms needed for data sampling, processing and storing.

Collected and communicated data sets should satisfy its acquisition purposes without data streaming congestions. The amount of data should not be so scanty as to put its usefulness at risk, nor should it be so roomy as to overwhelm processing. The developed model allows the fulfillment of this purpose through the application of some data sampling algorithms. Figure 6 shows an example of two raw data acquisition algorithms; the first algorithm is only for recording only values greater than targeted threshold value, while the second one only records only predefined significant changes in readings. In both algorithms, the times of each change are also recorded.

3.4 Productivity Measurement Algorithm

The developed productivity measurement algorithm employs multi-sensors data fusion. Table 1 shows the concept of how different sensory data acquisition sources are the inputs for the truck operational state classifier. Automatically collected data sets by GPS, OBDII, three axial accelerometer, and load cell are tabulated into the developed database, then based in the fused data captured by all employed sensors; developed MySQL procedures recognize different states of the hauling truck.

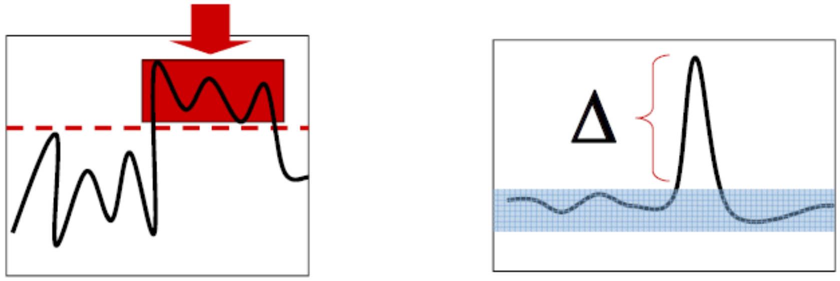


Figure 6: Example of raw data acquisition algorithms

The main necessary six states for calculating the productivity are waiting for loading, loading, hauling, waiting for dumping, dumping and returning. Once these states are recognized, productivity could be calculated using the associated timestamps that could be retrieved from the captured GPS data. The timestamps permit the determination of the start and end time of each state, and hence its duration, likewise the total duration of each earthmoving cycle. Equation 1 used for calculating each truck productivity. Soil volume determined using soil properties data obtained from specific or generic soil database and soil weights acquired from the load cell as shown in Equation 2.

$$[1]\ \text{Truck productivity}\ \ m^3/hr = \frac{\text{Soil Volume}\ (m^3)}{\text{Cycle time (hr)}}\ \text{x Load Factor}$$

$$[2]\ V = \frac{m}{\rho}$$

Where: V soil volume in m^3, m soil weight in tons, and ρ soil density in ton/m^3
Therefore, the total productivity of hauling fleet can be calculated using Equation [3].

$$[3]\ \text{Total Productivity} = \sum_{i=1}^{n} \text{Truck Productivity (i)}$$

Table 1: Conceptual overview of data fusion algorithm for truck state recognition (Salem 2018)

Detector \ State		Wait / Loading	Loading	Hauling	Wait / Dumping	Dumping	Return
GPS	Location	Loading Zone		Road	Dumping Zone		Road
	Speed	≈ Zero		> 0	≈ Zero		> 0
OBD II		Engine (ON / OFF) Low / No Fuel consumption Low Gear Speed / N / P		Engine (ON) Fuel consumption High Gear Speed	Engine (ON / OFF) Low / No Fuel consumption Low Gear Speed / N / P		Engine (ON) Fuel consumption High Gear Speed
Accelerometer		X, Y=0, Z ≈ g	X, Y≈ 0 Z > ±g	Fluctuated	X, Y=0, Z ≈ g	X(++), Y≈ 0 Z(--), Mirrored	Fluctuated
Load cell		Constant ≈ 0	Exponential (++) ≈Capacity	Constant ≈ Capacity	Constant ≈ Capacity	Exponential (-) ≈ Zero	Constant ≈ 0

3.5 Driving and Road conditions Analysis

The 3D accelerometer associated in the data acquisition module is used for recognizing undesirable driver behavior of hauling equipment. The algorithm shown in Figure 7 depicts driving and road conditions analysis. The application of this algorithm allows automated monitoring of hauling equipment drivers to detect and report any adverse behavior. Also, it recognizes access and traveling road deficiencies as well. Alerts are triggered by excessive speeding, harsh breaking, severe maneuvers, and unsafe lane changes. The boundaries in the movement direction i.e., X direction for safe and harsh accelerations and brakes are ±0.3g and ±0.5g respectively (Langle and Dantu, 2009; Fazeen et al. 2012, Li et al. 2017).

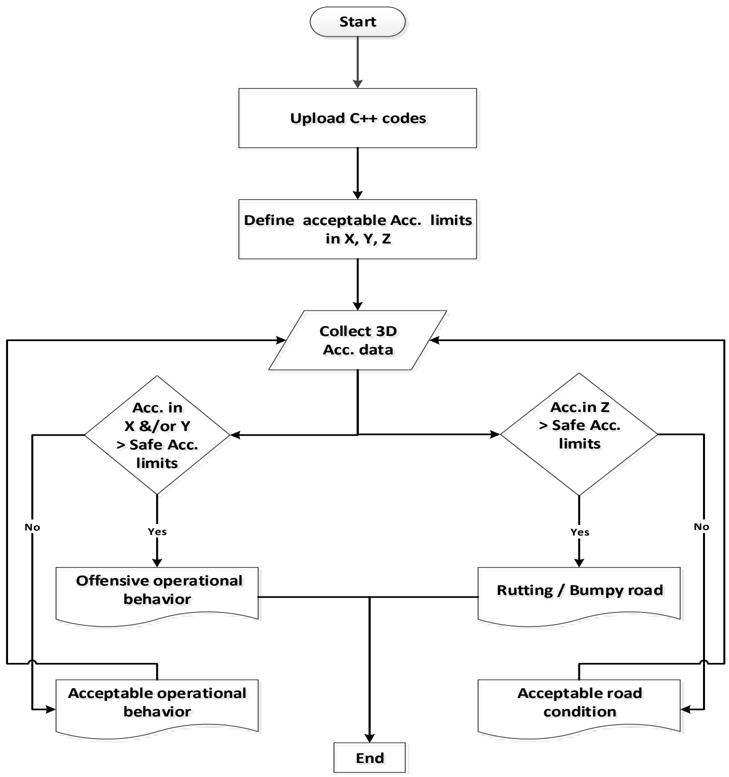


Figure 7: Flowchart of driving and road condition analysis algorithm (Salem and Moselhi 2018)

3.6 Automated Alerting System

Early warning decision support module is configured to report detected road and driving conditions as well as the status of actual productivity compared to that planned. For automating the early warning system, an embedded notification system is coded through the Waspmote IDE, and then uploaded to the microcontroller. Hence, the microcontroller dispatches the predefined notifications via associated GPRS module in the form of cellular short message service (SMS), email or recorded voice message. Figure 8 shows the schematic design flowchart of the proposed automated early warning system. These notifications address the need for intervention and permit decision makers to take prompt and proactive measures to improve the performance and related productivity. Hence, it assists in avoidance of schedule delays, cost overruns, and inefficient utilization of resources.

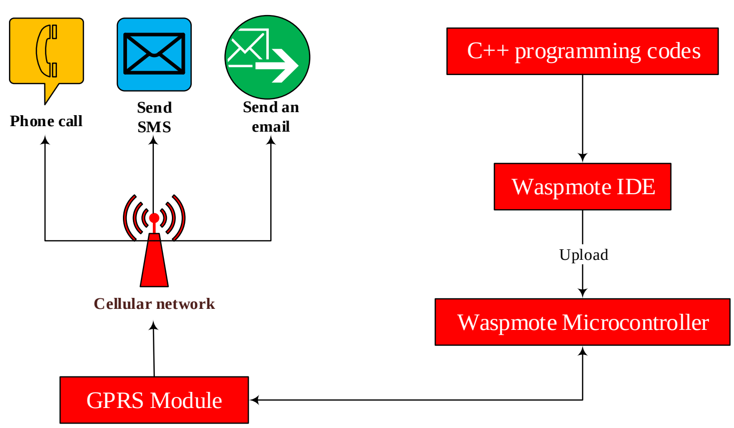


Figure 8: Schematic design flowchart of the proposed automated early warning system

4 CASE STUDY

The applicability of the developed model was examined through a designed hybrid case study to evaluate and validate the model. This case study is divided into two integrated phases to collect three types of data.

4.1 Phase I – Laboratory Experiment

The laboratory experiment was conducted in an open to sky terrace to allow a reliable contact to GPS' satellites. Also, to make a direct connection between Meshlium and a computer PC to observe the received data latency. A WiFi signal was available thru an Internet router connected to a PC computer. Connecting the gateway to WiFi aims to simulate its installation in loading and dumping zones as described in the developed automated productivity measurement model. In this Phase, thirty simulated earthmoving cycles were conducted using the scaled equipment. Where the truck has a payload capacity of 864 cm^3 and the loader bucket capacity is 175 cm^3. The performed cycles incorporate a total of 143 buckets with different fill capacities Acceleration data was recorded in a high sampling rate (100 reading/second). Also, the load cell records, water content sensor readings were filed in CSV format. All data sets were recorded in the SD card to be integrated with the data collected in the second phase.

4.2 Phase II – Field Experiment

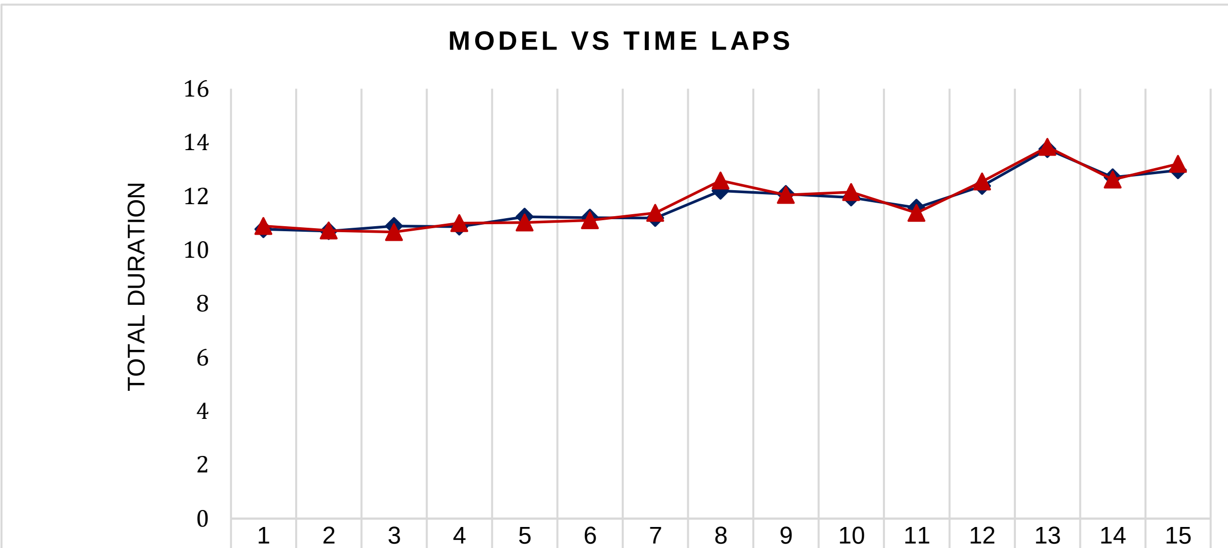
The second phase was conducted in field using a passenger vehicle. The selected site located in the city of Saint-Laurent, Montreal, Quebec, Canada. The data acquisition module was installed on the dashboard near the windshield of the mimicked truck i.e., the passenger vehicle. An OBD II scanner was appropriately attached to the car as explained in the developed model. Then the vehicle has performed fifteen trips between two designated locations, which identified as loading and dumping zones. A specific criterion has controlled the choice of the site for this phase, where the selected site provides two equal in length hauling roads with a significant alteration in road conditions. The selected site layout is shown in Figure *9*, the figure shows both loading and dumping zones in addition to hauling and the alternative roads. The vehicle has simulated different operational states of hauling truck as in real earthmoving operations, unless loading and dumping states which were done in phase I.

Duration of each state was recorded through time laps using a smartphone as a reference for evaluating the developed model in terms of automated determined durations. GPS, acceleration and OBD II data were stored in the SD card in a CSV format. Thereafter, all the acquired data from the two implemented phases were transmitted to the central MySQL relational database. The designed MySQL procedures were run for the application of the associated developed algorithms.

Figure 9: Case study field - loading, dumping zones and hauling roads

4.3 Results and Discussion

The model demonstrates ability to recognize different states even for the ones which take few seconds as in the states of exiting loading and dumping zones, where they have durations as little as 5 seconds.The developed model has shown perfect recognition of the state of truck throughout the fifteen field simulated earthmoving cycles. The developed road condition analysis algorithm has demonstrated an accuracy of 83.3% and 82.6% in recognizing road bumps and potholes, respectively. Also, the results indicated tiny variances in measuring the durations compared with actual durations using time laps displayed on a smart cell telephone; with an average invalidity percentage AIP% of 1.89 % and 1.33% for the joint hauling and return duration and total cycle duration, respectively. Figure 10 shows the total cycle duration for each of the fifteen trips; determined by the developed model and those of the recorded time laps method. The chart shows approximate coincide between the two methods.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Model	10.77	10.7	10.88	10.87	11.23	11.2	11.18	12.2	12.08	11.95	11.57	12.38	13.75	12.7	12.97
Time Laps	10.88	10.72	10.67	11	11.02	11.1	11.38	12.58	12.05	12.15	11.38	12.55	13.83	12.62	13.2

Figure 10: Output from model and time laps method for total duration of each cycle

5 Conclusion

This paper presents a model for automated monitoring and control of productivity in earthmoving operation, where a variety of sensors, smart boards, and microcontrollers are used to automate the data acquisition process. The model consists of two main modules, the first one is for data capturing, which encompasses onsite fixed unit and a set of portable units attached to each truck used in the earthmoving fleet. The fixed unit is a communication gateway (Meshlium®), which has integrated MySQL database with data processing capabilities. Each mobile unit consists of a microcontroller equipped with a smart board that hosts a GPS module as well as a number of sensors such as accelerometer, temperature and humidity sensors, load cell and automated weather station. The second module is for productivity measurement and analysis, which processes and analyzes the captured data automatically. It automates the analysis process using data mining and machine learning techniques; providing a near-real-time monitoring of measurement and analysis outcomes. Laboratory and field work was conducted for the development and validation processes of the developed models. The work encompassed field and scaled laboratory experiments. The developed road condition analysis algorithm has demonstrated an accuracy of 83.3% and 82.6% in recognizing road bumps and potholes, respectively. Also, the results indicated tiny variances in measuring the durations compared with actual durations using time laps displayed on a smart cell telephone; with an average invalidity percentage AIP of 1.89 % and 1.33% for the joint hauling and return duration and total cycle duration, respectively.

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