Automated Productivity Models for Earthmoving Operations

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ABSTRACT

Automated Productivity Models for Earthmoving Operations

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Earthmoving operations have significant importance, particularly for civil infrastructure projects. The performance of these operations should be monitored regularly to support timely recognition of undesirable productivity variances. Although productivity assessment occupies high importance in earthmoving operations, it does not provide sufficient information to assist project managers in taking the necessary actions in a timely manner. Assessment only is not capable of identifying problems encountered in these operations and their causes. Many studies recognized conditions and related factors that influence productivity of earthmoving operations. These conditions are mainly project-specific and vary from one project to another. Most of reported work in the literature focused on assessment rather than analysis of productivity.

This study presents three integrated models that automate productivity measurement and analysis processes with capabilities to detect different adverse conditions that influence the productivity of earthmoving operations. The models exploit innovations in wireless and remote sensing technologies to provide project managers, contractors, and decision makers with a near-real-time automated productivity measurement and analysis. The developed models account for various uncertainties associated with earthmoving projects.

The first model introduces a fuzzy-based standardization for customizing the configuration of onsite data acquisition systems for earthmoving operations. While the second model consists of two interrelated modules. The first is a customized automated data acquisition module, where a variety of sensors, smart boards, and microcontrollers are used to automate the data acquisition process. This module 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 is a productivity measurement and analysis module, which processes and analyzes the data collected automatically in the first module. It automates the analysis process using data mining and machine learning techniques; providing a near-real-time web-based visualized representation of measurement and analysis outcomes. Artificial Neural Network (ANN) was used to model productivity losses due to the existence of different influencing conditions.

Laboratory and field work was conducted in the development and validation processes of the developed models. The work encompassed field and scaled laboratory experiments. The laboratory experiments were conducted in an open to sky terrace to allow for a reliable access to GPS satellites. Also, to make a direct connection between the data communication gateway (Meshlium®), initially installed on a PC computer to observe the received data latency. The laboratory experiments unitized 1:24 scaled loader and dumping truck to simulate loading, hauling and dumping operations. The truck was instrumented with the microcontroller equipped with an accelerometer, GPS module, load cell, and soil water content sensor. Thirty simulated earthmoving cycles were conducted using the scaled equipment. The collected data was recorded in a micro secure digital (SD) card in a comma separated value (CSV) format. The field work was carried out in the city of Saint-Laurent, Montreal, Quebec, Canada using a passenger vehicle to mimic the hauling truck operational modes. Fifteen Field simulated earthmoving cycles were performed. In this work two roads with different surface conditions, but of equal length (1150 m) represented the haul and return roads. These two roads were selected to validate the developed road condition analysis algorithm and to study the model's capability in determining the consequences of adverse road conditions on the haul and return durations and thus on the tuck and fleet productivity. The data collected from the lab experiments and field work was used as input for the developed model. 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.

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First and foremost, I am very grateful to God for keeping me blessed and granting me the ability to follow through and achieve my goal to complete this research.

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This Thesis Is Dedicated To

The Soul of My Parents

My Beloved Wife

My Kids

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List of Abbreviations

3-AXIS	Cartesian axes X,Y and Z
3D	3 Dimension (X,Y,Z)
4D	4 Dimension (X,Y,Z, and time)
ABM	Agent-Based Modelling
ABMS	Agent-Based Modelling and Simulation
AI	Artificial Intelligence
AI	Agreement Index
AIP	Average Invalidity Percentage
AIR	Agreement Index Ratio
ANN	Artificial Neural Network
AP	Actual Productivity
API	Application Programming Interface
ASTM	American Society for Testing and Materials
AVP	Average Validity Percentage
BFF	Bucket Fill Factor
BIM	Building Information Modelling
BPNN	Back-Propagation Neural Network
CAD	Computer Aid Drawing
CE	Consumer Electronics / Comminute Europeenne
CSV	Comma Separated Value
dBm	Decibel relative to one mill watt
DES	Discrete Event Simulation
EPE	Equivalent Payload Capacity

FCC	Federal Communications Commission
GB	Giga Byte
GDP	Gross Domestic Product
GIS	Geographical Information System
GPRS	General Packet Radio Service
GPS	Global Positioning System
HTML	Hyper Text Markup Language
HVAC	Heat, Ventilation and Air Condition
IDE	Integrated Development Environment
IoT	Internet of Things
JASON	Java Script Object Notation
Kpa	Kilo Pascal
KSA	Kingdom of Saudi Arabia
LADAR	Laser Detection and Ranging
LGPL	Lesser General Public License
Li-Ion	Lithium Ion Rechargeable battery
LOH	Low-Optimum-High
LoRaWAN	Long Range Wide Area Network
mA	Milly Amber
OBD II	On-Board Diagnostic Scanner
OBIS	On-Board Instrumentation System
OZ	Onze
PC	Personal computer
PP	Planned Productivity
PR	Productivity Rate

RAM	Random Access Memory
RFID	Radio Frequency Identification
RTC	Real Time Clock
SD	Secure Digital
SD card	Secure Digital Card
SVM	Support Vector Machines
TA	Water Tension
UAE	United Arab Emirates
UAV	Unmanned Aerial Vehicle
UHF	Ultra High Frequency
USA	United States of America
USB	Universal Serial Bus
UWB	Ultra Wide-Band
WC	Water Content
WiFi	Wireless Internet for Frequent Interface
WSN	Wireless Sensor Network
XML	Extensible Markup Language

1 Chapter 1: Introduction

1.1 General Overview

It is generally unusual to find a construction project free of earthmoving operations. These operations might be either simple as in of moving soil from one location to another for dumping or filling or building a dam or highway. Earthmoving operations are typical in most civil engineering and infrastructure projects. It represents a considerable portion of civil infrastructure projects such as highways, mines, and dams (Hassanien, 2002).

Accordingly, numerous endeavors were done to improve the efficiency of such operations. Various studies were carried out on calculating, assessing and forecasting the productivity of earthmoving operations over the past decades. Moreover, several influencing factors and adverse conditions that could affect productivity were defined. Hauling equipment plays a pivotal role in the success of the earthmoving operations, as these operations are heavy-equipment oriented. Consequently, economic utilization of this heavy equipment has a significant impact on the profitability of contractors (Halpin, 2010).

Several factors can influence the productivity and cost of earthmoving operations, where these factors can be grouped as follows: (1) excavated soil conditions, (2) access and hauling roads conditions, and (3) equipment and operational conditions, (4) weather conditions.

Performance of earthmoving operations considerably contributes to the success or failure of construction projects. Cost of earthmoving operations represents about 20% of the total cost of construction projects (Kang et al., 2009), that clarifies the importance of monitoring the productivity variation in earthmoving operations. Variations in Productivity may lead to cost overruns, schedule delays and unnecessary depletion of resources in earthmoving operations. Low productivity may produce in schedule delays and inefficient utilization of resources. However, high productivity may lead to cost overrun and over depleted resources. Therefore, monitoring productivity of earthmoving operations is essential to avoid undesirable consequences that may be harmful to project objectives.

The performance level in earthmoving operations is closely related to production rate, which depends on various operational, environmental, technical and managerial factors. Therefore, assessment of productivity rate is an essential primary indicator for evaluating the performance in earthmoving operations. However, productivity assessment solely does not provide any indication of the possible occurrence of undesirable consequences. Therefore, only examining the productivity is unsatisfactory for assessing the performance of an operation (Fu, 2013). Hence, the assessment process should go deeper not only to identify the causes behind the undesirable variations but also to find out precisely the contribution of each of the influencing factors, which lead to loss of productivity.

1.2 Problem Statement and Motivation

Precise and timely monitoring, tracking and reporting of onsite progress of construction operations participate in promoting the management efficiency of these operations. There is a need to improve current practice in automated data acquisition systems to exploit the vast advancement in modern technologies and computation techniques to address this challenge in a cost-efficient manner. Most widely utilized on-site data acquisition systems configuration depends on subjective views and available technologies. Researchers have focused on efficient utilization of different wireless sensing technologies, but the majority integrates black-box and off-the-shelf technologies, where there is no means for customized configuration. The literature lacks a well-defined, standardized methodology for customizing the configuration of data acquisition systems. A comprehensive review of literature brings out limitations and gaps in interrelated research work and indicates the need for a standardized methodology that assists in enhancing on-site data acquisition system in a way that fulfills requirements of the production performance monitoring process, which meets its specific desires. In other words, the need for a systematic method to study, configure, design and develop a cost-effective automated data acquisition system was one of the primary motivations behind this research.

Furthermore, the vast majority of research has focused on assessment more than analysis of productivity of earthmoving operations. There is a need to use new methods for measuring and analyzing productivity in order to identify the leading causes behind productivity losses. Also, exploiting modern advancement in computation, artificial intelligence and remote sensing technologies promising efficiently automated potentials for data acquisition, processing and analysis.

This research was motivated by the need of automating the process of productivity measurement and analysis, starting with data collection and ending in near-real-time web-based monitoring of productivity. Analyzing productivity throughout a project guarantees expertise that supports realistic planning for future projects to guarantee, (1) robustness of the operations design, (2) early detection of the bottlenecks and vulnerable points of the system, (3) capability to take the necessary corrective actions timely and in a prioritized manner. Also, the advancement in computing and sensing technology can efficiently participate in automation of productivity measurement and analysis of earthmoving operations.

1.3 Research Objectives

The main objectives of this research is to study, design and develop a fully automated customized data acquisition model. In addition, to develop productivity measurement and analysis model that exploits the advancement of computation and innovative sensing technology. These objectives can be achieved through the following sub-objectives:

1. Study the literature to identify the factors that commonly influence productivity of earthmoving operations.
2. Study previous developed models for automating data collection and recognition of adverse factors and conditions.
3. Evaluate and prioritize those influencing factors to use the highly ranked factors in customizing the configuration of the proposed data acquisition system.
4. Study previous models of data acquisition to identify the associated gaps and limitations, then, to develop an automated data acquisition model that overcomes the identified limitations of previous models.
5. Overcome subjective configuration of data acquisition systems and provide a systematic selection procedure of necessary sensors based on the particular needs of each project.
6. Study and develop customized configuration of the data acquisition system using open-source software and hardware in a cost-efficient manner.

7. Develop near-real-time automatic productivity measurement model incorporating road and driving conditions engine.
8. Utilize artificial intelligence techniques to automate the analysis process, providing fast, robust and accurate analysis of productivity in earthmoving projects.
9. Develop web-based monitoring platform that allows efficient visual representation of productivity measurement and analysis output in near real-time.
10. Validate the developed models for customizing the configuration of data acquisition systems and automated productivity and analysis models.

1.4 Research Methodology

The flow chart shown in Figure 1-1 represents the methodology that was followed in this research. This methodology includes five phases: analysis, design, development, validation, and recommendations. The developed methodology started with a comprehensive investigation, study, and analysis of the literature and ended up with recommendations for future work after validating the developed models for productivity measurement analysis of earthmoving operations.

1.5 Thesis Organization

This thesis consists of eight chapters; Chapter 1 presents an introduction that includes a general overview, problem statement, research objectives, motivations, and methodology. Chapter 2 presents a comprehensive literature review, ended with a summary of the identified gaps and limitations. Chapter 3 depicts the research methodology, a framework of the three developed integrated models and the utilized hardware. Chapter 4 presents the first developed model for customizing the configuration of the developed data acquisition system. Chapter 5 presents a comprehensive description of the second developed model for automated productivity measurement, driving, and road conditions analysis. Chapter 6 presents the third model for automated productivity analysis of earthmoving operations. Chapter 7 represents the developed case study for validating the developed models. Also, it represents the web-based monitoring of productivity. Finally, Chapter 8 discusses the contributions and limitations of this research, as well as the recommendations and future work.

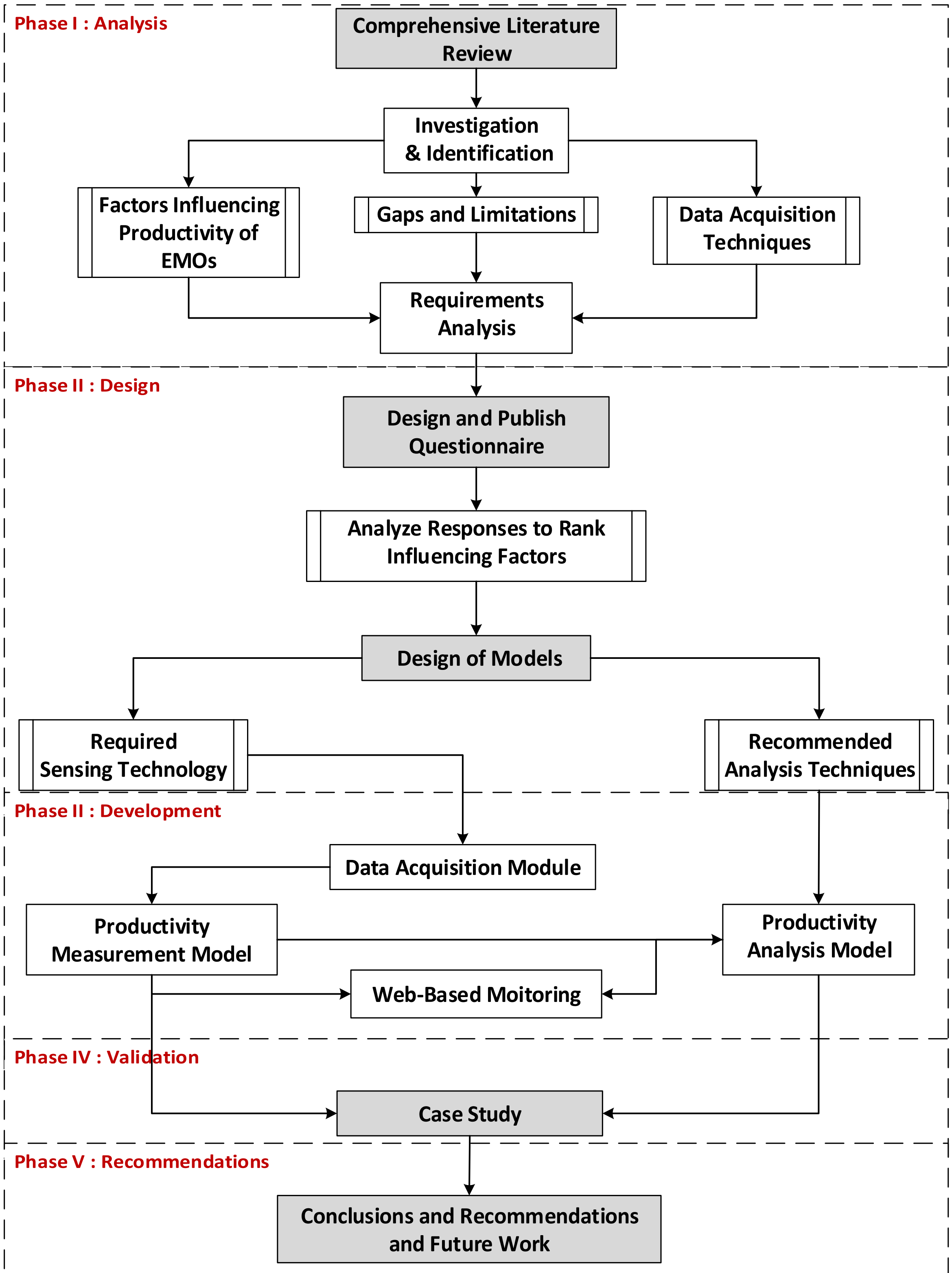


Figure 1-1: Research Methodology

2 Chapter 2: Literature Review

2.1 General Overview

This Chapter presents a comprehensive review of the literature on productivity in construction and earthmoving operations. It sheds light on previous and current practices related to types of construction site information and methods used in measuring activity progress and productivity measurement, the challenges associated with data collection and several methods that were and currently utilized in data collection. It also provides a review of the different methods used in measuring, predicting and analyzing productivity. It also includes a summary of previous studies of automated data-collection techniques and research efforts related to productivity assessment and analysis in earthmoving operations. Finally, it outlines the gaps and limitations. Figure 2-1 illustrates the organization of this chapter.

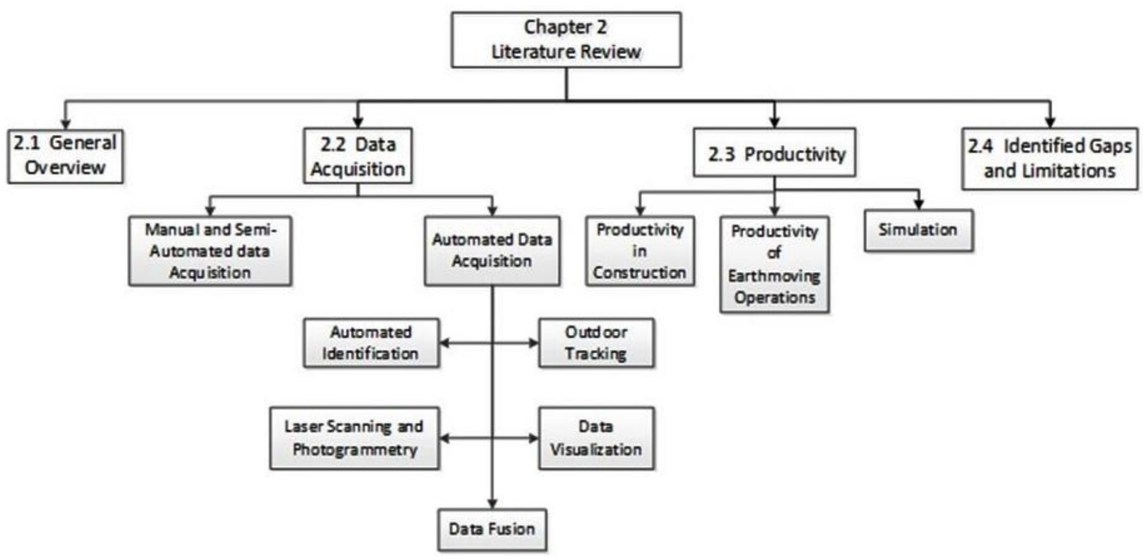


Figure 2-1: Chapter Organization

2.2 Data Acquisition

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).

2.2.1 Manual and Semi-Automated Data Acquisition

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 (Keziltas and Akinci, 2005). Studies concluded that site supervisory personnel spend about 30-50% of their working hours on construction sites in field data recording and analysis (McCullouch, 1997). Data collected using manual methods is based on the collector site personnel skills, judgment, and motivations; hence, it is neither reliable nor complete. Also, data collected manually is usually transferred and stored in papers, so it is difficult to explore and retrieve purposed data sets, which makes both processing and achievement of useful information expensive and unreliable. In other words, eventual valuable data may not be handy to the project's parties when required, and/or data turns out to be obsolete (Moselhi and El-Omari, 2006).

However, manual and semi-automated data collection and analysis approaches are subjective, expensive and time-consuming. Such practice leads to ineffective project management and creates the need for automated solutions that are accurate, efficient, timely and autonomous with minimal user intervention (Sacks et al., 2005). It is evidently concluded that current manual methods for data collection and progress tracking have limitations in studying project progress accurately, objectively, and promptly (Turkan et al., 2012). Hence, cost-effective automated data collection is needed where it can increase productivity, and reduce cost.

2.2.2 Automated Data Acquisition

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.

According to literature, numerous applications of automated data acquisition in construction were studied (Brilakis et al., 2011; Montaser and Moselhi, 2012b; Hegazy and Abdel-Monem, 2012; Ibrahim and Moselhi, 2014). These applications vary from on-site safety enhancement, project monitoring and control, progress tracking, infrastructure monitoring, equipment tracking, and monitoring, supply chain tracking, resources localization, and management, to data visualizations.

2.2.2.1 Automated Identification

Barcodes

Barcodes are the most mature and commonly used technology in automated identification of products in retail and manufacturing (Baldwin et al. 1994). Barcodes typically consist of a series of parallel bars representing identification information of the component, a barcode is read by a specific reader, this reader is an optical device works as a scanner. However, barcodes are being a mature and commonly existing technology; barcodes experience the drawback of the need for line-of-sight between the bar code reader and the component. Also, the reading range of the reader is limited to a few inches. Due to this limitation, scanning each required element for a typical construction site is time-consuming and labor-intensive.

Moreover, in harsh environments in construction sites, barcodes can get grimy and occulted, and then the line-of-sight does not be fulfilled. Another limitation is the read-only format of barcodes; hence, the data on barcodes cannot be updated. (Tesrng et al. 2005) has summarized the most common applications of barcode technology in the construction industry: (1) identifying materials and building components, (2) tracking and management of equipment, (3) tracking Job-site workforce tracking, and (4) identifying drawing sheets, documentation and project activities.

Radio Frequency Identification (RFID)

Radio Frequency Identification (RFID) is another automated identification technology. (RFID) is the wireless communication via radio waves. A typical RFID system includes an RFID reader, tags (chips), and at least one antenna. RFID systems are classified to active or passive depending on the utilized RFID tags. Tags can be categorized as passive or active, according to their power source (Jaselskis and El-Misalami 2003). Active systems utilize tags that contain a battery (active tags) that enable longer read ranges and larger storage capacity. Passive systems use (passive tags) tags without batteries. RFID does not have the barcode technology limitation, where the dependency on radio waves does not require line-of-sight between tags readers and tags. Unlike the automated identification using barcode, RFID is more suitable for harsh construction environments, where there are encapsulated tags. Some types of RFID have large communication range, which extensively facilitates automated identification. Tags working on Ultra High Frequency (UHF) typically have longer read ranges than tags working on high or low frequencies. Table 2-1 summarizes the main features of the two automated identification technologies

Table 2-1: Summary of the main features of barcode and RFID technologies

Technology / Feature	Barcode	RFID
Line-of-Sight	Required	Not required
Number of scanned items	One	Many
Data Storage	Very limited	Up to several KBs
Reading range	Few inches	Up to several meters
Data update	Not possible	Possible
Performance problems in metal media	Yes	No
Suitable for harsh environment	No	Yes

However, these technologies experience limited read range, where barcodes read range is about few inches, and passive RFID read range is 3 to 5 meters. Also, the cost of RFID readers is quite costly where the reader price approximately $1500. Also, the manual scanning and data analysis are time-consuming processes.

Both technologies were used for progress tracking of structural steel erection (Cheng and Chen, 2002), on-site data collection and information sharing between project members (Tserng et al., 2005), and tracking of different material delivery (Jaselskis et al., 1995; Akinci et al., 2002; Song et al., 2006; Lee et al., 2008; Montaser, 2013).

RFID technology has demonstrated efficient results in applications for emergency response, search, and rescue (Ergen et al. 2011). Wang (2008) Proposed RFID based model for quality inspection and management of concrete specimens' lab test. The models examine the influence of inserting the RFID tags inside the concrete specimens on the concrete strength and the RFID readability. The main objective of this study was the assessment of the RFID technology application as a promising solution to quality inspection and management of concrete specimens. Moreover, this study develops a web portal to solve information communication problems. The readability of the RFID tags inserted inside concrete specimens is a significant risk, with which the system is rendering failure. According to field test results, the maximum readable distance of RFID tags inserted inside the concrete specimen was 3 cm from the top surface of the concrete specimen.

Montaser and Moselhi (2012a) utilized the data acquired by 2 RFID gates readers (one in the loading area and the other in the dumping area). Through these data, the loading-dumping cycle could be calculated efficiently. This study proofs how economical the usage of RFID over GIS technologies in case of one loading, one dumping areas, and eight hauling trucks, as the number of loading areas increased, a less number of hauling trucks are economical to use RFID over GIS. Montaser and Moselhi (2014) developed a model utilizes passive RFID tags and two-step algorithm localization methods within a specially designed relational database to identify locations of worker(s) who are equipped with RFID readers and to track materials onsite. RFID reference tags with known location are used as a reference point within a predefined zone.

The coordinates of targets are calculated through triangulation or proximity methods, where the known locations of the reference tags are used in the estimation of the worker's location upon the signal strength received from those tags. The algorithm applied in two steps:

1. Detection of worker's location.

2. Identification of material location using the pre-detected locations of the RFID reader equipped worker.

(Ko et al.) 2016 Presented a cloud-based materials tracking system prototype integrated with RFID and barcode to eliminate the information bottleneck among designers, manufacturers, and installers, hence to improve teamwork in the construction supply chain. The system is suitable for (SMB) Small to Medium Business Contractors. The system is primarily dedicated to serving SBM contractor specializes in manufacturing and installation of commercial HVAC and process piping. The system's validation results indicate the need for using extra reliable RFID tags and reader, which will be more appropriate in the harsh work environment.

2.2.2.2 Out-Door Tracking

Global Positioning System (GPS) is the most commonly used technology in out-door localization and tracking. A variety of other technologies were utilized for progress tracking of outdoor construction operations such as radio frequency identification (RFID), ultra-wideband (UWB), and vision-based technologies. GPS is primarily a military system, but nowadays it has a numerous number of civil applications. Like any other technology; GPS has advantages and drawbacks. Unlike other technologies that might be influenced by weather and temperature, GPS can be used in varying conditions GPS system is consists of three component:

1. Space segment; where the satellite is orbiting the earth in predictable equally spaced orbits at an altitude of around 20,200 Km.
2. Control segment; where a Master Control Station (MCS) in Colorado, USA, in addition to another ten passive monitoring stations around the world are responsible for monitoring and retaining the satellites accurately on their orbits.
3. User segment; where this segment is usually associated to the GPS signal receiver, a GPS receiver calculates its position via solving a set of equations based on the distance between the receiver and three or more satellites (Ogaja, 2011).

Figure 2-2 shows the three segments of the GPS system.

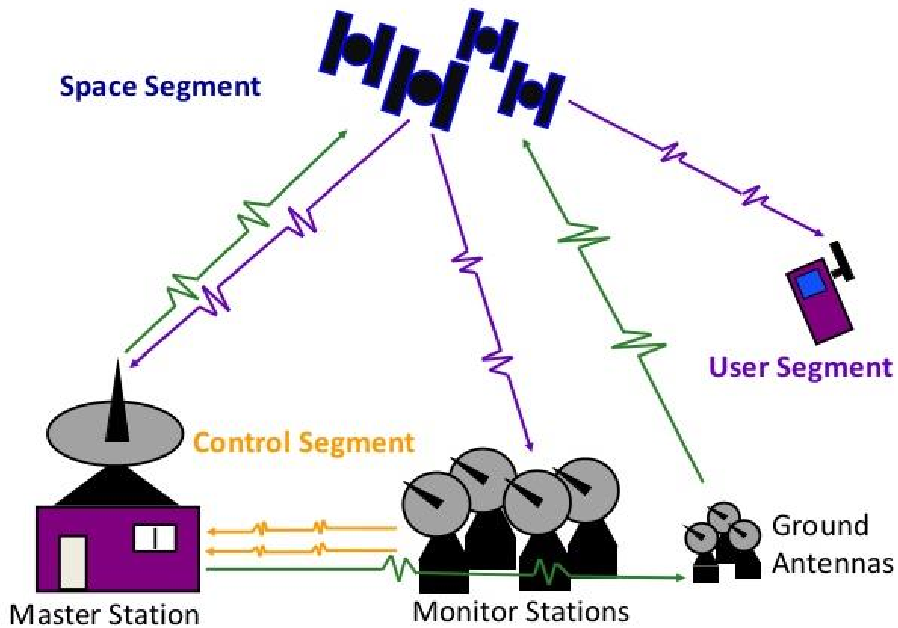


Figure 2-2: The three segments of GPS system (Leonard, 1999)

Civilian GPS receivers can be categorized into three different types based on the accuracy of location and proposed applications:

1. Navigational / Recreational receivers.
2. Mapping-Grade receivers.
3. Geodetic-Grade (Scientific) receivers.

Figure 2-3 illustrates an overview of civilian GPS receiver classification and associated approximate accuracy of each class (Ogaja, 2011).

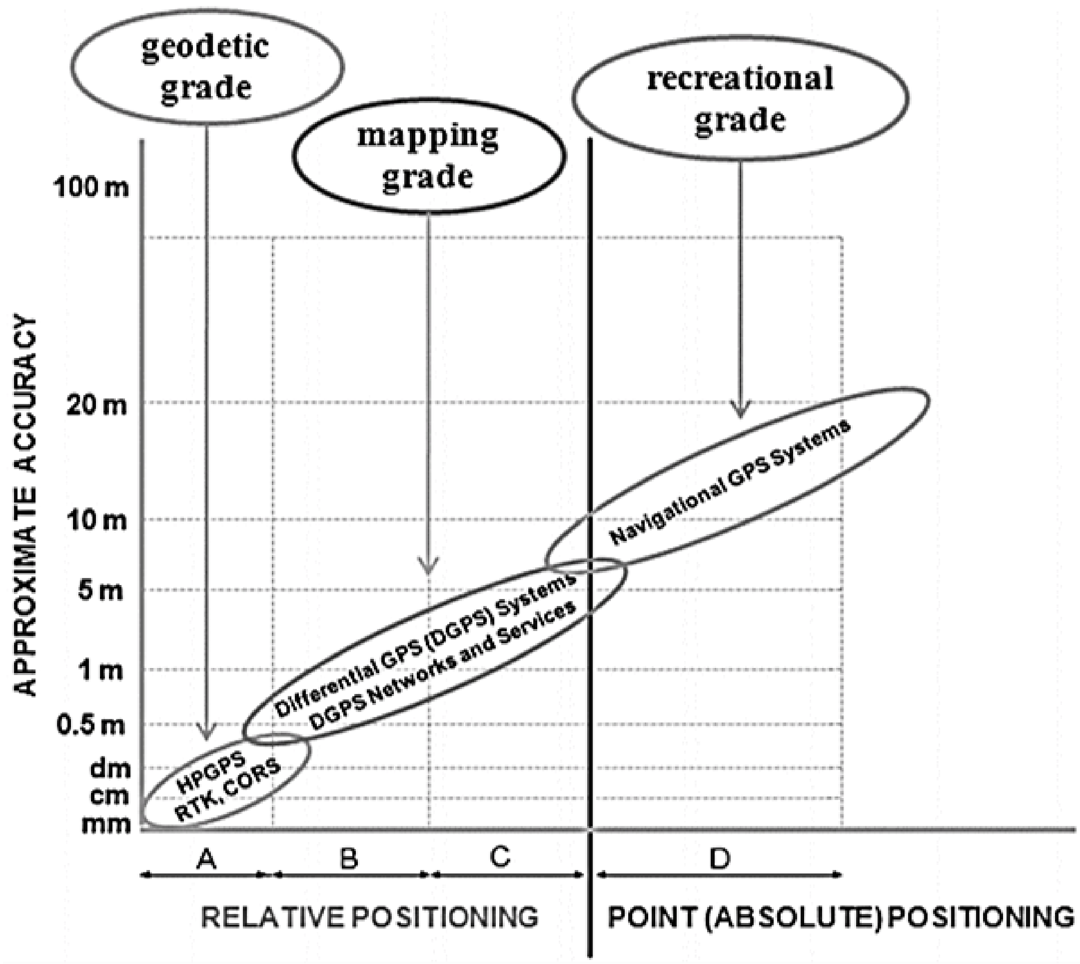


Figure 2-3: Overview of civilian GPS receiver classification (Ogaja, 2011)

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 (Montaser et al., 2012;Alshibani and Moselhi, 2007; Hildreth et al., 2005; Navon and Shpatnitsky, 2005), also in tracking pipe spools position in a construction project (Caldas et al., 2006).

Pradhananga and Teizer (2013) Presented an automatic spatiotemporal analysis for construction site equipment operations using a low price commercial GPS data logger for continuous acquisition of equipment location. The system presents technology and algorithms supporting the automated assessment of construction site equipment operations. A software interface was created where equipment trajectories can be shown for a user-defined duration, which allows the user to set, analyze, and visualize several important factors related to the equipment to achieve more realistic equipment operation analysis and potential for utilization in simulation models. This work permits support for project managers to make better decisions to plan, manage, monitor and control equipment as well as its related work activities on construction sites.

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).

(Montaser and Moselhi, 2012b) utilized RFID to collect data related to earthmoving operations to calculate the loading-dumping cycle. This study verified how economical is the utilization of RFID over GIS technologies in case of single loading and dumping areas using a fleet of eight hauling trucks.

2.2.2.3 Laser Scanning and Photogrammetry

Laser Scanning (LADAR)

Laser scanning has started using a single point to measure systems such as total stations. Currently, this technology yields the collection and creation of (x, y, z) coordinates which are known as 3D point clouds. 3D laser scanner uses a laser beam to determine the distance to an object. Laser Scanning is the most 3D imaging common technology utilized for spatial measurements to capture shapes of objects, buildings, and landscapes. There are multiple names like 3D laser scanning, 3D object scanning or LADAR, but all are referring to the same technology. The most common applications of this technology are often related to systems that are utilized to measure or to capture the existing conditions of the detected objects. These applications include tracking and monitoring the progress of concrete casting surveying, earthmoving operations, paving operations, road alignment, monitoring, and control of construction quality (Lytle, 2011).

Bosché (2008) and Bosché et al. (2008, 2009) proposed an object detection method for as-built modeling using a 3D CAD model together with real data obtained with a laser scanner. In Bosché's algorithms, STL format was used in the exportation of the 3D CAD model and converted to a point cloud demonstration. For the alignment of the coordinate system of the actual, single-scan data with the coordinate system of the 3D CAD model a semi-automated process is used. Finally, a recognition of a 3D CAD component is given, and an as-built model of it is constructed. The study reports that 83% of the as-built steel components already completed, were recognized by this method as being completed, in case of the number of actual 3D data covering the surface of that component is larger than some pre-established limit. The approach was efficiently verified in a steel construction project. Figure 2-4 shown Bosché 3D scan and 3D model object recognition for steel construction.

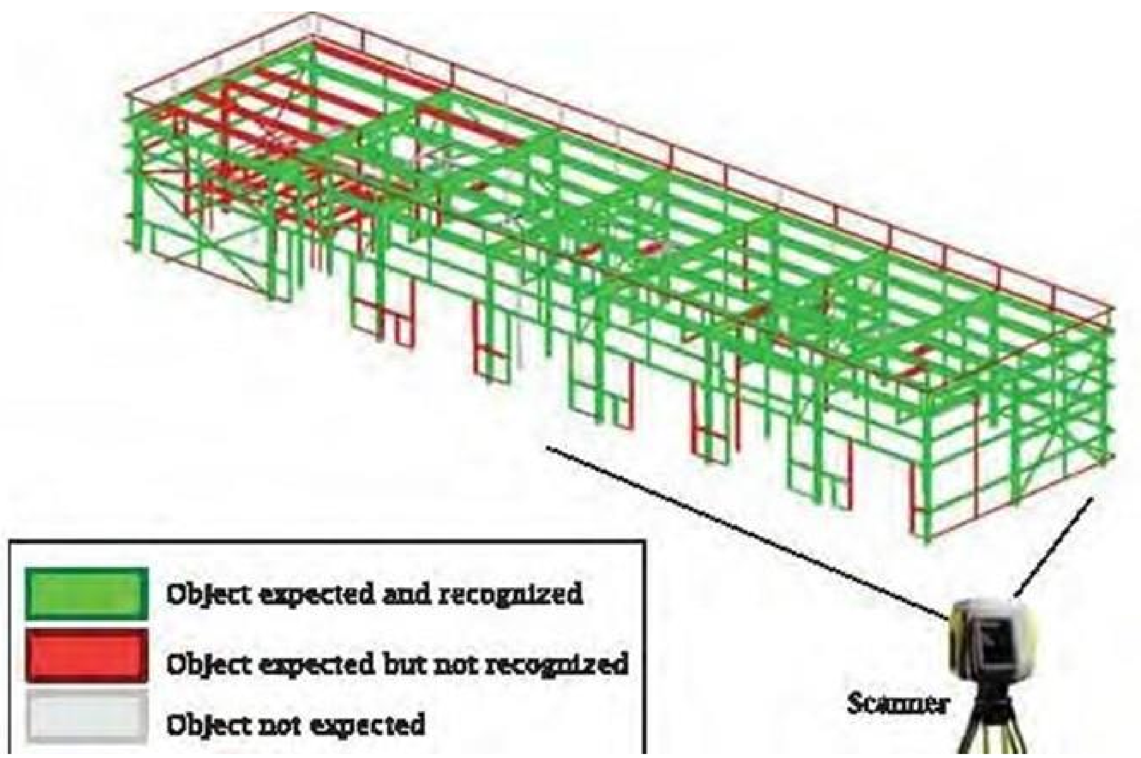


Figure 2-4: 3D scan and 3D model object recognition (Bosché et al., 2009)

Nahangi et al. (2014) presented an automated approach to register as-build status data acquired via a laser scanner, with prefabricated steel assemblies' 3D CAD models in two steps; registration and processing respectively. The proposed model aims to enable the user to monitor the fabrication and installation processes remotely. (Turkan et al., 2012) Used 3D point clouds acquired by the

3D laser scanner and 4D model, which provides the as planned status. Both 3D point cloud and 4D BIM model to be registered in the same coordinate system, hence as-built objects can be recognized, progress estimated, and the schedule updated, all automatically. The recognition is accomplished through three steps; coarse registration (manual matching), fine registration using ICP algorithm and finally, object recognition. Kim et al. (2013) presented a method for construction progress measurement based on information contained in a 4D BIM model and 3D data obtained from a construction site via remote-sensing technology, the method still valid even if the 3D data set is incomplete. The framework for measuring the progress is divided into three stages: First, alignment of the as-built data with the as-planned model. Second, matching of the as-built data to the BIM.

Bosché et al. (2015) presented a method that automates the recognition and identification of objects with circular cross-sections (e.g., pipes) in 3D TLS data collected from construction sites, and given BIM model. This method integrates an object detection and recognition technique, which employed in Scan-to-BIM applications. Son et al. (2015) Presented a method for modeling 3D as-built data of structural elements using data acquired by 3D laser scanner during the construction. This method recognizes the elements of interest from the whole point cloud using color value for distinguishing between various elements. Then the method uses supervoxel algorithm to generate a graph of connected linear patches. Once the connected linear areas are generated a convexity graph is formed by classifying edges to concaves and convexes. From the created convexity graph, each of the elements connected by convex edges is found. Convexity graph demonstrates the way elements are connected in addition to the consequences of the connectivity between patches. The method capabilities were evaluated through a field experiment. The results demonstrate that method could be used for semantic as-built BIM without any prior information from an as-planned model.

Photogrammetry

Photogrammetry is the discipline of creating measurements from photographic images by extracting the geometrical properties of an object from an image (Styliadis, 2007). Photogrammetry has an advantage over the laser scanning; this advantage is the value of obtaining information about texture and color from images (Zhu et al., 2010).

Golparvar-Fard et al. (2012) proposed an automated approach to measuring the progress, where daily construction photographs and a 4D BIM are used to collect information about the as-built status of each structural component for schedule updating. For the generation of 3D data from photographs, structure-formation (SfM) techniques were used. An alignment to be done for the coordinate systems of the 3D data and the 4D BIM, and the progress of each activity is calculated by using information about the as-built status of each element, which is achieved using a support vector machine (SVM) classifier. This method is robust, even in the face of differences in the density of the 3D data. However, it too recognizes only the noticeable elements that are not entirely occluded. Moreover, the 3D registration was carried out using only a semi-automated approach, and it was applied only to the 3D data obtained from the photographs. For that reason, although the method was verified for very simple structures, it accomplished an average of 83–91% accuracy in terms of progress recognition.

Zhu et al. (2016) presented a Photogrammetric vision-based tracking method using particle filtering to track labor and equipment in construction sites. The system tries to solve the issues raised from an occlusion in visual tracking. The system embraces generating hundreds of particles for each detected object, then calculating the weight of each particle, finally, those particles to be assembled and hence followed. This method has the ability to track only one object at the same time. Brauna et al. (2015) presented photogrammetric-point clouds based and precedence relationship graphs system for automated progress monitoring. The system reconstructs as-built point clouds from images and then compare them to an existing 4D BIM model. The images could be captured manually using a calibrated commercial cameras or using unmanned aerial vehicles (UAV). The system tries to overcome the occlusion of some executed elements by automatically investigating the interdependences of elements in the 3D BIM model in addition to the temporal information from the fourth BIM dimension (schedule) that can be done through the usage of precedence relationships. Integrating precedence relationship graphs permits not only higher accuracy to the utilized detection algorithm but also occluded element recognition. Ahmed et al. (2011) Introduced a rapid monitoring and progress tracking system of Pipe-Works using Digital Photogrammetry. This system consists of a hand-held digital camera and Photogrammetry software which utilized for constructing a 3D model of as-built pipe-works.

Most of the developed systems are only able to register and recognize the visible components. Furthermore, nowadays construction projects become larger and more complex, and so it becomes more challenging to acquire complete data sets. The collected incomplete data sets are still considered a significant effect to the automated construction progress measurement in the construction projects (Kim et al., 2013).

The drawback of many systems that individually utilize 3D laser scanning or Photogrammetry may be overcome through the integration of both techniques. This integration alleviates the limitations associated with the utilization of each of them individually such as the required number of scans and the needed duration for each scan to turn out in satisfactory results in the 3D modeling process (El-Omari and Moselhi, 2007; El-Omari, 2008).

2.2.2.4 Data Visualization

BIM stands for Building Information Modeling. BIM is defined as a digital representation of the physical and functional characteristics of a facility (Eastman et al., 2008). BIM Models are the most common visualization of building information. According to National building information modeling standard, *"A basic premise of BIM is collaboration by different stakeholders at different phases of the life cycle of a facility to insert, extract, update or modify information in the BIM to support and reflect the roles of that stakeholder"* (NIBS, 2013). One of the advantages of a BIM over a 3D - CAD models is that the objects in BIM models are parametric, are associated with each other, and hold an array of attributes. This long-term advantage of the BIM may rationalize the permanent attachment of sensors, such as RFID tags, to some of the key components (Motamedi and Hammad, 2009).

Many studies have introduced a variety of approaches to combining those 3D BIM models with project management information, such as time, cost, and as-built data. Responding to rising need for visualization, its techniques are used for visual simulations with Augment Reality (Behzadanet al. 2008) and the viewing of time-lapsed image (Golparvar Fard et al., 2009; Abeid et al. 2003; Abeid and Arditi, 2002) within 3D and 4D (3D BIM + schedule) models. Motamedi et al. (2011) presented a model that integrates BIM and RFID for facilities lifecycle management. RFID tags attached to the targeted components within the facility, subsequently retrieving the data from BIM database to RFID tags.

Zhang and Arditi (2013) presented an automated system that measures construction progress through the integration of 3D - BIM models and 3D laser scanning. This system has three steps to do this. First, linking 3D model and schedule to develop a 4D model. Second, capturing the point cloud data using 3D laser scanner in a daily bases. Third, superimposing the point clouds on the 3D model. A Java syntax was developed to evaluate the construction progress in terms of the percentage complete.

Montaser and Moselhi (2012b) presented an automated method utilizing 4D - BIM models and tablet PC for reporting the progress in construction job sites. This method integrates the 3D - BIM model and project. The integration process generated a 4D model which utilized to simulate the planned construction sequence. A tablet PC is used to collect the as-built progress data using the built-in RFID reader, barcode reader, a camera for capturing images, recording notes, sounds, and video clips. The collected data is then utilized to update the project status on the 4D model, which is then used for comparison with the as planned conditions. Figure 2-5 shows As-Build and As-Planned 4D Models that obtained using the tablet PC.

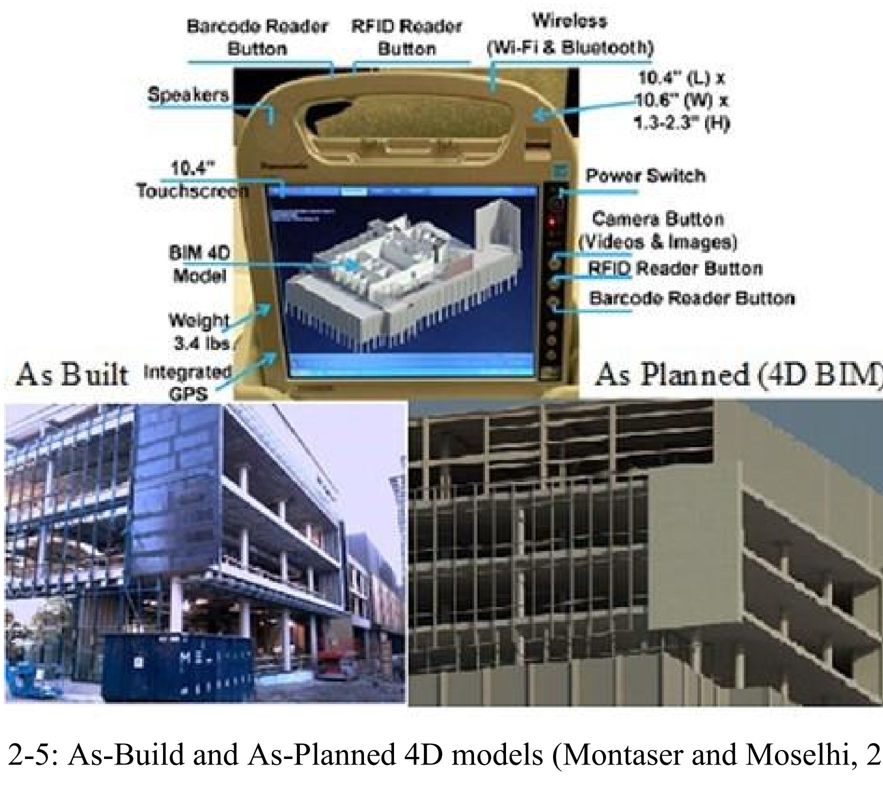


Figure 2-5: As-Build and As-Planned 4D models (Montaser and Moselhi, 2012b)

Mawlana et al. (2015) integrated 4D modeling and discrete event simulation by introducing a new method for generation and assessment of reconstruction phasing plans. This method calculates the probability of stochastic spatiotemporal clashes associated with the finest practical phasing plan. 4D visualization modeling is presented to show the feasible progression in which the sections of the bridges can be constructed or demolished. Montaser and Moselhi (2015) presented an automated outdoor data acquisition system for progress reporting and visualization in near real time. The system integrates 4D BIM models, GPS and tablet PC. The tablet Pc integrates many sensing technologies and data communication protocols, e.g., RFID reader, camera, Wi-Fi, and Bluetooth. The usage of tablet PC not only adds a lot of automated data acquisition capabilities, but also it is used as an integration platform. The system collects on-site data and stores it in a database for processing, hence to generate progress reports. The methodology was applied on a real construction site in Montreal, Quebec, Canada to illustrate the features of the system.

2.2.2.5 Data Fusion in Construction

Data fusion is the process in which multiple data and knowledge are integrated for representing the same object into a consistent, accurate, and useful representation. The goal of data fusion is to improve the quality of information obtained separately from each source (Haghighat et al., 2016). A construction site often has many types of data which usually collected from multi sources. This data is needed for assessing a large variety of aspects such as progress tracking and safety management. Both objective assessment of those aspects and relating informed decision are necessitating the combination of different data sources because not all of the needed information can be obtained using a single data source. Tablet PCs and pen-based computers were an ideal integration platform in some models, where tablet PC allows the user a variety of data collection forms, such as handwritten notes, taking images, or even videos and voice comments (El-Omari and Moselhi, 2011).

The last two decades were the prosperous era of developing multisensory data fusion models that serving the construction industry. Cheng & Chen (2002); Song et al. (2006); Ergen & Akinci (2007); Moon & Yang (2009) and Razavi (2010) have developed models in which the acquired data from GPS, RFID, and other sources of information is fused for locating and tracking construction materials.

El-Omari and Moselhi (2011) presented an integrating control model within a centralized database. The model integrates several data acquisition technologies; RFID, barcodes, 3D laser scanning, Photogrammetry and multimedia using a pen-based computer as a media of integration and the main interface tool. This model integrates. A relational database was developed using MS-Access to ease the interaction with the scheduling software. Once the captured data are well organized through the different entities of the database, it can help in progress reporting, production of as-built drawings and claim management. Object-based models have employed data fusion for the automated of progress tracking of construction projects through the development of automated object-recognition models (Cheng et al., 2012; Golparvar-Fard et al., 2013; Turkan et al., 2013) and automated object-tracking models (Khaleghi et al., 2013; Shahandashti et al., 2011).

Shahi (2012) and Shahi et al. (2014) presented an activity-based framework for multisensory data fusion for tracking the progress of construction activities throughout the entire duration of the project. The developed data fusion processes enabled the tracking of objectless activities such as welding and inspection, which were not possible with other object tracking and recognition methods. This framework was done by complementing various sources of information with the 3D marking data collection system, which incorporates ultra wide band (UWB) positioning system for tracking structural and non-structural construction activities. Although the scope of the validation experiments was limited to ductwork, HVAC, and piping activities of an industrial-type project, results show that the developed data fusion framework improves on the existing object-based material tracking and automated object recognition algorithms.

Ibrahim & Moselhi (2014) and Ibrahim (2015) presented an automated system for actual productivity assessment of earthmoving operations in near real-time. The system fusses data captured via various sensing technologies. The system includes hardware and software development. The hardware incorporates the latest advances in sensing technologies; it consists of: microcontroller, GPS and different types of sensors (Strain gauges,3-Axis accelerometer, and barometric pressure sensor). Bluetooth wireless communication is used for data streaming and proximity detection.

Liu et al. (2016) presented a system for real-time monitoring and control of pavement lift thickness for highway construction. The system integrates a robotic total station, inclinometer (for tilt angle measurement), laser ranging sensor (for measuring the distance to the road service) and GPRS (communication protocol). The robotic total station continuously tracks a platform cart which is connected to the road paver. The platform cart is equipped with the laser ranging sensor and the inclinometer. GPRS communication protocol then is used to transfer data to the database and server for processing. The management team can retrieve the results through laptops and PDAs devices. According to the conducted field applications, the system demonstrated its capability for real-time, automated and accurate monitoring of pavement lift thickness.

2.3 Productivity

Productivity is defined as a process output over input, in another word; earned outcomes over input resources. Productivity measurement for an operation can be simply realized by dividing the number of produced units over the total input resources in this operation. The main purpose of evaluating productivity is to measure the efficiency of input resources. Over the decades, literature has provided many methods for Productivity measurement, e.g., work sampling, craftsman questionnaire, foreman daily survey and craftsman questionnaire sampling (Jeffrey et al. 1987), Activity sampling and recording present work-face practices (Oglesby et al., 1989). Upon the advancement of imaging and video recording technologies, photographing, video and time-lapse recording became a common productivity measurement tool. Each of the above-mentioned methods has its advantages and disadvantages. Getting information is a crucial issue to measure and assess productivity. All methods of productivity measurement and evaluation depend on gathering data. One of the better ways to get data that can be useful in productivity measurement is to observe the process in the study to develop realistic records of how it is being done (Oglesby et al., 1989). Potential advancement in remote sensing technologies provides innovative models for productivity measurement and evaluation, for example, but not limited to (Ibrahim & Moselhi, 2014; Ibrahim, 2015; Alshibani and Moselhi, 2016).

2.3.1 Productivity in Construction Industry

The construction industry plays a significant role in national economies in most countries around the globe, where it is influencing both GDP and the workforce of these countries (Arditi & Mochtar, 2000; Haupt, 2001). Upon that importance of the construction industry, it is fundamental to improve productivity. Hence it is vital to understand and measure productivity, which leads to analyze the factors that influence it and the degree of impact of each. Evaluating construction performance was mostly measured using two criteria; productivity and unit costs(Nunnally, 2000; Schaufelberger, 1999). Productivity measurement utilities as a pointer for the status of the construction operation. Obtaining relevant information is crucial, where which can improve productivity. There are many ways to get information that can be helpful in productivity improvement. Two of the superior ones are to ask those who are involved in the processes and the observation of the process to obtain factual records of how it is being done. Each of these two approaches has its advantages while no fixed rules on which is better (Oglesby et al., 1989). Estimating productivity of construction operation is commonly experience-based due to the complexity involved. However, primarily empirical practices do not pledge a reliable estimate because of the absenteeism of a fastening system that relates the current case to previous patterns (Chao & Skibniewski, 1994; Rueda & Javier, 2011).

2.3.2 Earthmoving Operations

Earthwork projects involve moving substantial magnitudes of earth from source locations to specific destinations. Construction contractors use various procedures and equipment to move earth depending mostly on their equipment availability and hauling distance (Kannan et al., 1997; Rueda & Javier, 2011). However, appropriate selection of size and type of equipment by the project managers should consider many factors such as soil condition, operation zone, and required specification. The conventional deterministic method of production rate estimation is as follows:

Loading equipment production rate

$$Production\ rate = \frac{3600sec.x\ Q\ x\ F\ x\ (AS{:}D)}{t}\ x\ \frac{E}{60\ min\ hr}\ x\ \frac{1}{Voume\ Correction} \qquad \text{Equation (2-1)}$$

Where;

Q = bucket capacity

F = bucket fill factor

AS: D = angle of swing and depth (height) of cut correction

t = cycle time in seconds

E = efficiency (min. per hour)

Hauling trucks

Hourly completed trips by the hauling trucks is a function of cycle time. Truck cycle time has four components: (1) loading time, (2) hauling time, (3) dumping time, and (4) returning time. Many factors could affect each of those four components. Management and operating conditions are considered combined influencing factors. The loading time depends on the percentage of bucket capacity to hauling truck capacity. The hauling and returning cycle times depend on the truck weight, the engine capacity, the haul and return roads distances, in addition to the condition of these roads. Dumping time is a function of the type of equipment and dumping site conditions (Shapira et al., 2010).

2.3.3 Calculating Production of Hauling Truck

1. Number of bucket loads

$$Balanced\ number\ of\ bucket\ loads = \frac{Truck\ capacity}{Bucket\ capacity}$$ Equation (2-2)

2. Loading time

Load time = Number of bucket loads x Bucket cycle time Equation (2-3)

3. Truck load

Truckload (volumetric) = Truck volumetric capacity Equation (2-4)

Truckload (gravimetric) = Vol. load x Unit weight (loose vol.) Equation (2-5)

4. Hauling time

Hauling time primarily depends on the traveling distance and the traveling speed. Based on the total weight of the truck including the load of the soil, and considering the rolling and grade resistance from the loading area to the dump area, the estimated speeds can be obtained using the manufacturer's performance chart of the truck. Figure 2-6 shows the Performance chart of 777G off Highway truck as an example. Performance charts do not consider the acceleration and deceleration in addition to the road condition that can affect the speed of the truck. Hence the truck is not necessarily traveling at the speed indicated using performance charts (Peurifoy et al., 2006). The expected effective speed is what should be used in estimating travel time (Equation 2-6).

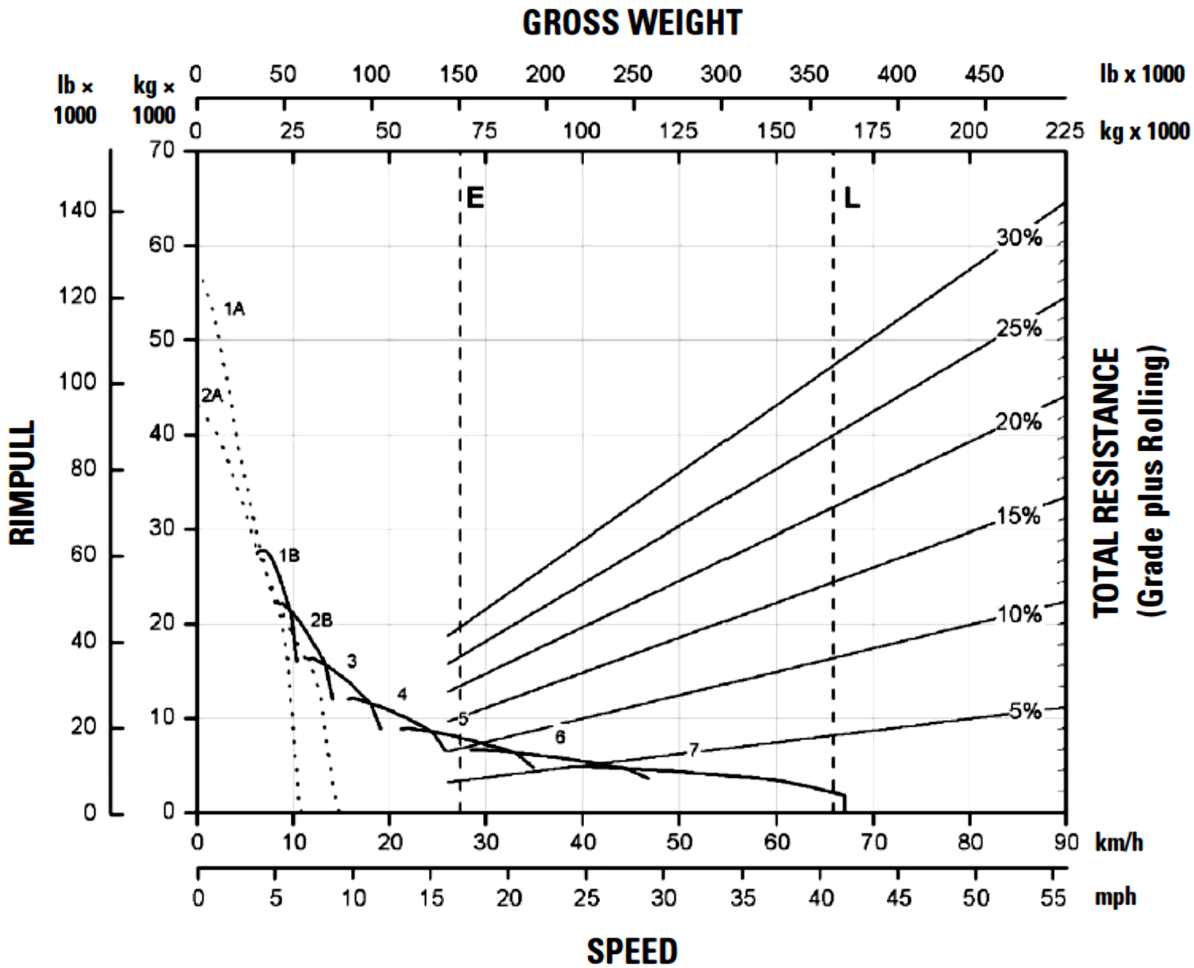


Figure 2-6: Performance chart of 777G off Highway truck - © 2012 Caterpillar Inc. Extracted from: https://mining.cat.com/cda/files/3352106/7/AEHQ6553-00.pdf

$$Hauling\ time = \frac{Haul\ distance\ (Km)}{Haul\ Speed\ (\frac{Km}{hr})}\ x\ 60\ (\frac{min}{hr}) \qquad \text{Equation (2-6)}$$

5. Returning time

Similarly, as in the calculation of hauling time but considering the emptiness of the truck returns from the dumping point to the loading area. Performance charts might be used in order to determine the possible maximum speed.

$$Returning\ time = \frac{Return\ distance\ (Km)}{Return\ Speed\ (\frac{Km}{hr})}\ x\ 60\ (\frac{min}{hr}) \qquad \text{Equation (2-7)}$$

6. Dumping time

Dumping time depends on the dumping site conditions and waiting time resulting from site congestion. Moreover, the operational and management conditions within the dumping point.

7. Truck cycle time

$Truck\ cycle\ time = Load_{time} + Haul_{time} + Dump_{time} + Return_{time} + Wait\ for\ Load\ \&\ Dump_{time}$ Equation (2-8)

8. Number of trucks required

$$Balanced\ number\ of\ trucks = \frac{Truck\ cycle\ time\ (min)}{Loading\ Equipment\ cycle\ time\ (min)}$$ Equation (2-9)

9. Production

Production controlled either by the trucks or by the loading equipment. The number of trucks must be an integer number. If this integer number of trucks lower than the calculated balanced number of trucks obtained using equation 2-9., then the trucks will control production and therefore:

Production (m3/h)

$= Truck\ load\ (m^3)\ x\ Number\ of\ trucks\ x\ 60\ min\ /\ Truck\ cycle\ time\ (min)$ Equation (2-10)

While, if the integer number of trucks is greater than the calculated balanced number of trucks produced by equation 2-9., then the loading equipment will control production and therefore:

$Production\ (m^3/h)$

$= Truck\ load\ \ x\ Number\ of\ trucks\ x\ 60\ /\ Loading\ equipment\ cycle\ time$ Equation (2-11)

10. Efficiency

The above-mentioned steps are showing the calculation of production based on a full 60 minutes working hour. Logically, it does not be the reality, so that production should be adjusted by an efficiency factor.

$Adjusted\ production = Production\ x\ Working\ time\ (min/hour)/60\ min$ Equation (2-12)

Finally, this production can be expressed by means of the desired units using the soil property information. Volumetric units are commonly used while gravimetric units are also necessary for evaluating the load capacity for the trucks.

2.3.4 Productivity of Earthmoving Operations

Earthmoving work package usually takes up around 20% of the total cost of construction projects (Kang et al., 2009). Therefore, estimating onsite earthmoving productivity is always a major concern for project managers (Zhang et al., 2009). Furthermore, productivity is a significant aspect when assessing the design of any process, and it is the most frequently used performance gauge in construction projects. In an earthmoving operation, productivity is defined as the total output from the entire fleet. However, only examining the productivity is unsatisfactory for assessing the performance of an operation (Fu, 2013). It is also important to use methods for analyzing the productivity in order to guarantee robustness of the operations design, moreover, to detect the vulnerability of the system to take the necessary corrective actions.

Earthmoving projects usually involve cyclic routine operations. These operations in most earthmoving projects are loading, hauling, dumping and travel back to the loading area to repeat the same cycle of work. The problem of accurate estimation of earthmoving productivity has attracted many researches for decades; however, a model that predicts the output of such operations with a satisfactory degree of confidence for all situations is not yet available (Smith, 1999).

The researchers' endeavors towards assessing and predicting the productivity of earthmoving operations followed deterministic or stochastic procedure. Experience-based models were commonly used in industry for earthmoving productivity forecasting. These heuristic methods are based on rules of thumb and engineering knowledge. The methods suffer from a lack of mathematical validity and credibility and also do not guarantee optimal solutions. Also, using heuristic methods do not adequately secure the proper solutions when the construction operations grow large and complex (Fu, 2013).

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, in order to develop a tool that aids estimation and generation of reference information to support decision making. Montaser et al. (2014) presented a tool for stochastic forecasting of productivity of earthmoving operations considering uncertainty. The proposed method integrates the use of 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 system for actual productivity assessment of earthmoving operations in near real-time. The developed method includes hardware and software development. The hardware incorporates the latest advances in sensing technologies; it consists of: microcontroller, GPS and different types of sensors (Strain gauges,3-Axis accelerometer, and barometric pressure sensor). Bluetooth wireless communication is used for data streaming and proximity detection. Alshibani & Moselhi (2016) presented an automated web-based system for estimating productivity, time and cost of earthmoving operations. This system utilizes samples of collected GPS data as representation to the whole operations, where these data utilized to develop realistic probability distribution curves for actual duration of open cut excavation earthmoving operations, which utilize a fleet of loaders and trucks. The system accounts for uncertainty associated with activity durations and cost. The system has applied on two actual projects for validation; the results indicate the effectiveness of the system as a tracking and control tool for earthmoving operations.

2.3.5 Simulation

Simulation is *" The process of designing a model of a real system and conducting experiments on this model to understand the behavior of the system and/or evaluating various strategies for the operation of the system "* (Shannon, 1998). In construction, simulation is one of the most powerful methods for modeling, analysis, and understanding of construction operations. Simulation of construction operations permits planners and estimators to evaluate construction operations before starting site work and to predict productivity (Alzraiee et al., 2012).

There are three types of methodologies in the field of construction simulation: discrete event simulation (DES), system dynamics (SD) and agent-based modeling (ABM).

2.3.5.1 Discrete Event Simulation (DES)

The Discrete Event Simulation (DES) was established in the 1960s by Geoffrey Gordon (Greenberg, 1972). DES is utilized for modeling the sequences of a system (Koenig, 2011). Accordingly, it is usually used in simulating construction and earthmoving operations sequences. Halpin (1973) developed a powerful modeling system called CYCLONE, which simplified the simulation and modeling process for users with limited simulation background. CYCLONE was later used as a base for other simulation systems (Montaser & Moselhi, 2014). In 1996, Martinez created a more advanced simulation tool (STROBOSCOPE). This tool has the ability to handle uncertainty not only in time but also for various resource quantities. Once again, in 1999, Martinez and Ioannou went to reduce the complexity associated with their previous model (STROBOSCOPE) by developing the system (EZSTROBE).

2.3.5.2 System Dynamics (SD)

The System Dynamics (SD) was created in the mid-1950s by Jay Forrester, MIT scholar and electrical engineer (Forrester 1961). Most of the principles of system dynamics were developed in the 1950s and early 1960s. System Dynamics is *"The study of information feedback characteristics of industrial activity to show how organizational structure and time delays (in decisions and actions) interact to influence the success of the enterprise"* (Forrester, 1958, 1961). System dynamics helps in understanding the behavior of complex systems over time. It deals with internal feedback loops and time delays that affect the behavior of the entire system. In system dynamics, realistic processes are represented in as a stocks, e.g., of material, knowledge, people, money, flows between these stocks, and information that determines the values of the flows (Borshchev and Filippov, 2004). Stocks, e.g., people, money, and knowledge characterize the state of the system. Flows express the movement of items between various stocks within the system borders or in and out of the system (XJ Technologies, 2012).

2.3.5.3 Agent-Based Modeling and Simulation (ABMS)

Since the early 2000s, agent-based modeling (ABM) was adopted in academic research. The developments and applications of ABM were running in parallel in multiple research areas such as artificial intelligence, computer science, complexity science, and game theory, among others.

There is no standard definition of what are the properties and characteristics of the entity called agent. Agents are adaptive, pro-active, re-active, spatially aware, and self-learners. Moreover, agents have social abilities and have intelligence. Accordingly, they can influence and interact with each other. Also, they learn from their experiences and adapt their behaviors, so they are better fitted to their environment (Schieritz and Milling, 2003; Macal and North, 2010).

Many efforts were made by many researchers in the construction field to model and simulate various construction operations. Literature has many models for different computer simulation for modeling repetitive cyclic operations (Zayed, and Halpin, 2001, Marzouk and Moselhi 2004, AbouRizk, 2010 and Jabri, 2014).

2.4 Identified Gaps and Limitations

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. 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. The identified gaps and limitations are summarized as follow:

- Most automated data acquisition systems utilized black-box and off-the-shelf technologies.
- The need for automated data acquisition system which ables to collect and communicate all the valuable data needed for measurement and analysis of productivity. The system that improves its performance through the advancement of the new sensing technologies as well as communication techniques.
- Literature lacks systematic method to customize the configurations of data acquisition systems for earthmoving operations.
- Literature lacks data fusion algorithms application for near real-time productivity measurement and analysis.

- Most data fusion models in literature were more adequate for building projects than earthmoving operations and highway construction and usually they require human interventions.
- Uncertainty due to the dynamic nature of earthmoving operations and probability of sensors malfunction is not considered.
- Only examining the productivity is unsatisfactory for assessing the performance of an operation (Fu, 2013). Most research has focused on assessment more than analysis of productivity. Where assessment often indicates the presence of problems that have affected the productivity, it may evaluate problems and their consequences, while it does not identify these problems and their causes.

3 Chapter 3: Developed Models

3.1 General Overview

This chapter presents a description of the integrated developed models. The main aim of the developed models is to overcome the previous research identified gaps and limitations by addressing the research objectives. The developed models present the integration and automation of various methods and algorithms to support the process of productivity measurement and analysis of earthmoving operations. The automated models for productivity in earthmoving operations are discussed in details. Figure 3-1 depicts the main sections of the developed models, and how they are integrated.

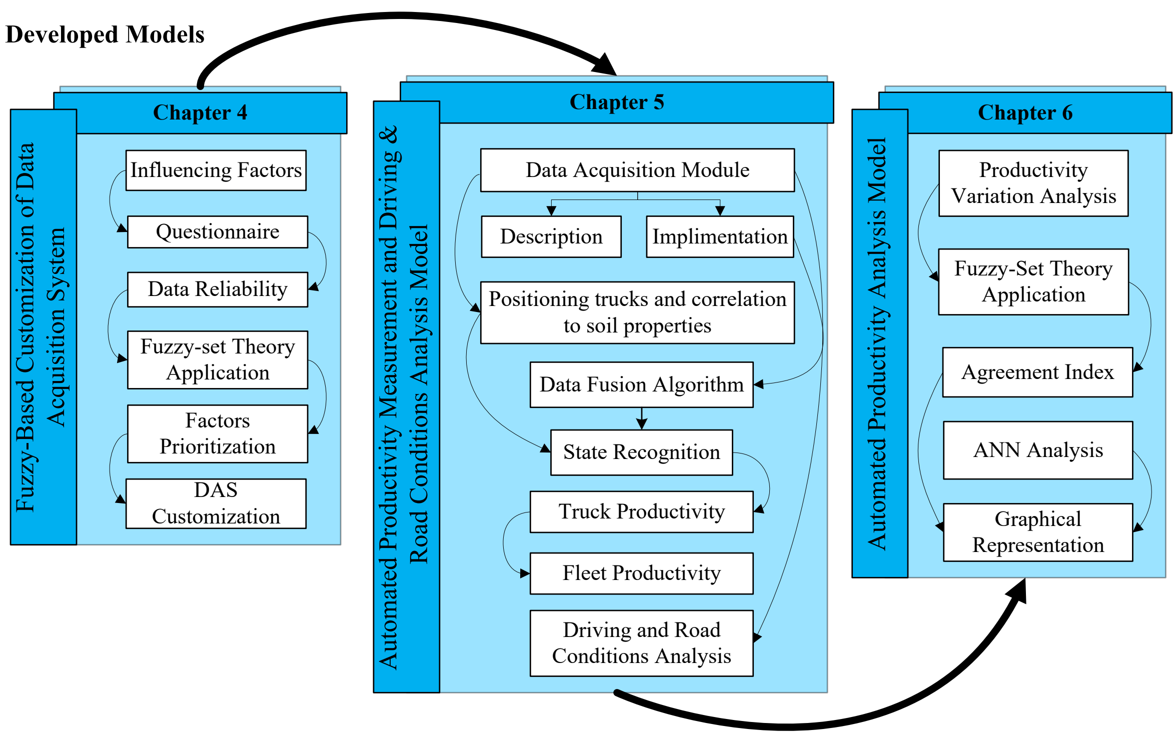


Figure 3-1: Main sections of the integrated developed models

3.2 Identification of Factors Influencing Productivity of Earthmoving Operations

Many factors could impact productivity of earthmoving operations. The timely detection of these factors aids management to avoid cost overruns and schedule delays. The advancement in wireless sensing technology and data communication enriched research and practice for identifying various factors that could influence earthmoving operations. The influence degree of these factors is varied from a factor to another. This variation of influence motivates the need for ranking these factors based on the degree of influence on productivity. A questionnaire was designed to reconnaissance the judgment of experts on the impact of each factor on productivity of earthmoving operations. Appendix I shows the questionnaire and Figure 3-2 shows literature based brainstorming for some factors that could lead to productivity losses in earthmoving operations. Each of these factors has identification signs as shown in the middle column, while the last column illustrates the type of data necessary to facilitate this identification as well as the sensing tool recommended.

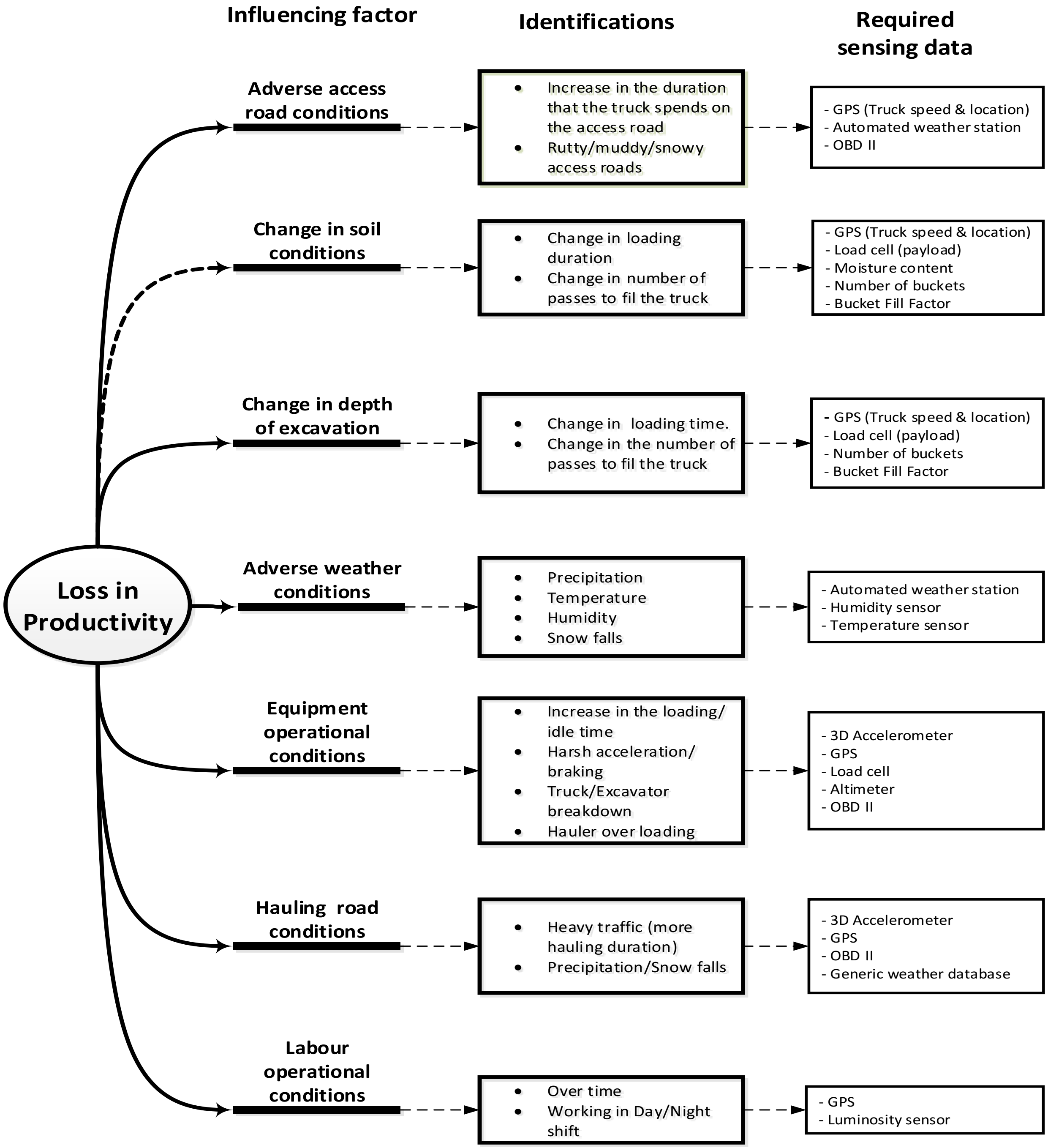


Figure 3-2: Major proposed factors influencing productivity of EMOs, required sensing data and recommended acquisition technology

3.3 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. To achieve this objective a framework of three integrated models was designed, these models are as follow:

1. Fuzzy-based model for customization of data acquisition system.
2. Automated productivity measurement, driving and road condition analysis model.
3. Productivity analysis model and web-based monitoring.

The three models are articulated in chapters 4, 5 and 6 respectively, while this chapter includes:

1. Automation framework and the scheme of linking the three models and showing how they work in an integrative manner.
2. Examination of the functionality of the utilized data acquisition system and its components.

The developed holistic framework of this research integrates data acquisition as well as productivity measurement and analysis in a near-real-time. Figure 3-3 shows a simplified overview of this framework.

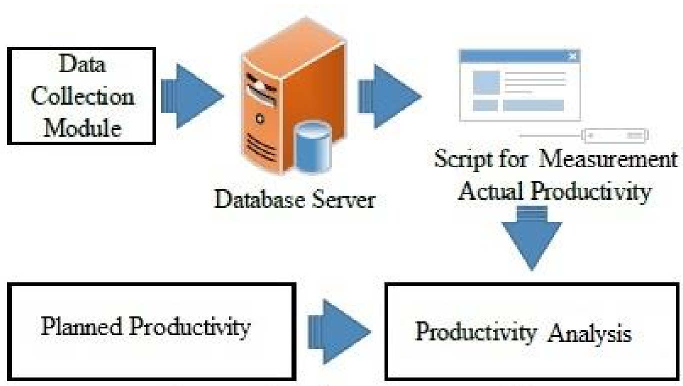


Figure 3-3: Simplified overview for productivity measurement and analysis framework

The developed automated models consist of two main modules; each module has one or more sub-modules. Figure 3-4 shows a schematic design of the proposed automated productivity analysis framework.

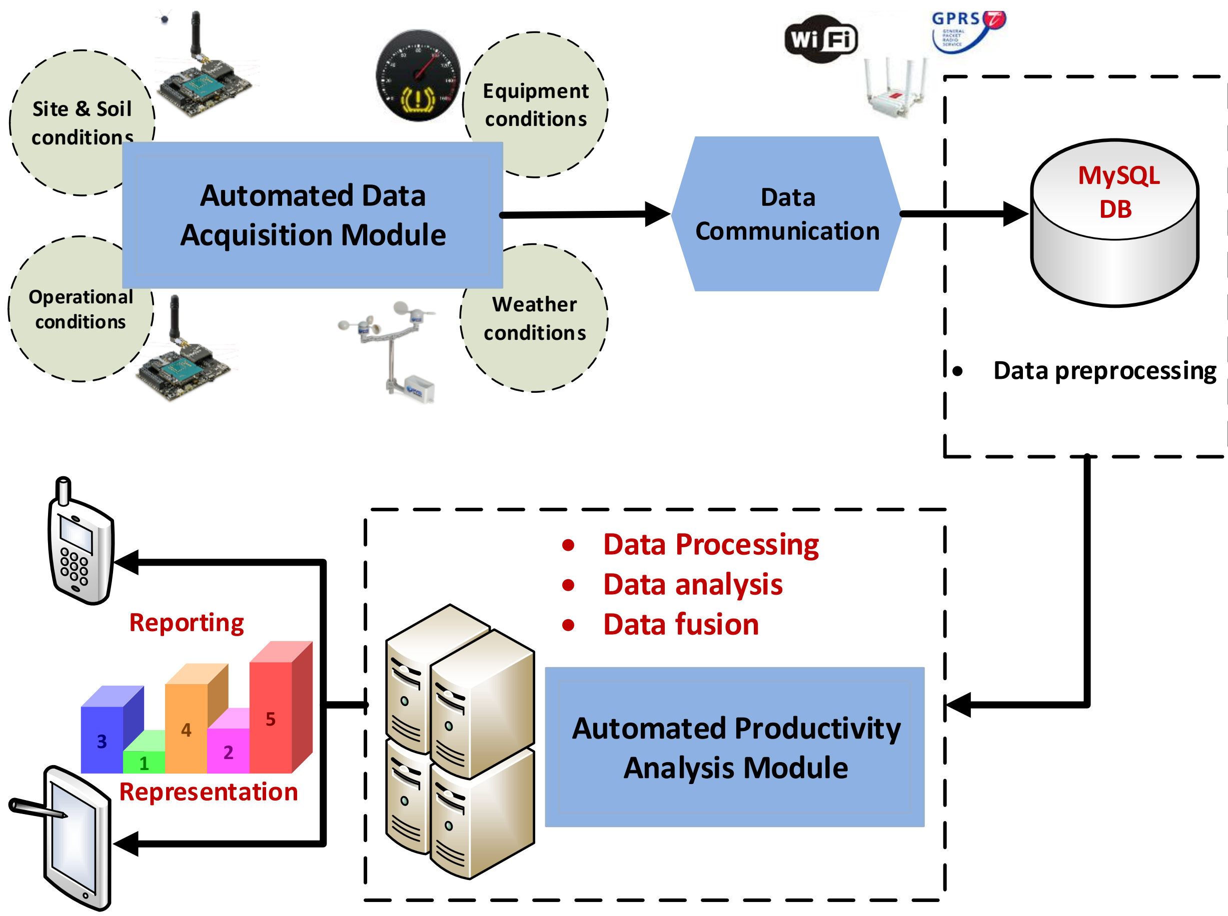


Figure 3-4: Schematic design of the developed automated productivity analysis framework

The developed model has the opportunity to use 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 data storage up to 40 GB. 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 sensor data. The main purpose of this preprocessing is to filter and hence to lighten the data load on the final processing distention on the host server (cloud). Figure 3-5 shows a framework of the developed automated productivity analysis model.

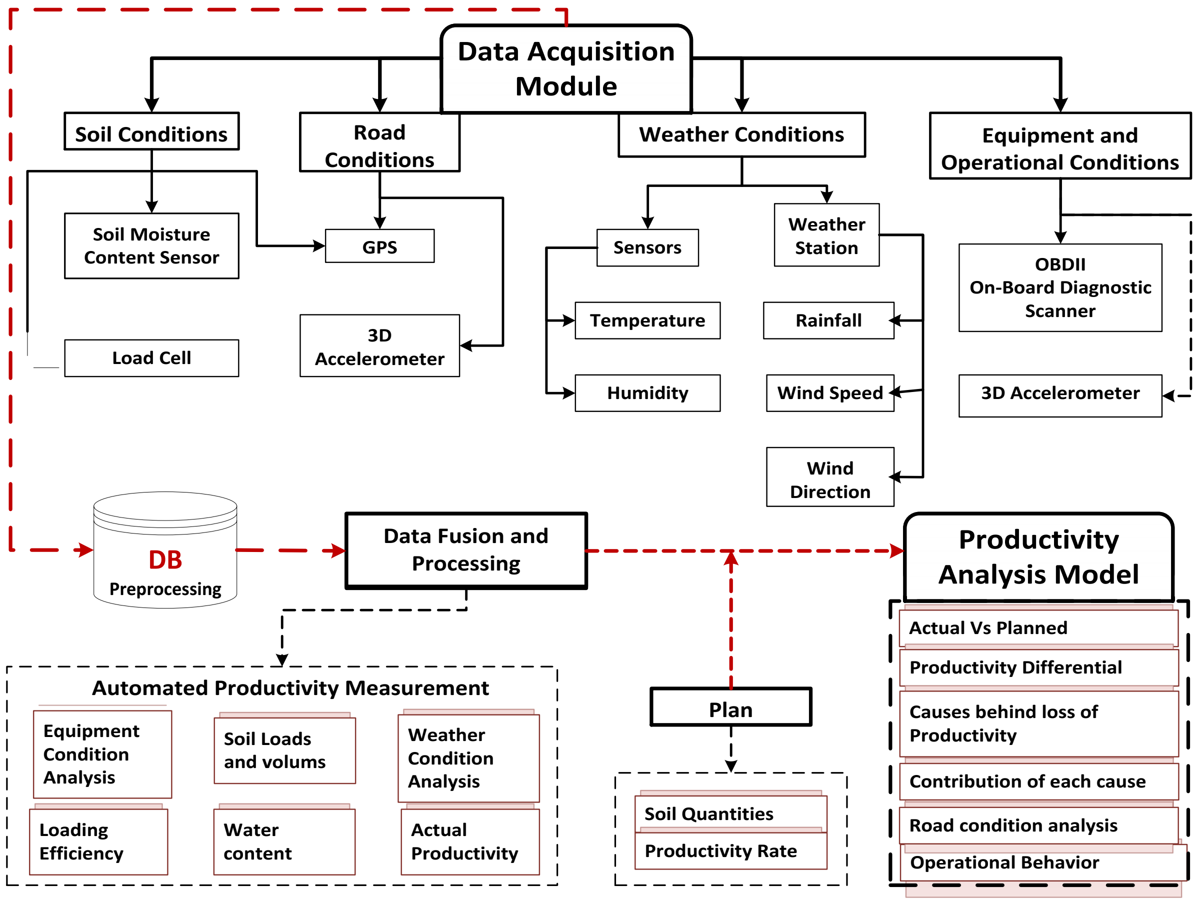


Figure 3-5: Framework of the developed automated productivity analysis model

3.4 Data Acquisition

3.4.1 Fuzzy-Based Model for Customization of Data Acquisition Module

The developed model is explained in details in chapter 4, where it introduces a new fuzzy set-based model that follows this procedure:

- Identify the factors that affect the productivity in earthmoving operations using a questionnaire that been sent to eighty experts involved in such industry.
- Evaluate the effects of each factor through the received responses from the responadent experts.

- Analyze the consequences of each factor and select the most influencing factors on the productivity of earthmoving operations.
- Configure the data acquisition system in a customized manner by selecting the most needed sensors based on the rank of their corresponding influencing factors.

The different influencing factors were categorized into four main groups as follow:

1. Excavated soil conditions.
2. Hauling and access roads conditions.
3. Equipment and operational conditions.
4. Weather conditions.

Figure 3-6 shows the data acquisition system, which covers different influencing categories and their required corresponding sensors.

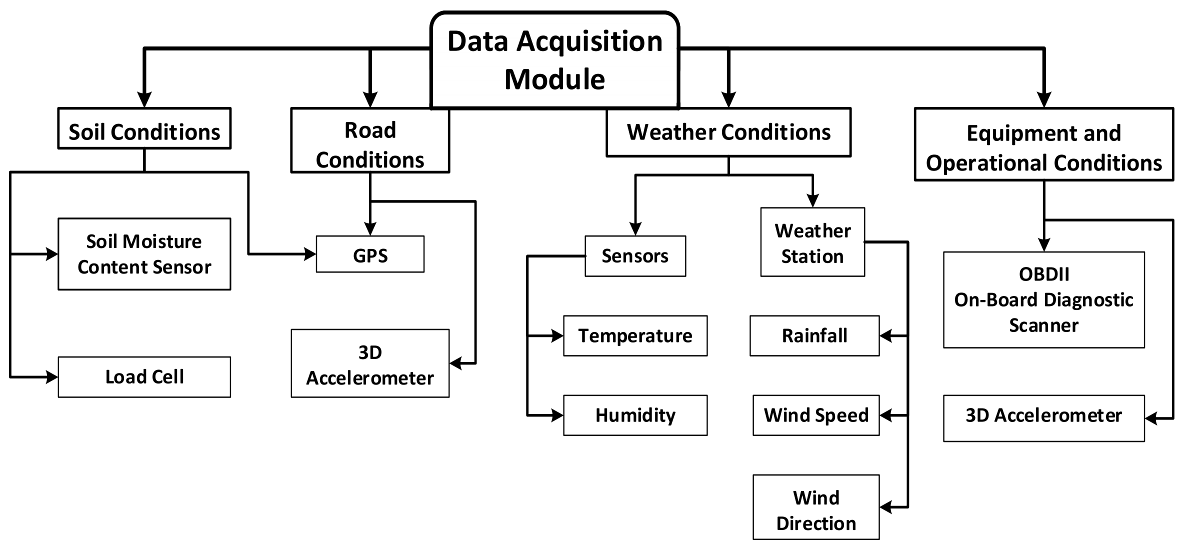


Figure 3-6: Data acquisition system, different influencing categories and required sensors

3.4.2 Automated Data Acquisition Module

Automated data acquisition module is responsible for the automated collection of a diversity of data associated with the different activities in earthmoving operations. Mega-projects, as well as highway construction projects, could benefit from this model. The proposed data includes moved and excavated soils, road conditions, as well, operational and weather conditions. The utilized components of the data acquisition module in this research are generally designed for numerous applications. Although the utilized smart boards, sensors and microcontrollers have comprehensive applications, construction activities are not a part of these applications. The utilized kit contains a low-cost open-source microcontroller, smart sensing board and variety of sensors. The smart sensing board is dedicated to bundle a particular type of sensors. Earthmoving operations, as well as highway construction, have different activities that mostly if not always take place in outdoor environment. The outdoor earthmoving operations will be monitored and tracked using a diverse group of sensors based on the customized configuration using the fuzzy-based customization model. The developed model has significant reliance on GPS, because of the useful spatiotemporal data that could be provided by GPS. A GPS low power consumption sensor is utilized for spatiotemporal recognition of the operations' resources, i.e., hauling equipment.

The outcome of the fuzzy-based customizing model aids the approach of engaging other supportive sensors. The utilization of other sensors within this module not only helps in overcoming the limitations of conventional standalone GPS but also the data collected from these sensors is efficient in productivity measurement and analysis. These sensors permit the availability of many data types that used in discrete or fused approach leading to efficient productivity measurement, assessment and analysis. Data acquisition module has the role of collecting all the necessary data required in calculating the actual productivity, also analyzing productivity, and road and driving conditions. 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 module integrates a GPS receiver module with the utilized Waspmote® microcontroller. Figure 3-7 shows the utilized A1084 (Vincotech) GPS receiver. This receiver has sufficient appropriateness to be used in earthmoving operations, where it permits reasonable sensitivity and accuracy, which are suitable for earthmoving operations. GPS receiver characteristics are shown in Table 3-1.

Figure 3-7: GPS receiver module A1084 (Vincotech)

Table 3-1: GPS receiver module A1084 (Vincotech®) characteristics

Movement sensitivity:	-159dBm
Acquisition sensitivity:	-142dBm
Accuracy Horizontal position	 < 2-5 m
Time To First Fix TTFF Hot start Warm Cold	 < 1 S < 32 S < 35 S
Dimension Length Width Height	 15.24 mm (0.6") 15.24 mm (0.6") 2-4 mm (0.042")
Weight	1.2 g (0.042 oz)
Acquired data	Latitude, longitude, altitude (height), speed, direction, date/time, ephemerides

Data acquisition module is responsible for collecting data through a group of sensors. However, the data collected by the data acquisition module forms the significant portion of data needed for the productivity measurement and analysis model, other sources of data is required too. Accordingly, the data is grouped into five sections. These sections were categorized based on the required information for productivity measurement and analysis. These sections are as follows:

I. Excavated soil conditions data collection: This section is responsible for collecting data related to excavated soils. Excavated soil characteristics influence the entire earthmoving operations. For example, the truck may reach its payload capacity before it reaches the usual utilized volumetric capacity when there is a change in soil density or water content. The payload of the truck is obtained using a load cell sensor. Once the load acquired, the volume of the loaded soil can be calculated using the excavated soil properties, i.e., density.

II. A. Road conditions data collection: This section is responsible for collecting data related to hauling and access roads conditions. Uneven surfaces, rutted and soft roads that have higher rolling resistance can affect the hauling duration (Kannan 1999). Rutting and bumpy roads are considered a principal cause of compulsory deceleration and many hauling trucks' mechanical damages. Hence, an extensive loss in productivity is expected in the presence of such adverse road conditions.

II. B. Operational behavioral conditions data collection: This section is responsible for collecting data needed in the analysis of operational behavior of the drivers of trucks. Achieving productivity targets usually leads equipment operators to stress the equipment ahead of its upper limit capacity. Also, due to limited durations and to achieve higher production rates, the operators stress the equipment. This stress affects the machine negatively and turns to mechanical damage (i.e., speeding, harsh acceleration, and braking). A 3D accelerometer is used for recognizing violent driver behavior against hauling equipment.

III. Equipment conditions data collection: This section is responsible for collecting data related to the hauling equipment which could remarkably affect the productivity of the machine itself and hence the operations' productivity. Trucks are considered a vital part of utilized equipment in earthwork. These trucks are subject to different types of faults, which may affect not only the machinery production but also it produces in delays and cost overrun. These faults are always related to one or more of the following: body, chassis, power-train and electrical network. Body and chassis problems are considered to be detected merely through visual inspection. Detection of Power-train and electrical network problems are usually done in a computerized way, especially on the trucks which were manufactured from mid-1990s onward, where they have OBD (On-Board

Diagnostics) system. The last two mentioned series of problems include transmission, fuel consumption, tire pressure monitoring and rolling resistance indicators. Figure 3-8 shows a simplified representation of OBD II scanning system and a sample gauge panel of the diagnostics and scanned items. One of the OBDII strengths is its capability to detect problems a long time before the driver is able to notice any symptoms, such as low-performance, low-fuel economy, and heavy emissions. Some modern scan tools can be connected to a desktop or laptop while other tools allow a smartphone or tablet to connect via Bluetooth and then turns the phone to a comprehensive scan tool

Figure 3-8: OBD II scanning system and sample outputs dashboard

OBDII is connected to a slot under the steering wheel of the truck. It can be connected to a USB port of the computer or laptop. Moreover, OBDII can send the acquired truck health data to database using Bluetooth or Wi-Fi protocol. Monitoring speed of the hauling truck is essential in the developed models. However, GPS data includes the speed; the utilized GPS receiver module did not show acceptable accuracy. This inaccuracy was the emitter to exploit the speed data obtained by the OBD II.

IV. Weather conditions data collection: This section is responsible for collecting the weather conditions data that have an influence on the productivity of earthmoving operations. The utilized weather station permits the delivery of real-time, accurate data, in a reliable and flexible way. Weather Station WS-3000, a kit that encompasses three productivity analysis advantageous sensors: wind gauge, anemometer, and wind vane as shown in Figure 3-9.

Figure 3-9: Libelium WS-3000 includes wind gauge, wind vane, and anemometer

V. Generic updated data sources: This section is a source of some required data that has not been acquired physically as in the sections explained above. As well, it is considered a system robustness element, where it adds redundancy to the system as another truthful source of data. The generic data sources such as soil databases and weather condition API databases. The developed model can benefit from data extraction from weather condition databases in a timely manner. Most of these weather API databases provide developers with an access to existing weather conditions as well as weather forecasts based on the location; as well as weather maps based on region. The usual practice uses such types of databases in many practical applications such as agriculture, while construction still mostly depends on conventional procedures to investigate weather conditions on job sites.

The developed model automates the usage of such databases to effectively support the level of confidence of the weather data collected via the different utilized sensors. The aim is to provide an automated vigorous model that accounting the uncertainty of sensors malfunction by adding additional automated authentic source rather than sensors. This API calls can be reached through web access to the current weather data for any location in the globe including more than 200,000 cities. Current weather is regularly updated based on global models and data from more than

40,000 weather stations. Data is available in many formats e.g. JSON, XML, or HTML format. An example of open source API respond, and explanation of all the associated parameters are presented in Appendix II. These responses can be tabulated as a part of the developed database. Weather API calls data could be compared with the collected weather sensing data. Comparing both online retrieved data and weather data from the automated weather station depends on the conformity of the timestamps for the same type of data. This comparison allows continuous synchronized calibration of all sensors utilized to capture different types of weather conditions data. As a conclusion, this approach permits not only higher reliance on the collected data, but also it considers the risk of any weather sensor malfunction.

Each of the sections mentioned above incorporates one or more type of data, for example weather condition has more than data type, i.e., temperature, humidity and rainfall. The collected data will be fused at succeeding steps. The aim of data fusion is to provide a better understanding of the whole picture of different operations. Also, to overcome the limitations of a utilized technology by benefiting from the data collected by other technologies.
It is worthy to refer to the flexibility of the proposed utilized tools, where the board gives consent to a customized usage of a wide variety of sensors. Waspmote agriculture smart board permits the usage of a wide range of sensors.

Figure 3-10 shows the board, where all the red marked blocks are sensing sockets, while some of the utilized sockets in the developed model are the ones with arrows. The same figure also shows the socket that allows the integration of the automated weather station with the smart board. Appendix III represent several programming syntaxes for different utilized sensors.

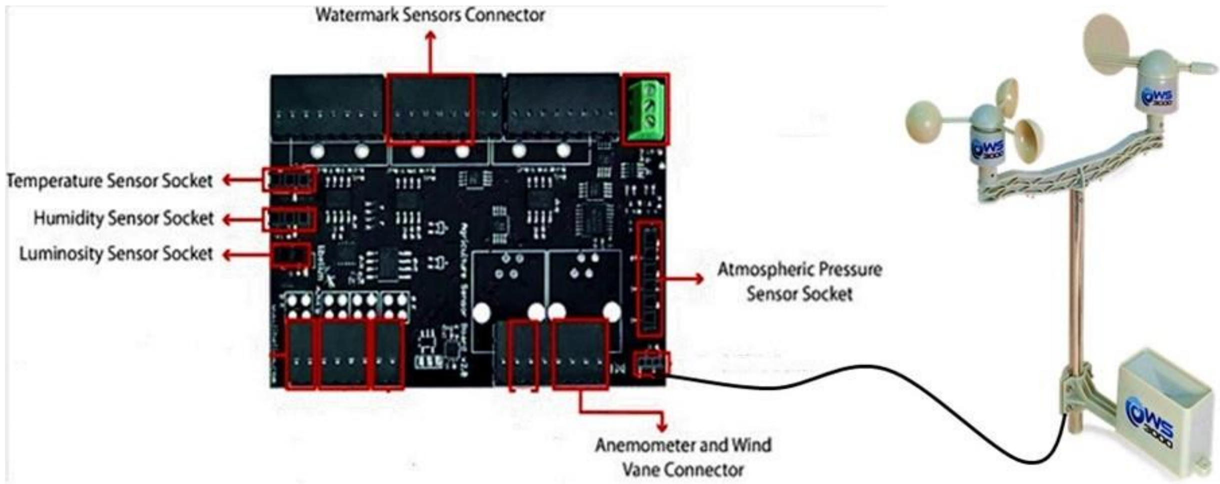


Figure 3-10: Sensor board, sensor slots, and integrated Libelium WS-3000

Figure 3-11 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 3-11, the main components of the data acquisition module are the microcontroller and the smart sensor board. Table 3-2 represents the main two components of the data acquisition module as well as the sensors integrated into the microcontroller and the sensors connected directly to it as well. Table 3-3 shows the specifications of sensors associated with the developed data acquisition module through the smart sensor board.

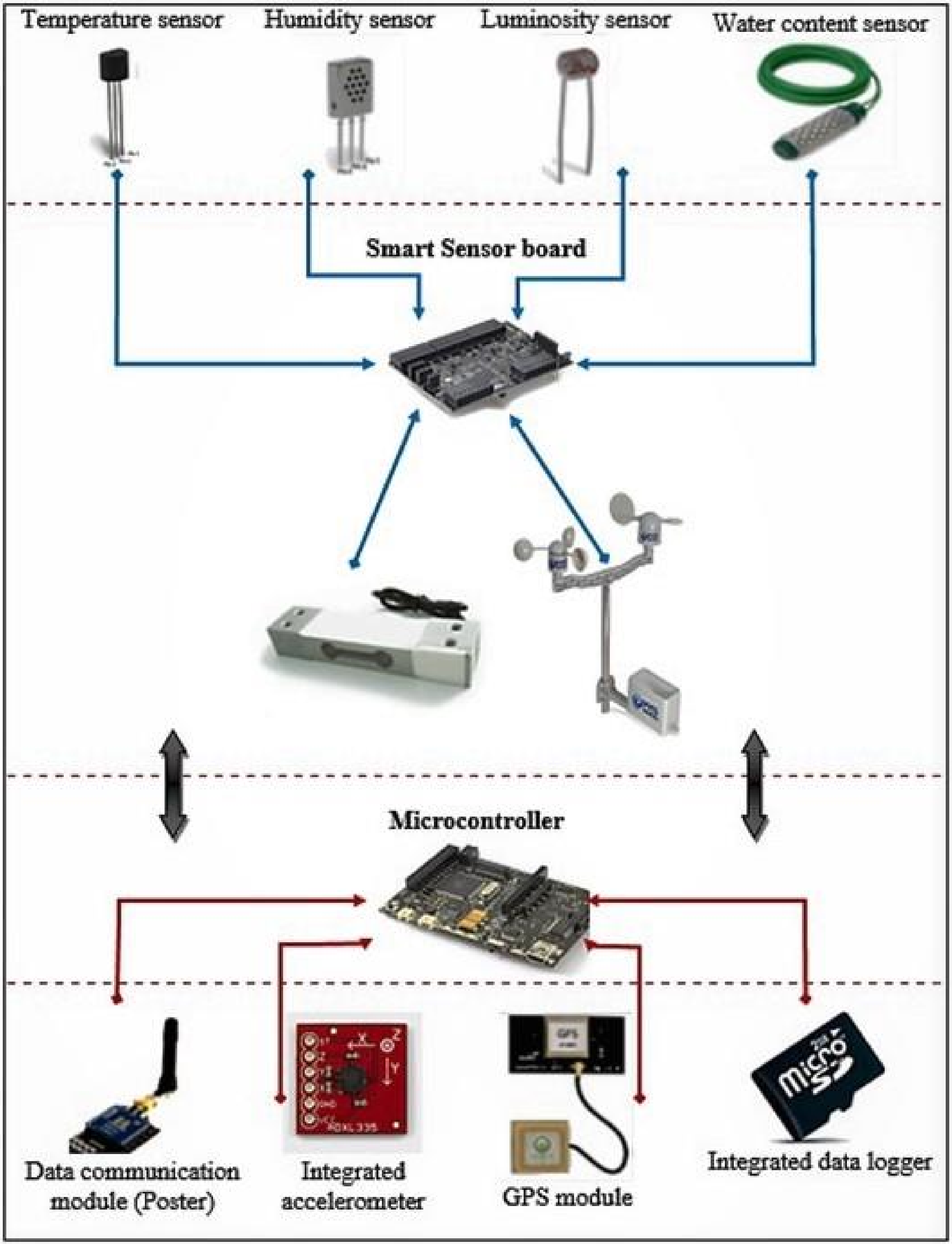


Figure 3-11: Onsite data acquisition module block diagram

Table 3-2: Specifications of main components of the developed data acquisition module

Component	**Specifications**
Waspmote microcontroller 	**Characteristics** SD Card: 2GB Weight: 20gr Dimensions: 73.5 x 51 x 13 mm Temperature range: [-10ºC, +65ºC] Clock: RTC (32KHz) **Consumption** ON: 15mA Sleep: 55uA
Sensor board 	**Characteristics** Weight: 20gr Dimensions: 73.5 x 51 x 1.3 mm Temperature range: [-20ºC, 65ºC] **Consumption** Maximum (continuous): 200mA Maximum (peak): 400mA The Agriculture 2-0 Board for Waspmote includes all the electronics and sockets required to connect a variety of sensors; from which the soil moisture content sensor.
3D Accelerometer (Build-in the microcontroller)  	The integrated accelerometer can make up to 2560 measurements per second from -6g to +6g on the 3 axes (X, Y, Z). This device is ideal to be used in portable wireless sensing networks, where it is possible to be integrated into trucks and equipment
Data communication module (poster)  	Different modules can be used as a data poster. Waspmote microcontroller can integrate Wi-Fi, Bluetooth, LoRa wan and Xbee modules to communicate data to a sister module which has the same characteristics as the receiver geteway. The chosen module depends on the required wireless coverage. In this research, **Wi-Fi and GPRS** are used to transfer data.

Table 3-3: Specifications of sensors associated with developed data acquisition module

Component	Specifications
Temperature sensor 	Measurement range: -40ºC ~ +125ºC Output voltage (0ºC): 500mV Sensitivity: 10mV/ºC Accuracy: ±2ºC (range 0ºC ~ +70ºC), ±4ºC (range -40 ~ +125ºC) Typical consumption: 6µA Maximum consumption: 12µA Power supply: 2-3 ~ 5.5V Operation temperature: -40 ~ +125ºC Storage temperature: -65 ~ 150ºC Response time: 1.65 seconds (63% of the response for a range from +30 to +125ºC)
Humidity sensor 	Measurement range: 0 ~ 100%RH Output signal: 0.8 ~ 3.9V (25ºC) Accuracy: <±4%RH (a 25ºC, range 30 ~ 80%), <±6%RH (range 0 ~ 100) Typical consumption: 0.38mA Maximum consumption: 0.5mA Power supply: 5VDC ±5% Operation temperature: -40 ~ +85ºC Storage temperature: -55 ~ +125ºC Response time: <15 seconds
Luminosity sensor 	Resistance in darkness: 20MΩ Resistance in light (10lux): 5 ~ 20kΩ Spectral range: 400 ~ 700nm Operating Temperature: -30ºC ~ +75ºC Minimum consumption: 0uA approximately
Water content sensor 	Measurement range: 0 ~ 200cb Frequency Range: 50 ~ 10000Hz approximately Diameter: 22mm Length: 76mm
Load cell 	Rate load: 3, 5, 6, 8, 10, 15, 20, 30, 35, 40, 50kg Output sensitivity: 2-0±0.1mv/V Accuracy grade: 0.02%F.S Nonlinearity: ±0.02%F.S Recommended excitation voltage: +9V ~ +12V Operation temperature: -20ºC ~ +60ºC Protection class: IP-65

3.4.3 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 3-12. 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.

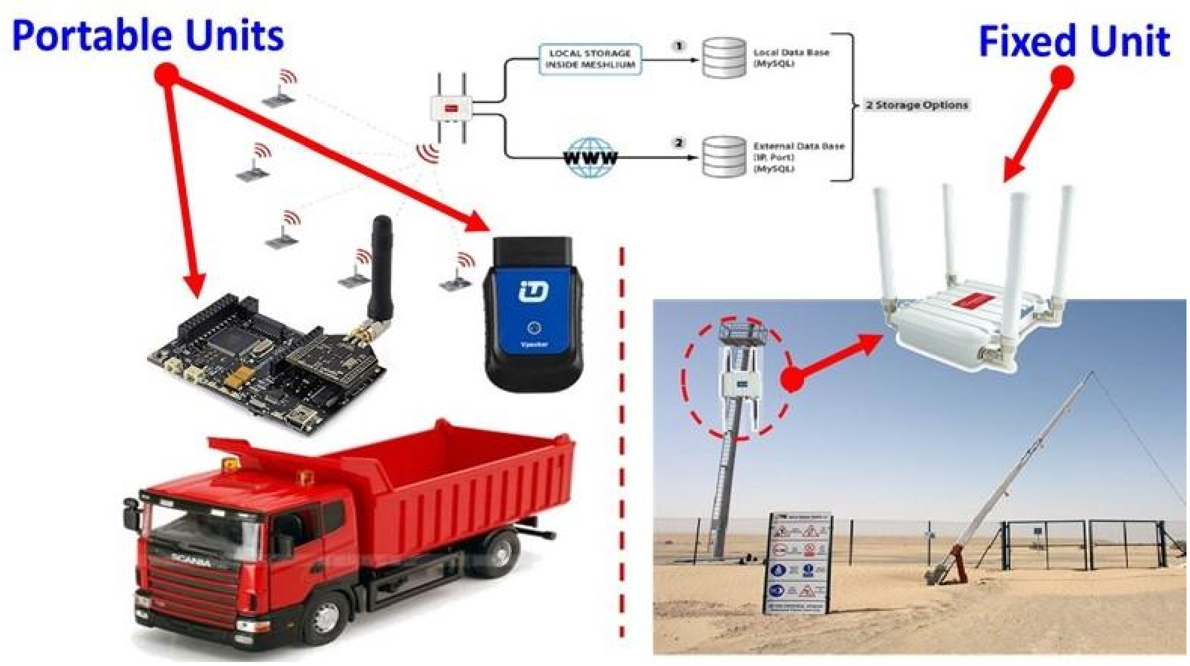


Figure 3-12: Data acquisition module deployment

3.4.4 Productivity Measurement, Assessment and Analysis Models

These models involve different algorithms that 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 grounds behind this productivity variation. 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 capture 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.

There are different trade brands of sensing boards and microcontrollers, such as Arduino™ Uno and Raspberry™ Pi. The last mentioned tools introduced good capability on some similar applications, while Waspmote™ has advantages over these mentioned microcontrollers. These advantages are revealed illustratively in chapter 5 in a comparative study between the most common microcontrollers available in the market. 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 3-13 shows an example of two raw data acquisition algorithms; the first algorithm is for recording only values greater than a threshold value, while the second one records only predetermined significant changes in readings. In both algorithms, the times of each change are also recorded.

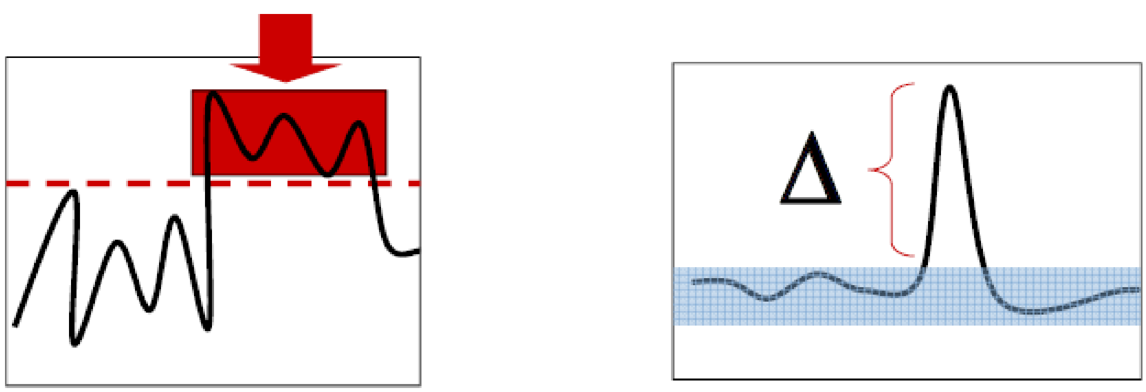


Figure 3-13: Example of raw data acquisition algorithms

Productivity Measurement Algorithm

The developed productivity measurement algorithm employs multi-sensors data fusion. Table 3-4 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 from all these sensor sources; developed MySQL procedures recognize different states of the hauling truck.

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, the productivity could be calculated using the associated timestamps that could be retrieved from 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 (3-1) 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 (3-2).

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

$$V = \frac{m}{\rho} \qquad \text{Equation (3-2)}$$

Where:

V: Soil volume in m^3

m: Soil weight in tons

ρ : Soil density in ton/m^3

Therefore, the total productivity of hauling fleet can be calculated using Equation (3-3).

$$\text{Total Productivity} = \sum_{i=1}^{n} \text{Truck Productivity } (i) \qquad \text{Equation (3-3)}$$

Table 3-4: Conceptual overview of data fusion algorithm for truck state recognition

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, Z ≈ 0	X, Y≈ 0 Z > 0	Fluctuated	X, Y, Z ≈ 0	X++, Y≈ 0 Z--, &Mirror	Fluctuated
Load cell		Constant ≈ Zero	Exponential (+) ≈ Capacity	Constant ≈ Capacity	Constant ≈ Capacity	Exponential (-) ≈ Zero	Constant ≈ Zero

3.5 Characteristics of Sensors Used in the Developed Model

The developed customized prototype is subject to testing procedures in laboratory and outdoor environment. These tests are conducted to ensure the functionality, accuracy, and reliability of the main components of the data acquisition module. The test procedure applied to the sensors in this study are:

- Functionality and accuracy of GPS as well as its detected coordinates.
- Functionality of 3D accelerometer.
- Functionality and accuracy of the soil moisture sensor.
- Functionality and accuracy of the load cell.

3.5.1 GPS Module Testing

The GPS module utilized in this research is capable of providing latitude, longitude, altitude (height), speed, direction, date/time, ephemerides. The latitude and longitude were audited to validate the accuracy of the GPS module. The following outdoor experiment was conducted to auditing to validate depending on the reliability of the Google® maps robust, refined and updated global information system (GIS). The experiment procedures have carried out as follows:

1. Waspmote® microcontroller equipped with the GPS module and its associated antenna. Also, a 2 GB micro SD card inserted into the data logging slot. 2300 mAh -3.7V Lithium-ion (Li-Ion) rechargeable battery was connected to the microcontroller as shown in Figure 3-14.

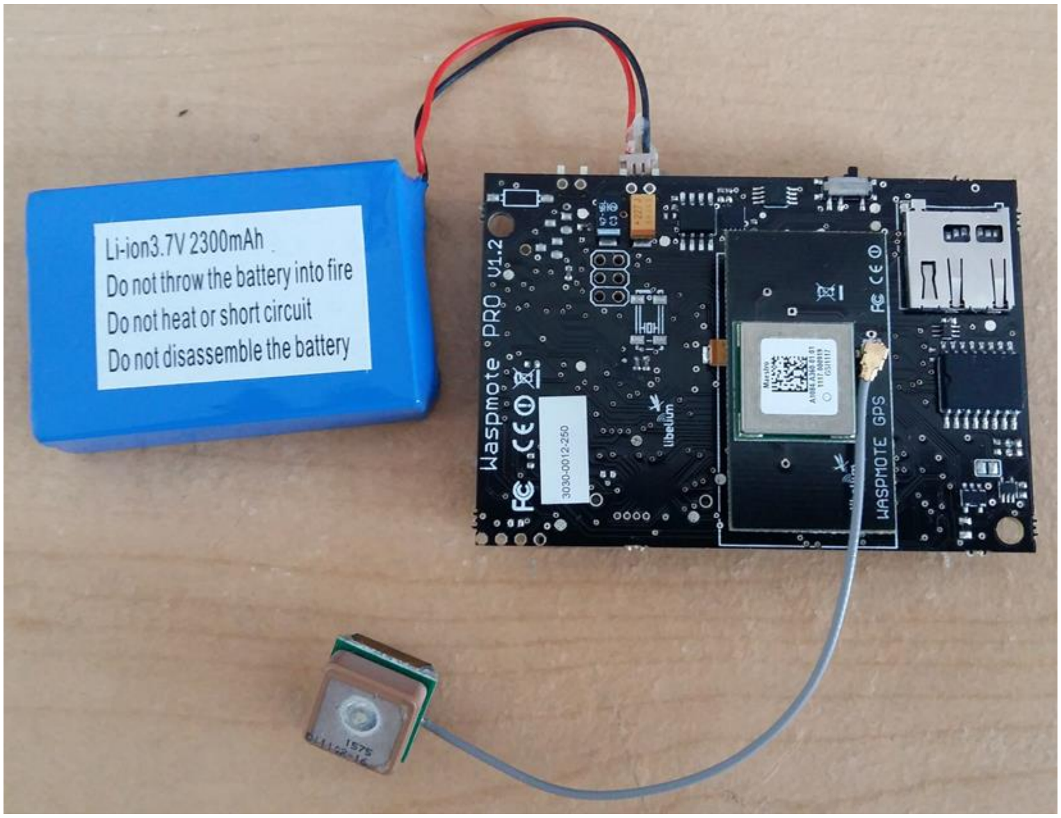


Figure 3-14: Microcontroller powered via rechargeable battery and equipped with GPS

2. The microcontroller connected to a laptop computer via standard mini-USB data cable, model B and then the microcontroller switched ON.

Waspmote's USB has different power sources as shown in Figure 3-15, where these sources are:

i. USB to PC connection.
ii. USB to 110 / 220V connection.
iii. USB to vehicle connector connection.

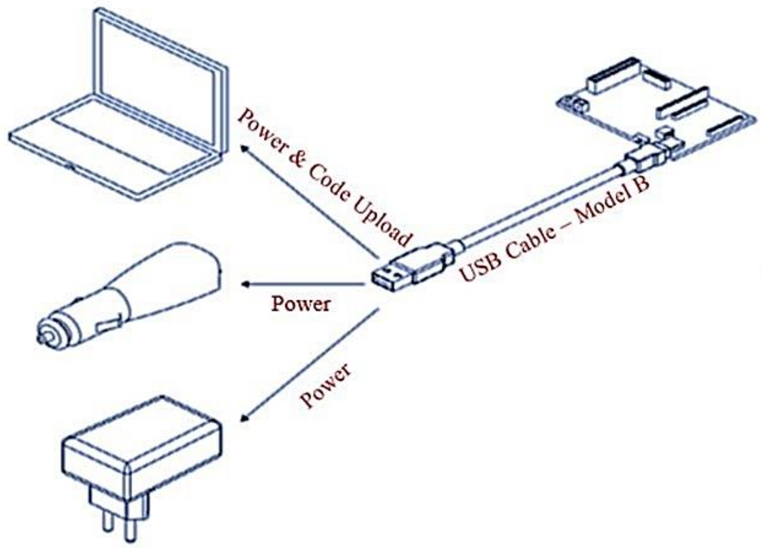


Figure 3-15: Possible connections for Waspmote USB

3. GPS basic data programming codes were written, compiled and therefore uploaded to the microcontroller using the installed Waspmote® IDE (Programming platform). The codes are written in C++ and C # programming languages where both are considered the most famous encoding languages for programming microcontrollers over its microprocessor. Figure 3-16 shows a snapshot of the encoding platform utilized for this outdoor experiment.

4. The microcontroller attached to a passenger car near the windshield to ease the detection of required satellite signals. The trip started and ended at a position that is well known with a civic number on Google® maps. The trip conducted in the city of Saint-Laurent, Montreal, Quebec, Canada.

5. The global positioning data was written to the data logger, i.e., micro SD card.

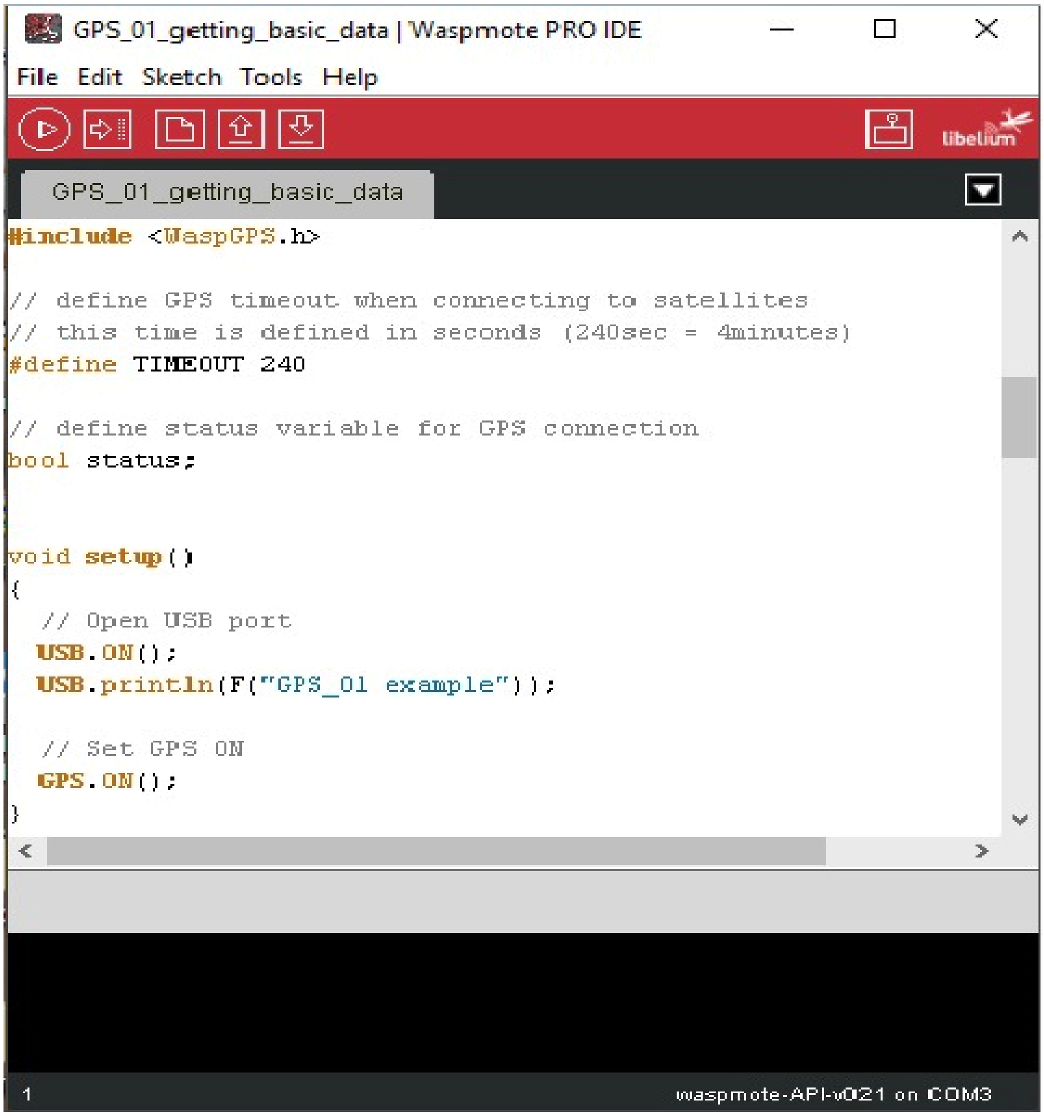


Figure 3-16: Snapshot of encoding platform (Waspmote IDE)

6. GPS acquired data has uploaded to a text file. Figure 3-17 shows a snapshot of a sample of the collected GPS real data. The data tabulated for better presentation as shown in Table 3-5, where starting point and destination data are shown in rows number 1 and 20 respectively.

Connected

GET POSITION:

Time [hhmmss.sss]: 194503.940

Date [ddmmyy]: 280216

Latitude [ddmm.mmmm]: 4531.8982

North/South indicator: N

Longitude [dddmm.mmmm]: 07340.1644

East/West indicator: W

Altitude [m]: 39.9

Speed [km/h]: 0.94

Course [degrees]: 46.37

CONVERSION TO DEGREES (USEFUL FOR INTERNET SEARCH):

Latitude (degrees):45.5316352844

Longitude (degrees):-73.6694030761

Figure 3-17: Snapshot for a sample of the collected GPS real data

Table 3-5: Tabulation of the collected GPS real data

#	Time [hhmmss.sss]	Date [ddmmyy]	Latitude [ddmm.mmmm]	North/South indicator	Longitude [dddmm.mmmm]	East/West indicator	Altitude [m]	Speed [km/h]	Course [degrees]	Latitude (degrees)	Longitude (degrees)
1	194503.94	280216	4531.8982	N	7340.1644	W	39.9	0.94	46.37	45.531635	-73.66940308
2	194510.939	280216	4531.8977	N	7340.1651	W	42.6	0.33	205.77	45.5316277	-73.66941833
3	194518	280216	4531.8981	N	7340.1683	W	40	0.55	5.92	45.5316353	-73.66947174
4	194525	280216	4531.899	N	7340.1692	W	40.5	0.18	265.7	45.5316505	-73.669487
5	194532	280216	4531.8985	N	7340.1672	W	41.4	0.14	76.6	45.5316429	-73.66945648
6	194539	280216	4531.8985	N	7340.1673	W	40.9	0.2	243.72	45.5316429	-73.66945648
7	194546	280216	4531.8984	N	7340.1672	W	41.1	0.33	62.5	45.5316391	-73.66945648
8	194553	280216	4531.8986	N	7340.1701	W	38.2	0.12	127.09	45.5316429	-73.66950226
9	194600	280216	4531.8984	N	7340.1701	W	37	0.16	109.51	45.5316391	-73.66950226
10	194607	280216	4531.8983	N	7340.1699	W	36.3	0.22	103.56	45.5316391	-73.66949463
11	194614	280216	4531.8982	N	7340.1698	W	36	0.46	178.58	45.5316353	-73.66949463
12	194621	280216	4531.8976	N	7340.1696	W	35.7	0.42	194.16	45.5316277	-73.66949463
13	194628	280216	4531.8977	N	7340.169	W	35.9	0.53	58.43	45.5316277	-73.669487
14	194635	280216	4531.8977	N	7340.169	W	35.8	0.2	99.65	45.5316277	-73.669487
15	194642	280216	4531.8979	N	7340.1606	W	36.2	9.68	90.74	45.5316315	-73.66934204
16	194649	280216	4531.8868	N	7340.1338	W	36.8	24.98	122.33	45.5314484	-73.66889954
17	194656	280216	4531.8597	N	7340.104	W	36.4	33.15	154.11	45.5309944	-73.66840363
18	194703	280216	4531.8286	N	7340.1014	W	36.7	31.24	183.51	45.5304756	-73.66835785
19	194710	280216	4531.7939	N	7340.1169	W	37.1	34.65	198.98	45.5298996	-73.66861725
20	195008.695	280216	4531.5958	N	7340.4386	W	48.2	0.81	236.96	45.526596	-73.67397308
21	194510.939	280216	4531.8977	N	7340.1651	W	42.6	0.33	205.77	45.53162765	-73.6694183349
22	194518	280216	4531.8981	N	7340.1683	W	40	0.55	5.92	45.53163528	-73.6694717407
23	194525	280216	4531.899	N	7340.1692	W	40.5	0.18	265.7	45.53165054	-73.6694869995

7. The last two columns have the latitude and longitude converted to degrees system in a specialized format, which is useful for such GIS platforms, i.e., google maps. Figure 3-18.a shows the original collected latitude and longitude data entry. Figure 3-18.b shows the automatic conversion to the civic number of the start point; it also shows the original data

entry for the destination. Figure 3-18.c shows the automatic conversion to the civic number of the destination point as well as the trip path.

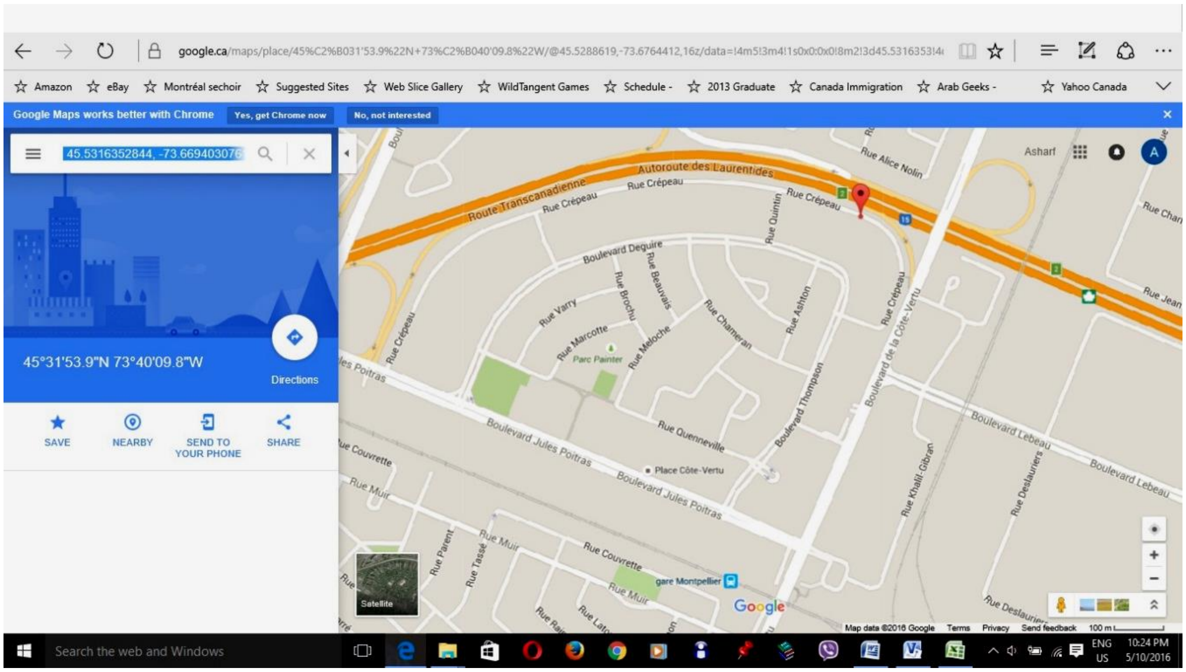


Figure 3-18.a: Start point - original collected latitude and longitude

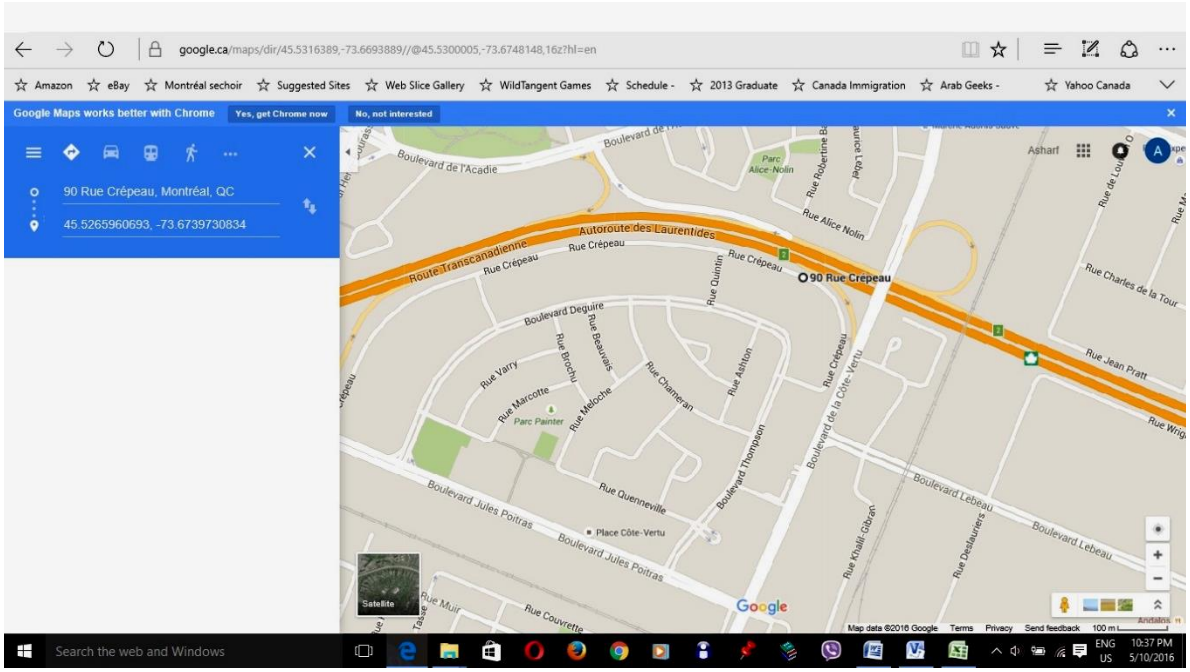


Figure 3-18.b: Automatic conversion to the civic number of the start point - Original data entry for the destination

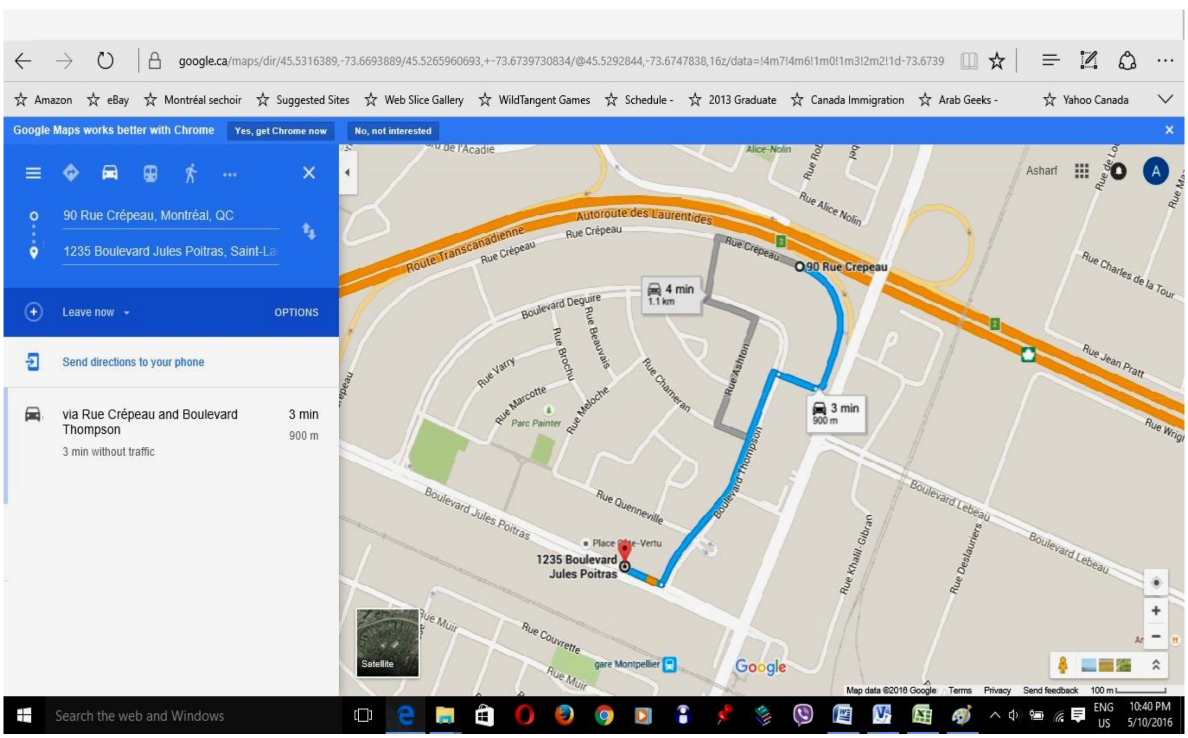


Figure 3-18.c: Automatic conversion to the civic number of the destination point - Trip path between the two positions

8. The final destination in this experiment was chosen to be two adjacent buildings to check how accurate the GPS can distinguish each building from the other. The coordinates of the first destination building was identified as 45.526632, -73.673757, while the coordinates of the other building was identified as 45.526620, -73.673709. The distance between these two coordinates can be calculated using "Haversine" formulas shown by Equation (3-4), Equation (3-5), and Equation (3-6) respectively.

   $a = \sin^2(\Delta\varphi/2) + \cos\varphi_1 \cdot \cos\varphi_2 \cdot \sin^2(\Delta\lambda/2)$ Equation (3-4)

   $c = 2 \cdot a.\tan2(\sqrt{a}, \sqrt{(1-a)})$ Equation (3-5)

   $d = R \cdot c$ Equation (3-6)

   Where;

   φ is latitude, λ is longitude, R is earth's radius (mean radius = 6,371km);

   noting that angles need to be in radians

   Therefore the distance d= 0.003970 Km (≈ 4 m)

Previous steps demonstrate the GPS module ability to detect a coordinate of a destination that is adjacent to another. Where the distance of the mapping system identified two coordinates is approximately 4 meters. Then the GPS module is accurate to recognize positions within two 2 meters (The distance between midpoints of the two acquired coordinates for the adjacent ends of the two buildings in this experiment).

3.5.2 3D Accelerometer Sensor

The utilized three-axial accelerometer sensor is built-in the Waspmote microcontroller. The 3D accelerometer was tested to evaluate its accuracy and functionality in the proposed applications in this research. These applications namely are driving and road conditions, i.e., bumpy and rutty roads detection. Also, monitoring truck operators' aggressive driving behaviors, i.e., unsafe lane change reckless maneuvers, harsh braking, and acceleration.

Each of X, Y, and Z axis reading is utilized for some of the aforementioned applications as shown in Table 3-6.

Table 3-6: Recognized driving and road conditions from each of 3-Axes records

Axis	Recognized driving or road conditions
X	Harsh braking, speeding, and frequent acceleration
Y	Reckless maneuvers, and unsafe lane change
Z	Bumps, and rutty segments

The first part of this experiment was a field test, in which Waspmote microcontroller was installed on the dashboard of a mimicked truck, where a passenger minivan was utilized instead. The microcontroller's built-in 3D accelerometer records are aligned to X, Y, and Z-axis of the truck. The microcontroller was aligned to fulfill the following orientation:

- X + axis is horizontally pointing towards the front of the truck in the direction of the road's traffic flow.
- Y + axis is horizontally pointing to the truck's right-hand side.
- Z + axis is vertically pointing towards the roof of the truck cabin.

Figure 3-19 shows the orientation of the 3D accelerometer. Acceleration readings were recorded while the car passes through a road that contains some segments that have bumps and potholes. During the passage in this road, the driver has frequently changed the lane in safe and unsafe manners. In addition, the driver has accelerated and deaccelerated smoothly and aggressively.

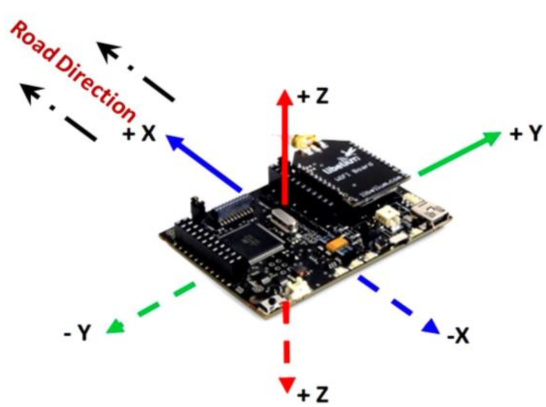


Figure 3-19: 3D accelerometer orientation

The 3-axes records were jointly taken in a synchronized manner, in other words, continuous capture of acceleration in X, Y, and Z-axis each millisecond as shown in Figure 3-20.

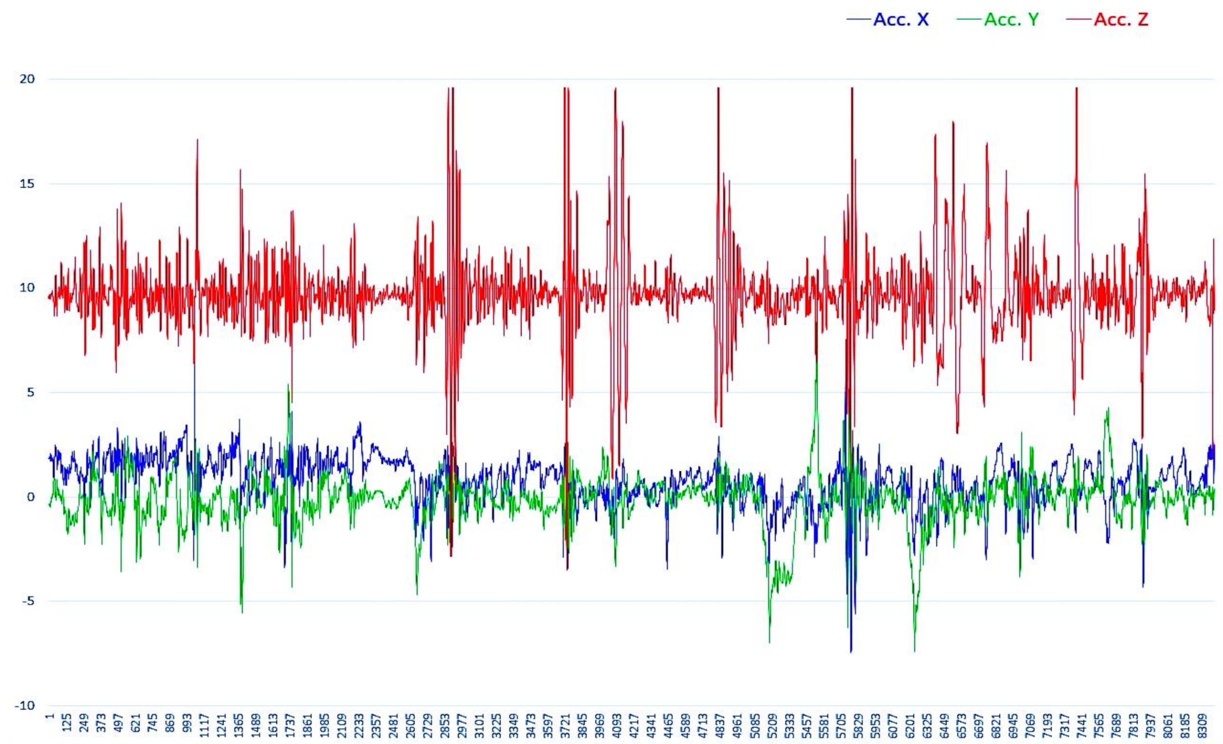


Figure 3-20: 3D acceleration reading for part of truck trip

In order to clarify the different acceleration patterns and their significance in driving and road conditions recognition process, the acceleration data set for each axis was extracted, and then represented separately. Figure 3-21 shows X-axis acceleration patterns, through which the developed algorithm can identify driving behaviors during a short trip of the mimicked hauling truck, where a passenger minivan was utilized instead. This figure illustrates graphically driving behavior in a schematic representation.

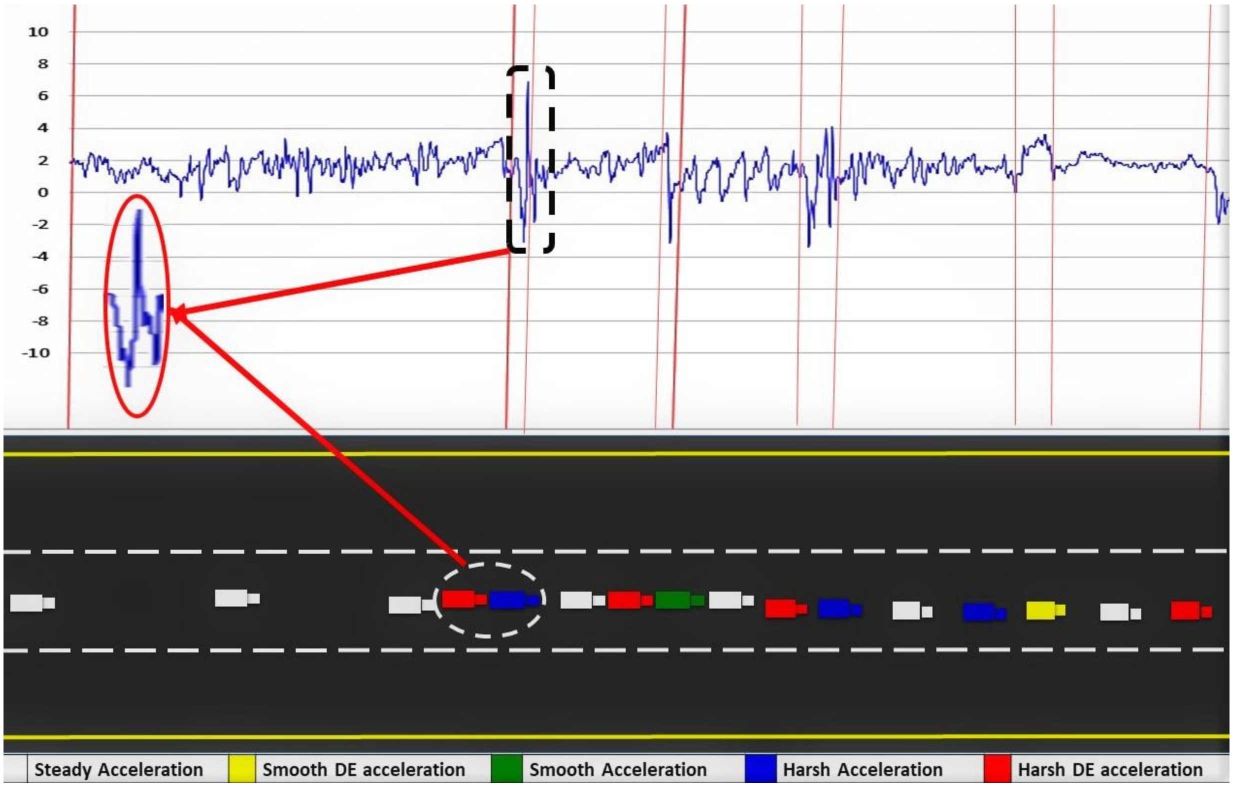


Figure 3-21: Acceleration patterns throughout different states of traffic flow direction driving

Likewise, a graphical representation of Y-axis acceleration data set signifies various patterns that demonstrate recognition of the studied driving condition. Figure 3-22 shows different patterns of smooth, safe, and unsafe lane change and impulsive maneuvers, where, substantial change in Y acceleration demonstrates unsafe detour. Such behaviors not only endanger the driver and the truck but also affect productivity because of the implicit risk of rising problems that might result in work crashes, i.e., traffic jams and collisions due to this undesirable driving behavior during hauling and returning trips. Trip durations are likely to increase due to resulted problems, which certainly in turn reduce productivity.

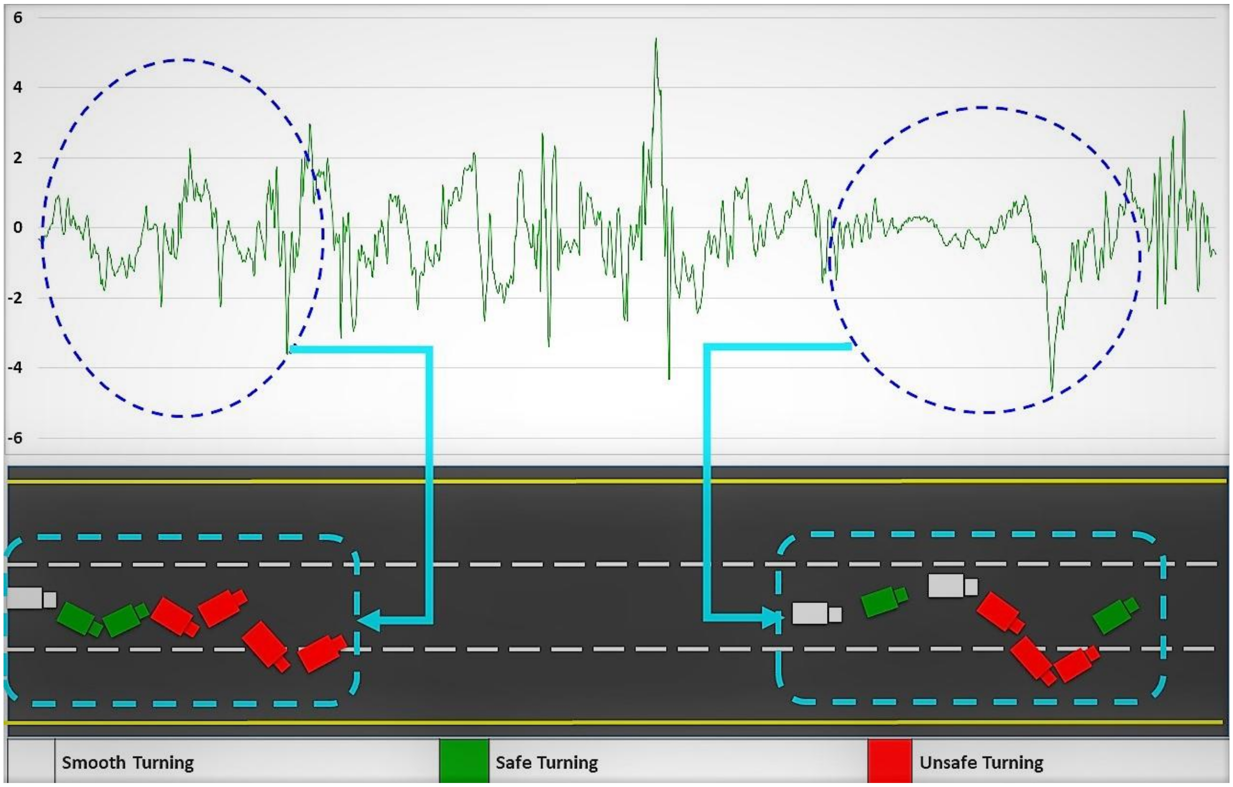


Figure 3-22: Acceleration patterns for safe and unsafe turning and maneuvers

Similarly, graphical representation of Z-axis acceleration data set signifies either patterns differentiating among smooth adequate, rutty, and bumpy road conditions. Figure 3-23 shows graphical representation of acceleration patterns in Z direction. In this figure, the developed algorithm can detect road conditions, i.e., rut, severe rutty segment, bump, and aggressive bump.

The developed model was tested; it was able to identify fifteen of eighteen bumps. Also, it recognized eighteen of twenty-three potholes. Based on the results of this test, the developed model has 83.3 % and 82.6 % in recognition of bumps and ruts respectively.

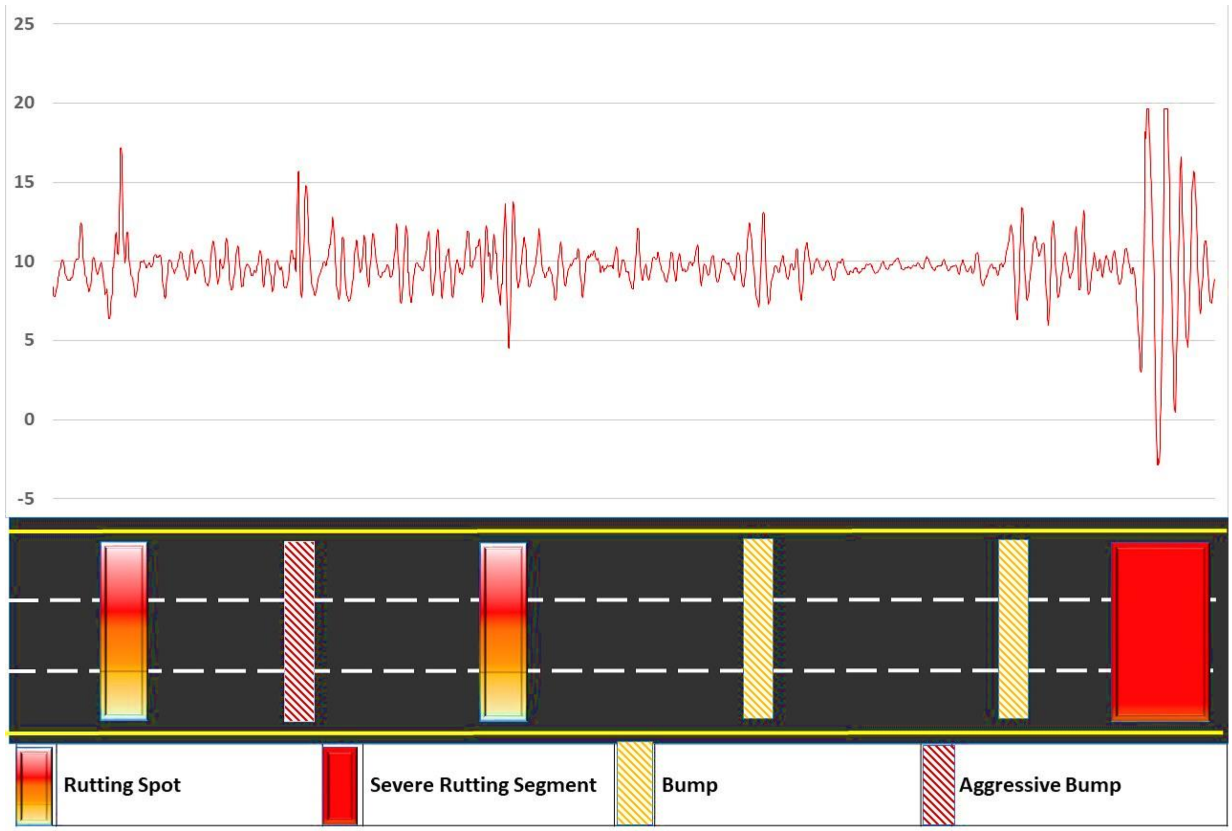


Figure 3-23: Acceleration patterns for bumpy and rutty road

The second part of this experiment was a lab test in which a 1:24 remotely control scaled dumping truck was used to simulate dumping action. The scaled truck is fully functional to dump the same way as well as the real one, upon that it considered a well-chosen prototype that simulates reality. The main goal of this experiment is the recognition of the unique pattern of unloading action for the dumping truck during dumping state. The microcontroller's built-in 3D accelerometer w aligned to fulfill the same orientation described earlier in the first part of this experiment unless it installed on the top front flat part of the truck bed. Figure 3-24 shows the installed microcontroller on the truck during dumping action.

Figure 3-24: Acceleration recording for a scaled truck during dumping

In this experiment, and based on the assumption that the truck mounted on a flat rigid surface and the accelerometer is adequately oriented as described above, X and Z axes exchange their positions to form symmetrical mirrored parabolas as shown in Figure 3-25. This pattern facilitates the distinction between dumping and other actions.

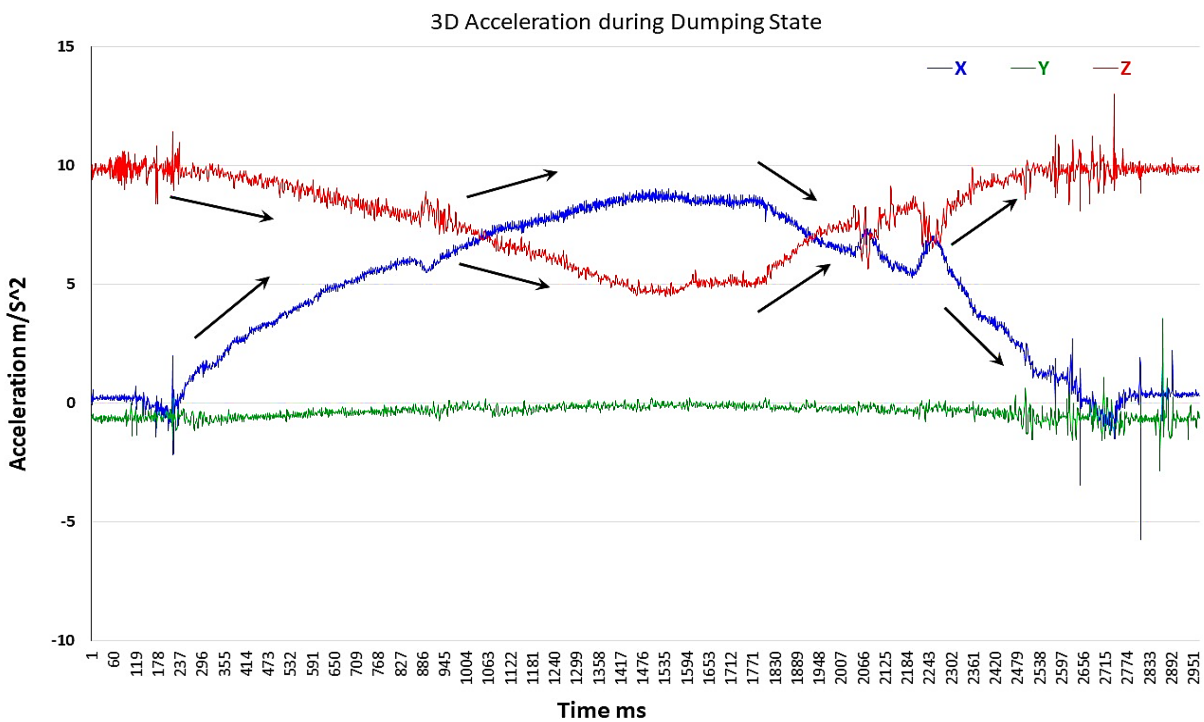


Figure 3-25: Graphical pattern for acceleration readings during dumping

3.5.3 Soil Water Content Sensor

Soil water content is an essential factor that influences compaction in most construction projects, i.e., highways, and earth dams. The compacted soil dry density raises with increasing soil moisture content until reaching a specific extent of watering. The soil water content that corresponds to the maximum dry density is called optimum moisture content. Therefore, soil water content is the key to guarantee quality of soil compaction. Soils naturally have a moisture content smaller than the required optimum moisture content needed for reaching desired compaction quality. Hence, appropriate adjustment of that content is needed by providing water supplements during compaction. This supplement usually added in the job site, and it is based on the quantification of the natural water content of the moved soils. Where the determination of this content has many methods, which summarized as follow:

A. Gravimetric soil sampling:

This is the most common technique used in determining soil water content, where a field sample of soil is weighted using a sensitive weighing scale, then to be dried in (105◦ C) oven. Subtracting the oven dry weight from the original field weight gives the soil water content by weight (gm/gm). The volume of soil sample can be used, so the water content could be evaluated using volumetric units as well. This method is time-consuming, and requires sampler equipment, weighing scale and an oven. A large number of samples must be taken to overcome the variability of soils and associated water content. Generally, this method is commonly used to evaluate and standardize indirect methods as described in the developed method using an analog sensor connected to a smart sensor board for determining soil water content.

B. Qualitative methods - Tensiometers

These methods are commonly used in the domain of agriculture to provide a qualitative measurement of soil water content for irrigation purposes. In another word, those methods are used to indicate the availability of water not the quantity of water kept in the soil. Although these methods use direct water content reading devices, they are not automated, and human intervention is essential. Figure 3-26 shows the vacuum tensiometer (one of the soil water content qualitative methods' devices).

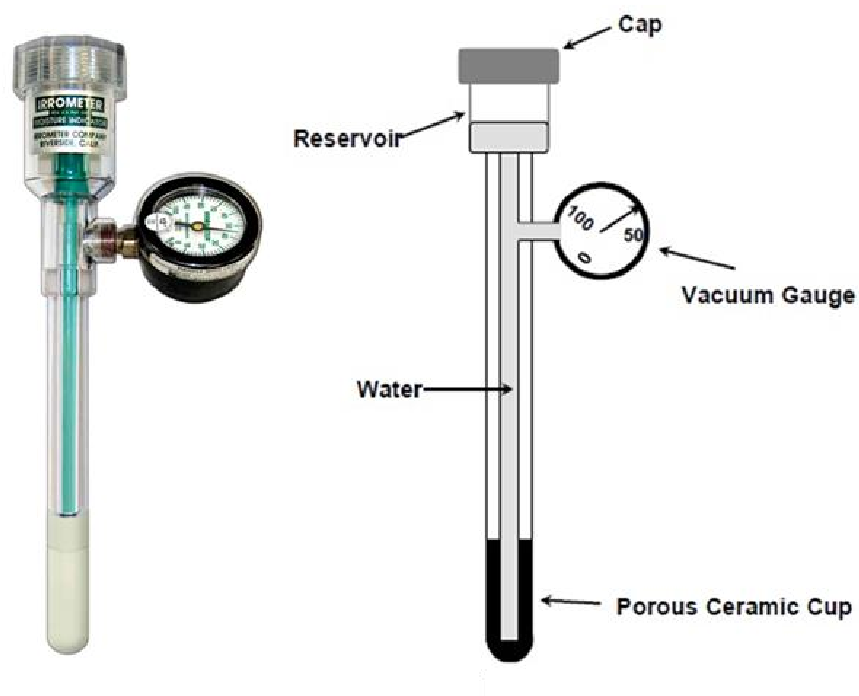


Figure 3-26: Vacuum tensiometer - AGRI Expo website

These methods measure how tightly the contained water in soil is held by soil particles. The energy required to extract this water is measured in tension units. Many terminologies are used for describing soil water energy status, i.e., soil water tension, soil water retention, soil water suction or soil water potential. The idea behind the tensiometer is a simulation of the plant root, whereas when the tension increases; water extraction becomes more difficult for the plant. Therefore, the higher the water tension, the lower the water content.

The relationship between soil tension and soil moisture content is not linear and it differs from soil type to another. Figure 3-27, and Figure 3-28 show typical curves for generalized relationship between soil moisture content and water tension for different types of soils.

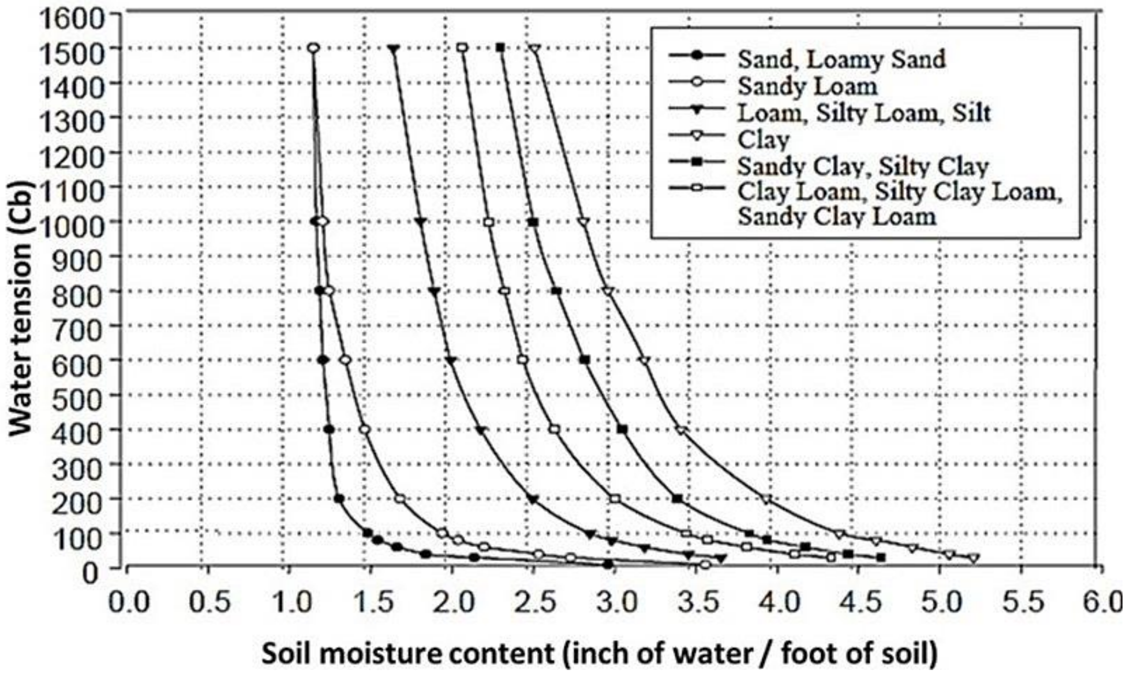


Figure 3-27: Generalized relationship between soil moisture content and water tension (Ley et al., 1994)

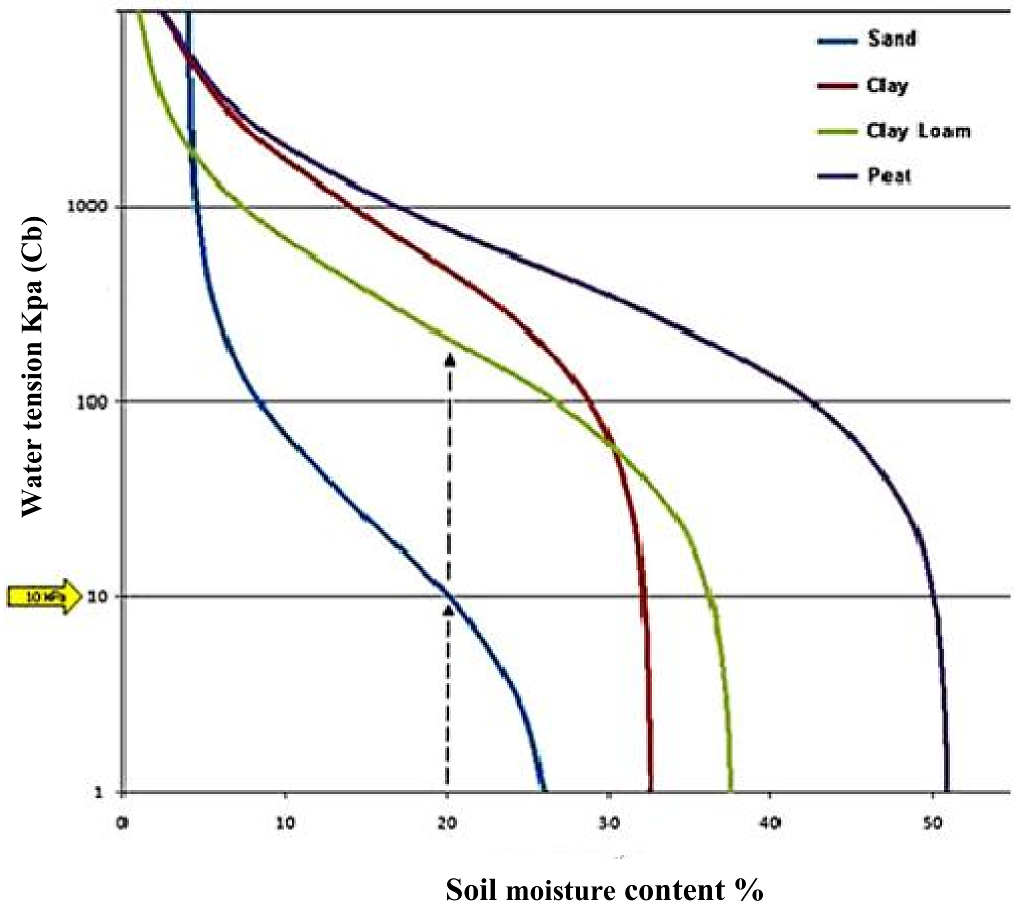


Figure 3-28: Relationship between soil moisture content (%) and water tension (Kpa)

However, such curves were developed in a research-based manner, and they were not worthy to rely on them quantitatively in practice. In this study, such identical curves were digitized in order to quantify soil water content using the developed most fitted relationship between soil moisture content and soil water tension as illustrated in chapter 5. Where an analog tensiometer is used to measure the loaded soil water content quantitatively. The proposed sensor was evaluated to examine its functionality and measuring accuracy. The evaluation test was a comparison between the water content results determined by the proposed sensor and those of the common standard gravimetric soil sampling in which ASTM D2216 (2010) laboratory standard test was followed.

Ten samples of sand was dried, then the shown processes in Figure 3-29, A to E were conducted respectively to determine the water content experimentally, while image F shows the proposed water content sensor embedded into the same wet sample and connected to a laptop to record soil water content in frequency units (Hz). The correlation between frequency and water tension was articulated in chapter 5. Experimental results for conventional laboratory test and sensor records are shown in Table 3-7, and represented graphically in Figure 3-30.

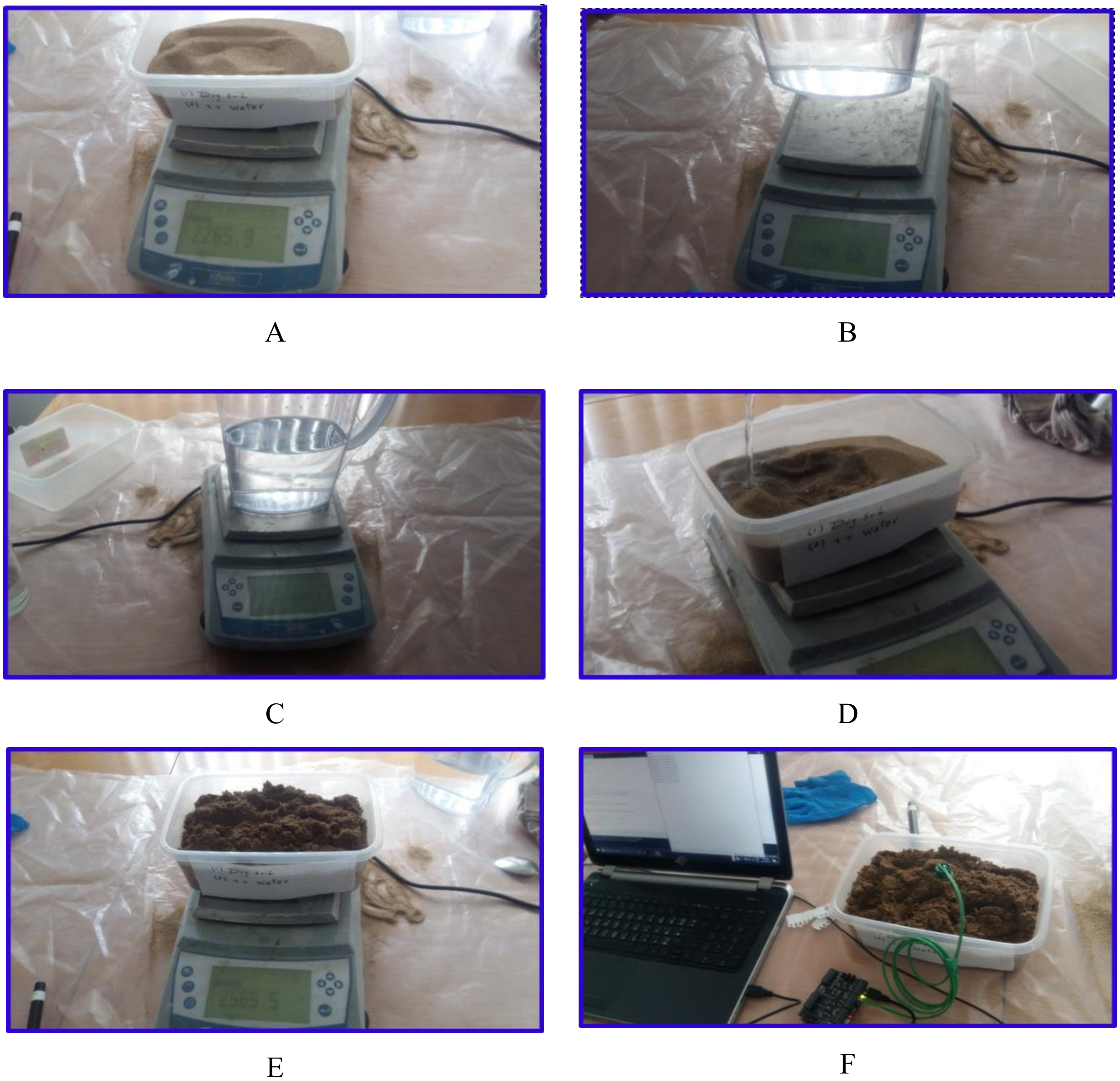


Figure 3-29: Soil water sensor functionality and accuracy test

Table 3-7: WC % using conventional laboratory test and soil moisture content sensor

Sample #	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Lab. Wc (%)	0.2439	0.1519	0.1940	0.2489	0.1976	0.1099	0.1757	0.2317	0.1706	0.2010
Sensor Reading 1	0.2639	0.1419	0.1900	0.2629	0.1826	0.1125	0.1507	0.2198	0.1844	0.2185
Sensor Reading 2	0.2521	0.1386	0.1979	0.2603	0.1760	0.1107	0.1776	0.2458	0.1868	0.2105
Sensor Reading 3	0.2493	0.1577	0.1840	0.2571	0.2008	0.0973	0.1697	0.2291	0.1676	0.1986
Sensor - Mean	0.2551	0.1461	0.1906	0.2601	0.1865	0.1068	0.1660	0.2316	0.1796	0.2092
Sensor - Min.	0.2493	0.1386	0.184	0.2571	0.176	0.0973	0.1507	0.2198	0.1676	0.1986
Sensor - Max	0.2639	0.1577	0.1979	0.2629	0.2008	0.1125	0.1776	0.2458	0.1868	0.2185

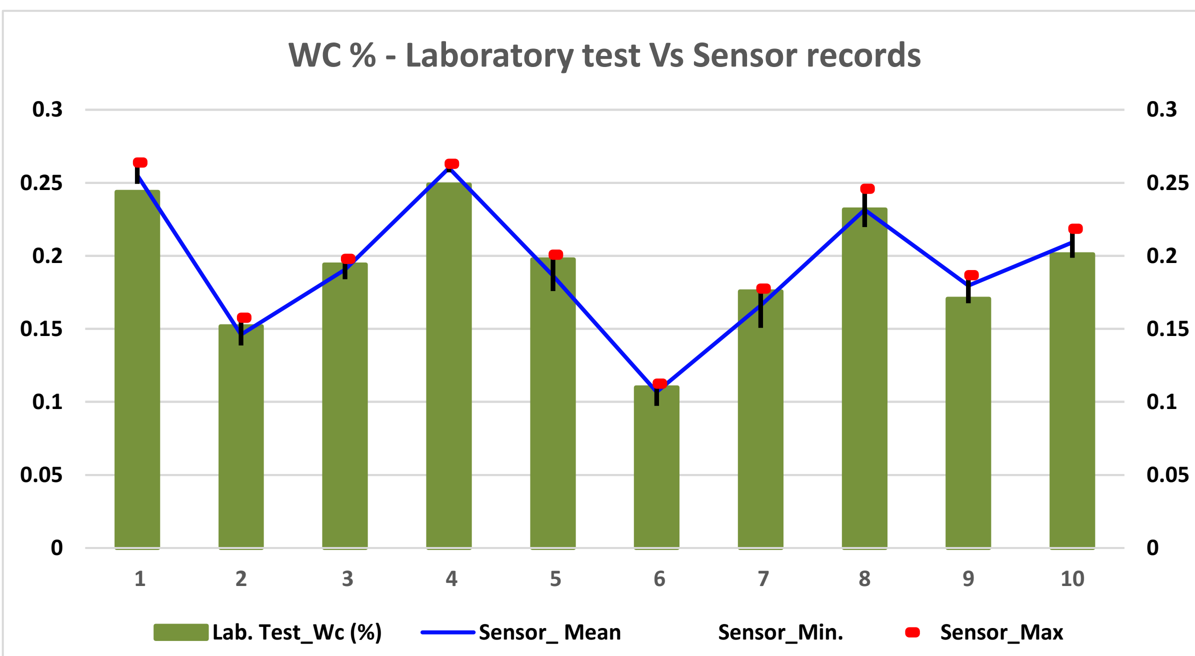


Figure 3-30: Experimental results for conventional laboratory test and water sensor records

Based on the relevant literature recommendations (Ley et al., 1994; MEA, 2018); the reference is the laboratory standard test results according to ASTM D2216 (2010). Therefore, relying on the conventional gravimetric soil sampling laboratory test; mean error value for each sample was determined as shown in Table 3-8. The calculated mean error values are insignificant, as they do not approximately exceed ± 1%. Figure 3-31 depicts sensor mean error values against both laboratory test and sensor mean readings for each sample.

Table 3-8: Sensor mean error values against standard laboratory test

Sample	Lab. Test-WC (%)	R1 - Lab.	R2 - Lab.	R3 - Lab.	Sensor Mean Error
1	0.2439	0.02	0.0082	0.0054	0.0112
2	0.1519	-0.01	-0.0133	0.0058	-0.0058
3	0.194	-0.004	0.0039	-0.01	-0.0034
4	0.2489	0.014	0.0114	0.0082	0.0112
5	0.1976	-0.015	-0.0216	0.0032	-0.0111
6	0.1099	0.0026	0.0008	-0.0126	-0.0031
7	0.1757	-0.025	0.0019	-0.006	-0.0097
8	0.2317	-0.0119	0.0141	-0.0026	-0.0001
9	0.1706	0.0138	0.0162	-0.003	0.0090
10	0.201	0.0175	0.0095	-0.0024	0.0082

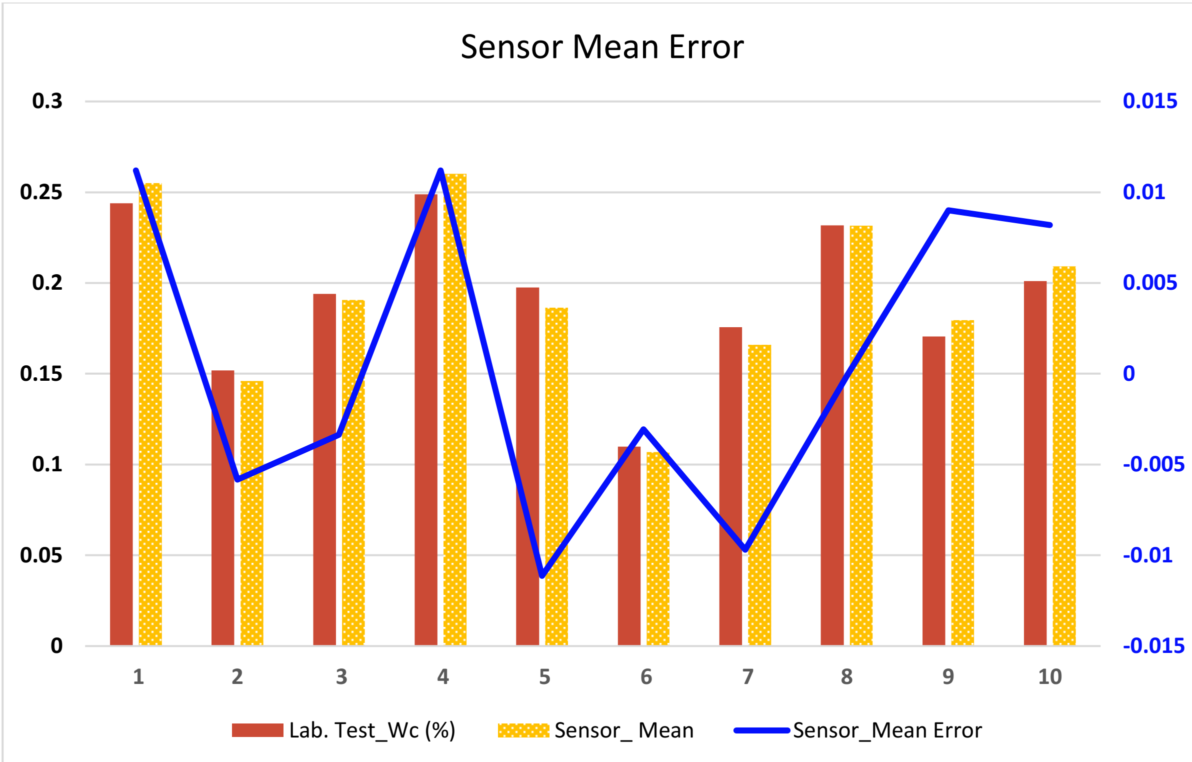


Figure 3-31: Sensor mean error values against both laboratory test and sensor mean readings

3.5.4 Load Cell Sensor

The utilized load cell in the smart board is a cell with a Wheatstone bridge output. The principal of measuring weight using load cells is determining unknown resistance due to applied voltage between a pair of opposite corners in a simple electrical circuit. The result is a differential voltage that is amplified and filtered to obtain an analog voltage proportional to the weight on the cell. Figure 3-32 shows the linear relationship between the output voltage of the cell in microVolt and the corresponding loads in kilograms.

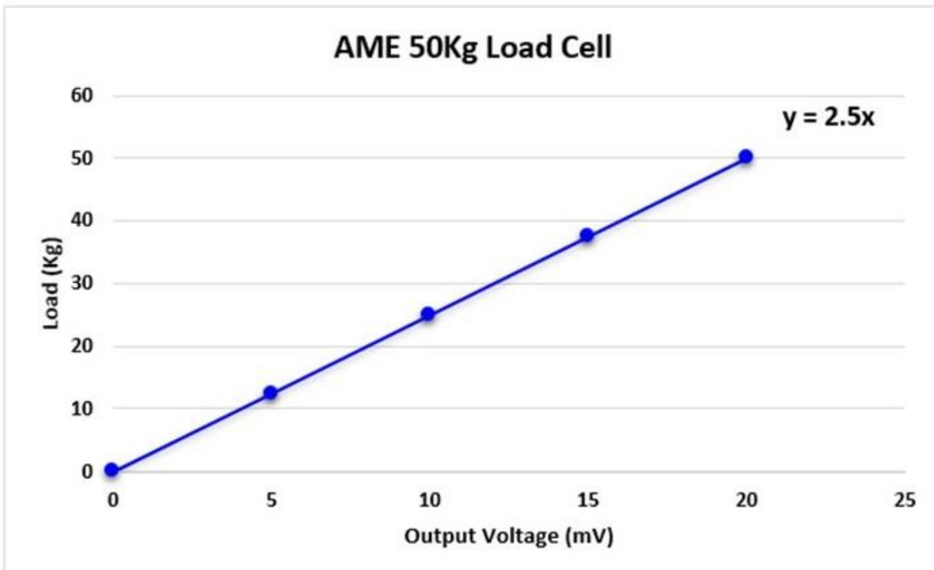


Figure 3-32: Relationship between load cell output voltage and load

The developed model employs the load cell to measure not only the truck payload but also to determine loading efficiency in a novel automated method. Figure 3-33 shows C# code associated with the coding logic comments to read load cell and writing the measured voltage value to the USB. This syntax is uploaded to the microcontroller, which connected to a laptop computer. Then load cell reading values in microvolts can be shown on the computer screen via a serial monitor, copied to SD card, or transmitted by a communication protocol, i.e., WiFi, or GPRS to a local or cloud-based server. The imported data to the receiving media, i.e., database in a server; is then subjected to be processed, filtered and converted to loads in kilograms.

```
#include <WaspSensorSmart_v20.h>
// Variable to store the read value
float value;
void setup()
{
  // Swich on USB and print a start message
  USB.ON();
  USB.println(F("start"));
  delay(100);
  // Swich on sensor board
  SensorSmartv20.ON();
  // Swich on RTC (Real Time Clock)
  RTC.ON();
}
void loop()
{
  // Part 1: Sensor reading
  // Turn on the sensor and wait for stabilization and response time
  SensorSmartv20.setSensorMode(SENS_ON, SENS_SMART_LCELLS_10V);
  delay(5000);
  // Read load cell
  value = SensorSmartv20.readValue(SENS_SMART_LCELLS_10V);
  // Turn off load cell
  SensorSmartv20.setSensorMode(SENS_OFF, SENS_SMART_LCELLS_10V);
  // Part 2: USB printing
  // Print the voltage value through the USB
  USB.print(F("Voltage: "));
  USB.print(value);
  USB.println(F("V"));
  delay(1000);
}
```

Figure 3-33: C# code for reading load cell

The load cell is proposed to be fixed on the chassis of the dumping truck underneath its bed. Figure 3-34 shows a sketchy explanation for fixation of the load cell. In reality, mechanical modification might be need by adding additional stringer between the two girders of the chassis.

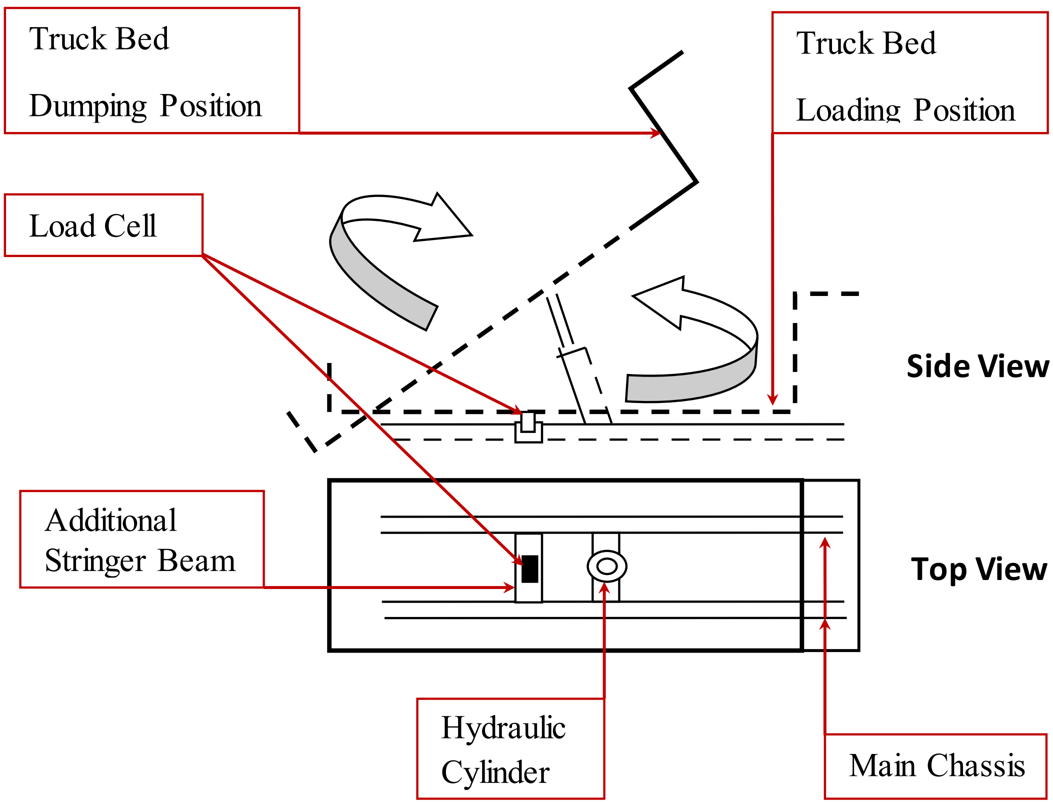


Figure 3-34: Fixing the load cell to dumping truck chassis

The load cell was subjected to a loading test to examine its functionality and accuracy. The loading test was conducted in a laboratory environment, the procedure was as follow:

1. Attaching rigid cardboard to the load cell using two screws as shown in Figure 3-35. A, and B. The cardboard in this experiment is simulating the truck bed.
2. Connecting the load cell to the smart board, which connected to the microcontroller.
3. Connecting the microcontroller to a laptop as shown in Figure 3-35. C. Hence, uploading the designated C# code shown in Figure 3-33 to the microcontroller.
4. Loading the cardboard with pre-known precise weights as shown in Figure 3-35.D, E and F. A small gradual flask was utilized, where it was filled with different volumes of water; 5, 8, 10, 12 and 14 Ounce (OZ). Water was chosen as it has equal volume and weight. The volume of water is shown in OZ, and then it converted arithmetically to liter or kilogram as shown in Table 3-9. A 22 gm (weight of the flask) will be added to each weight.

5. Recording three voltage values for each load. Then, determining equivalent loads using Equation (3-7).

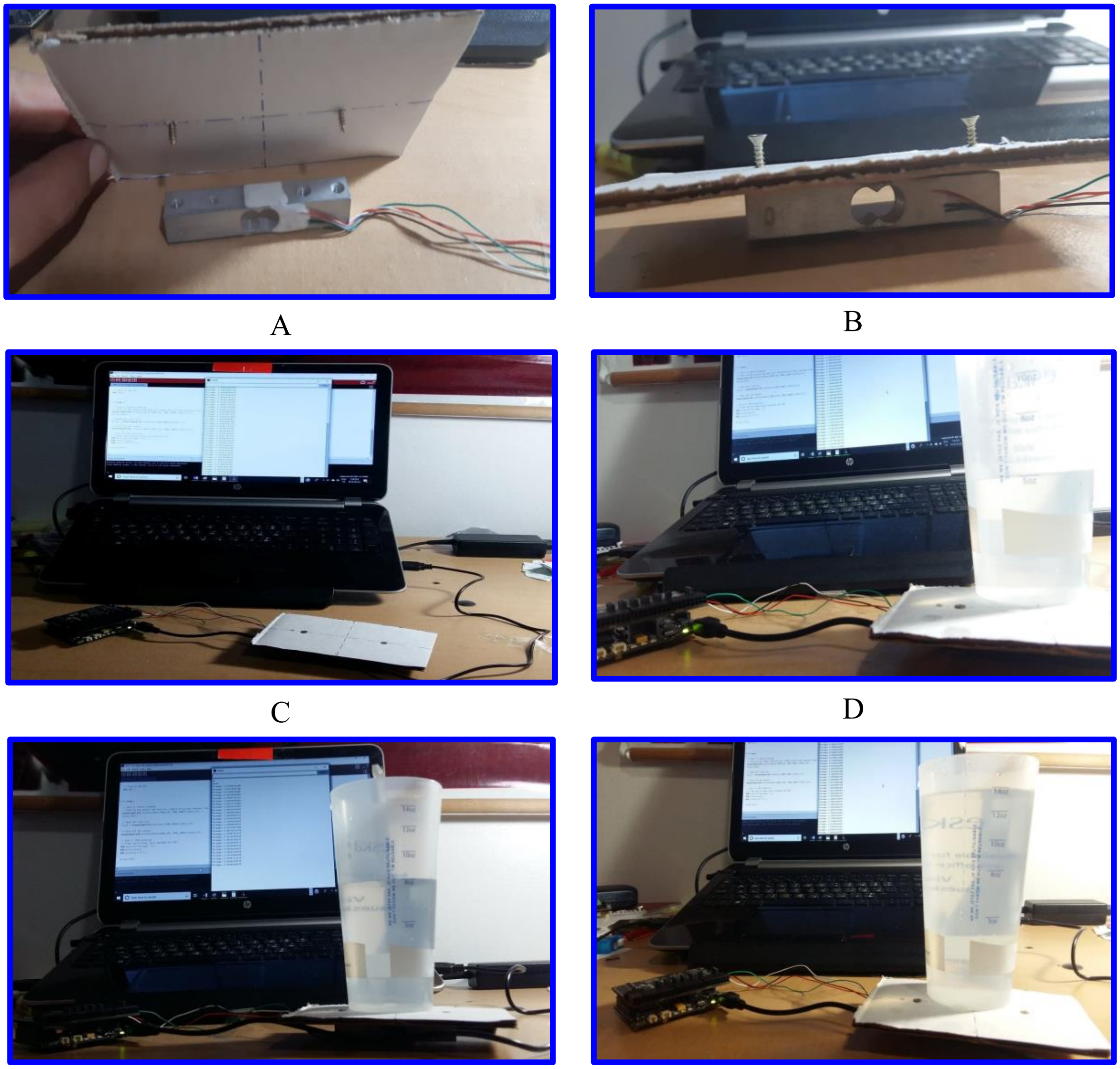


Figure 3-35: Load cell functionality and accuracy test

$$W = 2.5\ V \qquad \text{Equation (3-7)}$$

Where;

W is weight in kg, and v is voltage in microvolt mv.

Table 3-9: Applied water loads conversion from Ounce to Liter and Kilogram

Water Volume (OZ)	Volume (Liter)	Weight (kg)
5	0.147868	0.147868
8	0.236588	0.236588
10	0.295735	0.295735
12	0.354882	0.354882
14	0.414029	0.414029

The voltage values were recorded three times for each of the applied loads, and then the equivalent weight in Kg was determined. Then, the mean value for each load was calculated, also the mean error as well as shown in Table 3-10.

Table 3-10: Conversion between mV and kg – Error associated with the load cell

Volume (OZ)	5	8	10	12	14
Volume (L) - Weight (Kg)	0.17357	0.25649	0.31434	0.37948	0.43793
1st. Record – Voltage (mV)	0.06943	0.10260	0.12573	0.15179	0.17517
2nd. Record – Voltage (mV)	0.06699	0.10416	0.12757	0.15199	0.17389
3rd. Record – Voltage (mV)	0.06731	0.10216	0.12825	0.14999	0.17565
Mean – Voltage (mV)	0.06791	0.10297	0.12719	0.15126	0.17490
Load Cell - Weight (Kg)	0.16977	0.25742	0.31797	0.37815	0.43726
Mean Error	-0.00380	0.00093	0.00363	-0.00133	-0.00067

Figure 3-36 Comparison between reference precise loads and those measured by the load cell and the produced mean error as well.

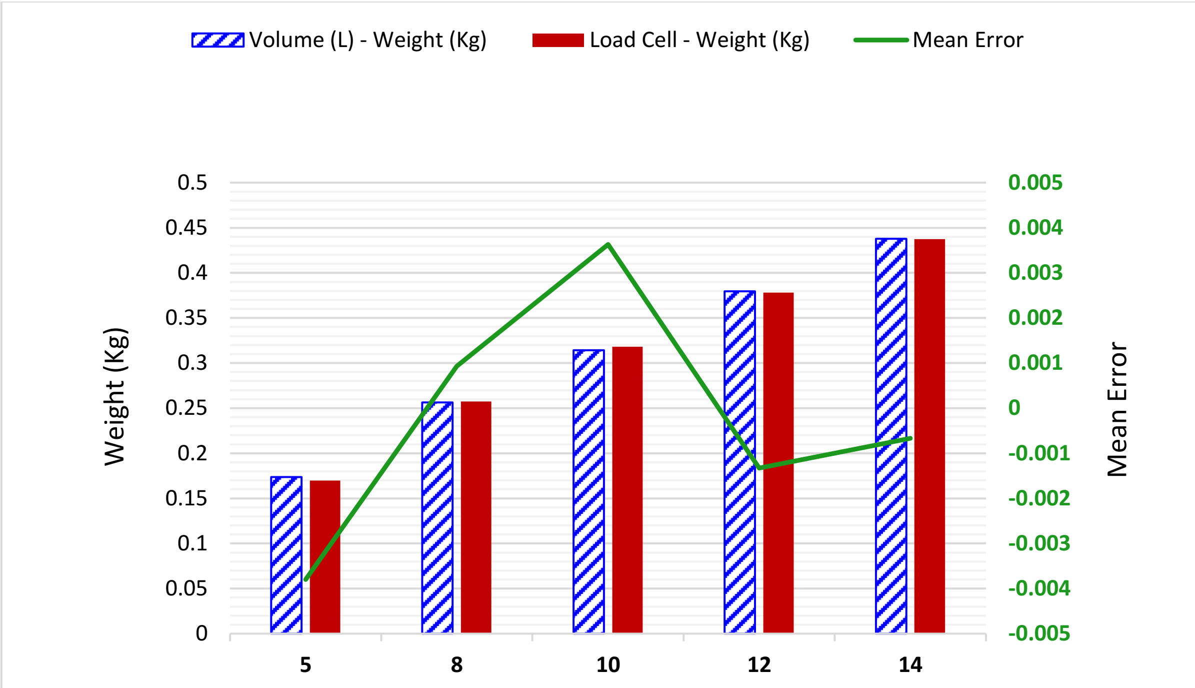


Figure 3-36: Mean error between reference loads and those measured by load cell

4 Chapter 4: Customising the Configuration of Data Acquisition Systems for Earthmoving Operations

4.1 General Overview

This chapter presents a description of a fuzzy-set-based model for customizing the configuration of efficient and cost-effective onsite automated data acquisition systems for earthmoving operations. The developed model overcomes subjective configuration of data acquisition systems and provides a systematic selection procedure of the needed sensors. The developed model identifies, evaluates and analyzes the factors affecting the performance of earthmoving operations in construction projects. The results of this analysis are then used to customize the configuration of the required data acquisition system. This procedure includes selection of necessary sensors for efficient tracking of earthmoving operations. Finally, results are discussed, and conclusions are drawn highlighting the key features of the developed method and how it can assist project managers in customizing the configuration of automated onsite data acquisition systems considering the unique nature of their projects. Figure 4-1 depicts the structure and main sections of this chapter.

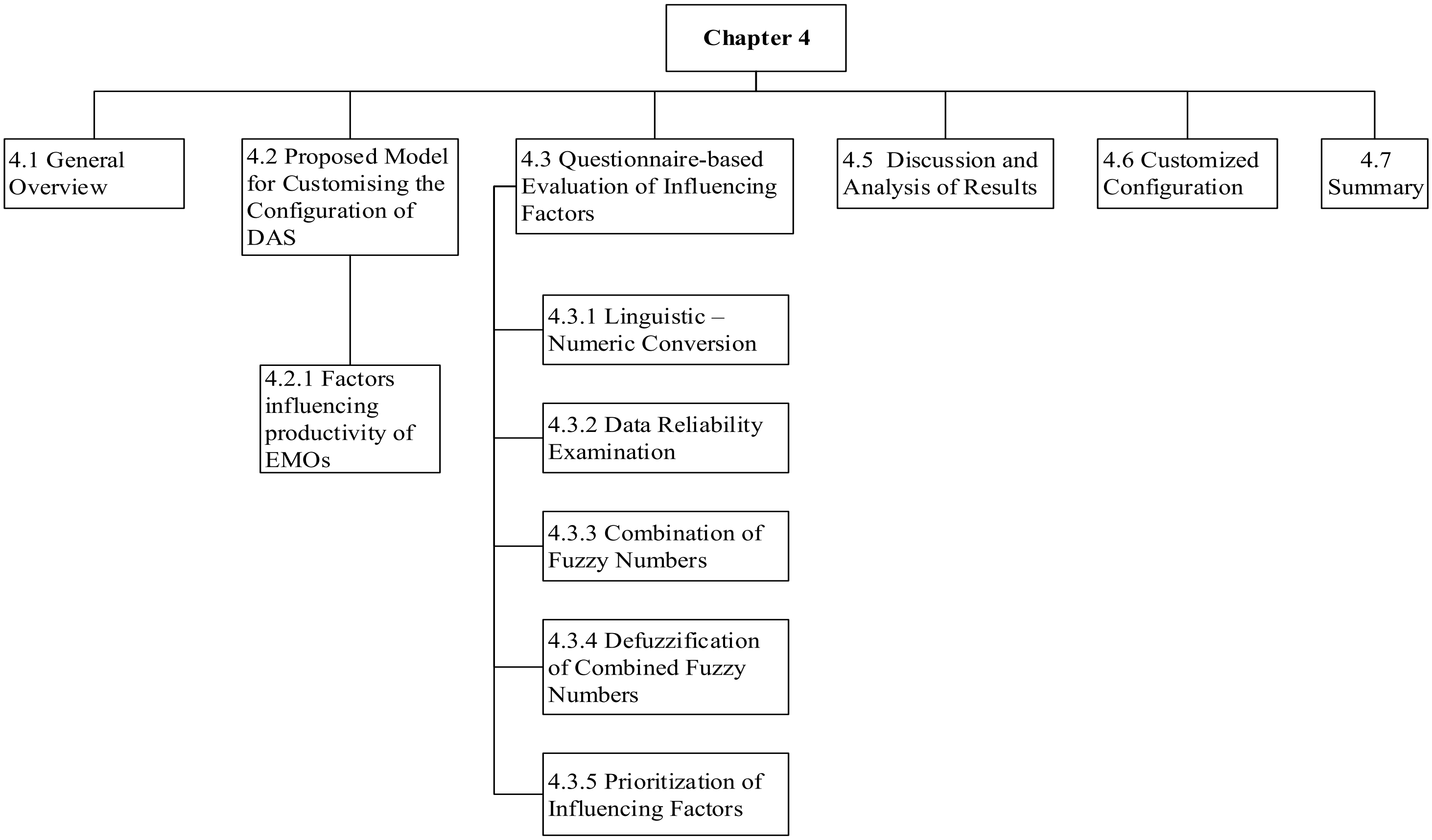


Figure 4-1: Chapter 4 – Structure and main sections

4.2 Developed Model for Customising the Configuration of DAS

The developed model introduces a new fuzzy set-based model that follows this procedure:

1. Identify the factors that impact the performance of earthmoving operations using a questionnaire that was send to a variety of experts involved in such industry.
2. Evaluate the effects of each factor thru the received responses from the responadent experts.
3. Analyze the consequences of each factor and select the most influencing factors on the performance of earthmoving operations.

Hence, results of the analysis are utilized to customize the configuration of the required data acquisition system and to select the necessary technologies and sensors for efficient tracking and monitoring of these operations. Figure 4-2 shows the flowchart of the proposed method.

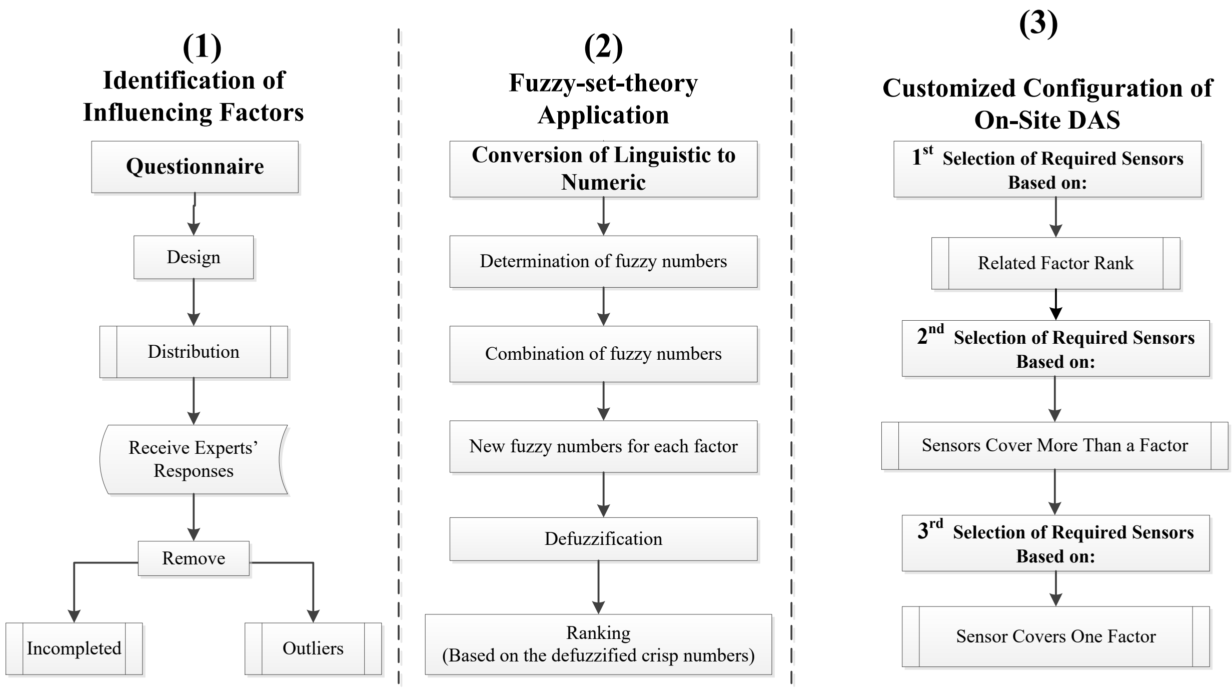


Figure 4-2: Proposed model for customizing configuration of DAS flowchart

4.2.1 Factors Influencing Productivity of Earthmoving Operations

Investigating the literature related to monitoring and control of earthmoving operations led to different findings. A significant part of those findings is considerably justified the substantial need for timely discovery of the grounds behind the variations in actual productivity compared with the planned productivity of earthmoving operations. The analysis process requires different information items, which are varied according to many scenarios where different factors could affect the productivity of earthmoving operations. In a real environment of earthmoving projects, these factors might be randomly combined based on a specific adverse scenario. Different factors could influence the productivity of earthmoving operations, where each of these factors has some signs that can help in its identification. These signs are mainly detected by collecting data from specific sensors.

Many factors that could influence the productivity of earthmoving operations. The hauling equipment is a principle participant in earthmoving operations; consequently, the various factors that may affect the hauling trucks are certainly influencing productivity of earthmoving operations and highway construction as well. However, the factors that might influence the productivity of earthmoving operations are extensive; the literature is worthy of the identification of these factors. Although a wide range of factors were cited to have an impact on productivity of earthmoving operations, the reasons behind their impact are not well documented and require further studies. There is a need for prioritizing those factors with respect to their impact on productivity of these operations. Then, the customized on-site data acquisition system is appropriately configured, and required sensing technologies are selected to measure and monitor the status of these factors. In other words, the sensors related to influencing factors are those to be integrated into the utilized data acquisition system.

In brief, different factors could affect the productivity of earthmoving operations in various influencing scenarios; either individually or collectively. Distinctive signs ease the identification of each factor using a particular sensor or set of sensors. Hence, the efficient selection process of sensors, which need to be incorporated in the data acquisition system, has a crucial role in recognition of the factors affecting the productivity of earthmoving operations. The different influencing factors were categorized into four main groups; (1) excavated soil conditions, (2) hauling and access roads conditions, (3) equipment and operational conditions, and (4) weather conditions. Figure 4-3 shows the different influencing categories and their respective factors.

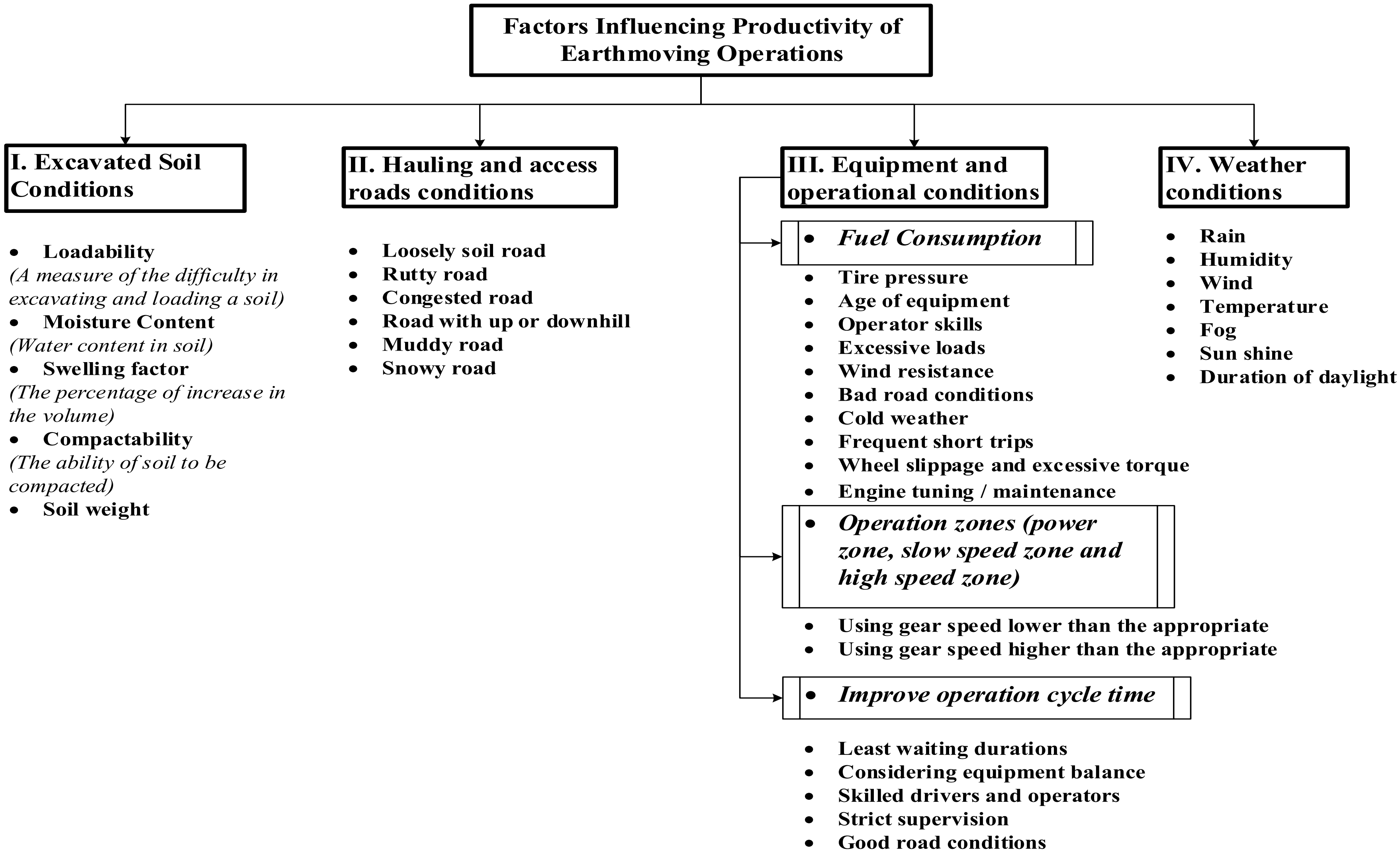


Figure 4-3: Factors influencing productivity of earthmoving operations

4.3 Questionnaire-based Evaluation of Influencing Factors

Literature was investigated to identify the different factors that are mostly influencing productivity in earthmoving and highway construction projects. Consequently, a questionnaire was designed to comprise the majority of those factors to acquire the evaluation of their impact on productivity using a fuzzy-set-based model. Then the questionnaire distributed online to eighty construction firms and professionals who are involved in such kind of construction projects. The targeted sample of experts was considered to include professionals from different countries. Table 4-1 shows the number of contacts from the different regions, where North America has the majority of questionnaires.

Table 4-1: Country-based number of contacted experts

Country	Number of Contacts	Percentage
Canada	40	50.00 %
USA	3	03.75 %
United Arab Emirates (UAE)	10	12.50 %
Qatar	10	12.50 %
Kuwait	12	15.00 %
Kingdom of Saudi Arabia (KSA)	5	06.25 %
Total Number of Contacts	**80**	**100 %**

Twenty-seven responses out of eighty distributed questionnaires were received from experts from different countries and in different job positions as shown in Figure 4-4, and Figure 4-5 respectively. While Figure 4-6 represents the number of years of experience of the respondents and the annual value of work in their firms is shown in Figure 4-7.

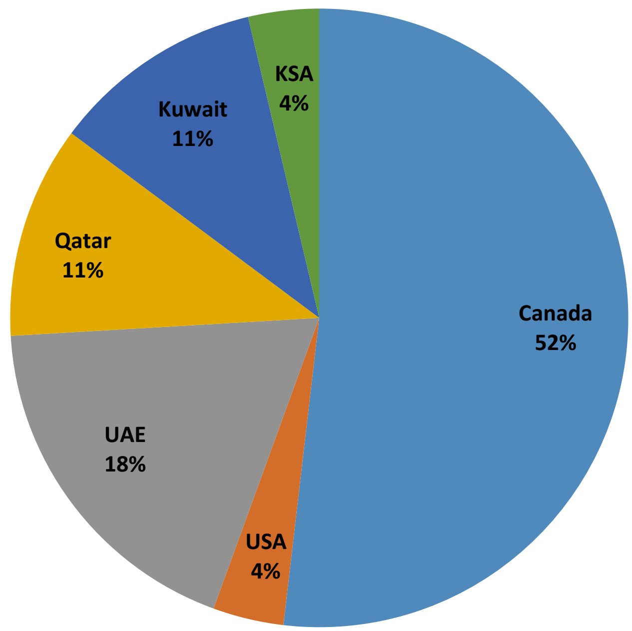


Figure 4-4: Location-based distribution of the respondents

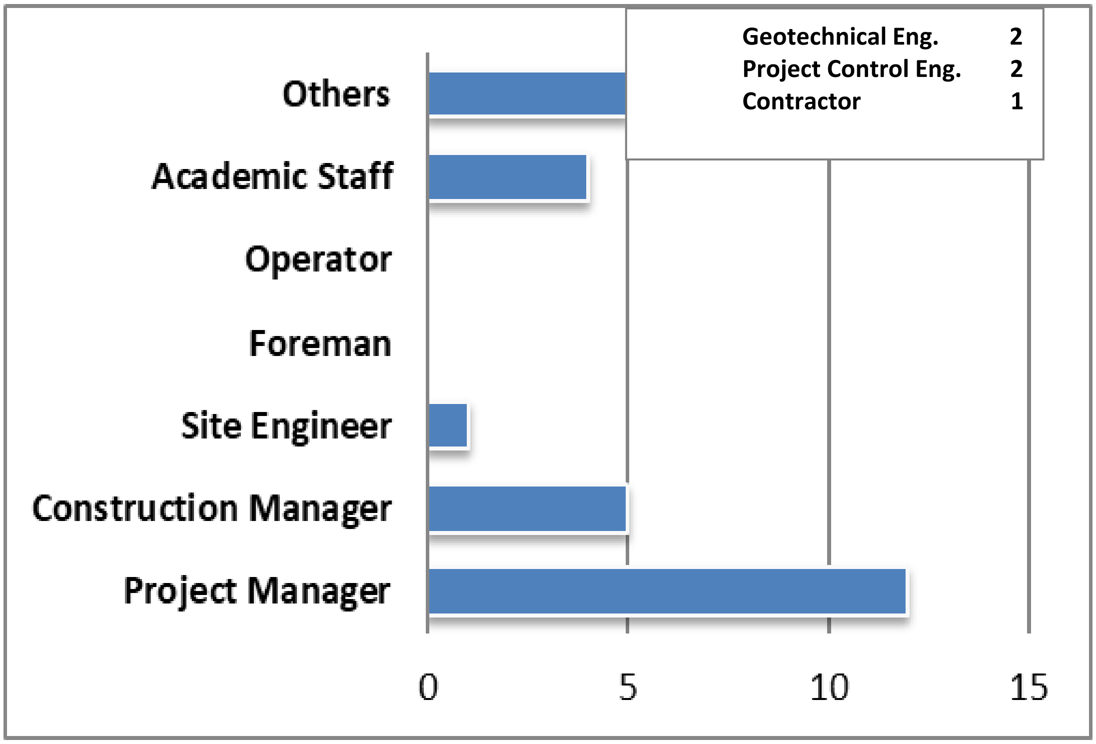


Figure 4-5: Position-based distribution of the respondents

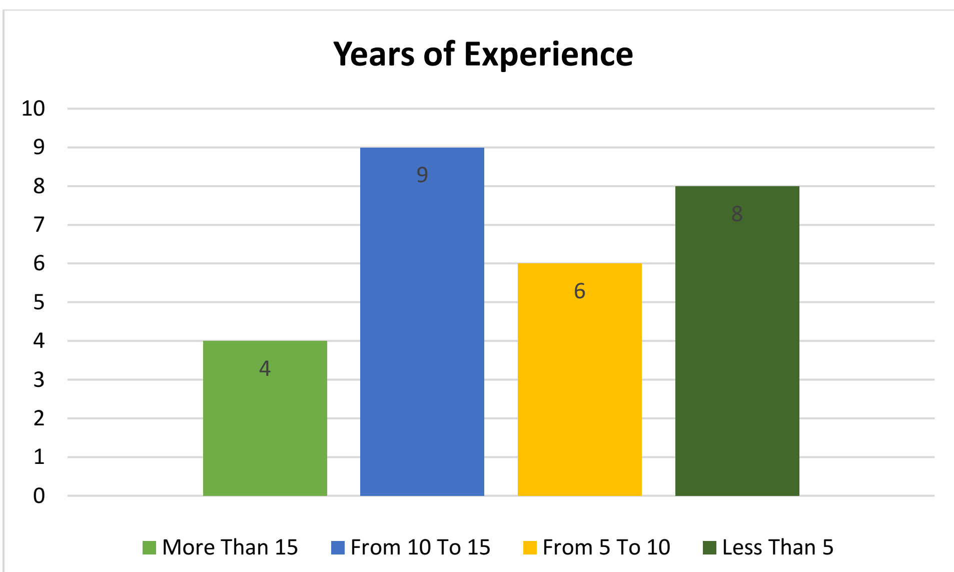


Figure 4-6: Years of experience of the respondents

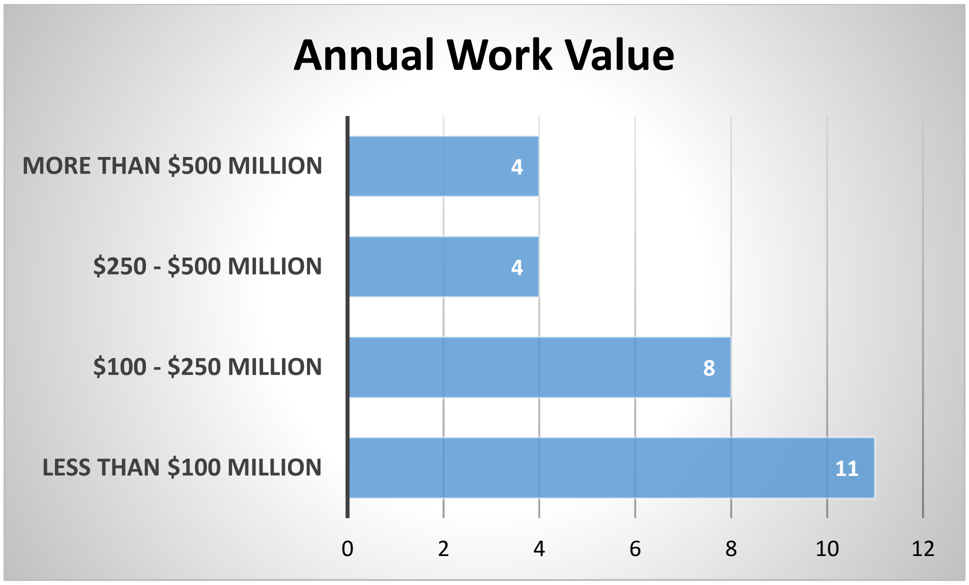


Figure 4-7: Annual work value of the participating firms

This questionnaire aimed to get experts' evaluation of various factors that affect productivity of earthmoving operations. Evaluation is usually a subjective and qualitative process that often associated with uncertainty. Fuzzy-Set-Theory (Zadeh, 1965) was recommended to model and account for the uncertainty and imprecision associated with expert judgment. Fuzzy set theory can be used regardless of the availability of historical data (Salah and Moselhi, 2016). Also, fuzzy theory eases the utilization of linguistic evaluation, or natural language terms, which is complicated to express with probability theory (Salem et al., 2017, Salah et al., 2017, Pinto et al., 2011). Therefore, fuzzy set theory was selected to model the subjectivity associated with the input received from experts. The developed method applies fuzzy set theory for the identification, assessment, and prioritization of the factors influencing the efficiency and productivity of earthmoving operations and highway construction. The respondents were advised to express their experience and knowledge to evaluate the impact of each factor in a linguistic term for more convenience.

4.3.1 Linguistic – Numeric Conversion

Quantitative assessment approach is used for conversion of expert linguistic evaluation into numeric fuzzy numbers (Salem et al., 2017, Salah and Moselhi, 2016). Figure 4-8 (a) shows the linguistic-numeric conversion scheme for the different expert evaluations; from no effect up to extreme effect on productivity. Figure 4-8 (b) shows the numeric consequence for the various influencing factors on 1-10 scale. Membership functions can be of different shapes, but practically, trapezoidal and triangular membership functions are most frequently used. In the majority of practical applications, trapezoidal membership functions work well (Barua et al., 2013). Also, the application of trapezoidal membership function eases and simplifies getting target results without any distortion. Based on that, the fuzzy membership functions were established.

This Linguistic-Numeric scheme provides flexibility in reflecting the predefined organization scale for each linguistic term that represents an impact. The incorporated effects on productivity for each factor vary from; no effect (NE) to extreme effect (EE) as shown in Figure 4-8. Explicitly, the different included effects were; no effect, low effect, moderate effect, high effect and finally extreme effect. The projected linguistic terms were labeled to cover a scale of 1:10. Each linguistic term covers a particular organization's predefined range; for example, a factor has a moderate effect means it has an expert evaluation 5 to 6 on the 1:10 organization's predefined scale.

The linguistic-numeric conversion scheme shown in Figure 4-8 supposed to be created once for each influencing factor to convert the respective linguistic evaluations of experts into numeric fuzzy numbers as shown in Table 4-2.

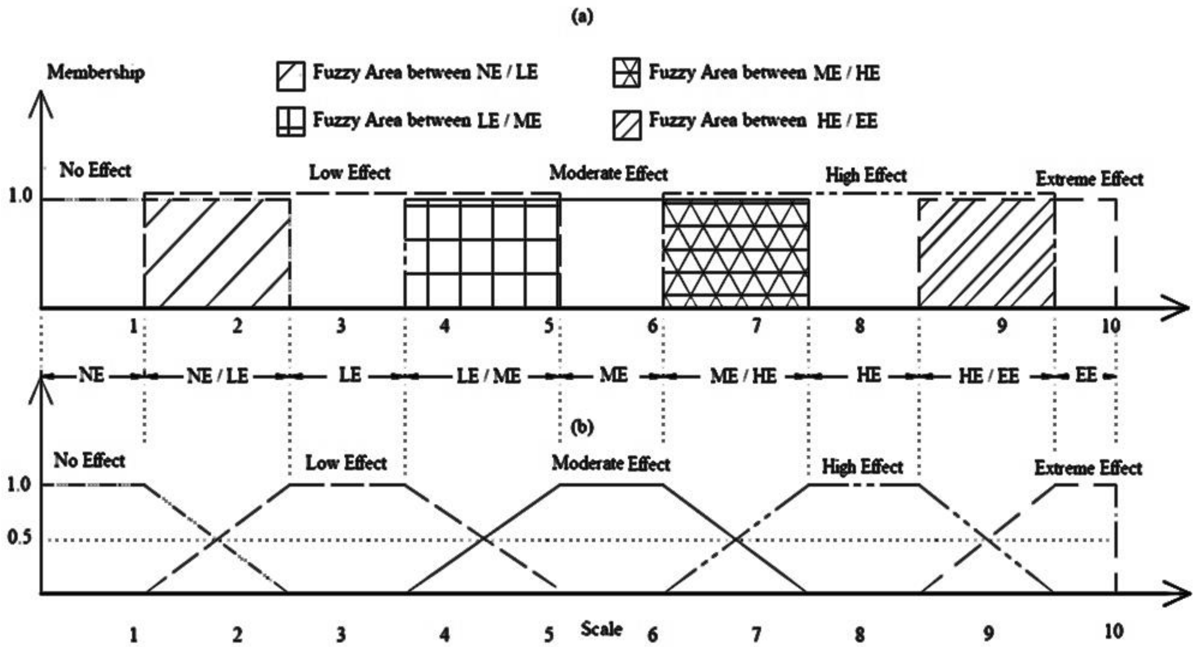


Figure 4-8: Fuzzy linguistic - numeric conversion scheme: preliminary (a) and final (b)

Table 4-2: Numerical fuzzy numbers for each influencing state

Linguistic Evaluation	Numerical Fuzzy Numbers
No Effect	[0.0 0.0 1.0 2.5]
Low Effect	[1.0 2.5 3.5 5.0]
Moderate Effect	[3.5 5.0 6.0 7.5]
High Effect	[6.0 7.5 8.5 9.5]
Extreme Effect	[8.5 9.5 10.0 10.0]

The distribution of experts' assessments for the effect of each factor is shown in Table 4-3.

Table 4-3: Experts' votes on the effect of each influencing factor

Influencing Factors		Experts' Evaluation					Influencing Factors		Experts' Evaluation				
		N	L	M	H	E			N	L	M	H	E
I. Excavated Soil Conditions							***A. Fuel Consumption ...Continue.***						
A. Soil Properties							4.	Excessive loads	0	0	7	16	4
1.	Loadability	0	2	7	14	4	5.	Wind resistance	0	4	14	8	1
2-	Moisture content	1	1	9	15	1	6.	Bad road conditions	0	2	5	17	3
3.	Swelling factor	0	2	14	7	4	7.	Cold weather	0	4	13	8	2
4.	Compactability	0	3	10	10	4	8.	Frequent short trips	0	4	13	9	1
5.	Soil Weight	0	3	14	7	3	9.	Wheel slippage / excessive torque	0	2	19	6	0
B. Bucket Fill Factor							10	Engine tuning / maintenance	0	0	13	9	5
1.	Soil hardness	0	3	8	11	5	***B. Operation zones***						
2-	Change of cut depth	0	1	8	16	2	1.	Using improper lower gear speed	1	3	13	8	2
3.	Operator skills	0	2	3	12	10	2-	Using improper higher gear speed	1	3	6	15	2
4.	Excavated soil particle size	0	1	9	12	5	***C. Improve Operation Cycle***						
5.	Power of machine	0	3	7	13	4	1.	Least waiting durations	0	3	4	6	14
II. Hauling and Access Roads Conditions							2-	Considering equipment balance	0	2	6	15	4
1.	Loosely soil road	0	2	5	17	3	3.	Skilled drivers and operators	1	0	4	17	5
2-	Rutty road	0	1	10	12	4	4.	Strict supervision	0	4	5	15	3
3.	Congested road	0	4	4	4	15	5.	Good road conditions	1	1	3	16	6
4.	Road with up or downhill	1	3	5	14	4	**IV. Weather Conditions**						
5.	Muddy road	0	2	6	13	6	1.	Rain	0	1	4	18	4
6.	Snowy road	0	3	1	10	13	2-	Humidity	1	9	15	0	2
III. Equipment and Operational Conditions							3.	Wind	0	2	9	14	2
A. Fuel Consumption							4.	Temperature	0	4	17	4	2
1.	Tire pressure	1	2	9	14	1	5.	Fog	0	0	6	8	13
2-	Age of equipment	0	2	3	18	4	6.	Sun shine	13	2	6	3	3
3.	Operator skills	1	3	4	15	4	7.	Duration of daylight	0	2	3	7	15

4.3.2 Data Reliability Examination

Reliability in statistics is the overall consistency of a measure. A measure is said to have high consistency if it produces alike results under steady conditions. Reliability is usually expressed through the internal consistency, where internal consistency is a measure based on the inter-correlations between items on the same test. It measures whether several items that propose to measure the same general concept produce related scores. For example, if a respondent expressed agreement with the statements "I like to ride horses" and "I've enjoyed riding horses in the past," and disagreement with the statement "I hate knighthood", this would be an indication of good internal consistency of the test. Internal consistency is commonly measured with Cronbach's alpha, which calculated from the pairwise correlations between items. Internal consistency ranges between negative infinity and one. Coefficient alpha could be negative when there is bigger within-subject inconsistency than between-subject inconsistency (Knapp, 1991).

There are different reports about the acceptable values of alpha, ranging from 0.70 to 0.95 (Bland and Altman, 1997). A low value of alpha could be due to a low number of questions, poor correlation between items or heterogeneous constructs. (George and Mallery, 2003) described a commonly established rule of thumb for labeling internal consistency as shown in Table 4-4.

Table 4-4: Cronbach’s Alpha values and corresponding internal consistency

Cronbach's alpha	**Internal consistency**
$\alpha \geq 0.9$	Excellent
$0.9 > \alpha \geq 0.8$	Good
$0.8 > \alpha \geq 0.7$	Acceptable
$0.7 > \alpha \geq 0.6$	Questionable
$0.6 > \alpha \geq 0.5$	Poor
$0.5 > \alpha$	Unacceptable

Reliability of the data collected through the questionnaire is a fundamental aspect of the evaluation of measurements, and it is a vital mean to enhance the accuracy of the collected data evaluation. A statistical reliability analysis was done to examine the consistency of the received data through the questionnaire. Cronbach's alpha (α) measure was used to check the internal consistency of the acquired data. Cronbach's alpha (α) test was applied using IBM® software package SPSS. Table 4-5 shows the different item statistics, where the word item refers to the experts who evaluated the forty influence factors.

Table 4-5: Different item statistics

Item #	Mean	Std. Deviation	N	Item #	Mean	Std. Deviation	N
1	2.6563	1.23184	40	15	7.9719	1.67454	40
2	3.4469	1.09225	40	16	8.0344	1.52411	40
3	4.2594	1.36179	40	17	8.0938	1.46808	40
4	4.6969	1.28443	40	18	8.4219	1.19919	40
5	5.4063	.99588	40	19	8.5063	1.10323	40
6	5.9125	1.60583	40	20	8.5063	1.10323	40
7	5.9969	1.67095	40	21	8.5063	1.10323	40
8	6.3344	1.87070	40	22	8.7906	.70221	40
9	6.6719	1.99332	40	23	8.8531	.73483	40
10	6.9844	2-03538	40	24	9.1000	.72235	40
11	7.3000	1.94821	40	25	9.2031	.69838	40
12	7.6125	1.88742	40	26	9.3969	.31123	40
13	7.7281	1.89104	40	27	9.4844	.09882	40
14	7.9406	1.65080	40				

Inter-item covariance matrix in Table 4-6 shows the covariance between different items .

Table 4-6: Inter-Item covarience matrix

Inter-Item Covariance Matrix

	Item1	Item2	Item3	Item4	Item5	Item6	Item7	Item8	Item9	Item10	Item11	Item12	Item13	Item14	Item15	Item16	Item17	Item18	Item19	Item20	Item21	Item22	Item23	Item24	Item25	Item26	Item27
Item1	1.517	.618	.632	.650	.355	.166	.412	.747	.682	.609	.400	.381	.237	.413	.464	.350	.371	.303	.332	.332	.332	.215	.243	.302	.304	.086	-.006
Item2	.618	1.193	.821	.620	.295	.496	.673	.735	.580	.653	.725	.798	.745	.748	.774	.609	.582	.432	.393	.393	.393	.079	.170	.177	.096	.047	.007
Item3	.632	.821	1.854	1.289	.373	1.017	1.125	1.338	1.334	1.299	1.108	1.289	1.180	1.006	1.006	.789	.864	.481	.372	.372	.372	.117	.156	.246	.159	-.011	-.020
Item4	.650	.620	1.289	1.650	.632	1.049	1.118	1.396	1.241	1.066	.949	1.207	1.262	1.185	1.211	.966	1.015	.636	.489	.489	.489	.107	.158	.281	.252	-.005	-.013
Item5	.355	.295	.373	.632	.992	1.040	1.049	1.081	1.113	1.144	1.014	1.044	1.055	.823	.880	.590	.596	.627	.635	.635	.635	.262	.268	.292	.228	-.010	-.002
Item6	.166	.496	1.017	1.049	1.040	2.579	2.543	2.400	2.257	2.125	1.831	1.699	1.704	1.362	1.403	1.080	1.055	.971	.935	.935	.935	.468	.496	.500	.382	.044	.007
Item7	.412	.673	1.125	1.118	1.049	2.543	2.792	2.620	2.448	2.289	1.968	1.808	1.804	1.443	1.536	1.207	1.177	1.064	1.021	1.021	1.021	.530	.552	.534	.408	.053	.008
Item8	.747	.735	1.338	1.396	1.081	2.400	2.620	3.500	3.211	2.943	2.513	2.245	2.201	1.821	1.902	1.552	1.502	1.275	1.203	1.203	1.203	.613	.614	.565	.510	.088	.013
Item9	.682	.580	1.334	1.241	1.113	2.257	2.448	3.211	3.973	3.598	3.058	2.682	2.652	2.198	2.269	1.897	1.826	1.486	1.384	1.384	1.384	.750	.729	.703	.613	.124	.019
Item10	.609	.653	1.299	1.066	1.144	2.125	2.289	2.943	3.598	4.143	3.502	3.026	2.958	2.437	2.498	2.106	2.016	1.570	1.442	1.442	1.442	.717	.676	.723	.654	.157	.024
Item11	.400	.725	1.108	.949	1.014	1.831	1.968	2.513	3.058	3.502	3.796	3.219	3.113	2.523	2.574	2.162	2.052	1.500	1.345	1.345	1.345	.528	.520	.542	.440	.190	.029
Item12	.381	.798	1.289	1.207	1.044	1.699	1.808	2.245	2.682	3.026	3.219	3.562	3.420	2.762	2.802	2.370	2.242	1.585	1.402	1.402	1.402	.494	.521	.517	.382	.124	.034
Item13	.237	.745	1.180	1.262	1.055	1.704	1.804	2.201	2.652	2.958	3.113	3.420	3.576	2.892	2.929	2.490	2.354	1.659	1.466	1.466	1.466	.524	.543	.511	.363	.083	.036
Item14	.413	.748	1.006	1.185	.823	1.362	1.443	1.821	2.198	2.437	2.523	2.762	2.892	2.725	2.755	2.438	2.290	1.522	1.311	1.311	1.311	.491	.551	.564	.428	.105	.039
Item15	.464	.774	1.006	1.211	.880	1.403	1.536	1.902	2.269	2.498	2.574	2.802	2.929	2.755	2.804	2.485	2.335	1.557	1.343	1.343	1.343	.514	.572	.577	.437	.108	.040
Item16	.350	.609	.789	.966	.590	1.080	1.207	1.552	1.897	2.106	2.162	2.370	2.490	2.438	2.485	2.323	2.169	1.370	1.150	1.150	1.150	.519	.573	.562	.456	.115	.041
Item17	.371	.582	.864	1.015	.596	1.055	1.177	1.502	1.826	2.016	2.052	2.242	2.354	2.290	2.335	2.169	2.155	1.336	1.112	1.112	1.112	.464	.514	.587	.474	.121	.042
Item18	.303	.432	.481	.636	.627	.971	1.064	1.275	1.486	1.570	1.500	1.585	1.659	1.522	1.557	1.370	1.336	1.438	1.185	1.185	1.185	.441	.470	.460	.412	.102	.047
Item19	.332	.393	.372	.489	.635	.935	1.021	1.203	1.384	1.442	1.345	1.402	1.466	1.311	1.343	1.150	1.112	1.185	1.217	1.217	1.217	.448	.472	.440	.384	.057	.048
Item20	.332	.393	.372	.489	.635	.935	1.021	1.203	1.384	1.442	1.345	1.402	1.466	1.311	1.343	1.150	1.112	1.185	1.217	1.217	1.217	.448	.472	.440	.384	.057	.048
Item21	.332	.393	.372	.489	.635	.935	1.021	1.203	1.384	1.442	1.345	1.402	1.466	1.311	1.343	1.150	1.112	1.185	1.217	1.217	1.217	.448	.472	.440	.384	.057	.048
Item22	.215	.079	.117	.107	.262	.468	.530	.613	.750	.717	.528	.494	.524	.491	.514	.519	.464	.441	.448	.448	.448	.493	.499	.395	.362	.033	-.001
Item23	.243	.170	.156	.158	.268	.496	.552	.614	.729	.676	.520	.521	.543	.551	.572	.573	.514	.470	.472	.472	.472	.499	.540	.421	.381	.039	.000
Item24	.302	.177	.246	.281	.292	.500	.534	.565	.703	.723	.542	.517	.511	.564	.577	.562	.587	.460	.440	.440	.440	.395	.421	.522	.456	.065	.004
Item25	.304	.096	.159	.252	.228	.382	.408	.510	.613	.654	.440	.382	.363	.428	.437	.456	.474	.412	.384	.384	.384	.362	.381	.456	.488	.076	.005
Item26	.086	.047	-.011	-.005	-.010	.044	.053	.088	.124	.157	.190	.124	.083	.105	.108	.115	.121	.102	.057	.057	.057	.033	.039	.065	.076	.097	.008
Item27	-.006	.007	-.020	-.013	-.002	.007	.008	.013	.019	.024	.029	.034	.036	.039	.040	.041	.042	.047	.048	.048	.048	-.001	.000	.004	.005	.008	.010

The test result shows a robust data consistency with 0.962 as shown in Table 4-7.

Table 4-7: Reliability statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.962	0.961	27

This reliability could be impacted due to a nonresponse of one of the experts. Table 4-8 represent Cronbach's Alpha if a response (item) excluded from this data.

Table 4-8: Cronbach's Alpha if item delated

Item	1	2	3	4	5	6	7	8	9
Cronbach's Alpha if Item Deleted	0.963	0.962	0.961	0.961	0.960	0.960	0.960	0.959	0.959
Item	10	11	12	13	14	15	16	17	18
Cronbach's Alpha if Item Deleted	0.959	0.959	0.959	0.959	0.959	0.959	0.959	0.959	0.960
Item	19	20	21	22	23	24	25	26	27
Cronbach's Alpha if Item Deleted	0.960	0.960	0.960	0.962	0.962	0.962	0.962	0.963	0.963

4.3.3 Combination of Fuzzy Numbers

The combination process takes into account the significance of the fuzzy numbers produced from the evaluation of different impacts provided by respondents. Equation (4-1) is used to calculate the combination of fuzzy numbers used to calculate the fuzzy number that represents each factor influencing productivity of earthmoving operations. Prior realization of the combined fuzzy numbers, large figure of fuzzy numbers were obtained, where, these numbers depict the fuzzy number for each attribute versus each of the influence five criterion. Hence, these five fuzzy numbers were combined as shown in Table 4-9. Due to the sizable number of mathematical operations, the combination formula was programmed using a Microsoft Excel®.

$$\tilde{F}_i = \frac{N_r}{N_T} \times \widetilde{NoEffect} + \frac{N_r}{N_T} \times \widetilde{Minor} + \frac{N_r}{N_T} \times \widetilde{Moderate} + \frac{N_r}{N_T} \times \widetilde{High} + \frac{N_r}{N_T} \times \widetilde{Extreme} \qquad \text{Equation (4-1)}$$

Where;

$\tilde{F}_i$, represents the fuzzy number of factor i=1...to 27

N_r, represents the number of responses for each attribute A (e.g., No Effect)

N_T, represents the total number of responses each factor

Table 4-9: Combined Fuzzy number for each influencing factor

Influencing Factors		Combined Fuzzy Number	Influencing Factors		Combined Fuzzy Number
I. Excavated Soil Conditions			***A. Fuel Consumption, ...Continue.***		
A. Soil Properties			4.	Excessive loads	[5.722 7.148 8.074 9.056]
1.	Loadability	[5.352 6.778 7.704 8.722]	5.	Wind resistance	[4.056 5.537 6.519 7.815]
2-	Moisture content	[4.852 6.315 7.259 8.426]	6.	Bad road conditions	[5.444 6.889 7.833 8.852]
3.	Swelling factor	[4.704 6.130 7.056 8.204]	7.	Cold weather	[4.241 5.704 6.667 7.907]
4.	Compactability	[4.889 6.315 7.241 8.333]	8.	Frequent short trips	[4.148 5.630 6.611 7.889]
5.	Soil Weight	[4.426 5.870 6.815 8.019]	9.	Wheel slippage / excessive torque	[3.870 5.370 6.370 7.759]
B. Bucket Fill Factor			10	Engine tuning / maintenance	[5.259 6.667 7.574 8.630]
1.	Soil hardness	[5.167 6.574 7.481 8.500]	***B. Operation zones***		
2-	Change of cut depth	[5.259 6.722 7.685 8.778]	1.	Using improper lower gear speed	[4.204 5.648 6.574 7.815]
3.	Operator skills	[6.278 7.593 8.407 9.130]	2-	Using improper higher gear speed	[4.852 6.296 7.222 8.333]
4.	Excavated soil particle size	[5.444 6.852 7.759 8.759]	***C. Improve Operation Cycle***		
5.	Power of machine	[5.167 6.593 7.519 8.556]	1.	Least waiting durations	[6.370 7.611 8.352 8.963]
II. Hauling and Access Roads Conditions			2-	Considering equipment balance	[5.444 6.870 7.796 8.796]
1.	Loosely soil road	[5.444 6.889 7.833 8.852]	3.	Skilled drivers and operators	[5.870 7.259 8.130 9.037]
2-	Rutty road	[5.259 6.685 7.611 8.667]	4.	Strict supervision	[5.074 6.519 7.463 8.519]
3.	Congested road	[6.278 7.500 8.222 8.815]	5.	Good road conditions	[5.870 7.241 8.093 8.963]
4.	Road with up or downhill	[5.130 6.537 7.426 8.444]	**IV. Weather Conditions**		
5.	Muddy road	[5.630 7.019 7.907 8.833]	1.	Rain	[5.800 7.220 8.140 9.080]
6.	Snowy road	[6.556 7.815 8.574 9.167]	2-	Humidity	[2-860 4.300 5.220 6.600]
III. Equipment and Operational Conditions			3.	Wind	[4.900 6.360 7.320 8.460]
A. Fuel Consumption			4.	Temperature	[3.900 5.360 6.320 7.620]
1.	Tire pressure	[4.667 6.130 7.074 8.259]	5.	Fog	[6.500 7.780 8.560 9.240]
2-	Age of equipment	[5.722 7.148 8.074 9.019]	6.	Sun shine	[2-660 3.880 4.380 5.640]
3.	Operator skills	[5.222 6.630 7.519 8.519]	7.	Duration of daylight	[6.521 7.771 8.521 9.125]

4.3.4 Defuzzification of Combined Fuzzy Numbers

The acquired combined fuzzy numbers are not suited for demonstrating the importance of each influencing factor and which of these factors transcends the others. Therefore, it is preferable to have these fuzzy numbers in a crisp format. Accordingly, each fuzzy number is defuzzified using Equation (4-2). The defuzzified value of each factor represents its score as shown in Table 4-10.

$$F_i = \frac{\int x\mu_A dx}{\int \mu_A dx}$$ Equation (4-2)

Where;

F_i, represents the defuzzified value of fuzzy number $\tilde{F}_i$

μ_A, represents the membership function for each attribute A (e.g., No Effect)

Table 4-10: Defuzzification output for the studied influencing factors

	Influencing Factors	Defuzzification Output		Influencing Factors	Defuzzification Output
I. Excavated Soil Conditions			***A. Fuel Consumption ...Continue.***		
A. Soil Properties			4.	Excessive loads	7.500
1.	Loadability	7.139	5.	Wind resistance	5.981
2-	Moisture content	6.713	6.	Bad road conditions	7.255
3.	Swelling factor	6.523	7.	Cold weather	6.130
4.	Compactability	6.694	8.	Frequent short trips	6.069
5.	Soil Weight	6.282	9.	Wheel slippage / excessive torque	5.843
B. Bucket Fill Factor			10.	Engine tuning/maintenance	7.032
1.	Soil hardness	6.931	***B. Operation zones***		
2-	Change of cut depth	7.111	1.	Using improper lower gear speed	6.060
3.	Operator skills	7.852	2-	Using improper higher gear speed	6.676
4.	Excavated soil particle size	7.204	***C. Improve Operation Cycle***		
5.	Power of machine	6.958	1.	Least waiting durations	7.824
II. Hauling and Access Roads Conditions			2-	Considering equipment balance	7.227
1.	Loosely soil road	7.255	3.	Skilled drivers and operators	7.574
2-	Rutty road	7.056	4.	Strict supervision	6.894]
3.	Congested road	7.704	5.	Good road conditions	7.542
4.	Road with up or downhill	6.884	**IV. Weather Conditions**		
5.	Muddy road	7.347	1.	Rain	7.560
6.	Snowy road	8.028	2-	Humidity	4.745
III. Equipment and Operational Conditions			3.	Wind	6.760
A. Fuel Consumption			4.	Temperature	5.800
1.	Tire pressure	6.532	5.	Fog	8.020
2-	Age of equipment	7.491	6.	Sunshine	4.140
3.	Operator skills	6.972	7.	Duration of daylight	7.984

4.3.5 Prioritization of Influencing Factors

The factors that are related to the same influencing category were ranked based on their respective scores as shown in Figures 4-9 to 4-13. Where the higher score, the higher priority the factor has. Figure 4-9 presents the prioritization of the factors related to the soil properties of the excavated soil. Figure 4-10 shows the prioritization of the factors that could affect the bucket fill factors (BFF) of the excavated soils. Figure 4-11 presents the prioritization of the factors related to hauling and access road conditions that might affect the productivity of earthmoving operations. Equipment and operational conditions were categorized into three sub-groups, where, the factors related to each group were ranked from higher to lower scores to determine the factors with higher priority to be detected using the proposed customized data acquisition system.

Figure 4-12, Figure 4-13, and Figure 4-14 show the fuzzy-set-based ranking of factors that have an impact on fuel consumption, operational zone and improving operational time respectively. Where, Figure 4-12 illustrates a group of ten factors related to equipment and operational conditions that might influence the equipment fuel consumption where, excessive loads, equipment age, and bad road conditions represent the factors that lead to uneconomic fuel consumption. The same demonstration philosophy applied to factors depict by Figure 4-13 and Figure 4-14, where the usage of an equipment gear speed higher than the appropriate diminishes the equipment utilization efficiency as shown in Figure 4-13. Figure 4-14 indicates the ranking of factors that contribute to the improvement of the operation cycle time. Finally, Figure 4-15 presents the ranking of the factors related to the weather conditions.

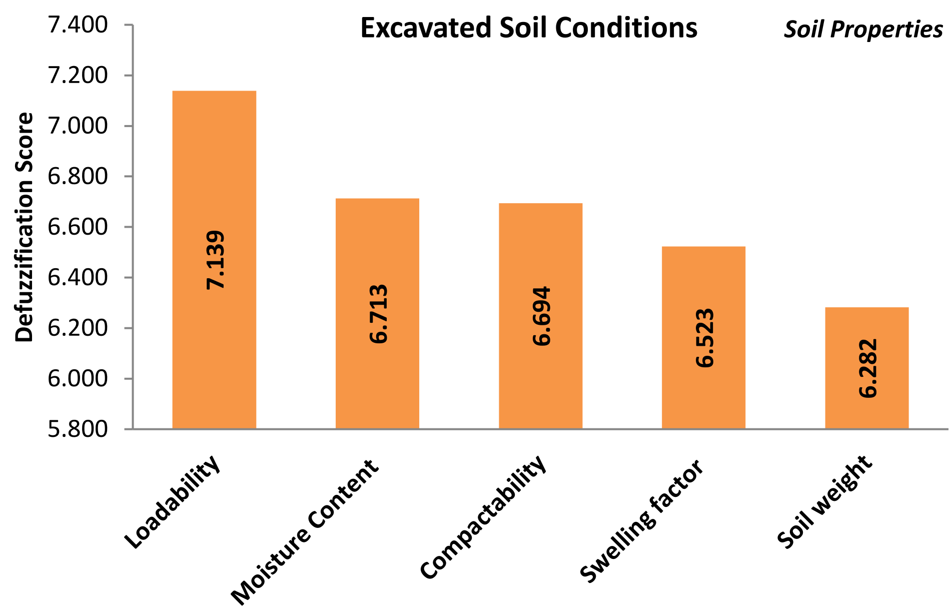


Figure 4-9: Ranking scores of excavated soil conditions- Soil properties

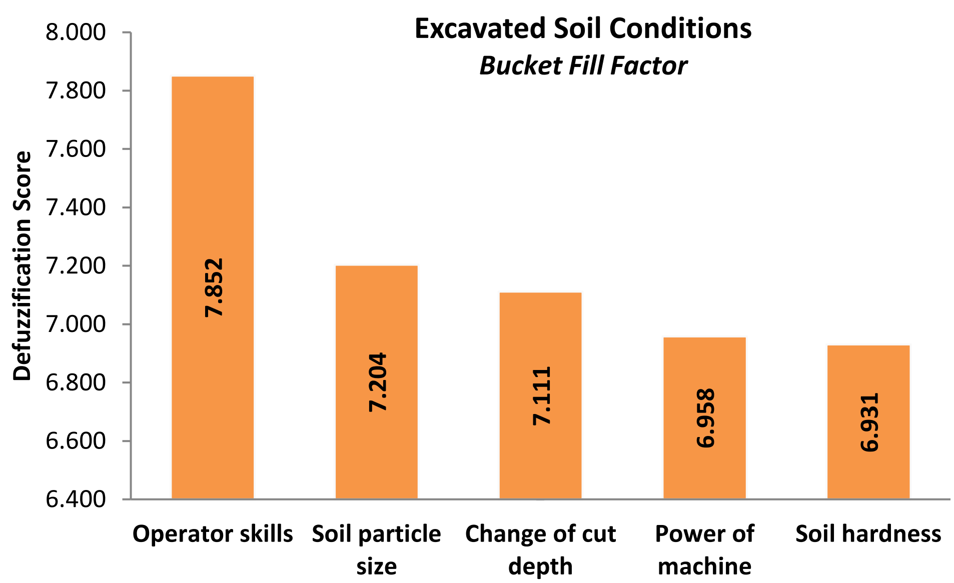


Figure 4-10: Ranking scores of excavated soil conditions-Bucket Fill Factor

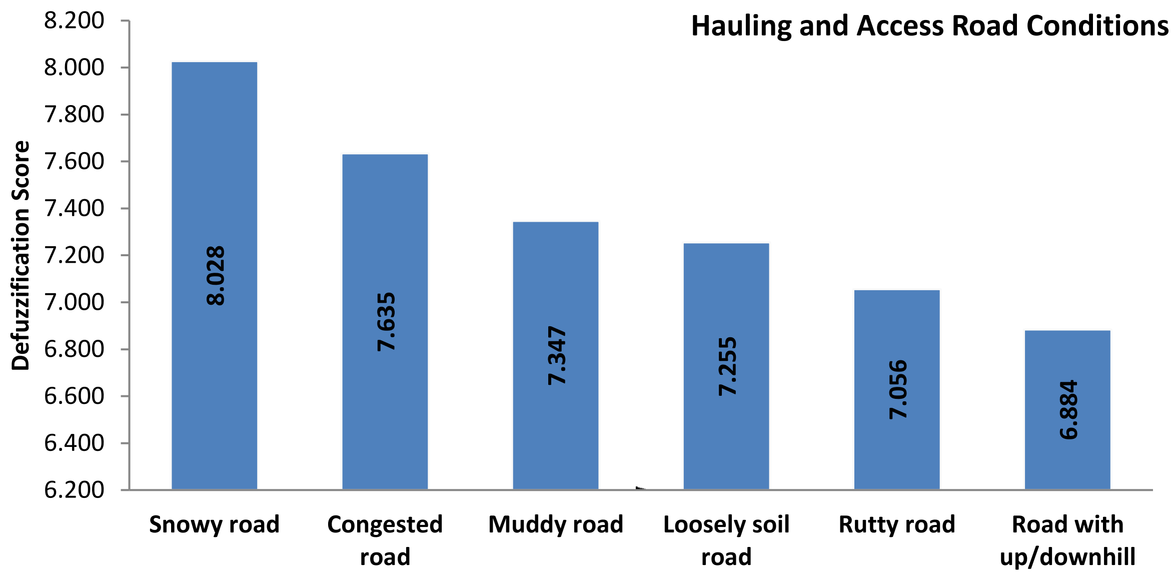


Figure 4-11: Ranking scores of hauling and access road conditions

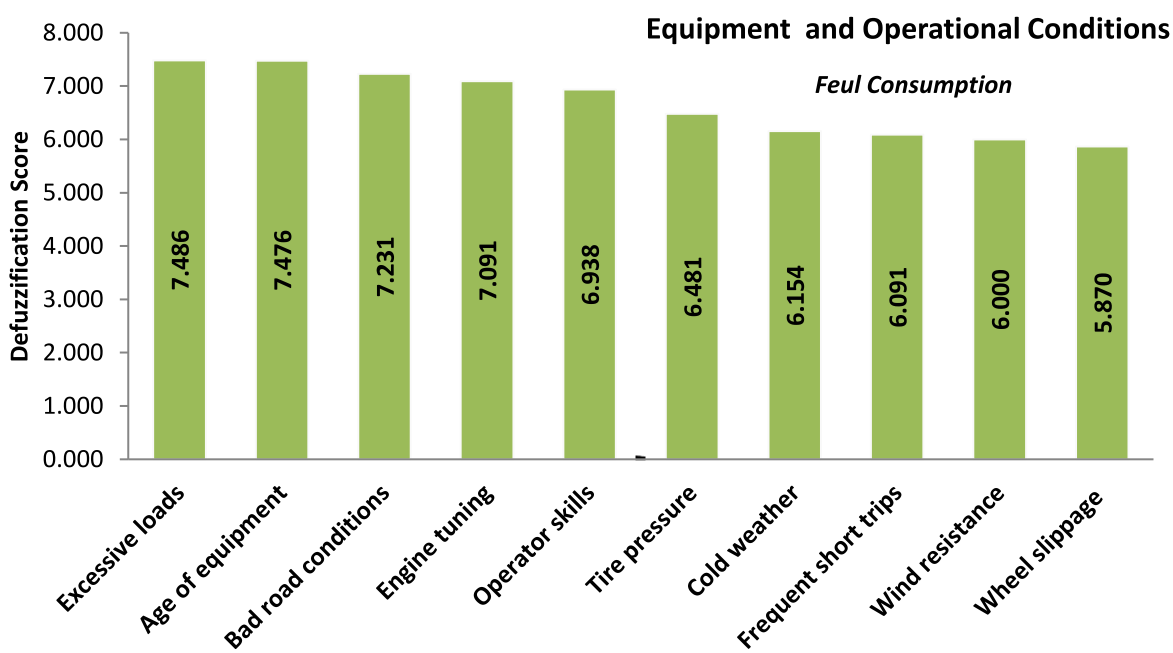


Figure 4-12: Ranking scores of equipment and operational conditions - Fuel consumption

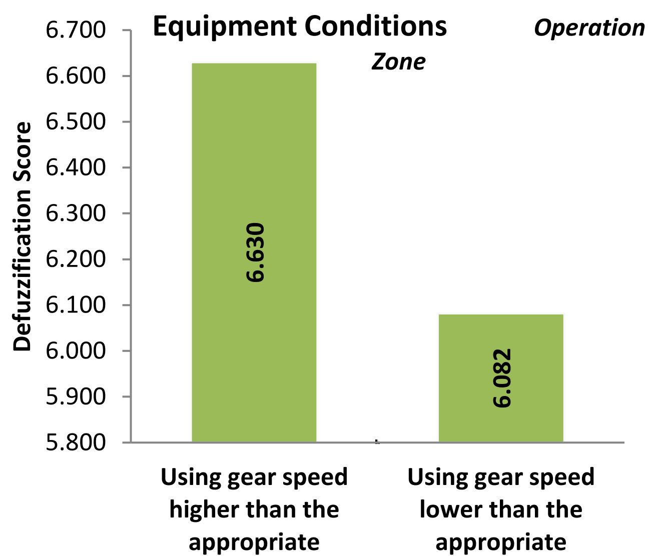


Figure 4-13: Ranking scores of equipment conditions- Operation zone

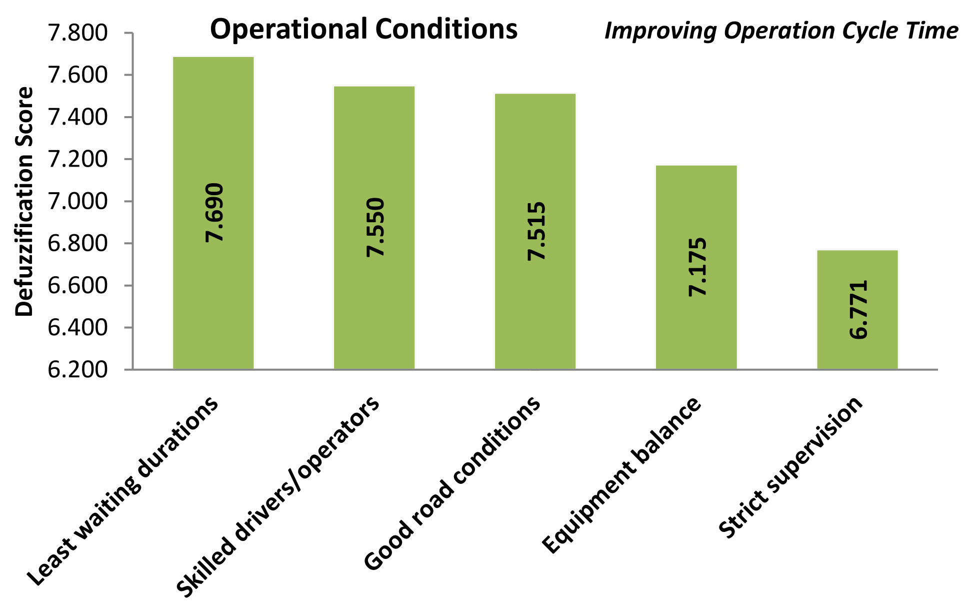


Figure 4-14: Ranking scores of operational conditions - Improving operation cycle time

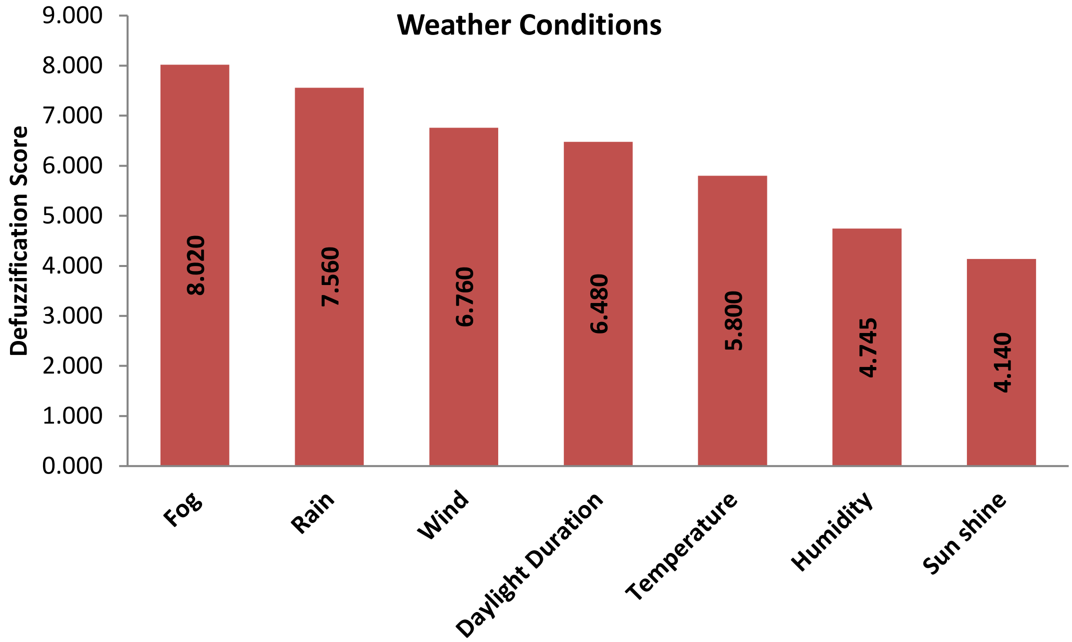


Figure 4-15: Ranking scores of weather conditions

4.4 Discussion and Analysis of Results

Ranking results identify the factors that have the higher priority to be recognized as compared to other factors. The first group of factors related to excavated soil condition includes two subgroups. First, the soil properties influencing factors subgroup, in which, Loadability (a measure of the difficulty in excavating and loading a soil), and soil moisture content have come in the first and second positions. This analysis is genuinely compatible with the logical engineering sense, where, the deficient loadable soil, the longest required duration to be loaded, and hence the less production of the fleet. Also, soil water content has a significant share from the actual loaded quantities perspective, where, in soils with high water content, trucks might reach their payload capacity before reaching its commonly usable volumetric capacity. Such consideration contributes to avoiding unintentional abuse of hauling trucks, consequently, less time out of the fleet for maintenance, and then more production. Second, the factors of excavated soil that impact the bucket fill factor, in which, operators' skills, the size of particles and depth of cut were respectively the most three important, affecting factors.

The second group of factors influencing productivity of earthmoving operations is the hauling and access road conditions. The different road conditions were ranked, where, snowy and congested roads have come in the first and second state respectively. Snowy roads result in higher rolling resistance, excessive torque, wheel slippage and hence slow speeds and long durations for hauling and returning trips. Similarly, the top-ranked factors in other groups are the most recommended factors to be recognized to detect as early as possible their respective influence on productivity. Hence, this early detection of factors influencing productivity of earthmoving operations permits the management personnel in charge to take the necessary actions in a timely and prioritized manner. Also, it helps in selecting the most appropriate configuration or customization of on-site data acquisition system to collect the data related to the selected significant influencing factors.

4.5 Customized Configuration

Over the last decades, automation technology market made noticeable advancements, in both hardware and software. In particular, is the advancement in remote sensing technologies, Wireless Sensing Networks (WSN) and data communication, which all provide an opportunity to detect these prioritized influencing factors and communicate their relating data sets using automated data acquisition and transmission systems. The majority of the existing data acquisition systems are off-the-shelf, expensive and in a black box format in both perspectives of software and hardware, such as On-Board Instrumentation Systems (OBIS). Those commercial data acquisition systems have traditionally been used, where, the user has no right neither to configure the hardware nor to access the relevant algorithms and modify it as they see fit, where the stored data is often difficult to be accessed without using the seller specific software.

Open-source technologies have a minute portion in data acquisition systems' marketplace. There are two pioneers in the domain of the cost-efficient available technologies, Arduino and Waspmote. Although Arduino has older existence than Waspmote, both platforms are using typical coding syntax. Arduino is considerably purposeful to learn how to use electronics and to do cheap, and simple projects, e.g., home automation projects, while Waspmote is a device specially designed to create long lifetime wireless sensor networks which expected to be installed in a real scenario like a city, agriculture farm or construction job site.

A detailed comparative study was done to select the most suitable open source technology for automated data acquisition and communication, Both Arduino and Waspmote are certified open source, so all the source code libraries are released under the Lesser General Public License

(LGPL). Moreover, Both Waspmote and Arduino boards are FCC and CE certified. However, Radio certification is needed in case of using a communication module, i.e., Wi-Fi, GPRS, and Xbee. Only Waspmote has the Radio Certification for all the possible combinations of the communication modules, i.e., 802-15.4, ZigBee, 3G, ZigBee + 3G, while, Arduino does not. Table 4-11 summarizes the different comparison aspects for both Arduino and Waspmote including the cost of various modules.

Table 4-11: Detailed Comparison between Arduino and Waspmote

Technology / Feature	Arduino		Waspmote
	UNO	Mega 2560	
Compiler/IDE	Same compiler and core libraries		
Code	Same code is compatible in both platforms		
Suitability	Automated home projects		Wireless sensor networks Long lifetime real scenarios
RTC (Real Time Clock)	Separate module		Built-in
3D Accelerometer	Separate module		Built-in
Data Logging	Separate module		Built-in SD card slot
Frequency	16 MHz	16MHz	14MHz
RAM	2 KB	8 KB	8 KB
External Storage (SD card)	No	No	Yes, 2GB
Consumption ON	50 mA	50 mA	15 mA
Sleep mode	No	No	Yes, 55µA
Hibernate mode	No	No	Yes, 0.7µA
Board	22,00 €	41,00 €	155.00 €
Arduino Xbee 802-15.4 + 2dBi antenna	45,00 €	45,00 €	
Triple axis accelerometer	7,75 €	7,75 €	
On Board Programmable LED + ON/OFF Switch	1,00 €	1,00 €	
RTC DS3234 + Button Battery	16,00 €	16,00 €	
uSD Adaptor	20,00 €	20,00 €	
Solar Panel Socket 6600mAh Battery	47,00 €	47,00 €	30,00 €
Total	**158,75 €**	**177,75 €**	**185,00 €**

The proposed data acquisition system is configured to be fully automated, accurate, reliable and cost-effective. The system is customizable to include a variety of sensors that able to detect the most important factors influencing performance and production of earthmoving operations. The customized selection of these sensors depends on the fuzzy-set-based application of the proposed questionnaire. Although the selection of the required sensors depends on the realized ranking, this selection could be prioritized by giving higher priority to a sensor which covers more than an influencing factor over another sensor which covers just one factor.

The factors took place in the top ranks of each influencing category or sub-category are the base for selecting the appropriate sensor. The sensors were selected to capture the reading related to these factors directly or indirectly to their indicators.

The chosen sensors should mainly and to satisfy the following configuration criteria: (1) cost-effective, (2) reliable, and (3) open-source based. In the light of this configuration criterion and the above-stated results of the proposed fuzzy-set-based ranking method, Table 4-12 shows the highly recommended, and top-ranked influencing factors and their relevant associated selected sensing technology. Figure 4-16 illustrates the architecture of the proposed customized data acquisition system.

Table 4-12: Top-ranked influencing factors and their relevant recommended sensors

Top Ranked Influencing Factors		Relevant Selected Sensors
Excavated Soil Properties		
Loadability	Indicator: Number of buckets	Pressure Atmospheric sensor
Soil Moisture Content		Moisture Content sensor
Bucket Fill Factor (BFF)		
Operators Skills	Indicator: Number of buckets	Pressure Atmospheric sensor
Soil Size Particles		
Change of Cut Depth		
Hauling and Access Road conditions		
Snowy Road	Indicator: Wheel slippage	OBDII Scanner
Congested Road	Indicator: Frequent Delays	GPS
Muddy Road	Indicator: Wheel slippage and Excessive torque	OBDII Scanner
Loosely Soil Road		
Rutting Road	Indicator: Frequent excessive vibration with distinct zones	3D Accelerometer
Road with Up / Down Hills		3D Accelerometer
Equipment and Operational Road Conditions		
Excessive loads		Load Cell
Bad Road Conditions		3D Accelerometer
Tire Pressure		OBDII Scanner
Weather Conditions		
Fog		Humidity sensor
Rain		Automated Weather Station
Wind (Speed and Direction)		
Daylight Duration		Luminosity sensor
Temperature		Temperature sensor
Humidity		Humidity sensor
Sunshine		Luminosity sensor

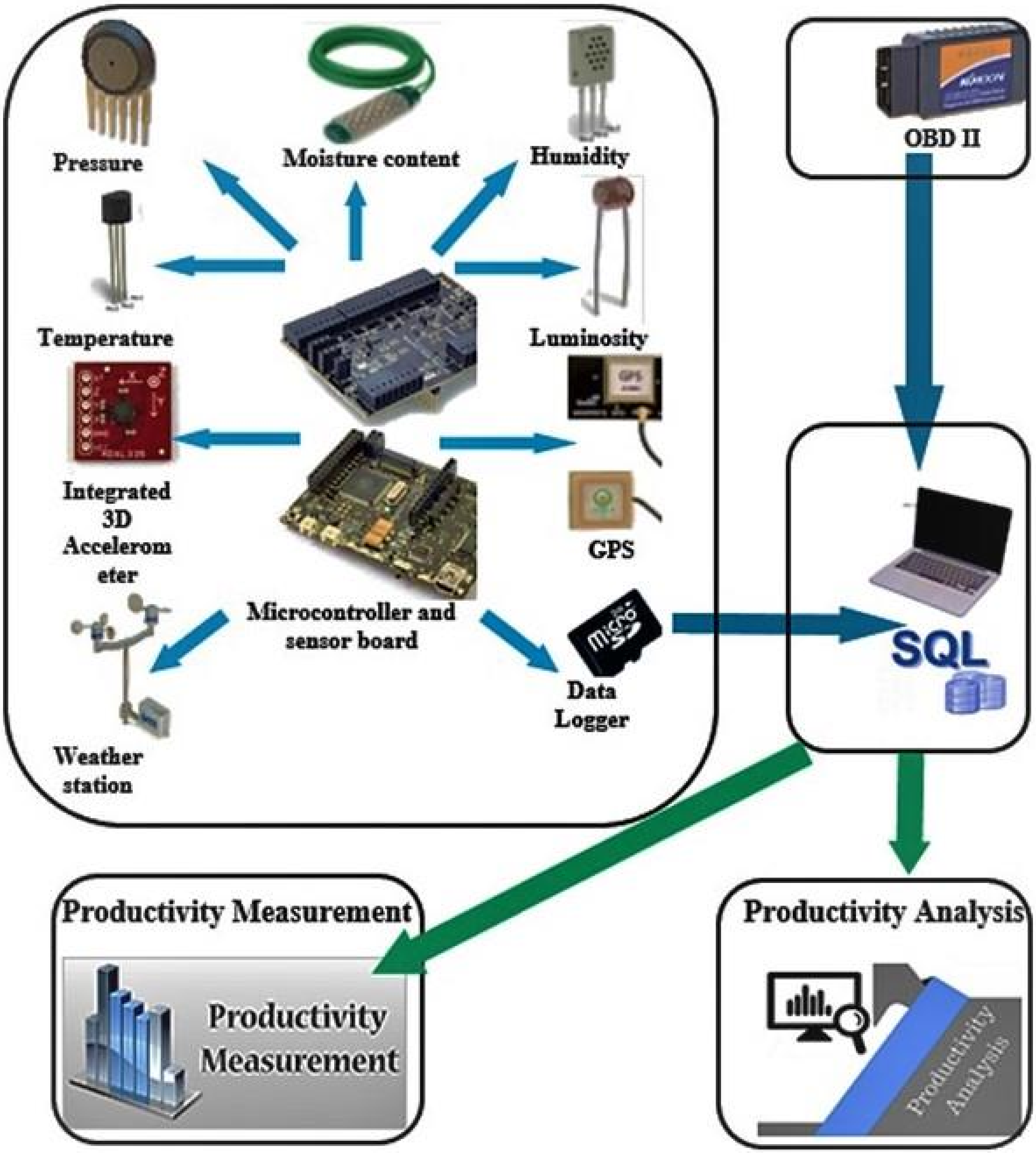


Figure 4-16: Architecture of the proposed customized data acquisition system

4.6 Summary

This chapter introduced a new method for customizing the configuration of on-site automated data acquisition systems for earthmoving operations. The method is efficient and less costly compared to other black box market available technologies. The data needed for the conducted study was collected using a questionnaire survey, after that, the questionnaire responses were analyzed using fuzzy set theory. This approach identifies, categorizes, evaluates and prioritizes vast scope of factors affecting productivity of earthmoving operations. The influencing factors were ranked based on scores calculated as the defuzzified values of fuzzy numbers representing those factors. The highly scored factors that belong to the same influencing category are selected to be measured using proper sensory tools to measure those factors. Then, the selected sensory tools are combined into one particular customized data acquisition system for automating the monitoring and tracking process in a manner that improves the performance of earthmoving operations.

In this chapter, the linguistic-numeric conversion was performed based on the answers of twenty-seven experts, and the results were reflected in the prioritization of influencing factors. The utilized linguistic-numeric conversion is updatable, where the opinions of more experts should are reflected. Hence, the combined fuzzy numbers, defuzzification output, and prioritization of influencing factors change. The developed method represents a proactive decision support assistive tool that helps owners and contractors to identify the most influencing factors. And, accordingly, allow them to cost-efficiently select the technologies that need to be included for customizing an automated data acquisition system that augments the productivity and elevates the utilization efficiency of equipment in earthmoving operations.

The developed methodology is flexible to be expanded and more factors that affect the productivity performance throughout the various cycles of earthmoving operations. Also, other factors that influence productivity can be investigated and included in a way that increases the effectiveness of the proposed method in tracking and monitoring productivity in either earthmoving projects or other applications in construction.

5 Chapter 5: Automated Productivity Measurement Model

5.1 General Overview

This chapter presents a comprehensive description of the developed model for automated productivity measurement, driving, and road conditions. The aim of the developed model is to overcome the previous research identified gaps and limitations through addressing the relating research objectives.

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 chapter 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. Detailed illustration of the developed model, different correlated modules, and applied algorithms are revealed in this chapter. Figure 5-1 depicts the main sections of this chapter.

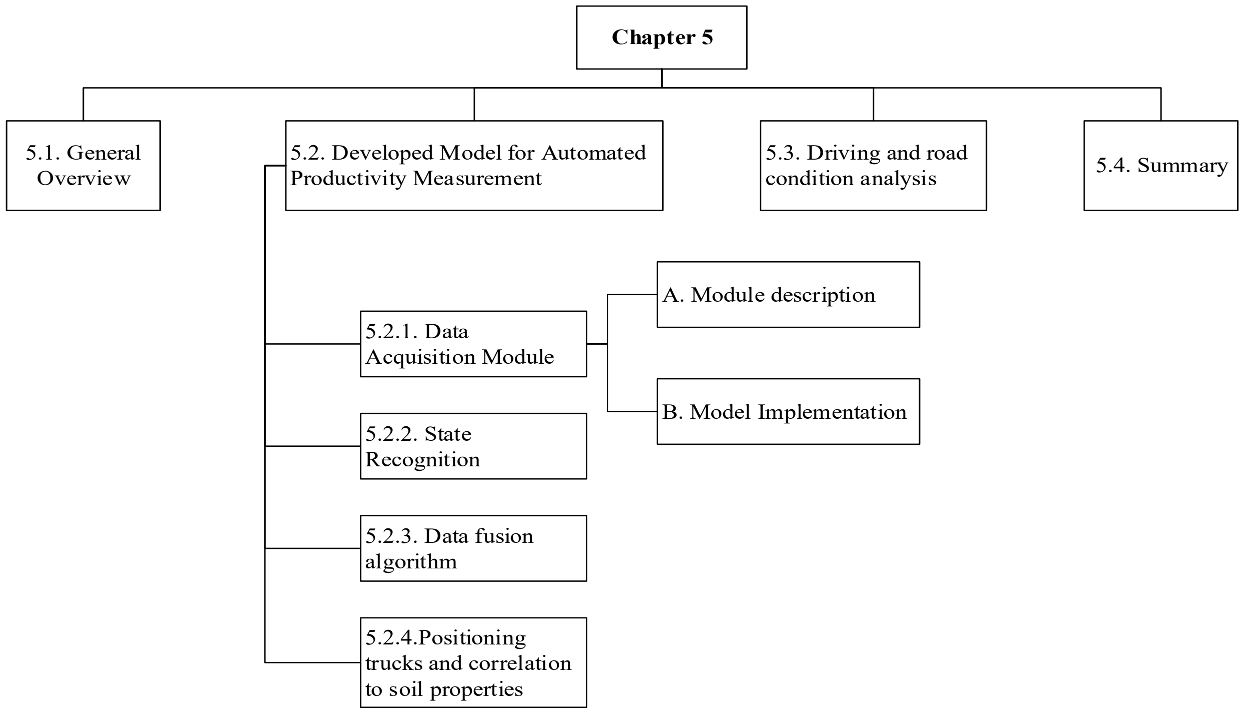


Figure 5-1: Main sections of chapter 5

5.2 Developed Model for Automated Productivity Measurement

The developed model introduces an automated model for tracking and monitoring productivity of earthmoving operations. The model automatically measures the productivity of hauling equipment (dump trucks) and hence the productivity of earthmoving fleet. The developed model has the following main roles:

(1) Collecting necessary data required for calculating actual productivity.

(2) Analyzing drivers' behavior of hauling equipment.

(3) Analyzing access and traveled road conditions.

Figure 4-1 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.

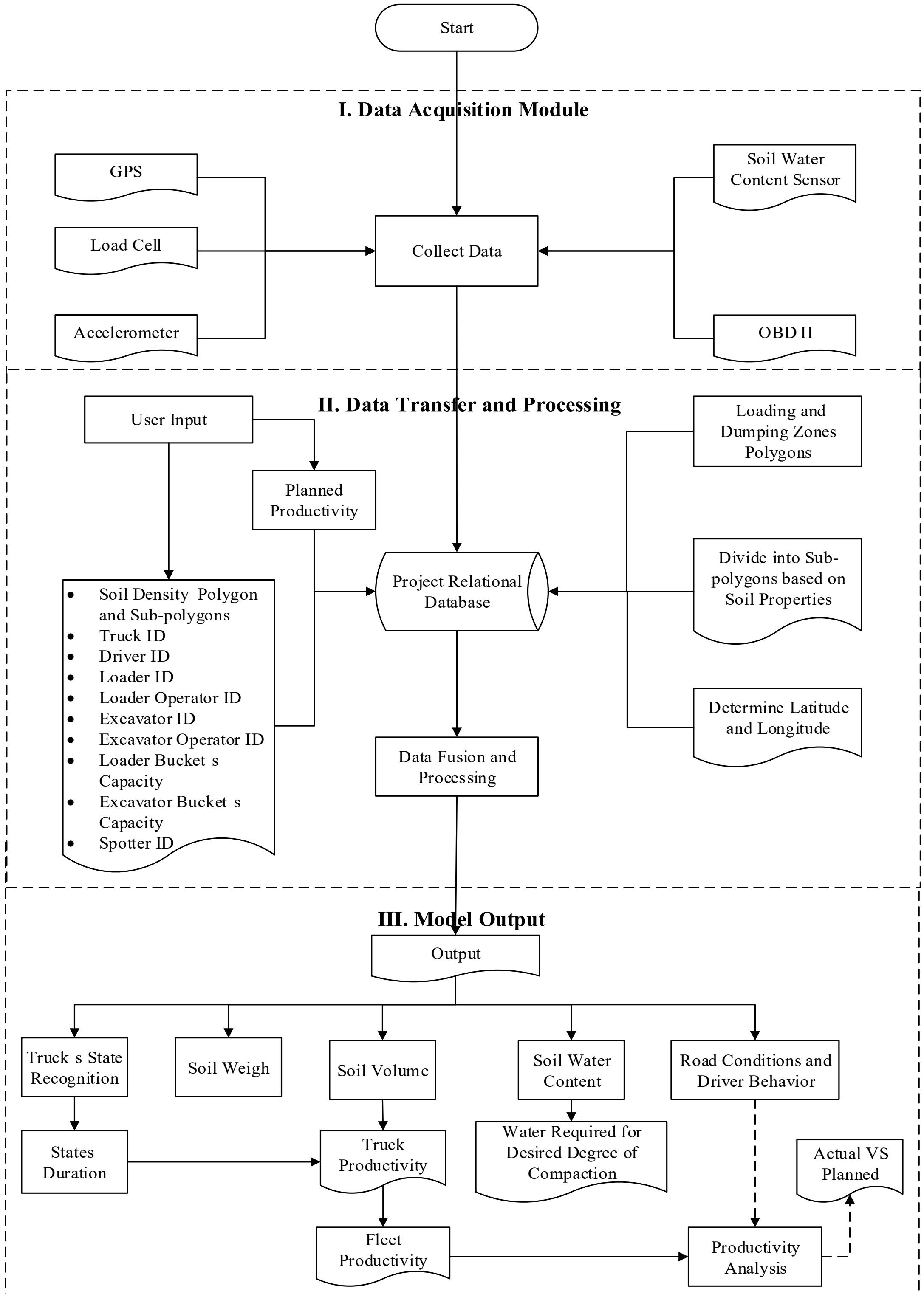


Figure 5-2: Developed model flowchart (Salem & Moselhi,2018)

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.

The model utilizes principally; two components as follow:

(1) Customized configured open source hardware (Waspmote®™) for multi-sensor data acquisition, where this module was developed using Arduino®™ open source platform.

(2) OBD (On-Board Diagnostic scanner).

The hardware designated for data acquisition consists of a smart sensing board associated with a microcontroller as shown in Figure 5-3. It is worthy to mention that the microcontroller and the smart board have a lightweight of 40 grams for both of them.

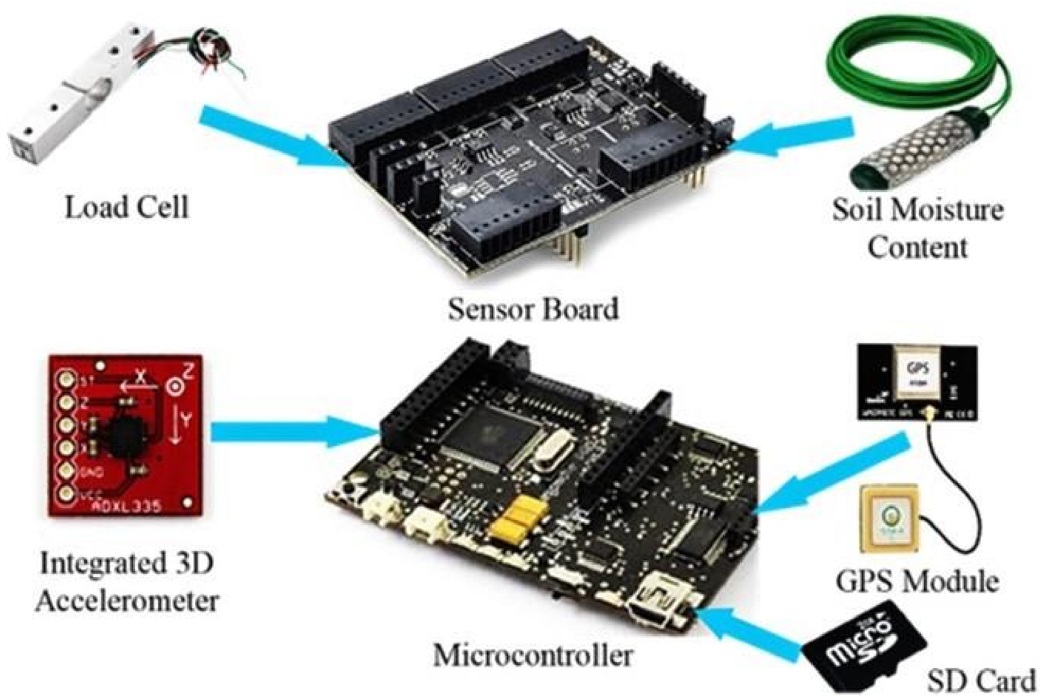


Figure 5-3: Components of the customized data acquisition module

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 was performed through questionnaire-base, where the experts' responses were analyzed to determine the most needed sensors in a ranked manner (Salem et al., 2017) as articulated in chapter 4. 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.

5.2.1 Data Acquisition Module

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 as follow:

```
{
    char* time; time=GPS.getTime( );
    // Get time given by GPS module
}
```

A soil moisture content sensor, and a load cell sensor are hosted by the smart board for collecting the percentage of water content that 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 can be laid to rest at any desired depth in the excavated soil, which was 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 (4-1) depicts the relationship between water tension and the sensor frequency reading according to the sensor's data sheet (Libelium website, 2018).

$$TA = \frac{150940+19.74\ \mathrm{F}}{2-8875\ \mathrm{F}-137.5} \qquad \text{Equation (4-1)}$$

The relation between these two parameters was determined for some soil types using the curves shown in Figure 5-4. Web-Plot- Digitizer® application was 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.

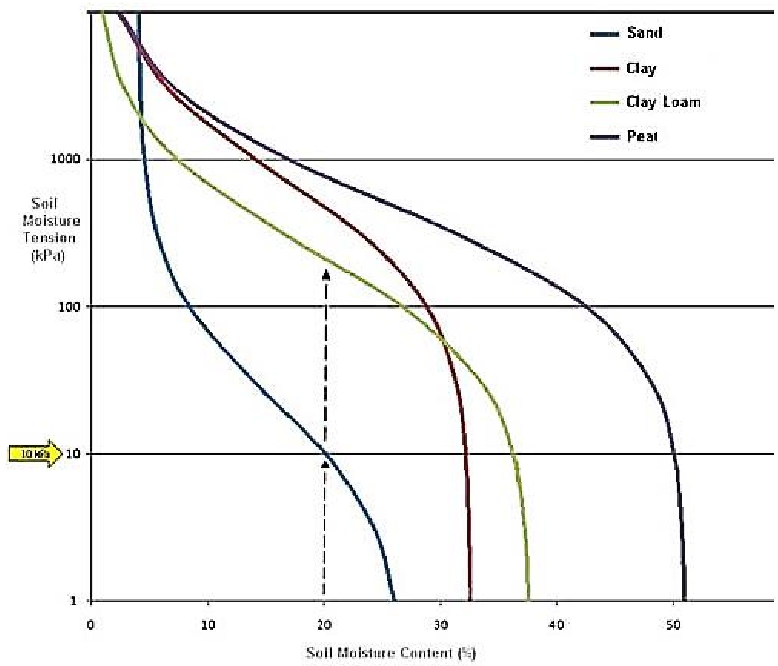


Figure 5-4: Typical relationship bet. soil water tension and soil water content (MEA, 2018)

The relationship was 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 the frequency, the higher the water content. This multi-step conversion process was coded thru series of queries in the developed MySQL database. Table 1 shows the developed equations (5-2), (5-3), and (5-4) 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.

Table 5-1: Best fit equations represent the relationship between (WC) % and TA

Soil Type	**TA 1:300 Kpa (Effective range)**		**R^2**
Sand	$(WC)\ \% = -\ 4.036 \ln TA + 28.342$	Equation (5-2)	0.9808
Clay	$(WC)\ \% = 3 \times 10^{-05}\ TA^2 - 0.0371\ TA + 32\text{-}298$	Equation (5-3)	0.9953
Clay Loam	$(WC)\ \% = 0.0002\ TA^2 - 0.1265\ TA + 37.741$	Equation (5-4)	0.9993

Figure 5-5, Figure 5-6 and Figure 5-7 represent these relationships for the three types of soil; sand, clay and clay loam respectively. Figure 5-8 shows the relationship between water tension in centibars (Kpa) and the frequency in Hertz according to the sensor's data sheet (Libelium website, 2018).

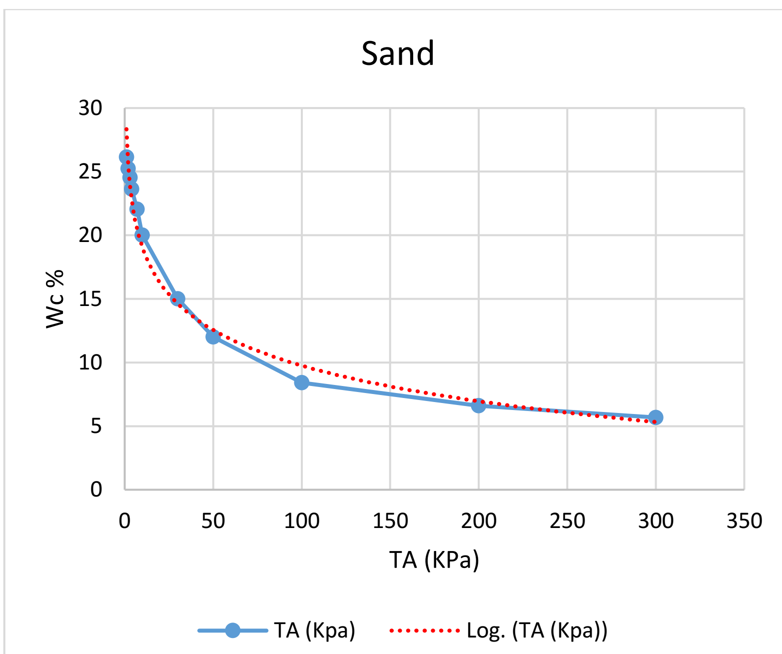


Figure 5-5: WC % - TA relationship for sand soil

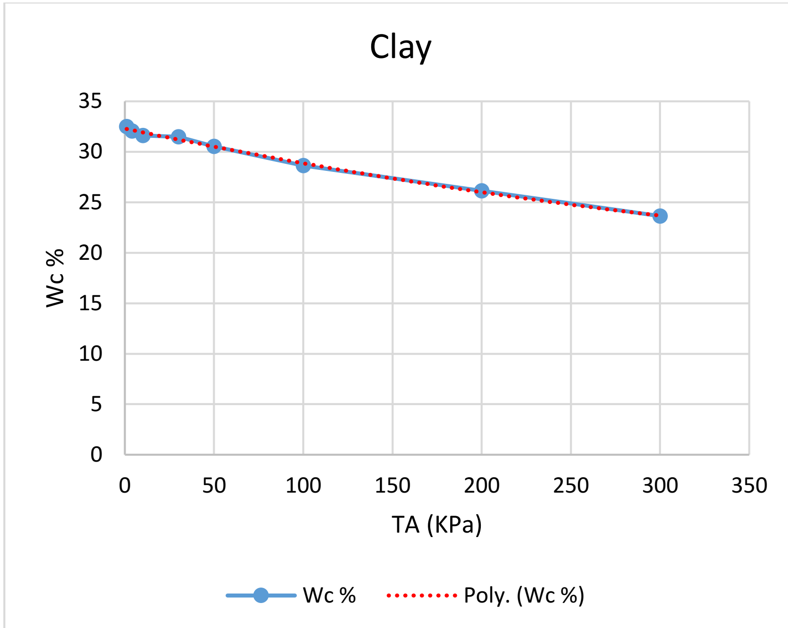


Figure 5-6: WC % - TA relationship for clay soil

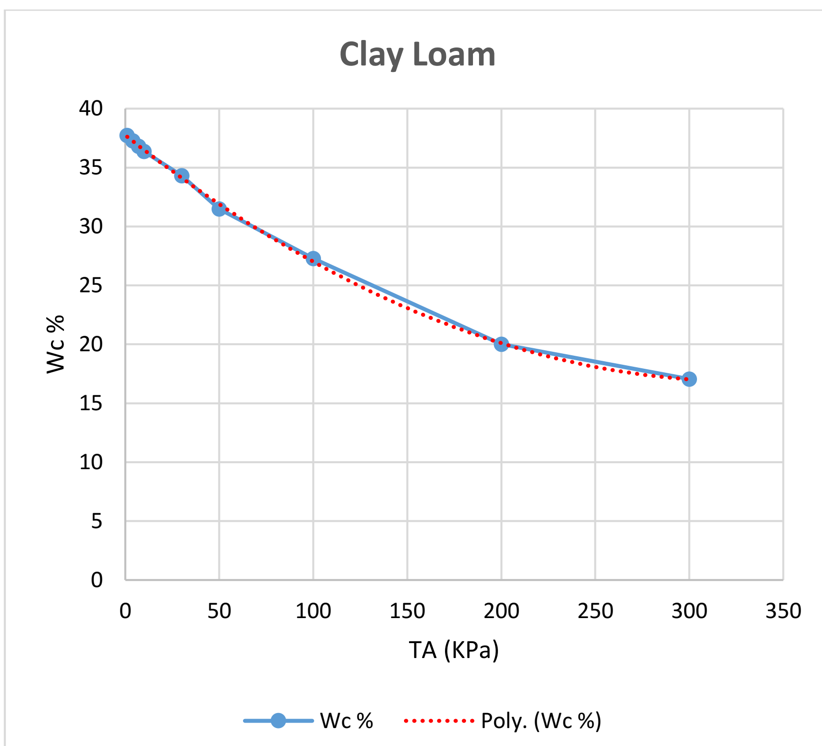


Figure 5-7: WC % - TA relationship for loam soil

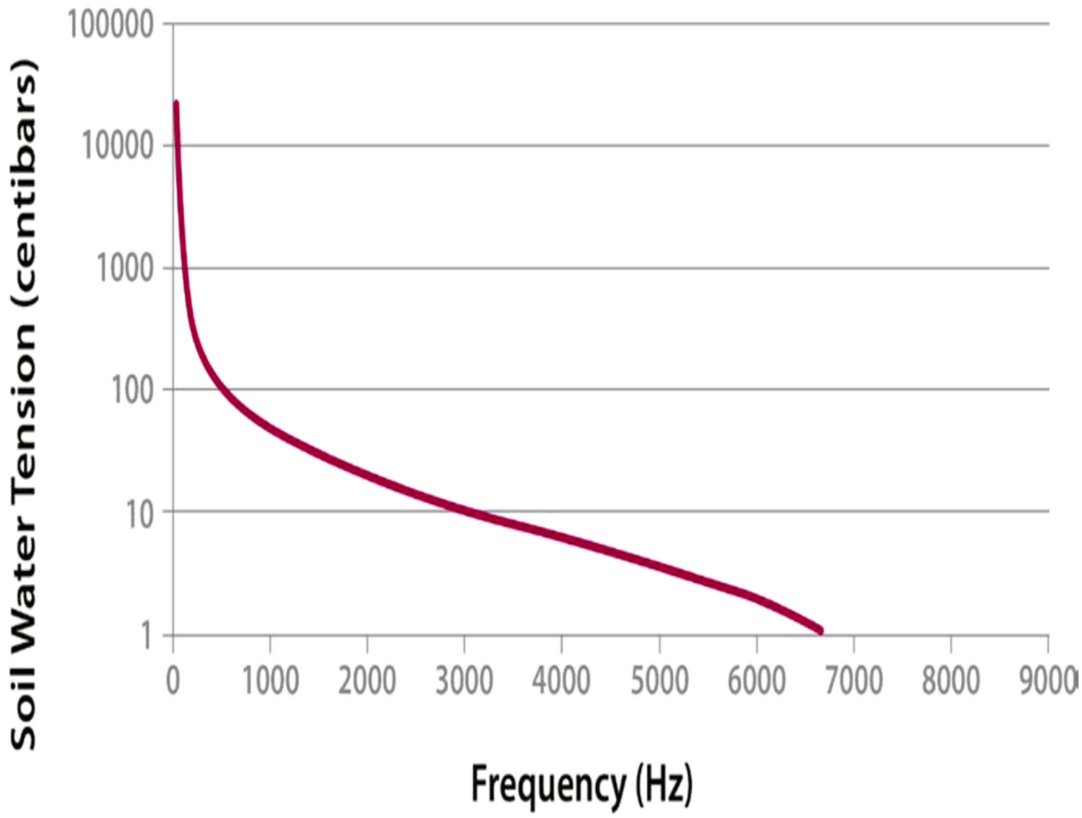


Figure 5-8: Relationship between water tension and frequency (Libelium®, 2018)

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 overloading, 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 (5-5) 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.

$$\mathrm{WC}_{Opt} = \mathrm{WC}_{Ext} + \mathrm{WC}_{Req} \qquad \text{Equation (5-5)}$$

The developed model works mainly on the hauling equipment (dump truck) in typical earthmoving operations. Figure 5-9 shows the different components of the developed model, where:

- 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.
- Part C: is a MySQL relational database, which forms the model's processing and reporting unit. Appendix IV shows the developed database structure plan, entity relationship diagram and the developed MySQL procedures' encoding for data processing.
- Part D: is the model's output.

Table 5-2 shows the data sets include different data components collected by the sensors associated with parts A and B.

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 are varied accordingly as shown in Table 5-3.

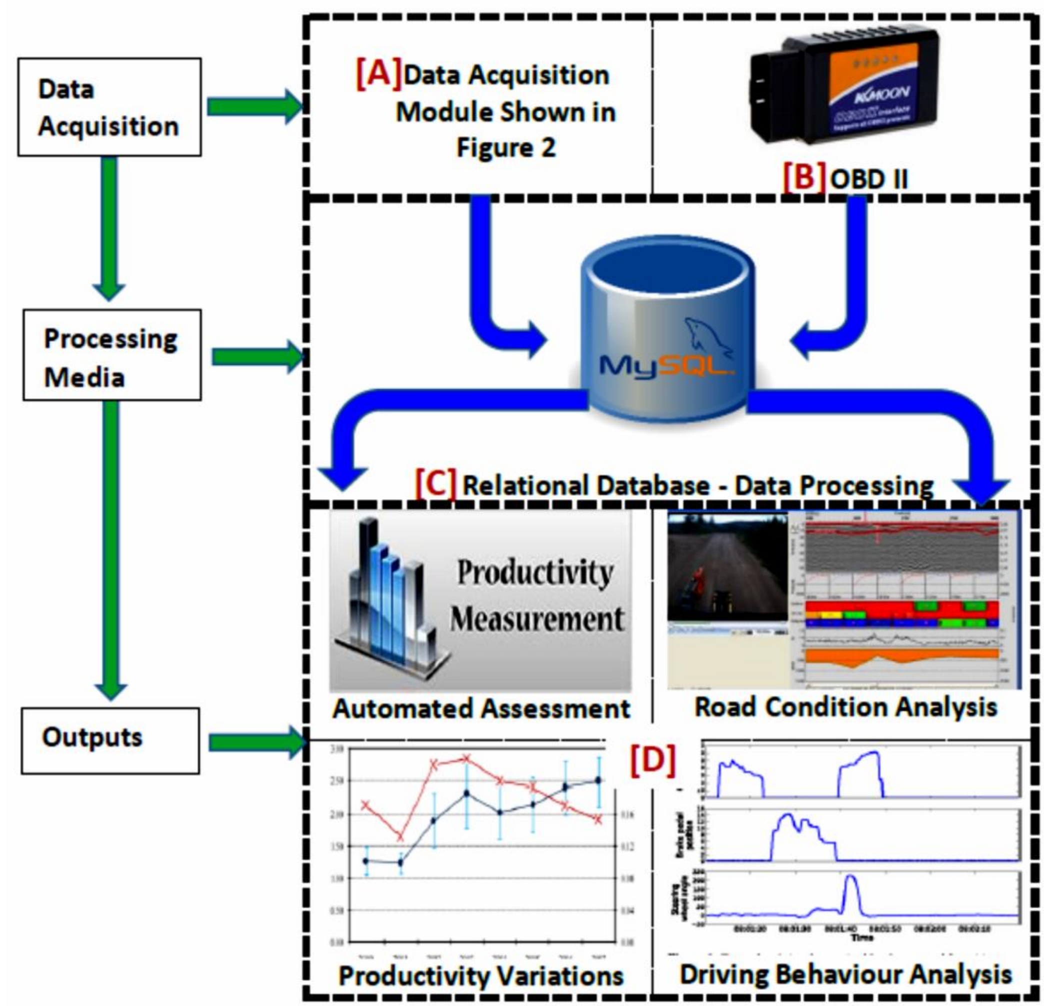


Figure 5-9: Components of the developed model (Salem & Moselhi,2018)

Table 5-2: Utilized sensor data and each dataset components

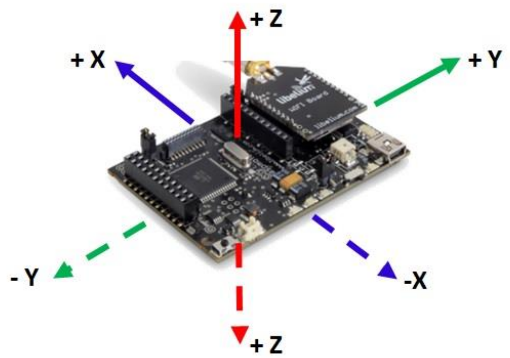
Sensor	Data Type
GPS	Timestamp, latitude, longitude, altitude, course, and speed
Accelerometer	Timestamp, acceleration in three direction X, Y, and Z (m / sec^2)
Load cell	Timestamp, Electrical potential in Microvolt (converted to weigh in Kg)
Water content sensor	Timestamp, frequency in Hz, which converted to water tension that converted to % of water content
OBD II	Timestamp, Speed, and engine rpm (revolution per minute)

Table 5-3: Data sampling rates for each of the utilized sensors

Sensor	Date record delay
GPS	3 Seconds (≈ record each 3 sec)
Accelerometer	0.01 Second (≈ 100 records / sec)
Load cell	10 Seconds
Water content sensor	10 Seconds
OBD II	0.2 Second (≈ 5 records / sec)

Model Implementation

The developed model was 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 5-10 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 in the protection of the data acquisition system in harsh environments.



3D Accelerometer Axis Orientation

Figure 5-10: Data acquisition modules implementation and orientation

Figure 7 Data acquisition modules implementation and orientation

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 5-11 shows a schematic architecture of the model's inputs and the interim CSV output files.

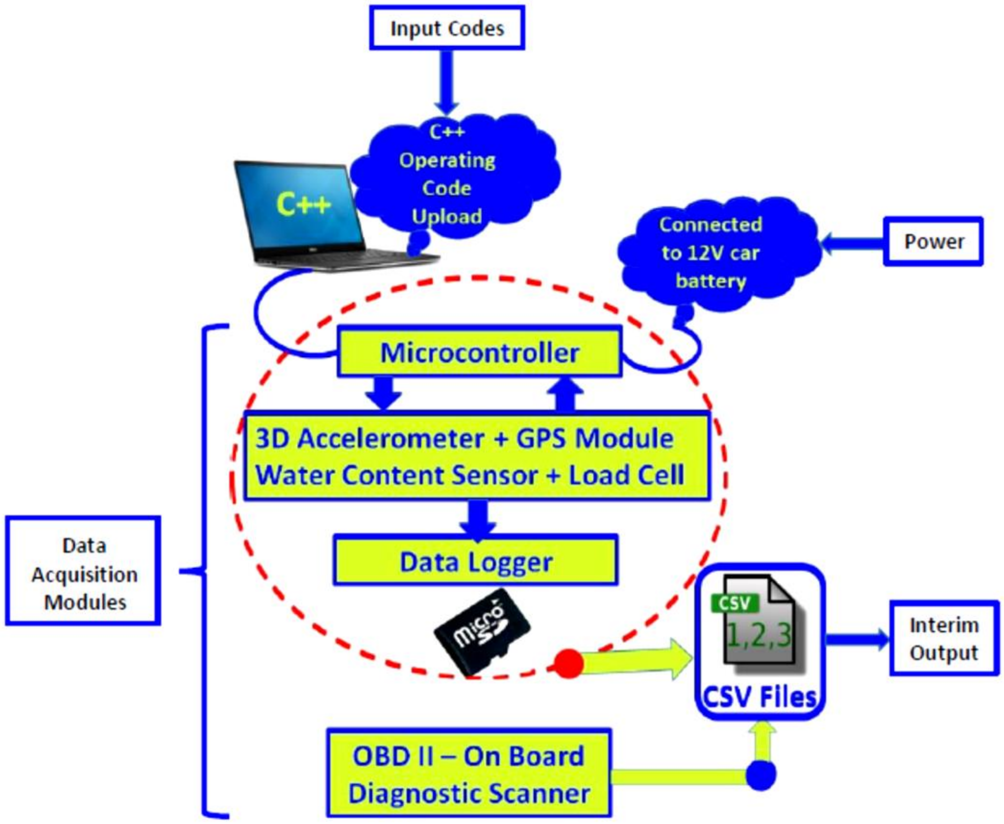


Figure 5-11: Schematic architecture of the model's inputs and interim CSV output files (Salem & Moselhi,2018)

5.2.2 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.

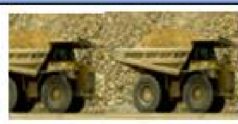
The vast sums of collected data make the manual observation of these patterns and trends a very challenging task that consumes time and lacks accuracy. The developed model overcomes this problem, where the developed relational MySQL database navigates through all collected sensor data regardless of its 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 was done to determine the prevalent ranges throughout each state. So, a number of experiments were 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 were 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.

5.2.3 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. Accordingly, determine the total duration of each earthmoving operations cycle. Figure 5-12 shows a tabulation of the prevalent sensor data patterns and trends, which are utilized to develop data fusion algorithm.

State's Duration	t_{QL0} Dur. = $t_{QL1} - t_{QL0}$ t_{QL1}			t_{L0} Dur. = $t_{L1} - t_{L0}$ t_{L1}			t_{H0} Dur. = $t_{H1} - t_{H0}$ t_{H1}		
State / **Technology**	 **Queue for loading**			 **Loading**			 **Hauling**		
GPS	Loading Zone						Not in Loading / Dumping Zones		
Accelerometer	X	Y	Z	X	Y	Z	X	Y	Z
	≈ 0[1]	≈ 0	≈ g	≈ 0	≈ 0	0.7g ≤ Z ≤ 1.2g	Fluctuated[2] Operational behavior and road conditions		
OBD II	0 ≤ Speed ≤ 10 Km/hr			Speed = 0 Km/hr			Speed > 0 Km/hr		
Load Cell	Mv[3] ≈ 0			Mv. Gradual ↑ +++ ve 0 ≤ Mv ≤ EPC[4]			Mv ≈ EPC		
State's Duration	t_{QD0} Dur. = $t_{QD1} - t_{QD0}$ t_{QD1}			t_{D0} Dur. = $t_{R1} - t_{R0}$ t_{D1}			t_{R0} Dur. = $t_{R1} - t_{R0}$ t_{R1}		
State / **Technology**	 **Queue for dumping**			 **Dumping**			 **Returning**		
GPS	Dumping Zone						Not in Loading / Dumping Zones		
Accelerometer	X	Y	Z	X	Y	Z	X	Y	Z
	≈ 0	≈ 0	≈ g	+++ve ↑	≈ 0	↓ - - - ve	Fluctuated Operational behavior and road conditions		
OBD II	0 ≤ Speed ≤ 10 Km/hr			Speed ≈ 0			Speed > 0		
Load Cell	Mv ≈ EPC			Mv. Gradual ↓ - - - ve EPC ≤ Mv ≤ 0			Mv≈0		

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 5-12: Prevalent sensor data patterns and trends utilized to develop the data fusion algorithm

5.2.4 Positioning Trucks and Correlation to Soil Properties

The database is programmed to run the algorithm shown in equation (5-6). Figure 5-13 shows graphical illustration the utilized algorithm. The aim of using this algorithm is 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.

$$Y0 = \frac{Yi+1-Yi}{Xi+1-Yi}\,(X0 - Xi) + Yi \qquad \text{Equation (5-6)}$$

Where: $X_i \leq X_0 \leq X_{i+1}$

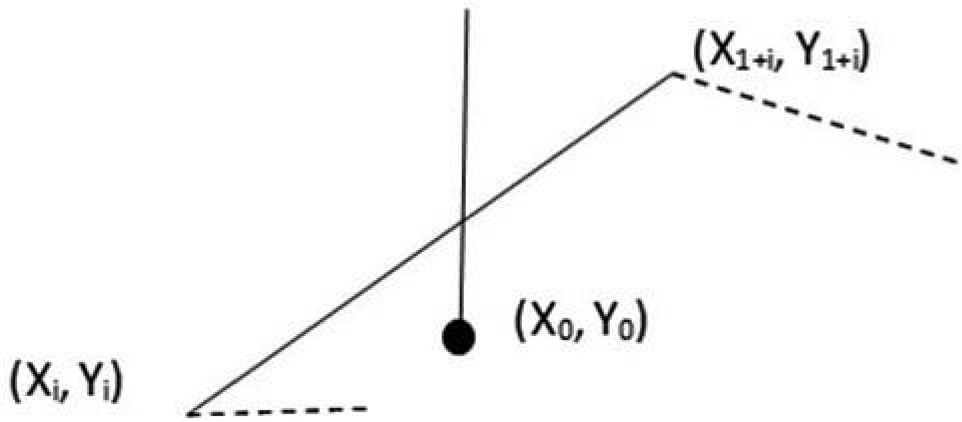


Figure 5-13: Graphical illustration of the utilized algorithm (in / out polygon recognition)

The polygons shaped by the coordinates of the different point 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 5-14 shows the change of soil properties within the same loading zone. 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.

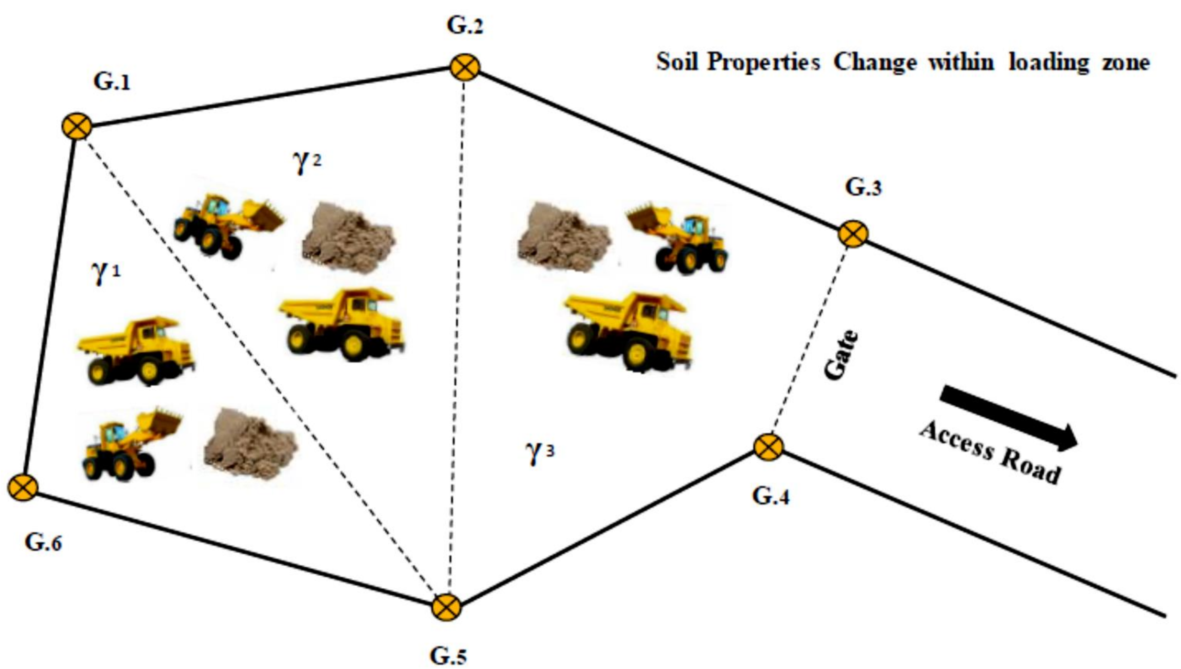


Figure 5-14: Change of soil properties within the same loading zone

The readings of the load cell are interpreted from the electrical potential in microvolt to weights in kilogram 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 the load cell and the specific soil density associated with exact area of the loading zone.

Figure 5-15 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.

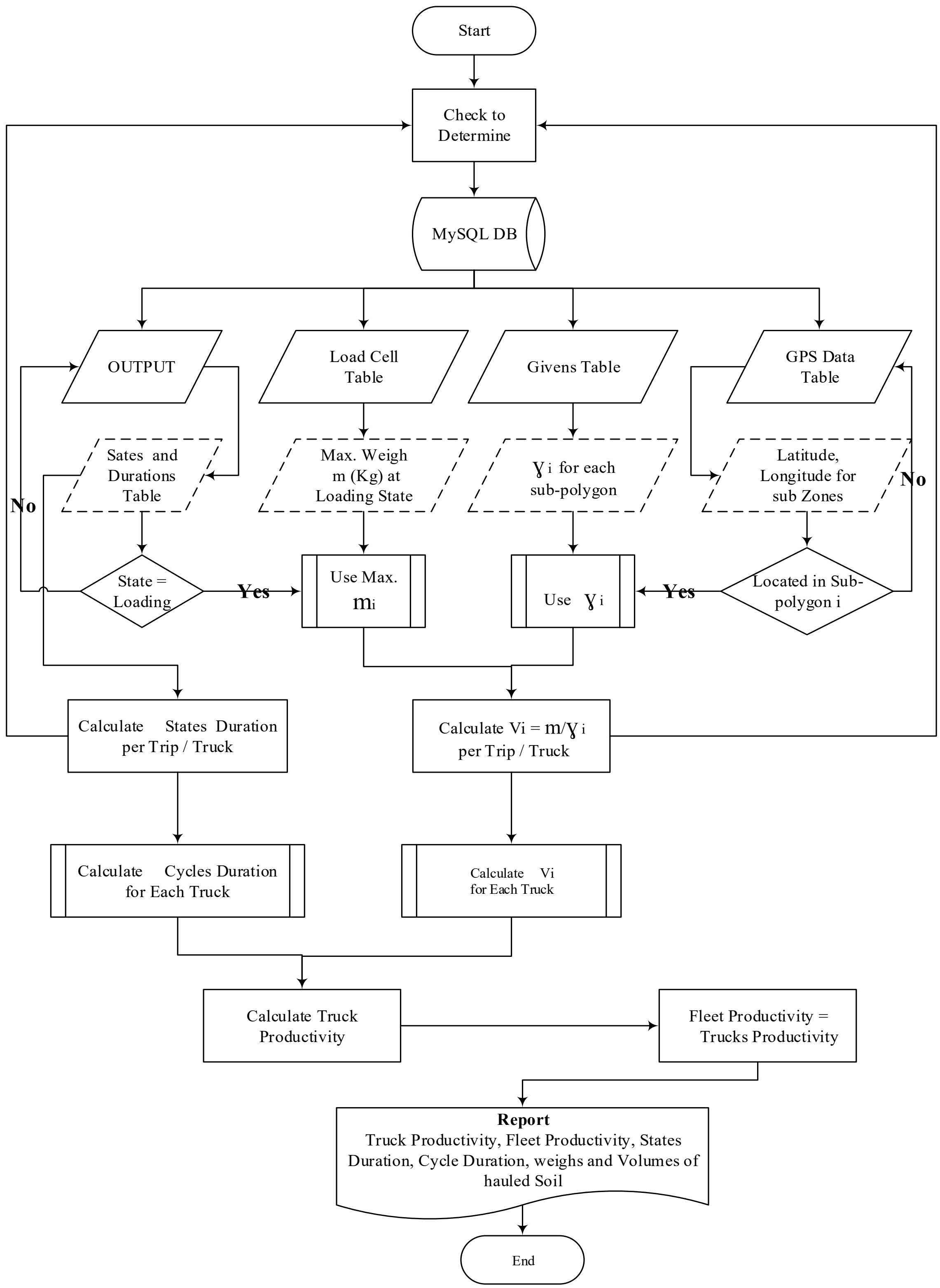


Figure 5-15: Flowchart of the productivity measurement algorithm (Salem & Moselhi,2018)

5.3 Driving and Road Condition Analysis

Operational behavior of truck drivers and traveled road conditions affects 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). Figure 5-16 represents an example from literature that depicts how the negligence of such adversarial access road conditions can lead to a catastrophic productivity degradation. The evaluation index that been used in this simulated case example is productivity differential, which introduced by American Society for Testing and Materials (ASTM E2691 - 09). Where equation (5-7) explains the method of determination of productivity differential.

$$\text{Productivity Differential} = \frac{\text{Current Productivity} - \text{Av.Productivity}}{\text{Av.Productivity}} \qquad \text{Equation (5-7)}$$

The graph shows how the percentage of productivity differential was descended starting from the 10th day, where the bad road condition initiated to show up.

However, figure 5-17 shows how the situation can be changed if the right information reaches the project manager or the responsible decision maker at the right time. The figure shows that corrective action was taken on the 17th day to improve the access road surface, and hence to correct the productivity path.

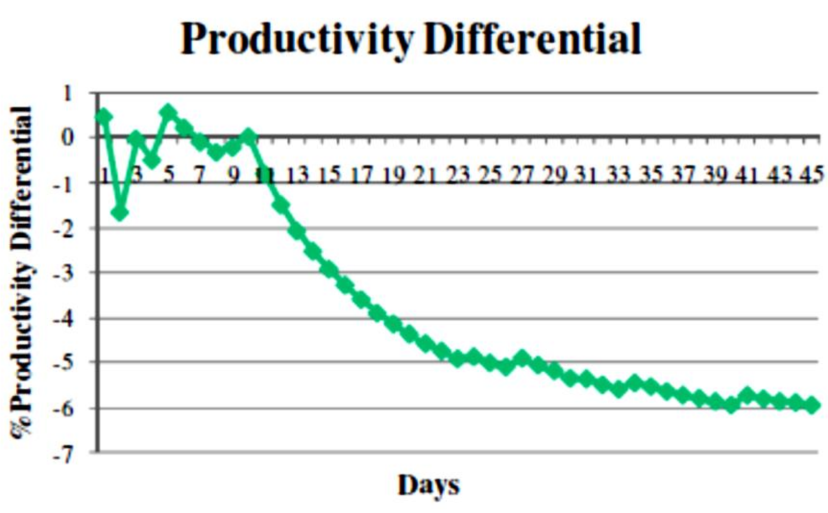


Figure 5-16: Productivity degradation due to bad access road surface (Shahandashti et al. 2010)

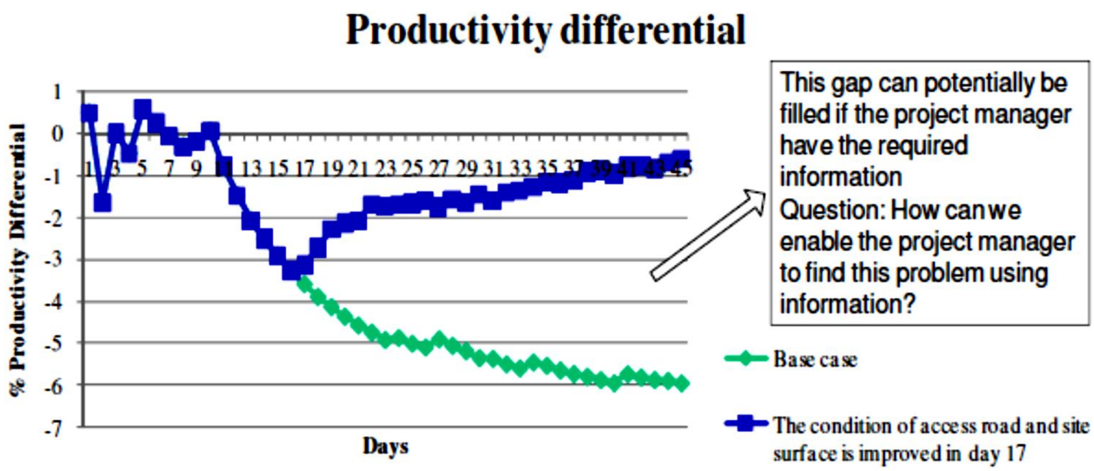


Figure 5-17: Potential ability of project manager if he/she received the right information at the right time. (Shahandashti et al. 2010)

The previous example shows the importance of monitoring the road conditions and acquiring its data. In addition, it shows how early recognition of road conditions problems could help the management to keep the right planned path of productivity. Figure 5-18 shows the flowchart of driving road conditions analysis algorithm. The algorithm profits in detection of adverse road conditions and operational behavior recognition using a tri-axial accelerometer. The proposed accelerometer is build-in the utilized Waspmote microcontroller.

The 3D accelerometer is used for recognizing undesirable driver behavior of hauling equipment. The Waspmote 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 5-18 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.

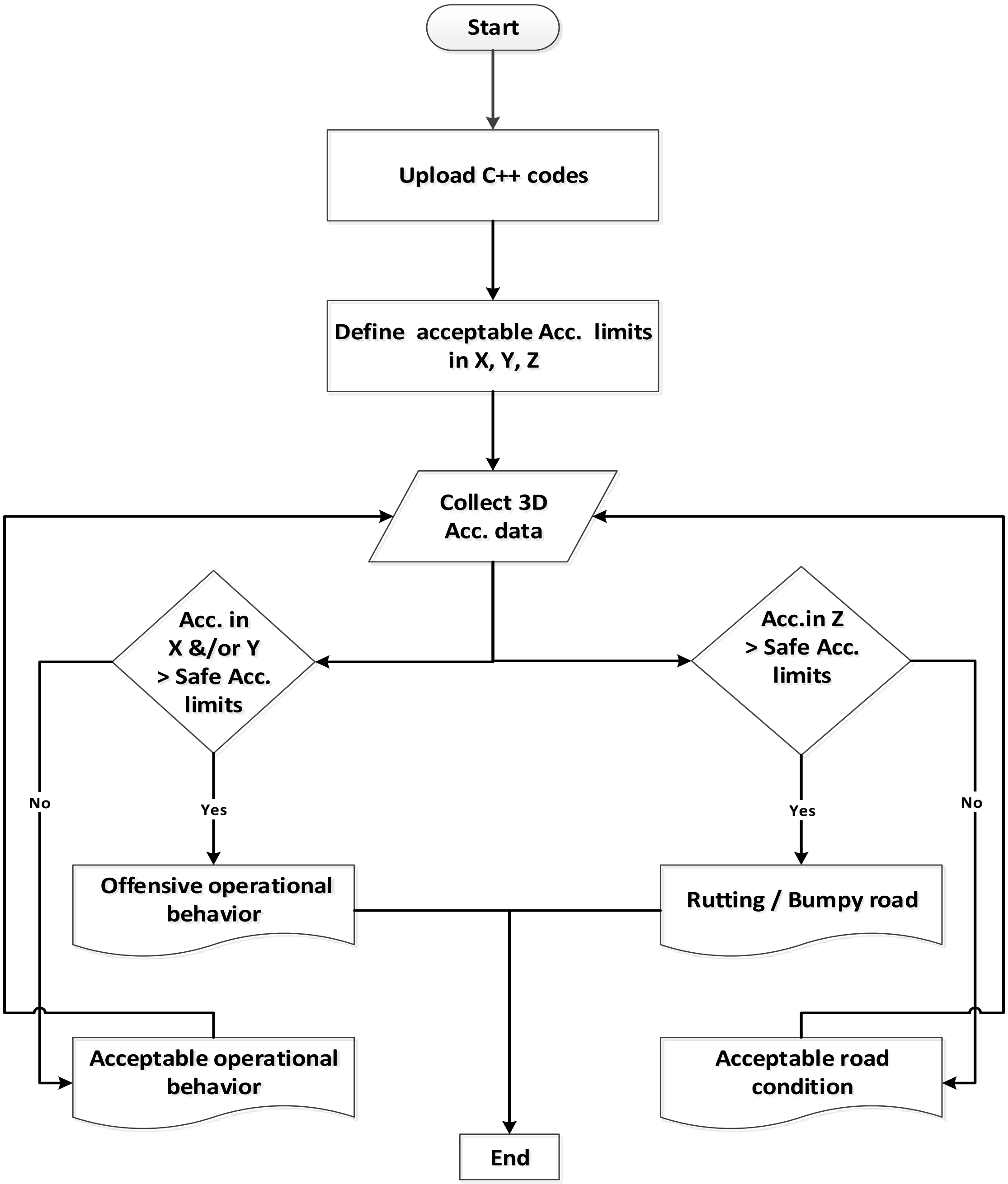


Figure 5-18: Flowchart of driving and road condition analysis algorithm

Figure 5-19 shows a sample of the 3D accelerometer data representation and driving and detection of abnormal road conditions. 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).

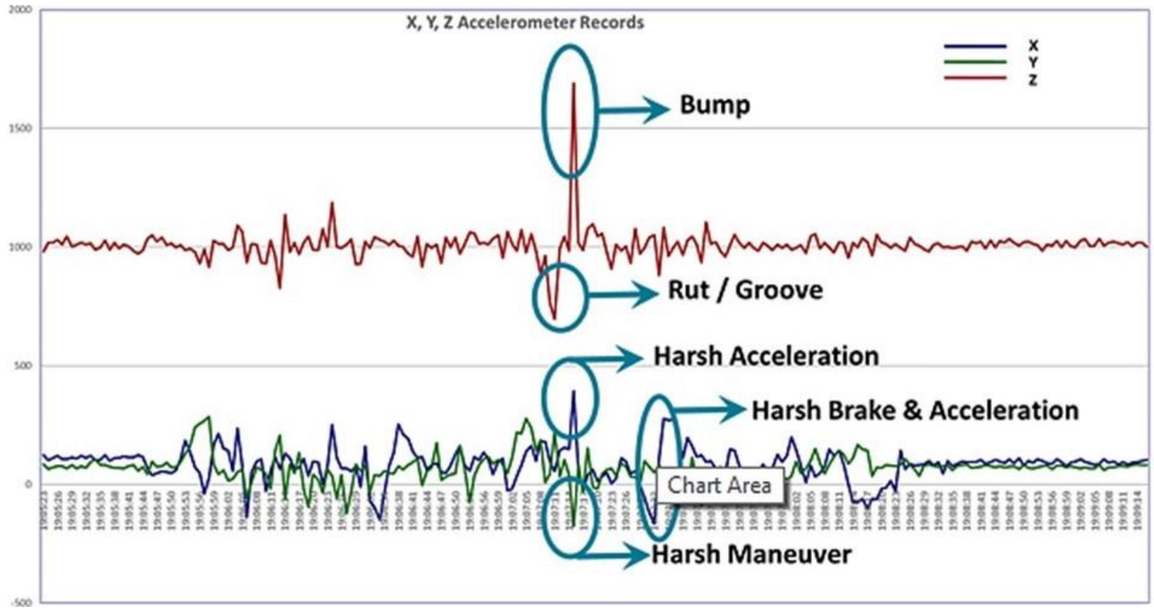


Figure 5-19: 3D accelerometer data representation, driving and road conditions recognition

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 the collected data in the microcontroller, which means in-sensing-node processing. Thereafter processing outcome can be send the right stakeholder by integrating a 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. Also, it allows exact momentous and rapid retrieval of analysis results.

The shortcoming of this algorithm that it does not take into consideration the risk of sensors malfunction. Another algorithm that uses data fusion and artificial intelligence techniques is conceptually explained as shown in Figure 5-20. The same expected results can be achieved in a sophisticated and robust approach using this algorithm, where it allows more redundancy, and it takes the uncertainty of sensors malfunction in consideration. The data from different sensors is fused. For automating this approach, different modes and patterns are recognized using a machine learning classifier. The proposed classifier utilized in this algorithm is Naive Bayesian.

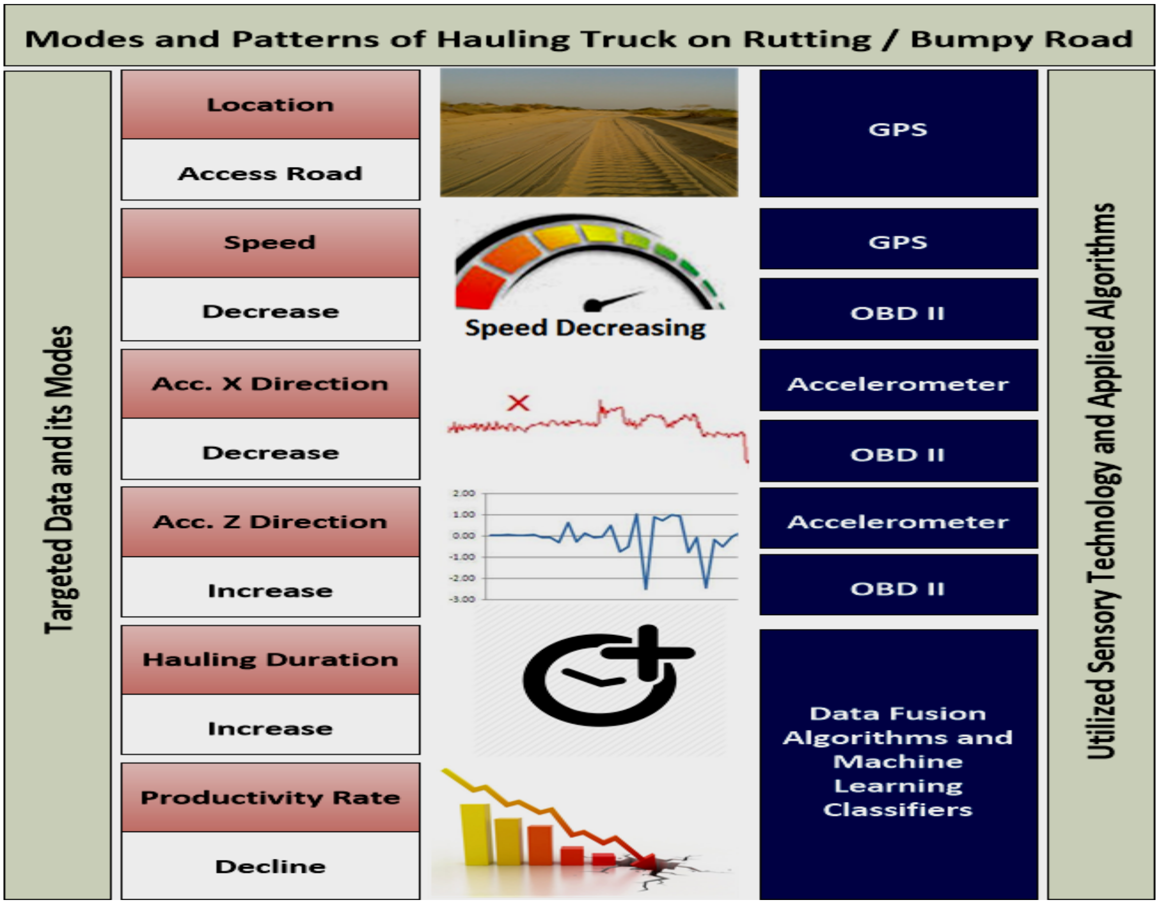


Figure 5-20: Data fusion and machine learning for modes of hauling truck

5.4 Summary

This chapter 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, hence truck, and fleet productivity. The driving and road conditions 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.

6 Chapter 6: Earthmoving Productivity Analysis

6.1 General Overview

This chapter presents a productivity analysis model that comprises two modules for assessing and analyzing the productivity of earthmoving operation. This model applies two different techniques on the acquired outputs from the developed automated productivity measurement model demonstrated in chapter 5. The developed two modules organize the assessment and analysis process in the form of two tiers.

The first tier module utilizes fuzzy sets theory to assess the variation between actual and planned productivity. The second tier module exploits the accessibility to vast scope of automatically collected sensor data to introduce a more in-depth analysis using artificial neural network (ANN). It is worthy to remark that the combined two tiers analysis modules provide early warning and decision support tool that allows contractors to early recognize the grounds behind the variations in productivity. Furthermore, it supports the decision making for appropriate and timely corrective actions. Figure 6-1 shows the main sections of this chapter.

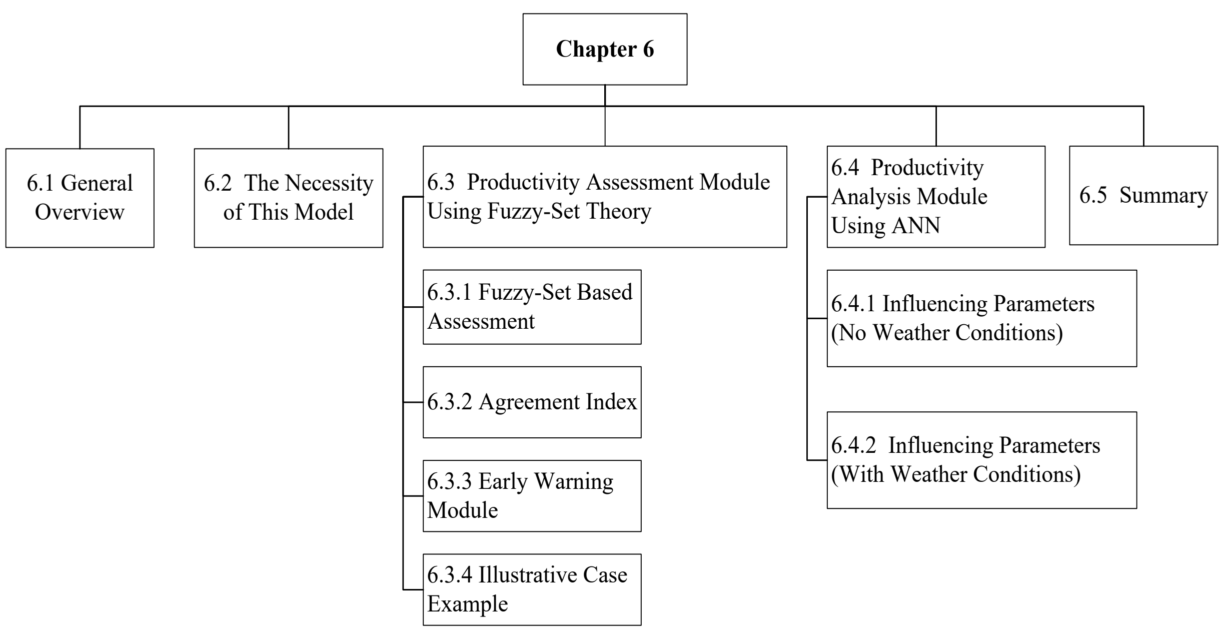


Figure 6-1: Main sections of chapter 6

6.2 The Necessity for this Model

According to most dictionaries, the linguistic definition defers between assessment and analysis where:

- **Assessment:** *((Examining system's outputs and performance))* (Oxford Dictionary, 2018)

- **Analysis:** *((Detailed examination of the elements of something))* (Oxford Dictionary, 2018)

Upon the understanding of this difference between assessment and analysis, it is easy to conclude that most research work in the domain of productivity of earthmoving operations has focused on assessment than analysis. However, the assessment has crucial importance; it does not individually satisfy all the productivity control needs. Assessment often indicates the presence of problems that have affected productivity. It may evaluate unidentified problems and its consequences, while it does not identify those problems and their causes. The project benefits from having a robust analysis tool in all stages, i.e., planning, execution, and operation as well. Analyzing productivity and project performance guarantee:

- Robustness and realistic operations design and planning.
- Early detection of weak points and bottlenecks of the system.
- Capability to take the necessary corrective actions timely and in a prioritized manner.

Based on the aforementioned facts, there is a need for such a model that combines both assessment and analysis. The following sections depict the developed model that performs productivity assessment and analysis of earthmoving operations. This model consists of two modules, one for assessment and the other goes deeper to model and analyze the productivity.

6.3 Productivity Assessment Module

Productivity assessment module utilizes the measured actual productivity obtained from the automated productivity measurement model depicts in chapter 5 of this thesis. In addition, it utilizes the planned earthmoving quantities and production rates. This planned data can be provided to the module manually, or it can be extracted from a 3D model using software like Autodesk Revit®. In case of inclusion of the schedule, the planned data can be delivered through the extraction from a 4D model using BIM 360 Field API. The assessment is performed at each period of time (t), the actual productivity (AP). Then, productivity ratio (PR) is calculated as the ratio between actual and planned productivities for the same period (t) using Equation (6-1).

$$PR(t) = \frac{AP\ (t)}{PP\ (t)} \qquad \text{Equation (6-1)}$$

Where;

PR (t), AP (t) and PP (t), represent respectively productivity ratio, actual productivity, and planned productivity at time (t).

6.3.1 Fuzzy Set-Based Assessment

In general, it is well known that the ideal productivity ratio is equal to one, where that means; the achieved production equals to the planned one. However, this is the usual planned situation, and the project management always desires to achieve it, but due to some conditions and risks the management usually accepts a lower productivity ratio, i.e., PR (t) < 1. In this case and upon the evaluation of these conditions and risks, the project management usually utilizes a new custom-made productivity ratio instead of the unachieved planned one. In another word, due to the project-associated risks, management may predefine an optimal accepted productivity ratio. This ratio might not be a specified determined number, but it could be a range based on each project associated uncertainty and conditions.

The developed assessment module presents a low-optimum-high (LOH) fuzzy set-based productivity-monitoring algorithm. The productivity is evaluated based on these three states; low, optimum, and high. Each of these states has higher and lower limits, where those limits are project management or organization dependent (Salah and Moselhi, 2016). Therefore, each contractor has to estimate lower and upper bounds of each fuzzy attribute (e.g., High) based on his experience in similar previous earthmoving operations projects.

Figure 6-2 illustrates the LOH fuzzy- set based productivity monitoring and assessment scheme. The productivity ratio (PR) values are represented on the x-axis of LOH fuzzy system while the fuzzy membership function (μ) is represented by y-axis. As reported, the ideal value of PR equals to one, whereas actual productivity ratio at period (t), PR (t), is acquired from the productivity measurement module and the manual input of the planned quantities. The productivity ratio indicator is shown on the proposed assessment scheme as a vertical indicator for the ideal state.

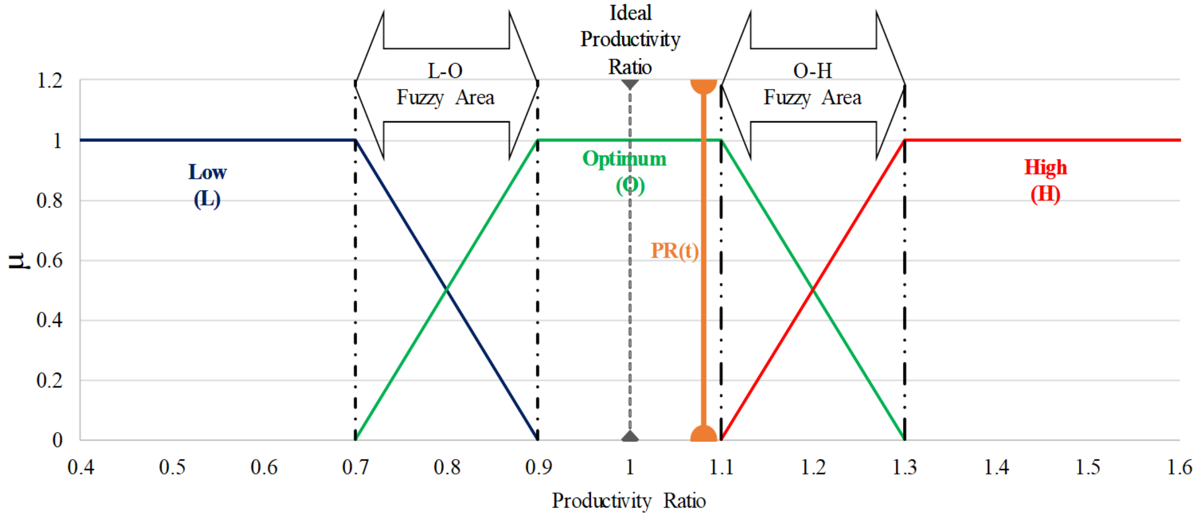


Figure 6-2: LOH fuzzy- set based assessment scheme

It should be noted that the productivity ratio monitoring indicator position directs the management to the required responding action, where no action is required as long as the indicator of productivity ratio is located within the optimum acceptable predefined range (e.g., between 0.85 and 1.15) as shown in Figure 6-2. However, if the indicator, at a particular period t, moves away from the optimum zone (i.e., Low or High), that means further advanced analysis is required. In other words, when there is a chance for occurrence of unwanted events that influence the productivity the advanced analysis module is commenced to identify and evaluate the consequences of the undesired event being considered. Then issuing an early warning that supports the decision making process in earthmoving operation in order to take the suitable corrective action to revert actual productivity to its desired planned path.

Figure 6-2 shows two fuzziness zones, where L~O and O~H fuzzy zones are shown. If the indicator is located in one of these two zones and intersects both membership functions, then the scheme represents the situations where the productivity performance cannot be evaluated without additional analysis. In this case, the fuzzy-set based productivity analysis module is initiated to differentiate between low – optimum and optimum - high states.

6.3.2 Agreement Index for Productivity Ratio Assessment

Kaufmann and Gupta (1985) have introduced the agreement index. The agreement index computes the ratio of the overlapped area between two fuzzy events and the entire area of the measured event. Arithmetically, different methods could be used in the calculation of the intersection area and thus the agreement index.

Agreement Index Calculation Using Partial Integration

Figure 6-3 shows an illustrative scheme for Agreement Index (AI) calculation using partial integration. First by identifying integration limits, in another word, the projection of the corner points on the productivity ratio axis. Then, formulating the equations of membership function for the boundary lines i.e., μ_A and μ_B for the intersection area as shown in Figure 6-3. Either developing an algorithmic procedure or using a graphical method to perform this task is valid. Then, the intersection area between the two fuzzy areas can be calculated using the partial integration, taking into account the membership functions of the boundary lines and their corresponding limits using Equation (6-2).

$$\text{AI} = \int_{X_4}^{X_5} \frac{1}{X_7 - X_4}\,(X_i - X_4)\,dx + \int_{X_5}^{X_8} -\frac{1}{X_6 - X_3}\,(X_i - X_6)\,dx \qquad \text{Equation } (6-2)$$

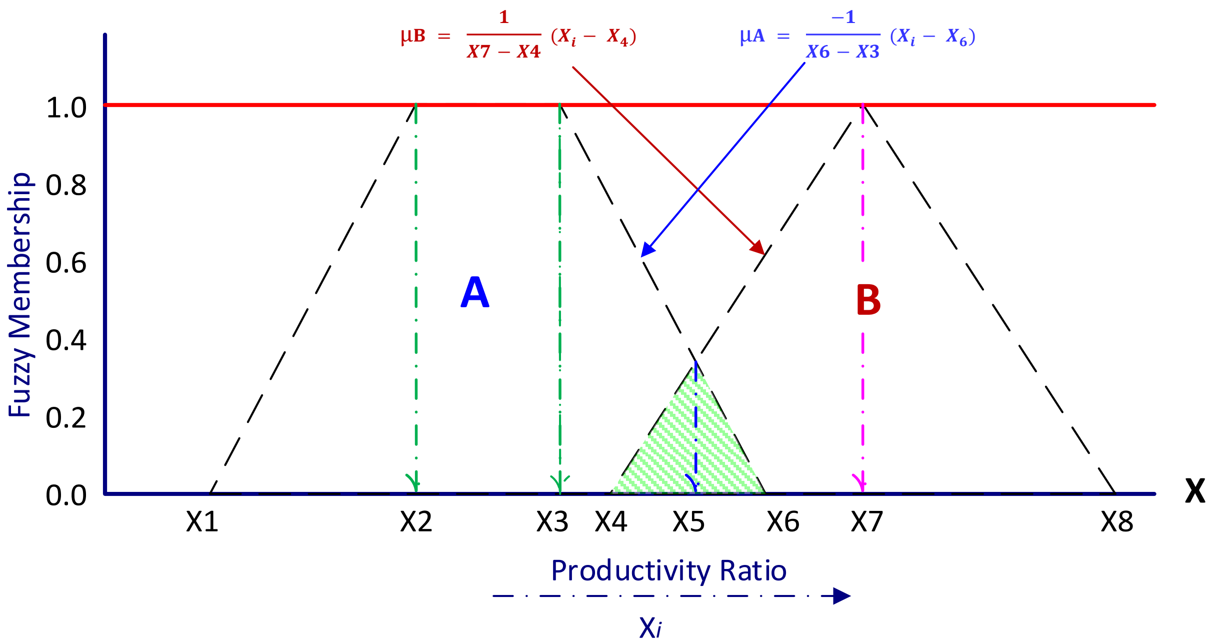


Figure 6-3: Illustrative scheme for Agreement Index (AI) calculation using partial integration

Agreement Index Calculation Using Algebra

Assuming that $\widetilde{A}$ represents one of the low or high states, and $\widetilde{B}$ represents the optimum state. The productivity analysis module generates the fuzzy membership function that represents the L~O and O~H fuzzy area based on low, optimum and high fuzzy numbers using Equation (6 -3). The relative weights of fuzzy numbers of $\widetilde{A}$ and $\widetilde{B}$ are measured respectively as membership of $\widetilde{A}$ and $\widetilde{B}$ at actual productivity ratio using Equation (6 – 4). It also utilizes the agreement index.

$$\widetilde{A} \sim \widetilde{B} = w_{\widetilde{A}} \times \widetilde{A} + w_{\widetilde{B}} \times \widetilde{B} \qquad \text{Equation } (6-3)$$

$$w_{\widetilde{A}} = \mu_{\widetilde{A}}(PR(t)) \qquad \text{Equation } (6-4)$$

Where;

$\widetilde{A}$ and $\widetilde{B}$, represent respectively two fuzzy numbers A and B.

$w_{\widetilde{A}}$ and $w_{\widetilde{B}}$, represent respectively two weights of fuzzy numbers A and B.

$\widetilde{A} \sim \widetilde{B}$, represents the fuzzy number that represents the fuzzy area between A and B, also noted as $\widetilde{A\sim B}$.

The agreement index represents the ratio of the intersected area between the fuzzy membership functions that represent the fuzzy area (i.e., L~O) and each of the two states (i.e., L and O) using Equation (6 - 5) and Equation (6 - 6).

$$\mathrm{AI}\,(\widetilde{A} \sim \widetilde{B}, \widetilde{B}) = \frac{\mathrm{Area}\,(\widetilde{A} \sim \widetilde{B} \cap \widetilde{B})}{\mathrm{Area}\,(\widetilde{A} \sim \widetilde{B})} \qquad \text{Equation (6 - 5)}$$

$$\mathrm{AI}\,(\widetilde{A} \sim \widetilde{B}, \widetilde{A}) = \frac{\mathrm{Area}\,(\widetilde{A} \sim \widetilde{B} \cap \widetilde{A})}{\mathrm{Area}\,(\widetilde{A} \sim \widetilde{B})} \qquad \text{Equation (6 - 6)}$$

Agreement index ratio (AIR) is presented to differentiate between the two different states at a given productivity ratio as introduced in Equation (6 - 7). Supposing that $\widetilde{A}$ represents the low or high state and $\widetilde{B}$ represents the optimum state, if AIR ($\widetilde{A}$, $\widetilde{B}$) is higher or equal to 1, then the productivity is considered optimum and hence no necessity for further action. Otherwise, (i.e., AIR ($\widetilde{A}$, $\widetilde{B}$) is lower than 1), it is considered low, and that motivates the initiation of early warning decision support module.

$$\mathrm{AIR}\,(\widetilde{A}, \widetilde{B}) = \frac{\mathrm{Area}\,(\widetilde{A} \sim \widetilde{B} \cap \widetilde{B})}{\mathrm{Area}\,(\widetilde{A} \sim \widetilde{B} \cap \widetilde{A})} \qquad \text{Equation (6 - 7)}$$

Where;

AI($\widetilde{A\sim B}$, $\widetilde{B}$) and AI($\widetilde{A\sim B}$, $\tilde{A}$) represent the agreement indices between the fuzzy area between $\widetilde{A}$ and $\widetilde{B}$.

AIR($\widetilde{A}$, $\tilde{B}$) represents the agreement index ratio between the fuzzy number $\widetilde{A}$ and $\widetilde{B}$.

6.3.3 Early Warning Decision Support Module

Early warning decision support module is initiated based on the productivity assessment module recognized state (e.g., low) as presented in section 6.2.2. If the identified state was low, that indicates the possibility of a schedule delay or ineffective use of resources then, the project management in charge personnel are notified. Vice versa, in case of the identified productivity state is high, that indicates the possibility of cost overrun or over depletion of resources (i.e., number of equipment is more than needed). Hence, the responsible parties should also be warned.

Figure 6–4 shows a flowchart of the proposed early warning module. This module identifies any predefined undesirable consequence and then notifies the responsible project parties.

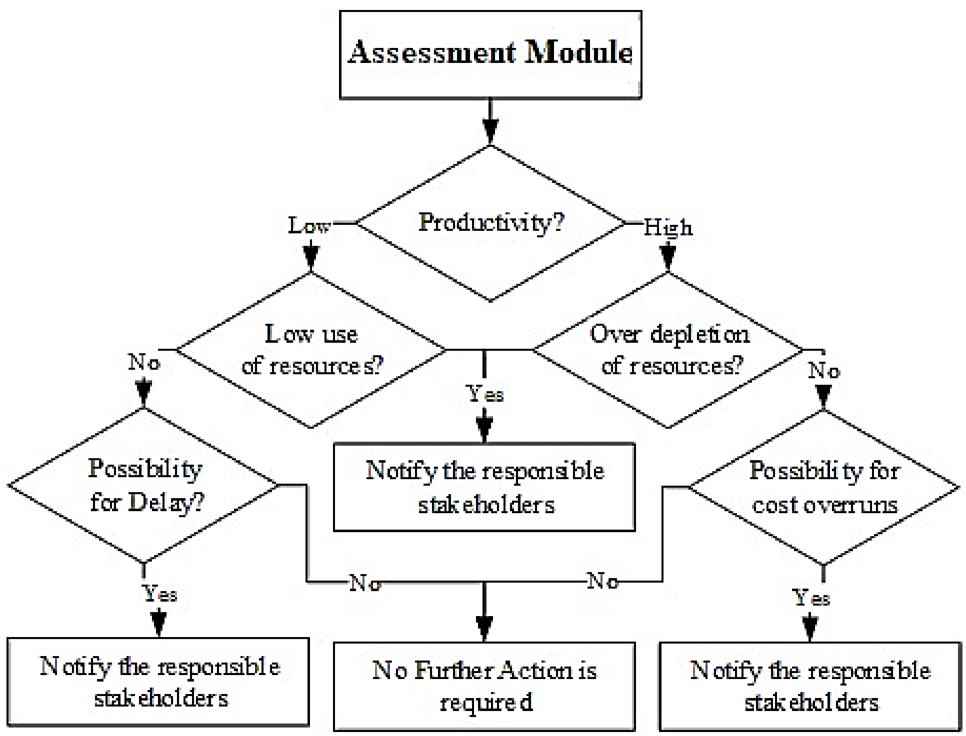


Figure 6-4: Early warning decision support module

An embedded notification system could be coded through the Waspmote IDE, and then uploaded to the microcontroller. Hence, the microcontroller dispatches the required notifications via the associated GPRS module in the form of cellular short message service (SMS), email or recorded voice message. Figure 6-5 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 decisions. Consequently, the timely intervention corrects the performance and so it increases the productivity. Hence, it assists in avoidance of schedule delays, cost overruns, and inefficient utilization of resources.

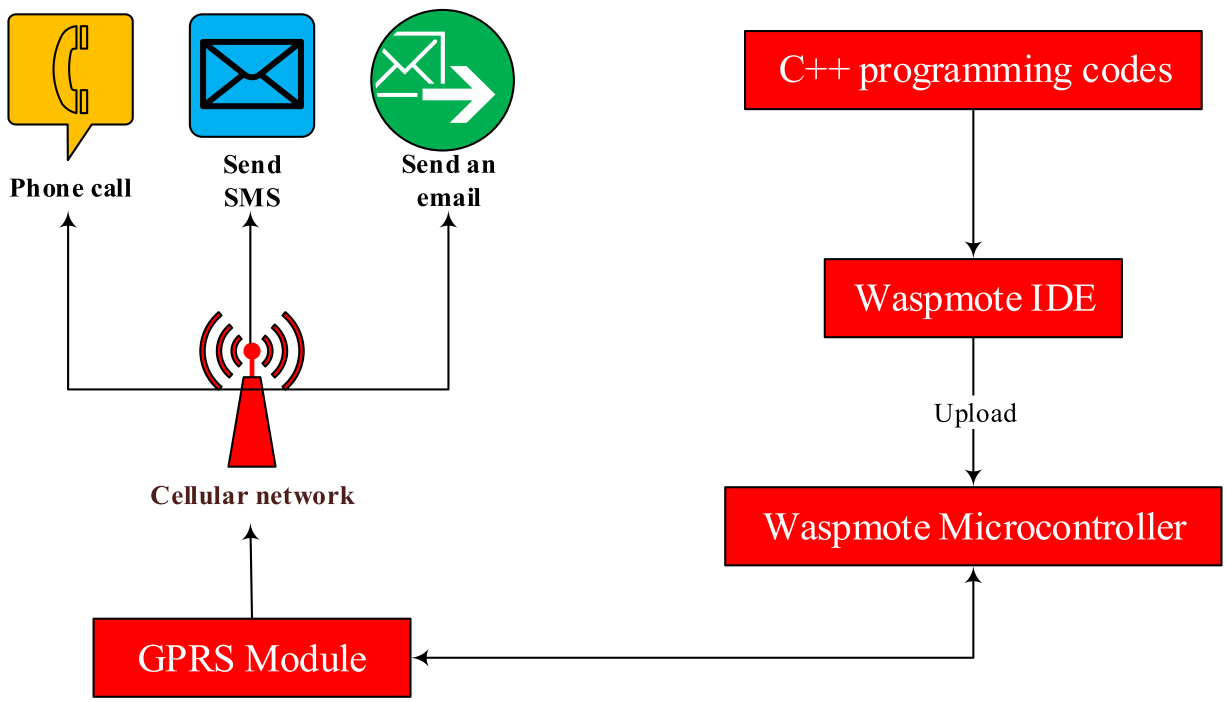


Figure 6-5: Schematic design flowchart of the proposed automated early warning system

6.3.4 Case Example

This hypothetical example is used to validate the applicability of the proposed method and to explain its features in monitoring the productivity of earthmoving operations. Assuming that the input sensor data are received from various technological sources (i.e., customized data acquisition system; as in chapter 4). Then, this data was used to measure the actual productivity (AP) at each period of time t (i.e., using automated productivity measurement model; as in chapter 5). Assuming that, the actual productivity at period t =50 was evaluated as 106 m3/day and for the same period of time, the productivity was planned as 125 m3/day. In this case, the productivity ratio for period t=50 is calculated using Equation (6-1) as 0.85. Hence, the developed LOH fuzzy monitoring system shows the indicator of actual productivity ratio in the $\widetilde{L\sim O}$ fuzzy area as shown in Figure

6-6. The weights of each fuzzy state $\tilde{L}$ and $\tilde{O}$ are calculated using Equation (6-3) as 0.25 and 0.75 respectively. A trapezoidal fuzzy number for $\widetilde{L\sim O}$ fuzzy area is calculated using Equation (6-3) and Equation (6-4) and the membership function that represents the $\widetilde{L\sim O}$ fuzzy number is generated as shown in Figure 6-6.

$$\widetilde{L\sim O}=0.25\times\tilde{L}+0.75\times\tilde{O}$$

$$\widetilde{L\sim O}=0.25\times[0,0,0.7,0.9]+0.75\times[0.7,0.9,1.1,1.3]$$

$$\widetilde{L\sim O}=[0.525,0.675,1.0,1.2]$$

Using the membership functions, the agreement indices of $\widetilde{L\sim O}$ with $\tilde{L}$ and that of $\widetilde{L\sim O}$ with $\tilde{O}$ are calculated using Equation (6-5) as follows:

$$AI(\widetilde{L\sim O},\tilde{L})=\frac{Area(\widetilde{L\sim O}\cap\tilde{L})}{Area(\widetilde{L\sim O})}=\frac{0.2}{0.5}=0.4$$

$$AI(\widetilde{L\sim O},\tilde{O})=\frac{Area(\widetilde{L\sim O}\cap\tilde{O})}{Area(\widetilde{L\sim O})}=\frac{0.3}{0.5}=0.6$$

$$AIR(\widetilde{L\sim O},\tilde{O})=\frac{Area(\widetilde{L\sim O}\cap\tilde{O})}{Area(\widetilde{L\sim O}\cap\tilde{L})}=\frac{0.3}{0.2}=1.5$$

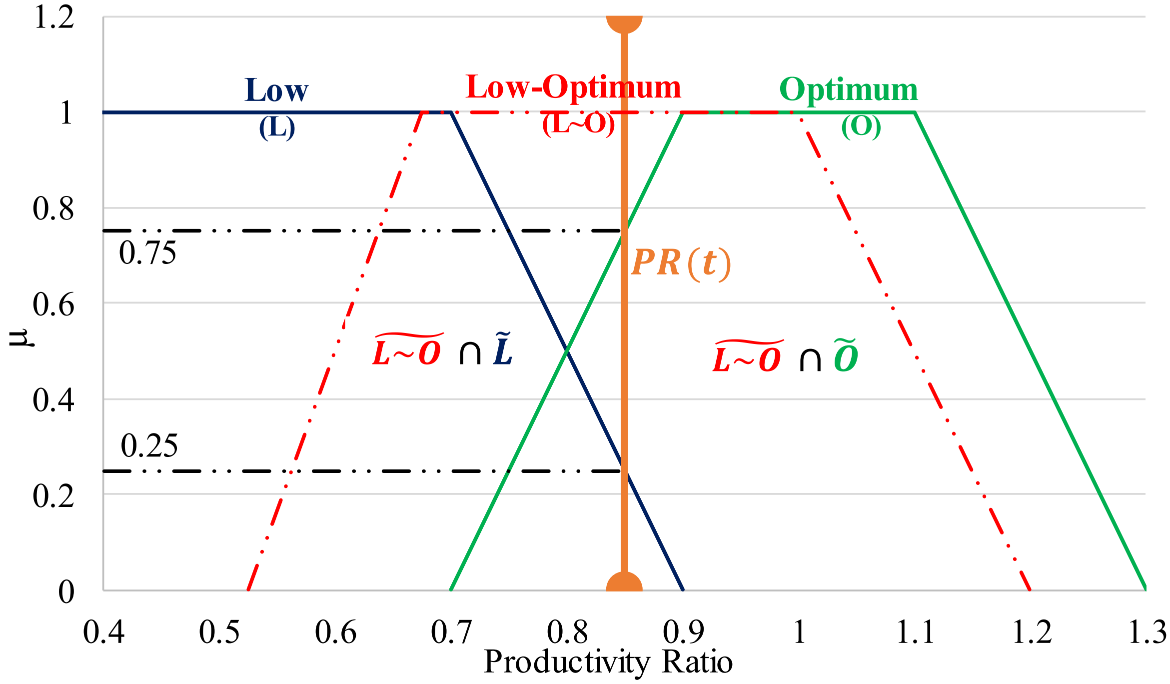


Figure 6-6: Agreement Index of Low Optimum with Optimum

In this case, the system identified the productivity as optimum that means no further action is required. However, if the productivity ratio remains to decrease and it reaches a level of 90 m3/day at period t=60 then, the calculation process is modified as follows:

$$PR(60)=0.8$$

$$\mu_{\tilde{L}}\big(PR(60)\big)=\mu_{\tilde{O}}\big(PR(60)\big)=0.5$$

$$\widetilde{L\sim O}=0.5\times\tilde{L} + 0.5\times\tilde{O}=[0.35,0.45,0.9,1.1]$$

$$AI(\widetilde{L\sim O},\tilde{L})=\frac{Area(\widetilde{L\sim O}\cap\tilde{L})}{Area(\widetilde{L\sim O})}=\frac{0.4}{0.6}=0.67$$

$$AI(\widetilde{L\sim O},\tilde{O})=\frac{Area(\widetilde{L\sim O}\cap\tilde{O})}{Area(\widetilde{L\sim O})}=\frac{0.2}{0.6}=0.332$$

$$\mathrm{AIR}(\widetilde{L\sim O}, \tilde{O}) = \frac{\mathrm{Area}(\widetilde{L\sim O} \cap \tilde{O})}{\mathrm{Area}(\widetilde{L\sim O} \cap \tilde{L})} = \frac{0.2}{0.4} = 0.5 < 1$$

In this case, the productivity is recognized as low which means it is prospect of schedule delay or inefficient utilization of resources. Consequently, the early warning decision support module should be initiated and notifications would be sent to the predefined responsible personnel in order to take corrective actions whether to overcome the schedule delay or to increase the efficiency of using resources if believed necessary.

6.4 Productivity Analysis Module Using ANN

Artificial Neural Network (ANN) is a computational model that is motivated by the way biological neural networks in the human brain process information. ANN is one of the famous machine learning techniques. Neural networks simulate the human brain in learning and utilizing experience to improve their performance. ANN is convenient in data modeling when there is no clear relationship among different data elements, even when dealing with noisy data (Du and Swamy, 2006). The central computational unit in a neural network is the neuron, often called a node. It gets inputs from some other nodes, or from an external source, i.e., database to compute outputs. Each input has an associated weight (w), which is assigned based on its relative importance to the other inputs. The node applies a function f (activation function) to the weighted sum of its inputs as shown in Figure 6-7. Where the network takes inputs X1 and X2, those inputs are associated with weights w1 and w2. In addition to the regular inputs that the node receives, there is another input 1 (as shown in the figure) with weight b (called Bias). The main function of Bias is to provide every node with a trainable constant value.

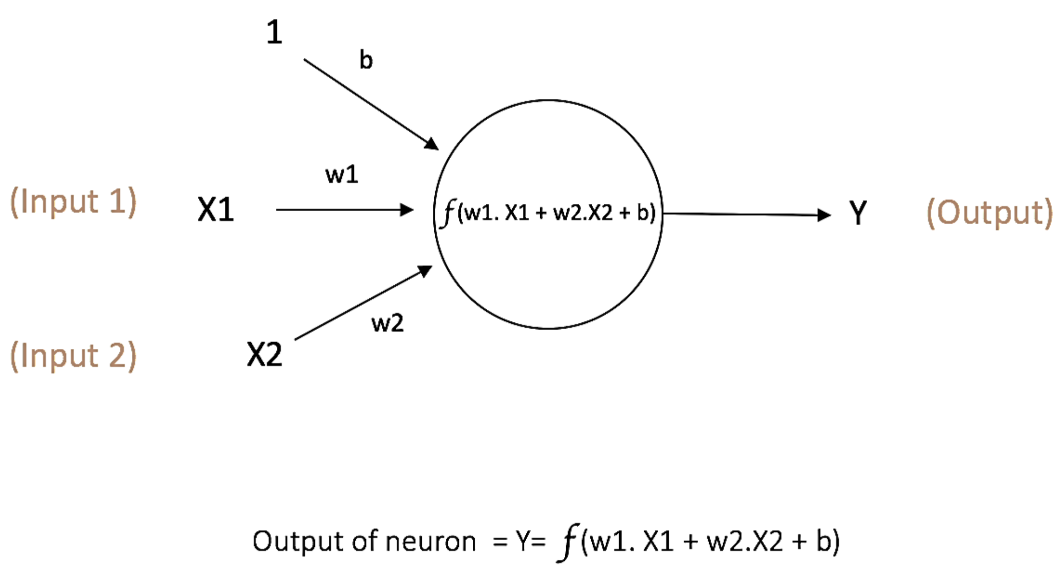


Figure 6-7: Single neuron structure

The neural network has many interconnected neurons each of them works as a processor. Those neurons are connected between weighted links passing signals from one neuron to another. Each neuron receives a number of input signals; hence, it produces only one output. Then, the different produced outputs from multiple neurons are brought into line with the initial outputs to determine the initial error. Based on that error; the network starts to adjust weights. ANN learns through repeated adjustment of weights of links between neurons. In other words, a training set of inputs and associated outputs are presented to the network. Then the network computes its output, and if there a difference (usually called error) between original and network output; the weights are adjusted to reduce this error. Neural networks are trained using pre-known data sets of inputs and their outputs. Generally, the establishment of an ANN should follow these steps:

1. Decide the network architecture, i.e., number of layers, hidden layers, how many neurons in each layer and how those neurons are connected. Figure 6-8 shows a typical architecture and components of artificial neural network.
2. Decide which learning algorithm to use.
3. Train the ANN (initialize and update weights from a set of training examples).

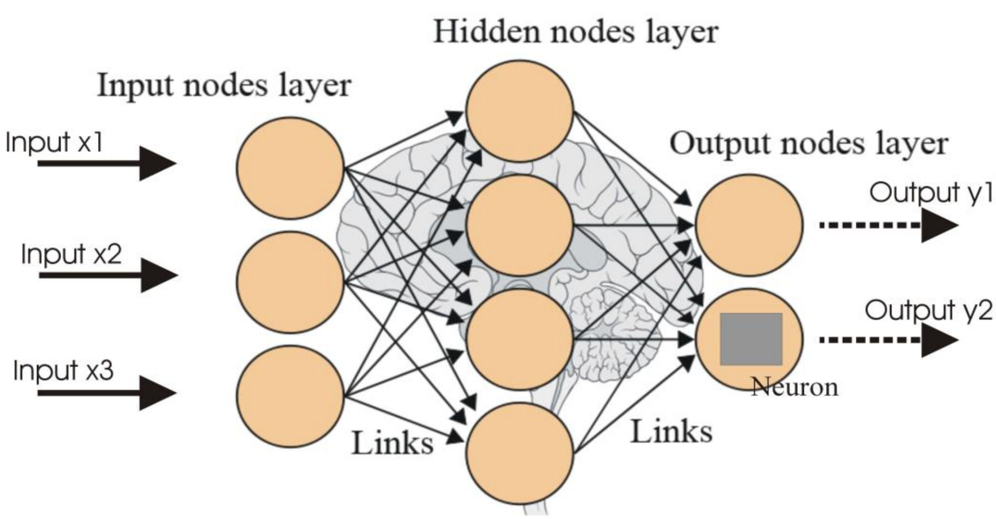


Figure 6-8: Typical ANN architecture and components

More than hundred different learning algorithms are available, but the most popular method is back-propagation. This method was first introduced by Bryson and Ho in 1969 but was ignored because of its challenging computations. Only in the mid-1980s was the back-propagation learning algorithm rediscovered (Negnevitsky, 2005). Back-propagation neural network (BPNN) is recommended when it is desired to correlate large amount of data arranged into inputs and output, and there is no clear relationship between the data. BPNN learns by examples; therefore, the user must provide a learning set that consists of some input examples with known output for certain cases (Sadiq et al. 2010).

There are a wide variety of factors that may influence the productivity of earthmoving operations. Any individual factor or a haphazard group of those influencing factors can affect productivity. In the case of an individual affecting factor, the selected corresponding sensor as explained in chapter 4 is capable of identifying this factor. However, the microcontroller's associated sensors are still able to capture a group of the influencing factors; the magnitude of influence is not quantified. Hence, there is a necessity to determine how much does each factor contribute to the total productivity loss. Also, to predict the impact of residual affecting factors on productivity.

The developed ANN model presents a dynamic tool for modeling and analyzing the productivity determined by the developed automated productivity measurement (explained in chapter 5). Fifteen affecting parameters are the network input. Those parameters can be categorized into four groups corresponding to loading efficiency, time spent in different states, road, driving and operational conditions and weather conditions. Table 6-1 depicts groups of the ANN input parameters and their corresponding items. The network output is the percentage of productivity differential, which represents the variation of productivity index.

Since earthmoving operations have a random nature, small samples of data not always represent a comprehensive picture of an operation. Hence, the more the data sets the best the network results. The available complete data sets collected from the developed field experiments were for fifteen cycles. While available, complete data sets collected from the developed laboratory experiments were for thirty loading-dumping data sets. In order to provide the network with a reasonable amount of data, fifteen cycles data sets were generated. The generation process was based on the statistical analysis, i.e., the type of distribution and descriptive indices of the original fifteen collected data sets.

Table 6-1: ANN input parameters groups

Loading Efficiency	**States Duration**	**Road and driving conditions**	**Weather Conditions**
Loading duration	Hauling and return	Number of bumps	Temperature
Bucket Fill Factor	Waiting in loading and dumping zones	Number of ruts	Humidity
	Time spent to exit load and dump zones	Number of harsh brakes	Rainfall
		Number of stoppages exceed certain duration	

Matlab® software was the selected computational platform as it can be integrated with MySQL databases to retrieve the required data for ANN analysis automatically. Iteratively, a variety of network architectures were developed to enhance the network learning. Figure 6-9 shows a sample for a network architecture, where it consists of one hidden layer of ten neurons in addition to the default output layer.

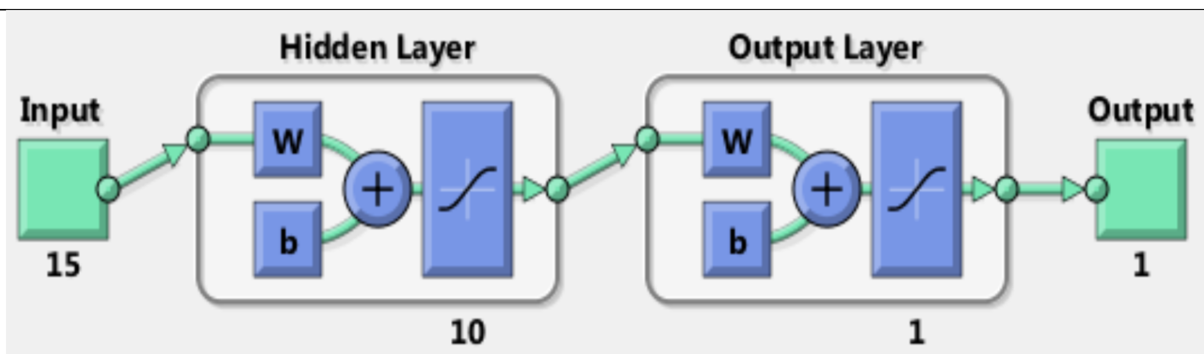


Figure 6-9: Sample for a network architecture

6.4.1 Influencing Parameters without Consideration of Weather Conditions

A network with two hidden layers has shown better performance than other networks regardless of the number of neurons. In order to evaluate the effect of adding or extracting items from the inputs, weather conditions were not considered in the first run of the utilized software. Table 6-2 shows the developed networks' architectural attributes and error associated with the corresponding outputs compared with the original productivity differential determined by the automated model. Mean absolute error and average invalidity percentage are expected to be diminished in case of larger number of data sets.

Table 6-2: Different ANN and corresponding errors and R^2 value – No weather input

Iteration	No. of Hidden Layers	No. of Neurons	Average Invalidity Percentage	Mean Absolute Error	R^2
1	2	10	32.54 %	1.43 %	0.900555
2		8	26.36 %	1.40 %	0.94427
3		6	23.81 %	1.18 %	0.951644

In case that weather conditions inputs were not considered, Figure 6-10, Figure 6-11 and Figure 6-12 show a graphical representation of actual productivity differential for thirty earthmoving cycles and those produced by the ANN1, ANN2 and ANN3 respectively.

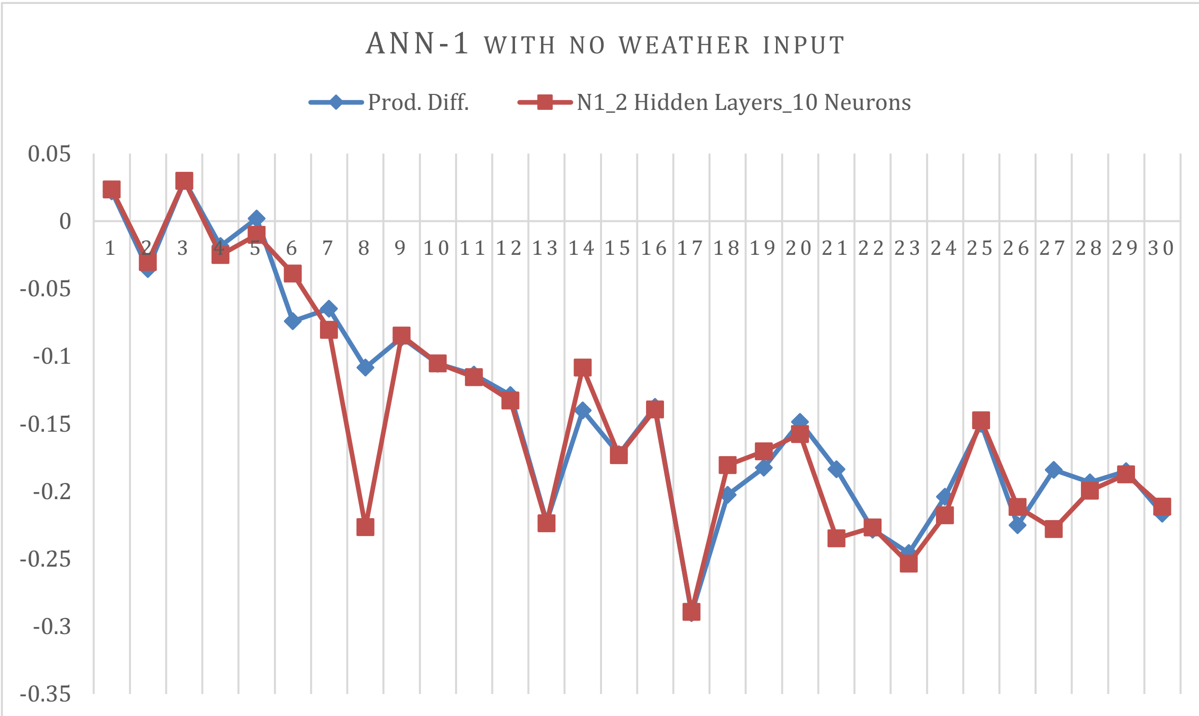


Figure 6-10: Determined productivity differential vs ANN1 output

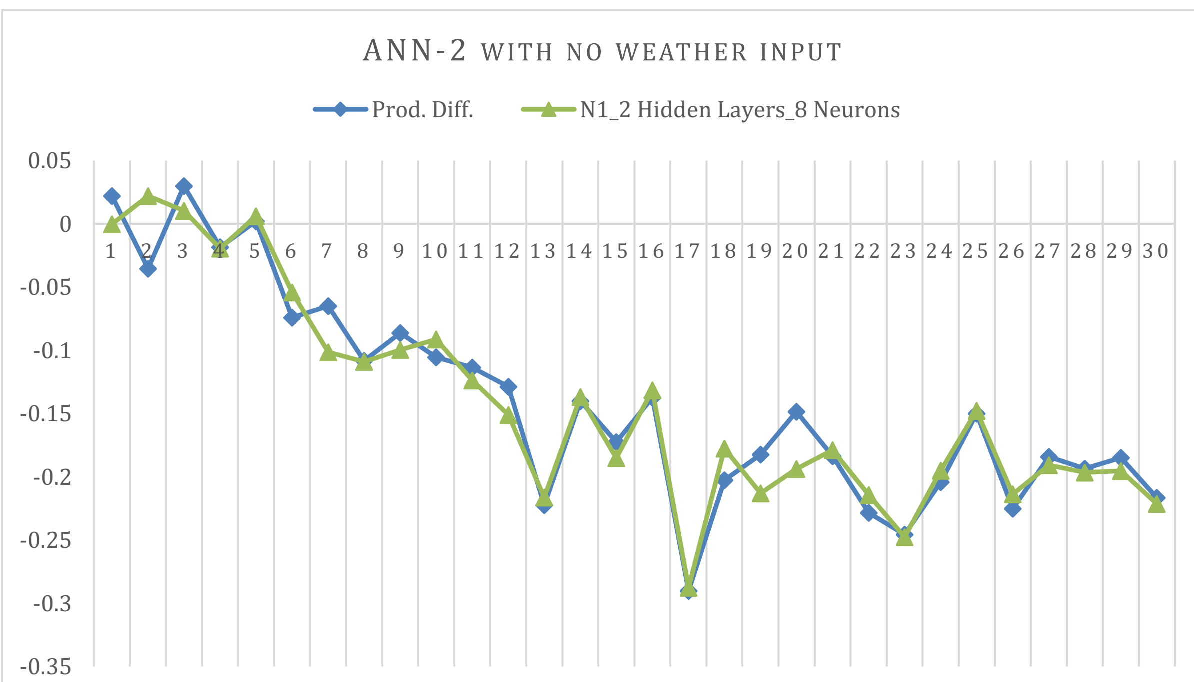


Figure 6-11: Determined productivity differential vs. ANN2 output

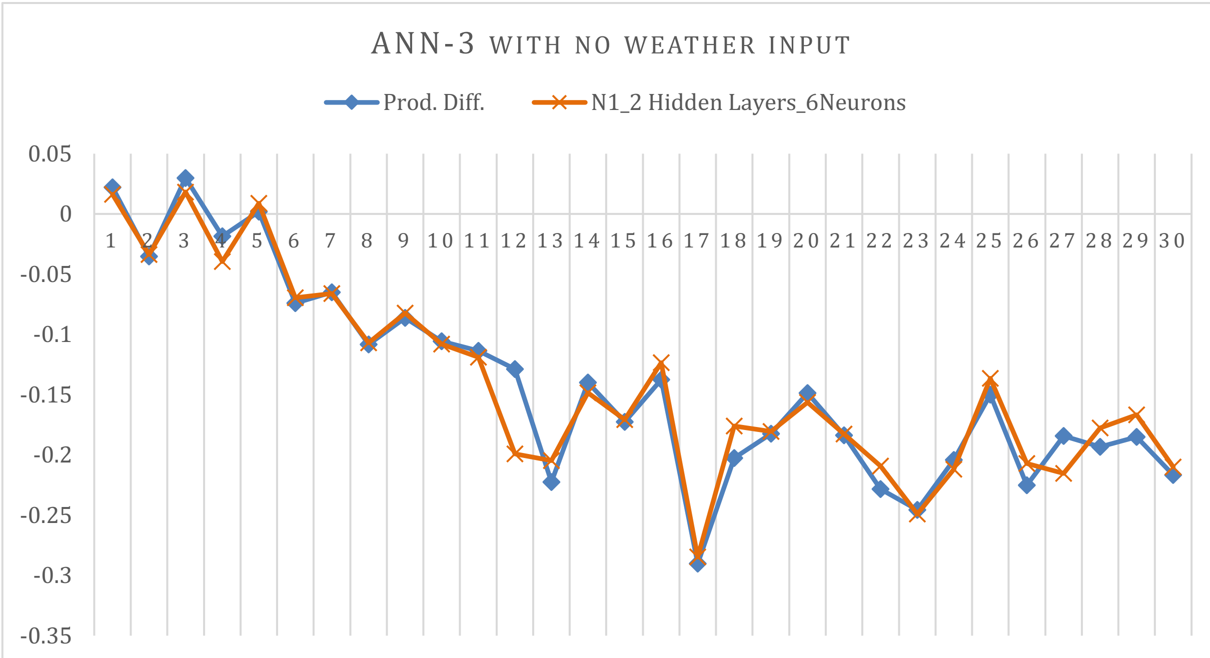


Figure 6-12: Determined productivity differential vs. ANN3 output

6.4.2 Influencing Parameters with Consideration of Weather Conditions

Based on the recorded temperature, humidity and rainfall quantity, the input items of the weather condition was categorized into two states for simplification; 1 for good weather condition and 0 for bad weather condition. Further states can be defined for more weather conditions. Weather condition was considered in the second run of the software. Table 6-3 shows the developed networks' architectural attributes and error associated with the corresponding outputs compared with the original productivity differential determined by the automated model.

Table 6-3: Different ANN and corresponding errors and R^2 value – weather input considered

Iteration	No. of Hidden Layers	No. of Neurons	Average Invalidity Percentage	Mean Absolute Error	R^2
4	2	10	25.06 %	0.97 %	0.9649248
5		8	45.22 %	1.49 %	0.9509133
6		6	9.29 %	0.81 %	0.9741865

In case that weather conditions inputs were considered, Figure 6-13, Figure 6-14 and Figure 6-15 represent the actual productivity differential for thirty earthmoving cycles and those produced by the ANN4, ANN5 and ANN6 respectively.

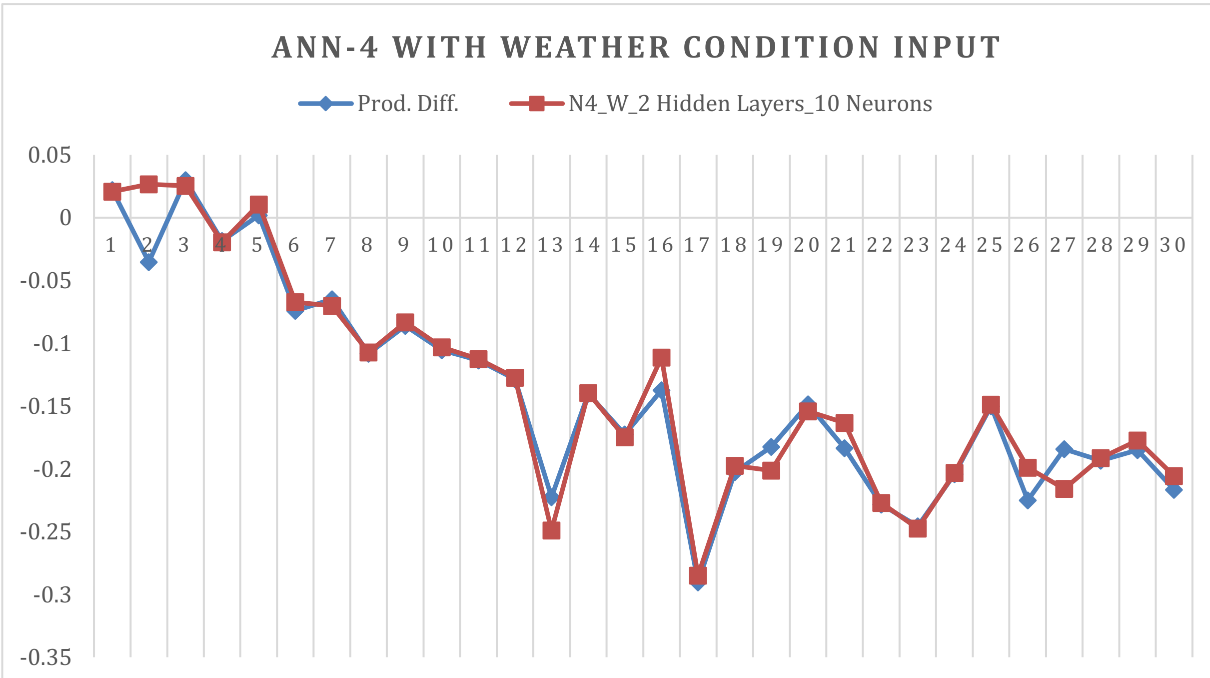


Figure 6-13: Determined productivity differential vs. ANN4 output

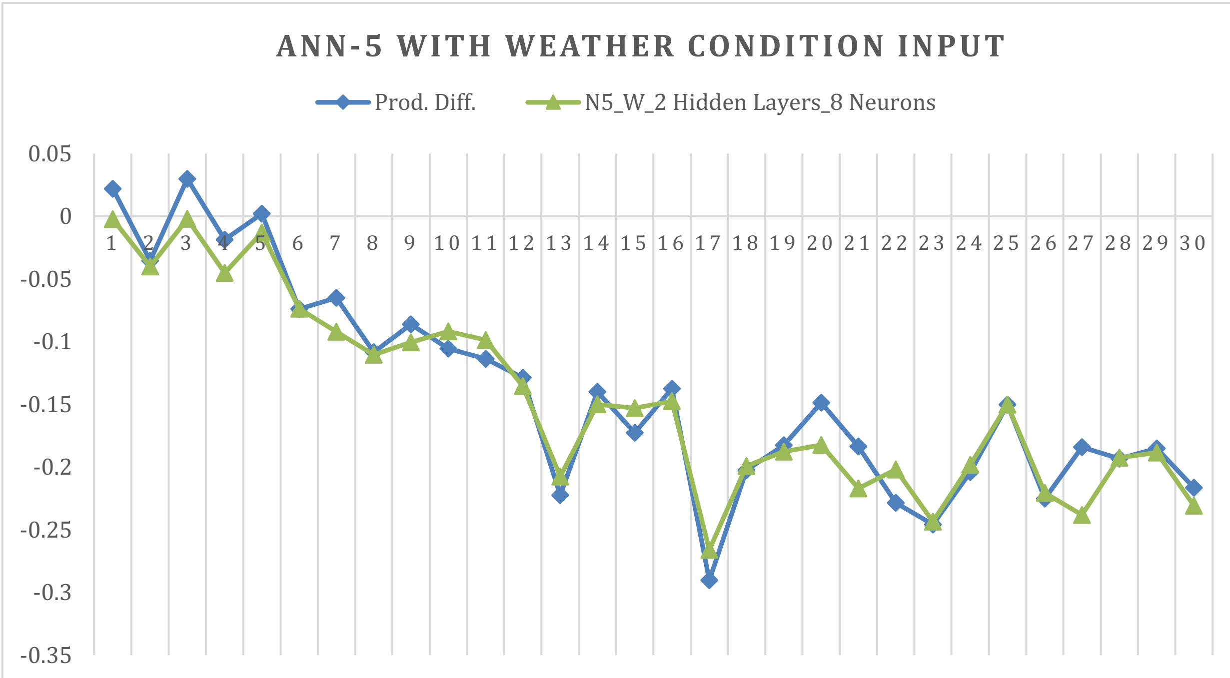


Figure 6-14: Determined productivity differential vs ANN5 output

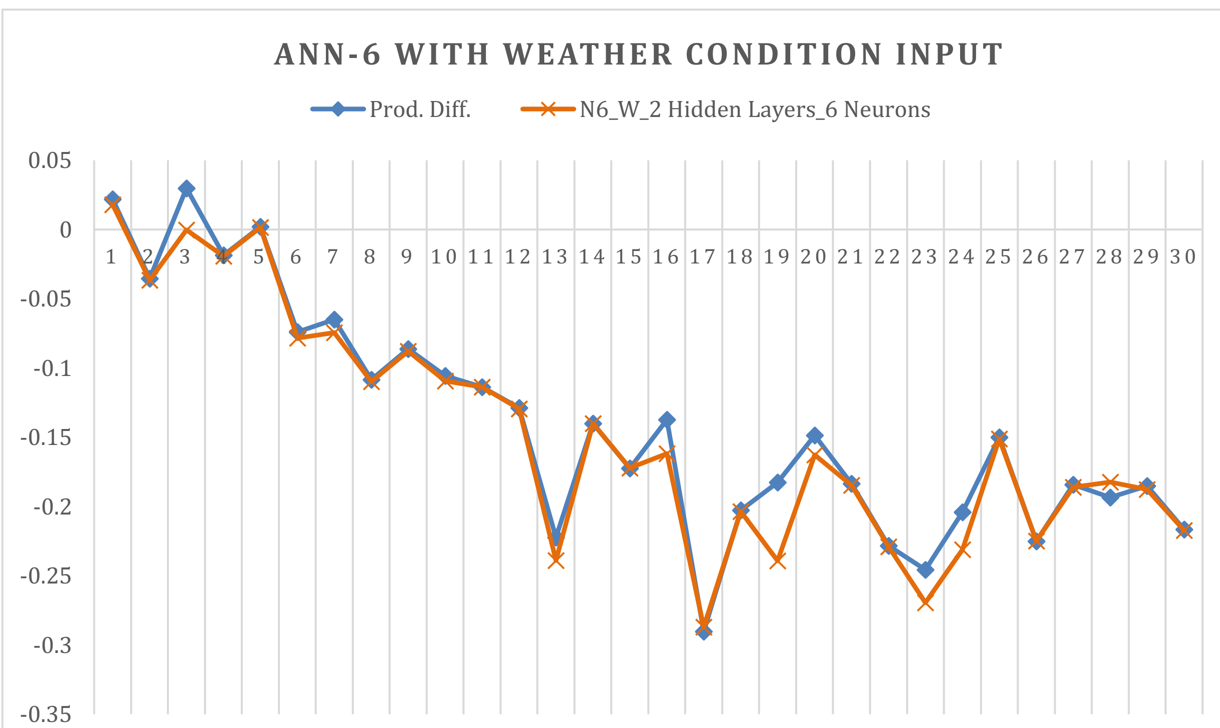


Figure 6-15: Determined productivity differential vs. ANN6 output

The sixth ANN iteration (ANN6) demonstrated higher accuracy in terms of lower average invalidity error, mean absolute error and better regression than all the other ANN iterations. The input items in this model are covering influencing factors associated with loading operation and each of the operational modes of the hauling truck on the road in addition to the influence of weather conditions.

6.4.3 Influencing Factors Contribution to the Loss of Productivity

Quantifying the contribution of each influencing factor on productivity; supports the effectiveness of management corrective decisions. The impact of each input variable on the output of the neural network can be expressed by the relative importance of input variables. Olden and Jakson (2002) introduced the connection weights algorithm (CW). This algorithm calculates the relative importance of each input variable based on the weights of connections between the different layers of the network which performed adequately in terms of accuracy and regression. Based on that, among all the iterations, ANN6 has shown adequate performance. Therefore, The relative importance of each of the utilized input variables can be derived using Equation (6-8).

$$\mathrm{RI}x = \sum_{y=1}^{n} Wxy\, Wyz \qquad \text{Equation (6-8)}$$

Where

RIx is the relative rank of input neuron x, i.e., Productivity influencing variable

$\sum_{y=1}^{n} Wxy\, Wyz$ is summation of the product of the of final weights of the connection from input neuron to hidden neurons with the connection from hidden neurons to output neuron.

y is the total number of hidden neurons.

z is output neurons.

Connecting weights were extracted from Matlab as shown in Figure 6-16. Summation of product of the different connecting weights were calculated. The final resulted weights and their corresponding ranks are shown in table 6-4.

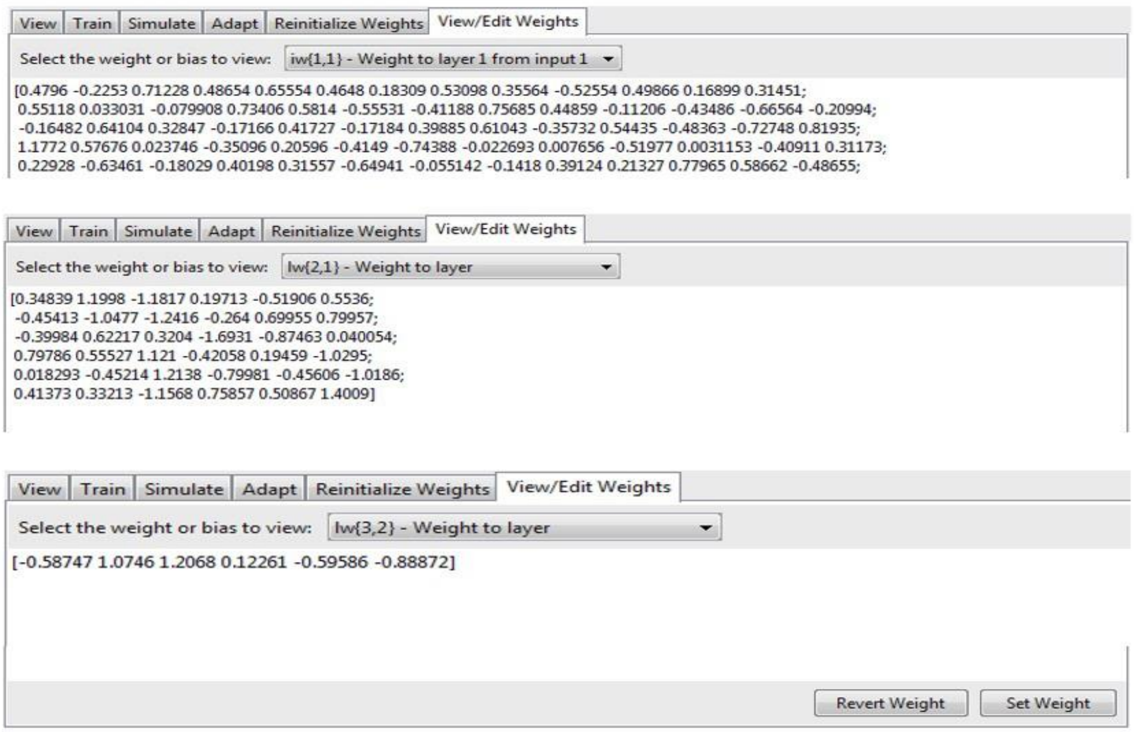


Figure 6-16: Weights of connections between ANN6 layers

Table 6-4: Final resulted weights and their corresponding ranks

Influencing Input Variable	**Relative Weight**	**Rank**
Hauling and Return Duration	-4.4422	1
No. of Stoppage	-2.0321	2
Wait for Loading Duration	-1.4039	3
Bumps	-1.2034	4
Wait for Dumping	-1.092	5
Ruts	-1.0106	6
Weather Conditions	-0.8183	7
No. of Brakes	-0.7513	8
Exit-Load Zone Duration	-0.6219	9
Loading Duration	0.9644	10
Exit-Dumping Zone Duration	1.3488	11
BFF	2.3158	12
Dumping Duration	2.4117	13

7 Chapter 7: Model Validation and Web-based Monitoring

7.1 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. Figure 7-1 shows the framework of the developed case study.

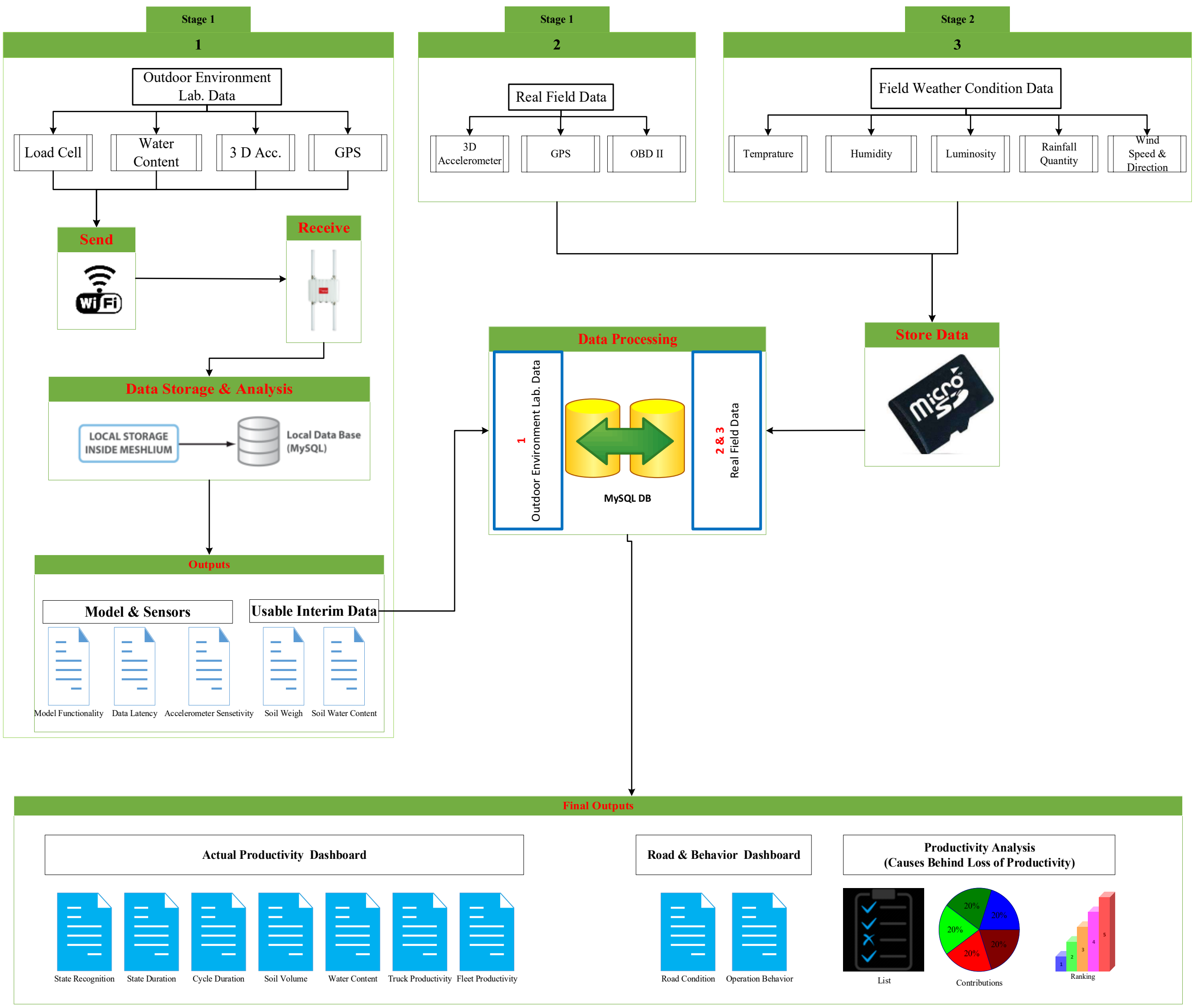


Figure 7-1: Framework of the developed case study

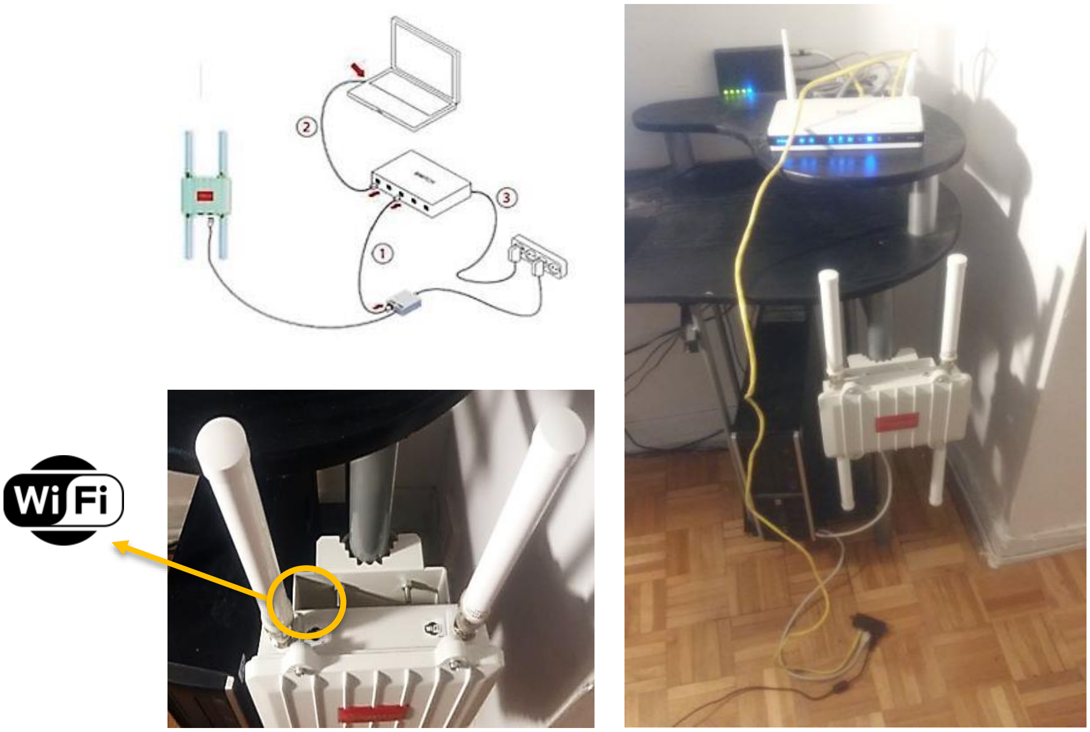
7.1.1 Phase 1: Laboratory Experiment

The first phase was performed in an outdoor laboratory environment using remotely controlled 1:24 scaled loading and hauling equipment due to unavailability of real loading and hauling equipment. The purpose behind this phase is:

1. Simulate loading and dumping operations.
2. Check the sensitivity of the utilized 3D accelerometer in detecting the change of acceleration in each of the three directions.
3. Collect the loaded soil weight and water content data.
4. Examine the prototype functionality in streaming collected data using WiFi to the built-in Meshlium MySQL database.

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 real application, the data acquisition module sends the acquired sensor data to Meshlium using GPRS, WiFi, Xbee or Bluetooth, while the communication protocol used in this laboratory experiment is WiFi. The experiment was conducted as follow:

1. Connecting the gateway (Meshlium) to the computer which connected to WiFi router. Then, the gateway is creating its particular identification protocol (IP). Figure 7-2. A, B respectively shows a schematic and physical connection of the gateway to both of the computer and the internet router.
2. Connecting the load cell sensor to the smart board associated with the microcontroller that hosts a WiFi shield (data poster) and GPS module. C# code was uploaded to the microcontroller to perform the data acquisition and communication. A 2GB micro SD card was used to record a copy of the acquired data for loading and dumping states to be integrated with the data collected for other earthmoving states in phase 2 field experiment.



A B

Figure 7-2. : Schematic and physical connection of the gateway to both of the computer and the internet router.

3. Connecting a rechargeable battery to the prototype, then installing and orienting the prototype in the top front of scaled truck bed above the cabinet as shown in Figure 7-3.

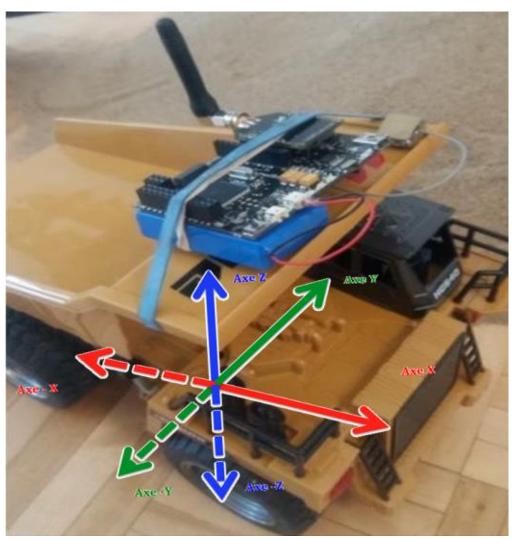


Figure 7-3: Set up of the oriented prototype on the scaled hauling truck

4. Starting a simulated loading, hauling and dumping operations. The loaded soil was sand with known density and different water contents, where specific various amounts of water were added to a fully dray sand. Figure 7-4 depicts the simulation of loading, hauling and dumping operations using scaled equipment.

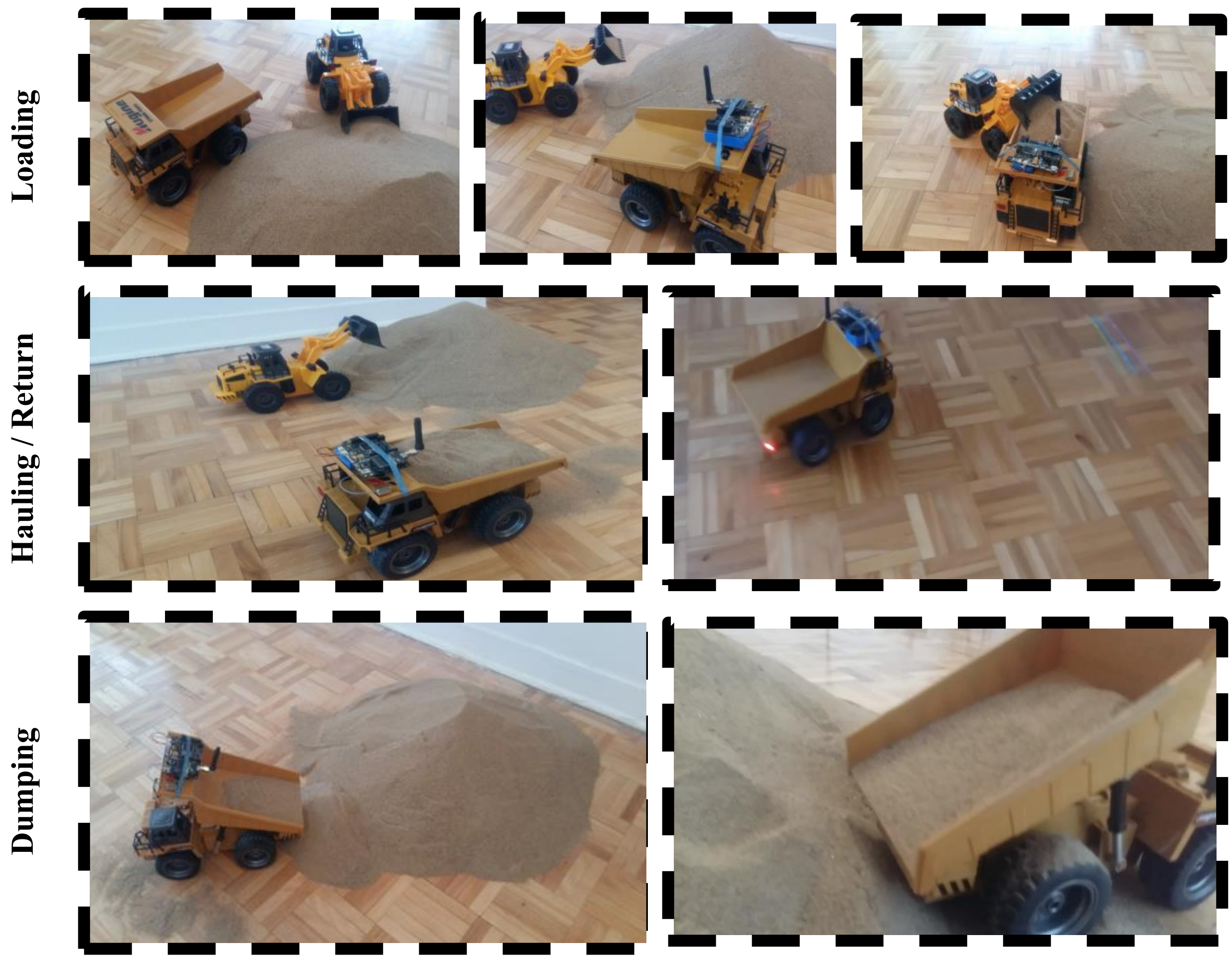


Figure 7-4: Simulation of loading, hauling and dumping operations using scaled equipment

5. Data was captured by the different sensors for loaded sand weights, latitude and longitude of the truck, and the acceleration in the three directions. Then the collected data streamed thru the WiFi shield to the Meshlium built-in database.
6. Soil water content data was collected separately using the soil water content sensor connected to the same prototype.

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. Figure 7-5 shows samples of the collected data from different sensors in the case study.

ID	Time	X	Y	Z
671	7:10:09 PM	26	19	1019
672	7:10:10 PM	22	1	1022
673	7:10:11 PM	14	30	1014
674	7:10:12 PM	26	26	1019
675	7:10:13 PM	-12	-58	956
676	7:10:14 PM	39	-45	1007
677	7:10:15 PM	38	7	1027
678	7:10:16 PM	35	0	1026
679	7:10:17 PM	19	-131	969
680	7:10:18 PM	30	2	1006
681	7:10:19 PM	15	92	1092
682	7:10:20 PM	24	0	1019
683	7:10:21 PM	27	2	1015
684	7:10:22 PM	18	-3	1021
685	7:10:23 PM	74	34	1048
686	7:10:24 PM	111	42	1012
687	7:10:25 PM	108	-8	1023
688	7:10:26 PM	111	-5	1027
689	7:10:27 PM	121	-64	1003
690	7:10:28 PM	100	-50	1021
691	7:10:29 PM	35	-16	1036
692	7:10:30 PM	-83	-50	992

Acceleration (cm/s^2)

ID	Time	Frequency (Hz)
49	7:02:17 PM	172.3283920288
50	7:02:22 PM	172.3841781616
51	7:02:27 PM	172.403224945
52	7:02:32 PM	172.4222869873
53	7:02:37 PM	172.4350013732
54	7:02:42 PM	172.4515419006
55	7:02:47 PM	172.4439048767
56	7:02:52 PM	172.4948501586
57	7:02:57 PM	172.4350013732
58	7:03:02 PM	172.496158322342
59	7:03:07 PM	172.511156914366
60	7:03:12 PM	172.526155506389
61	7:03:17 PM	172.541154098413
62	7:03:22 PM	150.556152690436
63	7:03:27 PM	150.57115128246
64	7:03:32 PM	150.586149874484
65	7:03:37 PM	150.601148466507
66	7:03:42 PM	137.616147058531
67	7:03:47 PM	137.631145650555
68	7:03:52 PM	137.646144242578
69	7:03:57 PM	97.6611428346018
70	7:04:02 PM	97.6761414266255
71	7:04:07 PM	81.6911400186491

Soil water content (Hz)

ID	Time	OutPut Voltage (mV)
31	7:03:17 PM	0.534128
32	7:03:27 PM	0.533264
33	7:03:37 PM	0.408176
34	7:03:47 PM	0.213652
35	7:03:57 PM	0.09208
36	7:04:07 PM	8.53200000000004E-03
37	7:04:17 PM	8.66400000000004E-03
38	7:04:27 PM	8.66400000000004E-03
39	7:04:37 PM	8.66400000000004E-03
40	7:04:47 PM	8.66400000000004E-03
41	7:04:57 PM	0.010712
42	7:05:07 PM	0.010712
43	7:05:17 PM	0.010728
44	7:05:27 PM	9.41600000000004E-03
45	7:05:37 PM	9.80400000000004E-03
46	7:05:47 PM	0.01024
47	7:05:57 PM	7.39600000000004E-03
48	7:06:07 PM	7.39600000000004E-03
49	7:06:17 PM	0.012332
50	7:06:27 PM	0.012624
51	7:06:37 PM	0.014628
52	7:06:47 PM	0.01468
53	7:06:57 PM	0.01468
54	7:07:07 PM	9.80000000000004E-03
55	7:07:17 PM	0.010356

Load cell (mv)

ID	Time	Date	Longitude	North/Soutl	Latitude	East/West ir	Altitude	Speed	Course	Latitude (de	Longitude ((
43	190311	10717	4532.0312	N	7339.6638	W	42.8	0.18	94.14	45.53385162	-73.66106415
44	190318	10717	4532.0311	N	7339.6638	W	43.2	0.11	103.9	45.53385162	-73.66106415
45	190325	10717	4532.0308	N	7339.6644	W	44.5	0.20	213.86	45.53384781	-73.66107178
46	190332	10717	4532.0299	N	7339.6655	W	47.2	0.16	215.7	45.53383255	-73.66109467
47	190336	10717	4532.0286	N	7339.6663	W	50.3	0.09	108.04	45.53380966	-73.66110229
48	190343	10717	4532.0284	N	7339.6662	W	51.6	0.11	272.78	45.53380585	-73.66110229
49	190350	10717	4532.0287	N	7339.6659	W	51.8	0.22	230.44	45.53381348	-73.66109467
50	190357	10717	4532.0292	N	7339.6655	W	51	0.11	163.15	45.53382111	-73.66109467
51	190404	10717	4532.0294	N	7339.6649	W	50.5	0.07	175.51	45.53382492	-73.66107941
52	190411	10717	4532.0315	N	7339.6647	W	49	5.24	4.15	45.53385925	-73.66107941
53	190418	10717	4532.0233	N	7339.6717	W	42.2	17.20	193.3	45.53372192	-73.66119385
54	190425	10717	4532.0018	N	7339.683	W	37.9	22.02	203.16	45.53336334	-73.66138458
55	190432	10717	4531.9801	N	7339.6953	W	35.5	22.55	202.11	45.53300095	-73.66159058
56	190439	10717	4531.9582	N	7339.7078	W	34	22.29	204.66	45.53263855	-73.66179657
57	190446	10717	4531.9351	N	7339.7225	W	33.3	23.94	204.11	45.53225327	-73.66204071
58	190453	10717	4531.9194	N	7339.7321	W	33.1	5.35	202.71	45.53199005	-73.66220093
59	190500	10717	4531.911	N	7339.737	W	33.7	17.63	202.16	45.53184891	-73.66228485
60	190507	10717	4531.8879	N	7339.7498	W	33.6	23.52	201.26	45.53146362	-73.66249847

GPS

Figure 7-5: Samples of collected sensor data in the case study

7.1.2 Phase 2: 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 7-6, the figure shows both loading and dumping zones in addition to hauling and the alternative roads.

The distance between loading and dumping area through any of the two roads is 1150 m. The marked hauling road has a good surface condition, while the marked alternative road has some segments in adverse conditions as it contains bumps and potholes. Trips were done from loading to dumping zone and versa in an average speed of 35 Km/hr. These trips have utilized the connecting two roads as shown in Table 7-1.

Table 7-1: Trips between loading and dumping zones and utilized roads

Number of Trips	Hauling Road	Road Condition	Returning Road	Road Condition
5	Main	Good	Main	Good
5	Main	Good	Alternative	Bad
5	Alternative	Bad	Alternative	Bad

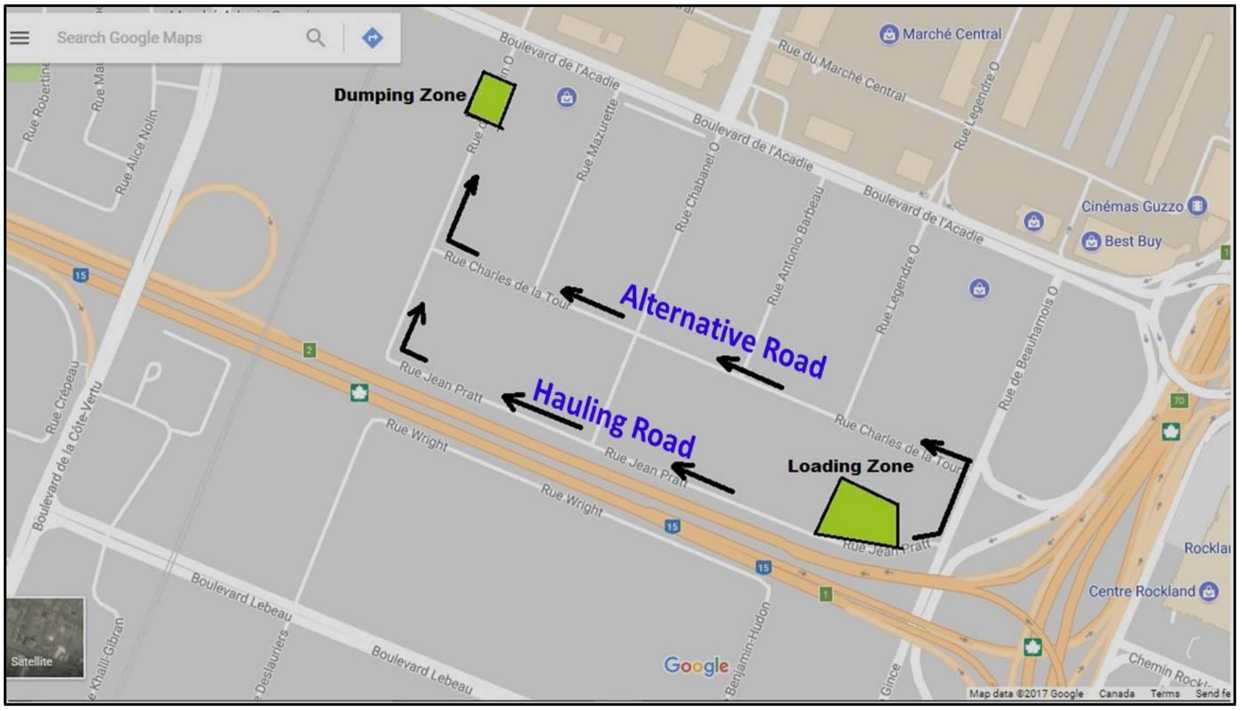


Figure 7-6: Case study field - loading, dumping zones and hauling roads

In this stage, 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 1. This phase could also incorporate weather data acquisition from the job-site using a smart board equipped with temperature and humidity sensors. In a real application, the smart board is attached to another microcontroller, while in this phase for simplification, data was retrieved from online weather records. 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. Preliminary evaluation was performed using the data of two trips. Figure 7-7 shows model outputs of the first two 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 indicates the end of this state. The figure also shows the developed procedure to calculate the 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.

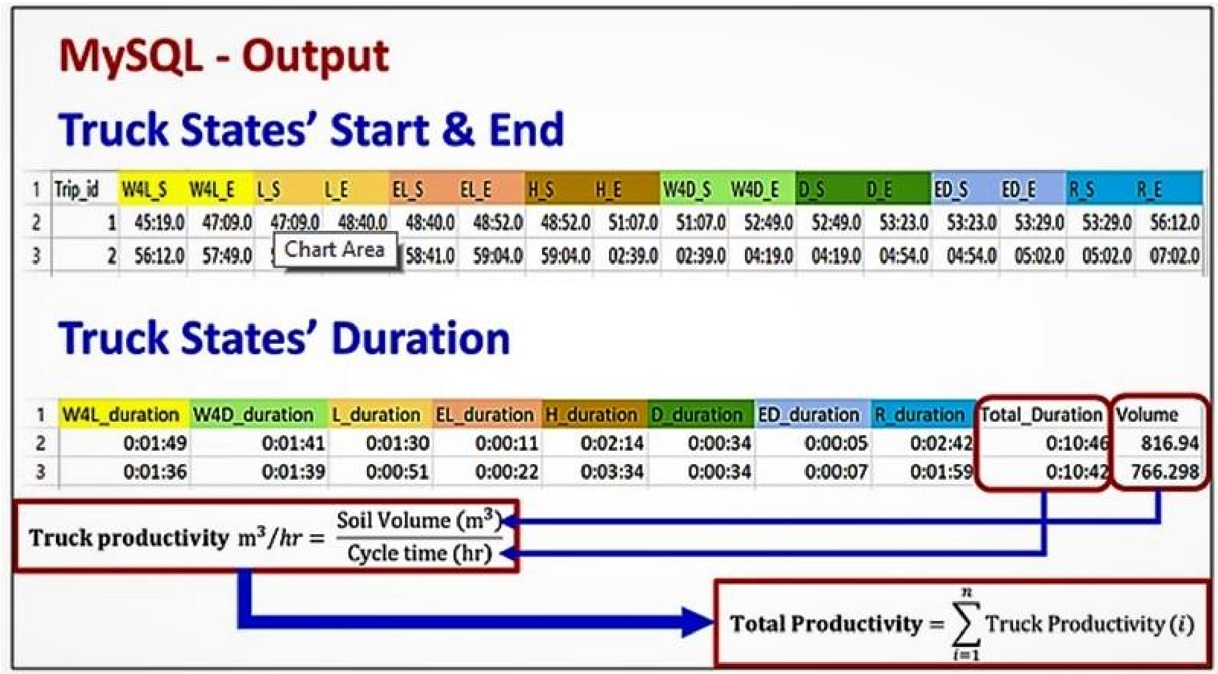


Figure 7-7: Automated Productivity model outputs for the first two trips of the case study

7.1.3 Results and Discussion

The application of the developed model through the first two earthmoving cycles in the case study demonstrated good capabilities of the developed model including the recognition of the tuck's state of operation and the duration each state. To simplify the comparison between manual and model's outputs; the first two trips are compared. Table 7-2 shows a comparison between the actual operational times for each state captured using a stopwatch in time laps and the calculated durations by 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.

Table 7-2: Actual manual versus the developed model's calculated records

Trip	**Trip 1**						**Trip 2**						**Total Dur. (Sec.)**
Recognized State	Wait for Loading	Loading	Hauling	Wait for Dumping	Dumping	Return	Wait for Loading	Loading	Hauling	Wait for Dumping	Dumping	Return	
Actual Dur. (1) (Sec.)	103	97	147	96	38	172	91	65	223	94	39	131	1296
Model Dur. (2) (Sec.)	109	90	145	101	34	167	96	51	236	99	34	126	1288
Difference (Sec.)	6	-7	-2	5	-4	-5	5	-14	13	5	-5	-5	-8
Error %	0.0583	-0.0722	-0.0136	0.0521	0.1053	-0.0291	0.0549	-0.2154	0.0583	0.0532	-0.1282	-0.0382	-0.0062

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

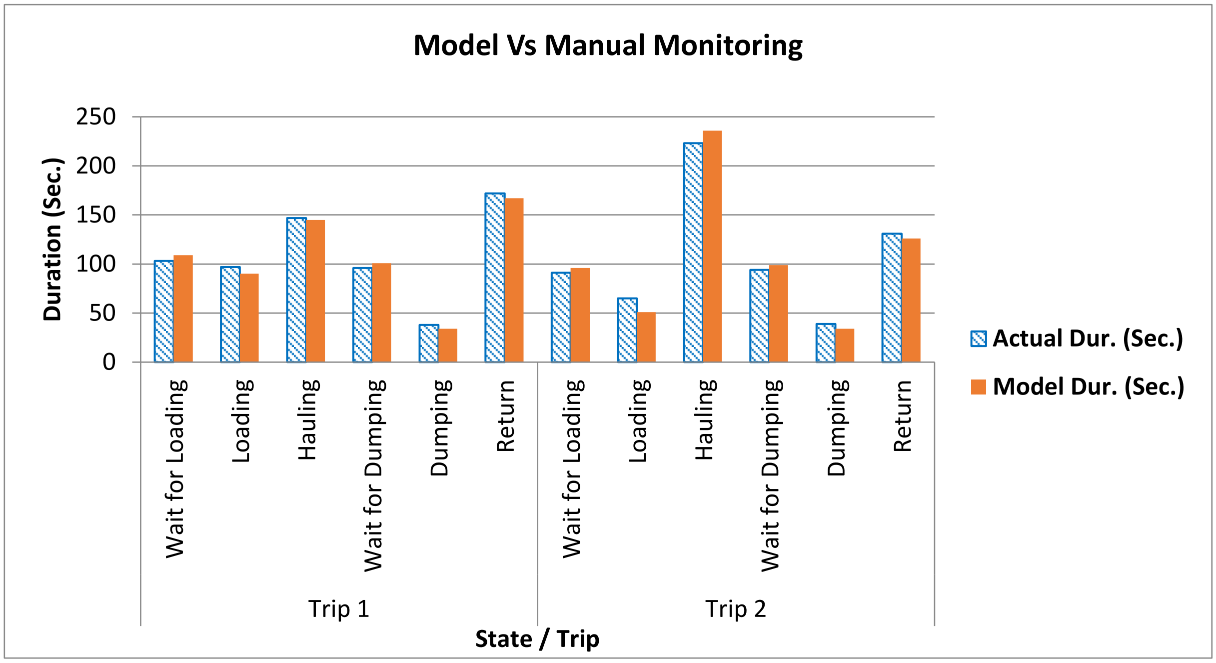


Figure 7-8: Duration of different states of operations for the first two trips

The variance between the manual and the automated monitoring ranges was from +5 to -12% for individual states. However the difference was varied from a state to another, the percentage of the total difference between manual and automated monitoring procedure was 0.06% which validates the model accuracy.

Discussion scope is extended to cover all the performed fifteen trips. This section illustrates in details the model's capabilities and validation. Table 7-3 shows the duration of each state using the developed model, while the duration of the same states using manual time laps method using a smartphone is shown in Table 7-4. The shown resulted numbers in the tables are automatically calculated by the database, while the number of decimals does not intended to reflect the precision.

Table 7-3: Duration of states by the developed model

	W4L_Duration	W4D_Duration	L_Duration	EL_Duration	H_Duration	D_Duration	ED_Duration	R_Duration	Total_Duration
1	1.816666667	1.683333	1.5	0.183333	2.233333	0.566667	0.083333333	2.7	10.76666667
2	1.6	1.65	0.85	0.366667	3.566667	0.566667	0.116666667	1.983333	10.7
3	1.75	0.833333	1.083333	0.216667	2.7	0.833333	0.216666667	3.25	10.88333333
4	1.483333333	1.266667	1.616667	0.25	2.75	0.716667	0.15	2.633333	10.86666667
5	0.983333333	1.383333	1.383333	0.3	3.066667	0.783333	0.266666667	3.066667	11.23333333
6	1.216666667	1.883333	1.3	0.216667	2.266667	0.65	0.2	3.466667	11.2
7	1.2	1.333333	1.266667	0.266667	2.483333	0.816667	0.15	3.666667	11.18333333
8	1.316666667	0.416667	1.45	0.316667	3.733333	0.783333	0.266666667	3.916667	12.2
9	0.966666667	1.583333	1.533333	0.3	2.633333	0.8	0.233333333	4.033333	12.08333333
10	1.116666667	1.55	1.616667	0.366667	2.316667	0.883333	0.25	3.85	11.95
11	1.05	0.916667	0.933333	0.516667	3.633333	0.966667	0.183333333	3.366667	11.56666667
12	0.933333333	0.766667	1.483333	0.433333	3.816667	0.866667	0.466666667	3.616667	12.38333333
13	0.866666667	1.15	1.583333	0.316667	3.983333	1.266667	0.433333333	4.15	13.75
14	1.4	0.666667	0.95	0.416667	4.116667	0.783333	0.35	4.016667	12.7
15	0.916666667	1.383333	1.05	0.366667	4.066667	0.833333	0.383333333	3.966667	12.96666667
Σ	**18.61666667**	**18.46667**	**19.6**	**4.833333**	**47.36667**	**12.11667**	**3.75**	**51.68333**	**176.4333333**

Where the notations in the heading of the table; stand for the different operational states of the hauling truck as follow:

W4L: wait for loading W4D: wait for dumping

L: loading D: dumping

EL: exit-loading zone ED: exit-dumping zone

H: hauling R: return

Table 7-4: Duration of states by manual time laps method

	W4L_Duration	W4D_Duration	L_Duration	EL_Duration	H_Duration	D_Duration	ED_Duration	R_Duration	Total_Duration
1	1.7166667	1.6	1.616667	0.15	2.3	0.633333	0.116667	2.75	10.88333333
2	1.5166667	1.566667	1.083333	0.283333	3.433333	0.65	0.116667	2.066666667	10.71666667
3	1.8	0.716667	1.083333	0.2	2.616667	0.75	0.15	3.35	10.66666667
4	1.4833333	1.2	1.583333	0.283333	2.816667	0.716667	0.2	2.716666667	11
5	1.05	1.433333	1.316667	0.266667	2.966667	0.783333	0.216667	2.983333333	11.01666667
6	1.2666667	1.783333	1.183333	0.266667	2.35	0.7	0.2	3.35	11.1
7	1.15	1.4	1.383333	0.216667	2.566667	0.75	0.2	3.716666667	11.38333333
8	1.4166667	0.55	1.35	0.316667	3.816667	0.8	0.316667	4.016666667	12.58333333
9	1.05	1.433333	1.6	0.366667	2.516667	0.716667	0.183333	4.183333333	12.05
10	1.15	1.583333	1.683333	0.316667	2.25	0.816667	0.283333	4.066666667	12.15
11	1.1166667	1.033333	0.866667	0.433333	3.483333	0.9	0.233333	3.316666667	11.38333333
12	1.0166667	0.816667	1.383333	0.483333	3.95	0.866667	0.383333	3.65	12.55
13	0.7833333	1.066667	1.716667	0.25	4.083333	1.233333	0.483333	4.216666667	13.83333333
14	1.3666667	0.783333	0.85	0.35	4.016667	0.916667	0.4	3.933333333	12.61666667
15	0.85	1.266667	1.15	0.416667	4.083333	0.883333	0.45	4.1	13.2
∑	**18.733333**	**18.46667**	**19.6**	**4.833333**	**47.36667**	**12.11667**	**3.75**	**51.68333333**	**177.1333333**

7.1.4 Validation of the Developed Model

The goal of this step is to examine the developed model's output efficiency and accuracy. Equation 7-1, Equation 7-2 and Equation 7-3 were applied for validating the model, where the first equation represents the average invalidity percentage (AIP), which expresses the percentage error, in another word, the relative difference between the developed model outputs and those of the time laps method, which used as a reference. If the AIP value is closer to 0.0, the model is performing well and a value closer to 1.0 shows that the model is not appropriate (Zayed and Halpin, 2005).

$$\mathrm{AIP} = (\textstyle\sum_{i=1}^{n}(1 - \left|\frac{\mathrm{Mi}}{\mathrm{Ri}}\right|) \qquad \text{Equation (7-1)}$$

$$\mathrm{AIP}\ \% = (\textstyle\sum_{i=1}^{n}\left(1 - \left|\frac{\mathrm{Mi}}{\mathrm{Ri}}\right|\right) * \frac{100}{n} \qquad \text{Equation (7-2)}$$

$$\mathrm{AVP}\ \% = 100 - \mathrm{AIP}\ \% \qquad \text{Equation (7-3)}$$

Where:

AIP is Average Invalidity Percentage and AVP is Average Validity Percentage

n is the number of records

M_i, and R_i are the output from the model and the corresponding reference output respectively

Table 7-5 shows the average invalidity percentage of the output total duration of each cycle for both the model and the manual time laps method. Also, the table identifies the minimum and maximum durations from which the management can notice how the change is in duration. The hauling and dumping roads were in a good surface condition in the second trip; hence, the minimum duration was recognized. Vice versa, the maximum duration was recorded in the thirteenth trip; in which the hauling and dumping roads were the ones with bad surface condition. The table also shows that the maximum absolute relative error is 3.04%, while the minimum absolute relative error as little as 0.16 %. Figure 7-9 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.

Table 7-5: Average invalidity percentage of total cycle durations determined by model

Total Duration (Minutes)		
Model	**Time Laps**	**AIP**
10.76666667	10.88333333	0.010719755
10.7	10.71666667	0.00155521
10.88333333	10.66666667	0.0203125
10.86666667	11	0.012121212
11.23333333	11.01666667	0.019667171
11.2	11.1	0.009009009
11.18333333	11.38333333	0.017569546
12.2	12.58333333	0.030463576
12.08333333	12.05	0.002766252
11.95	12.15	0.016460905
11.56666667	11.38333333	0.016105417
12.38333333	12.55	0.013280212
13.75	13.83333333	0.006024096
12.7	12.61666667	0.00660502
12.96666667	13.2	0.017676768

AIP (%)	**1.335577667**
AVP (%)	**98.66442233**
Minimum	**10.7**
Maximum	**13.75**

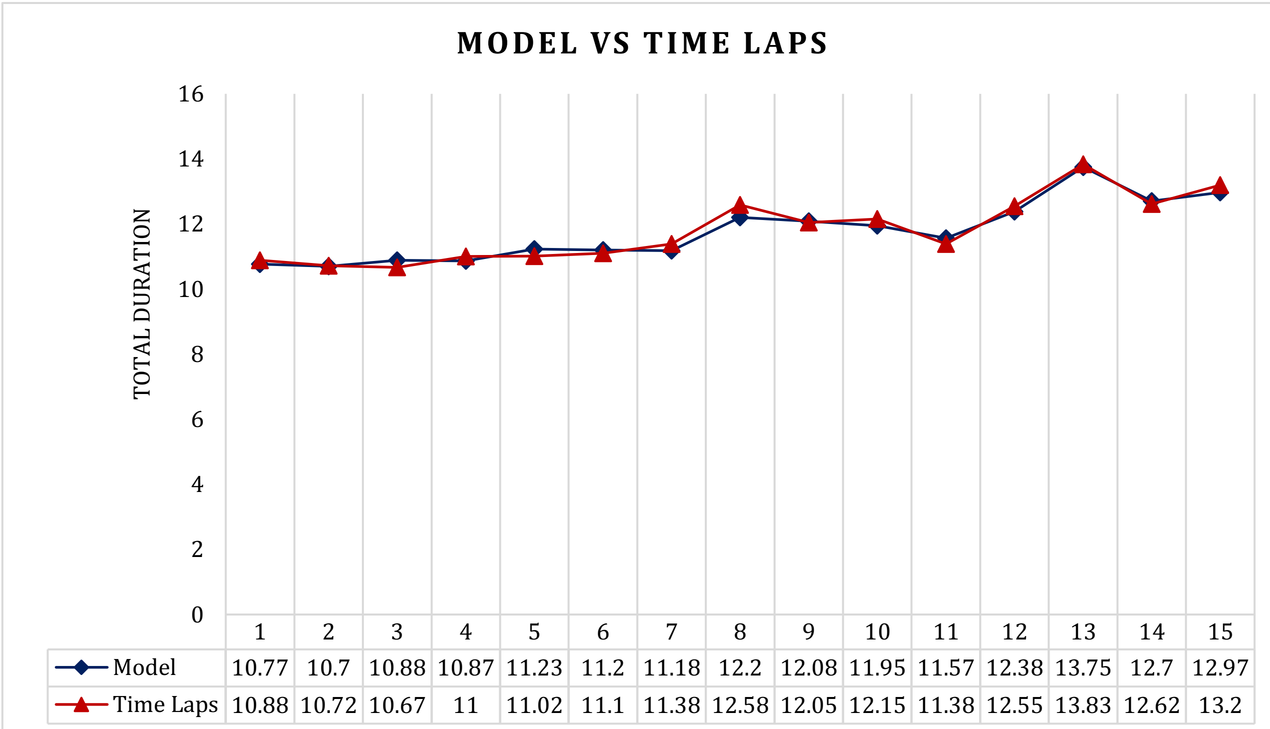


Figure 7-9: Output from model and time laps method for total duration of each cycle

The conditions of hauling roads have a considerable influence on the haul and return durations and hence the total duration of the earthmoving cycle. As mentioned before; the first five trips were utilized the good surface road in haul and return, the second five trips were utilized the good condition road in hauling and the bad condition surface road in return and the last five trips were utilized the bad condition road in both haul and return. Table 7-6 shows the average invalidity percentage of the output hauling and return duration of each cycle for both the model and the manual time laps method. Also, the table identifies the minimum and maximum durations from which the management can notice how the change is in duration. The minimum hauling and return duration were recorded in the first trip, where the hauling and dumping roads were in a good surface condition. While the maximum duration was recorded in the thirteenth and fourteenth trip; in which the hauling and dumping roads were the ones with adverse surface conditions. The table also shows that the maximum absolute relative error is 3.08%, while the minimum absolute relative error as little as 0.27 %. Figure 7-10 shows haul and return 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. The table shows as well the average duration of hauling and return for each of the three groups in which, the duration is elevated incrementally, as the road conditions are of more inferior quality.

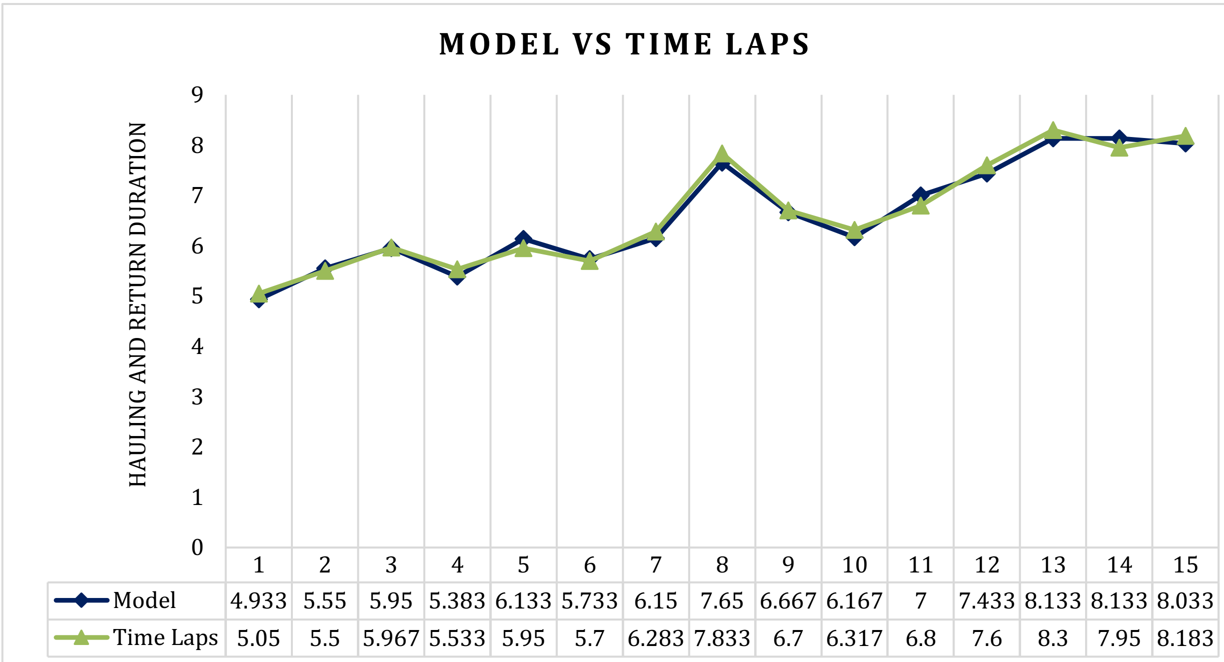
Table 7-6: Average Invalidity Percentage of hauling and return durations determined by model

Trip	Hauling + Return (Minutes)			Average Model
	Model	**Time Laps**	**AIP**	
1	**4.933333333**	5.05	0.02310231	
2	5.55	5.5	0.009090909	
3	5.95	5.966666667	0.002793296	**5.59**
4	5.383333333	5.533333333	0.027108434	
5	6.133333333	5.95	0.030812325	
6	5.733333333	5.7	0.005847953	
7	6.15	6.283333333	0.021220159	
8	7.65	7.833333333	0.023404255	**6.473333333**
9	6.666666667	6.7	0.004975124	
10	6.166666667	6.316666667	0.023746702	
11	7	6.8	0.029411765	
12	7.433333333	7.6	0.021929825	
13	**8.133333333**	8.3	0.020080321	**7.746666667**
14	**8.133333333**	7.95	0.023060797	
15	8.033333333	8.183333333	0.018329939	

AIP (%)	**1.899427427**
AVP (%)	**98.10057257**
Minimum	**4.933333333**
Maximum	**8.133333333**

Where,

AIP is average invalidity percentage.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Model	4.933	5.55	5.95	5.383	6.133	5.733	6.15	7.65	6.667	6.167	7	7.433	8.133	8.133	8.033
Time Laps	5.05	5.5	5.967	5.533	5.95	5.7	6.283	7.833	6.7	6.317	6.8	7.6	8.3	7.95	8.183

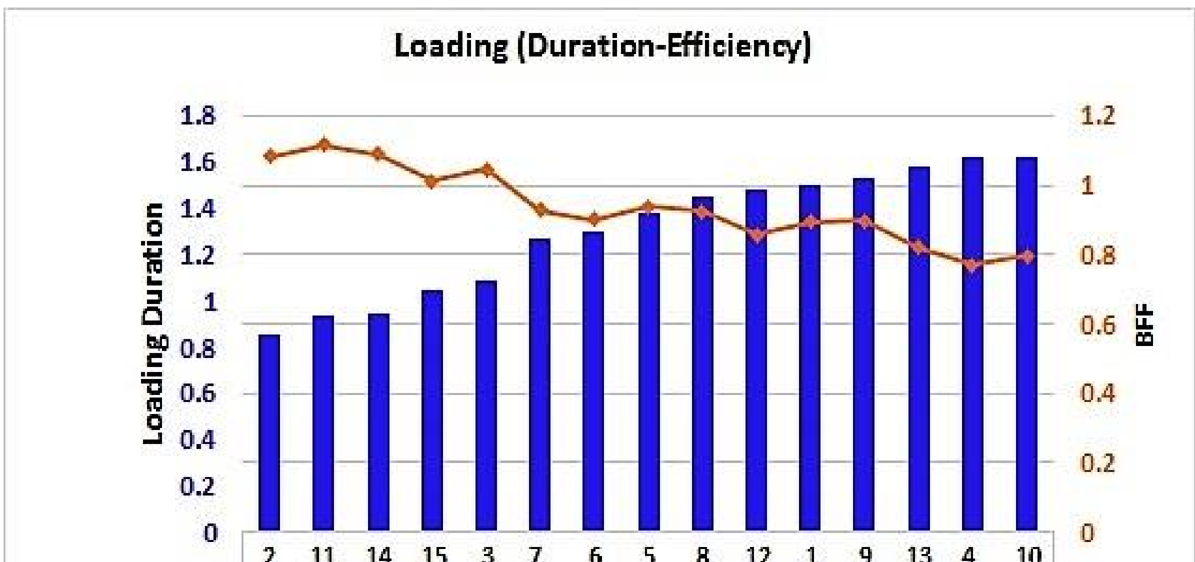
Figure 7-10: Output from model and time laps method for hauling and return durations

Table 7-7 shows the discrete record of hauling and return durations for each cycle in the three groups of the conducted field experiment. Moreover, it shows the average duration of each group. This average facilitates the comparison for easier preliminary detection of the trip with a fault that produces in increasing the duration. As shown in the table, the model recognizes a stoppage throughout hauling state in trip two and eight as well. The model is able to recognize start, end, and duration of any stoppage during the operations; furthermore, it recognizes the stoppage location.

Loading efficiency is one of the most influencing factors on productivity of earthmoving operations. Defects in loading efficiency are referenced to many factors, i.e., operational skills, soil type, and cut depth. Monitoring the bucket fill factor (BFF) is the direct approach to primarily identify any defect to the loading efficiency. Figure 7-11 shows ascended loading durations and corresponding BFF. The chart depicts that; the lesser the efficiency, the longer the loading duration and vice versa. Both durations and BFF were used as input variables of a linear regression model using Minitab® 17.

Table 7-7: Hauling and return duration compared to the average duration under different road conditions

Cycle	Hauling	Average	Return	Average	Remarks
1	2.233333333		2.7		
2	**3.566666667**		1.983333333		
3	2.7	2.863333333	3.25	2.726666667	Stoppage through hauling (Trip 2)
4	2.75		2.633333333		
5	3.066666667		3.066666667		
6	2.266666667		3.466666667		
7	2.483333333		3.666666667		
8	**3.733333333**	2.686666667	3.916666667	3.786666667	Stoppage through hauling (Trip 8)
9	2.633333333		4.033333333		
10	2.316666667		3.85		
11	3.633333333		3.366666667		
12	3.816666667		3.616666667		
13	3.983333333	3.923333333	4.15	3.823333333	
14	4.116666667		4.016666667		
15	4.066666667		3.966666667		



	2	11	14	15	3	7	6	5	8	12	1	9	13	4	10
L_duration	0.85	0.93	0.95	1.05	1.08	1.27	1.3	1.38	1.45	1.48	1.5	1.53	1.58	1.62	1.62
BFF	1.08	1.12	1.09	1.01	1.05	0.93	0.9	0.94	0.92	0.86	0.9	0.9	0.82	0.77	0.8

Figure 7-11: Ascend loading duration and BFF

Equation 7-4 shows the linear regression modeling of the relationship between BFF and loading duration.

$$\mathrm{BFF} = 1.4443 - 0.3876\ \mathrm{L\_Duration} \qquad \text{Equation (7-4)}$$

In order to validate the derived relationship between loading efficiency and duration, the regression model was used to calculate the predicted BFF for all the given loading durations as shown in Table 7-8. The model shows tiny average invalidity of 3.13%. Figure 7-12 shows the model's determined loading durations, corresponding efficiencies and the calculated efficiencies using the developed linear regression modeling equation. Moreover, the chart shows the average absolute error between developed model results and those of regression model.

Table 7-8: Validation of loading duration and BFF regression model

Trip #	L_Duration (minutes)	BFF	Predicted BFF	AIP
2	0.85	1.081309524	1.11484	0.031009
11	0.933333333	1.115236508	1.08254	0.029318
14	0.95	1.090244173	1.07608	0.012992
15	1.05	1.011582328	1.03732	0.025443
3	1.083333333	1.045090596	1.0244	0.019798
7	1.266666667	0.928200739	0.95334	0.027084
6	1.3	0.899941514	0.94042	0.044979
5	1.383333333	0.937064454	0.90812	0.030888
8	1.45	0.923005413	0.88228	0.044123
12	1.483333333	0.855569158	0.86936	0.016119
1	1.5	0.89538872	0.8629	0.036284
9	1.533333333	0.896953466	0.84998	0.05237
13	1.583333333	0.820291781	0.8306	0.012567
4	1.616666667	0.770840553	0.81768	0.060764
10	1.616666667	0.796873946	0.81768	0.02611
			AIP %	**3.13231564**
			AVP %	**96.86768436**

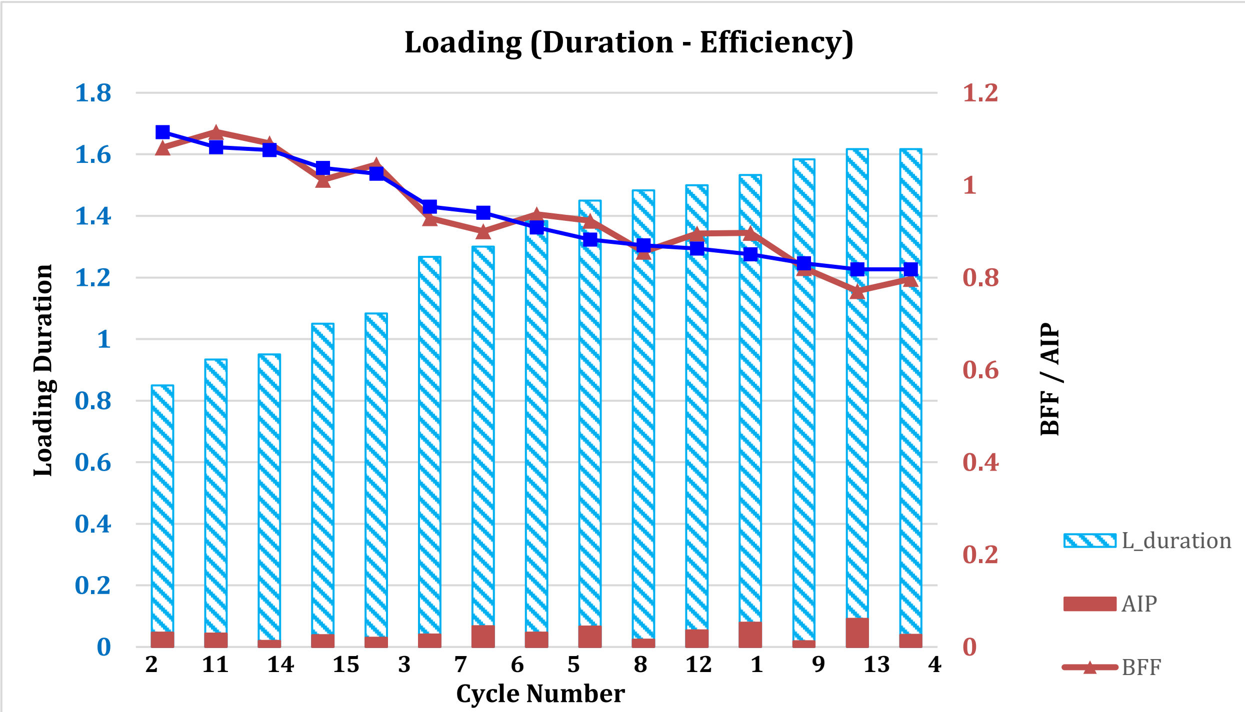


Figure 7-12: Loading durations and corresponding efficiencies by model and regression model

The developed model permits productivity analysis capabilities, where it utilizes planned productivity rate as a reference. In a real project, planned rates are organization predetermined; usually from preceding practise and historical data of past similar projects. In this case study; due to unavailability of historical data, the average productivity rate of the first five trips was considered as a planned productivity rate. The developed model measures actual productivity rates and then analyses those rates by applying two correlated analysis indices. These indices are productivity differential percentage and cumulative productivity differential percentage. American Society Testing and Materials (ASTM E2691 - 09) has introduced this index. Equation (7-5) illuminates the method of determination of productivity differential.

$$\text{Productivity Differential} = \frac{\text{Current Productivity} - \text{Av.Productivity}}{\text{Av.Productivity}} \qquad \text{Equation (7-5)}$$

Table 7-9 shows the measured productivity rates by the developed model and corresponding productivity and cumulative productivity differential percentage. Figure 7-13 shows the productivity differential of each cycle independently. The chart shows fluctuated losses in productivity. While Figure 7-14 depicts the cumulative productivity differential percentage. The chart shows how the percentage of productivity differential was descended starting from the 6th cycle. The frequent inclined records of productivity differential percentage address a problem that affects production rates. The model has the ability to evaluate these negative variances of productivity in near real time and allows web-based visualized representations.

Table7-9: Evaluation of the influenced productivity using productivity differential index

Trip #	Productivity Rate cm^3/min.	Average Productivity Rate	Productivity Differential %	Cumulative Productivity Differential %
1	**75.87682**	**74.24339**	0.022001	0.022001082
2	**71.6166**	74.24339	-0.03538	-0.013379706
3	**76.46126**	74.24339	0.029873	0.016493272
4	**72.86926**	74.24339	-0.01851	-0.002015172
5	**74.393**	74.24339	0.002015	-7.6588E-16
6	68.74543	74.24339	-0.07405	-0.074053175
7	69.42314	74.24339	-0.06492	-0.138978101
8	66.19916	74.24339	-0.10835	-0.247327556
9	67.84835	74.24339	-0.08614	-0.333463644
10	66.40674	74.24339	-0.10555	-0.439017161
11	65.80538	74.24339	-0.11365	-0.552670481
12	64.68586	74.24339	-0.12873	-0.681402815
13	57.73363	74.24339	-0.22237	-0.903776318
14	63.84796	74.24339	-0.14002	-1.043794556
15	61.43607	74.24339	-0.1725	-1.216299022

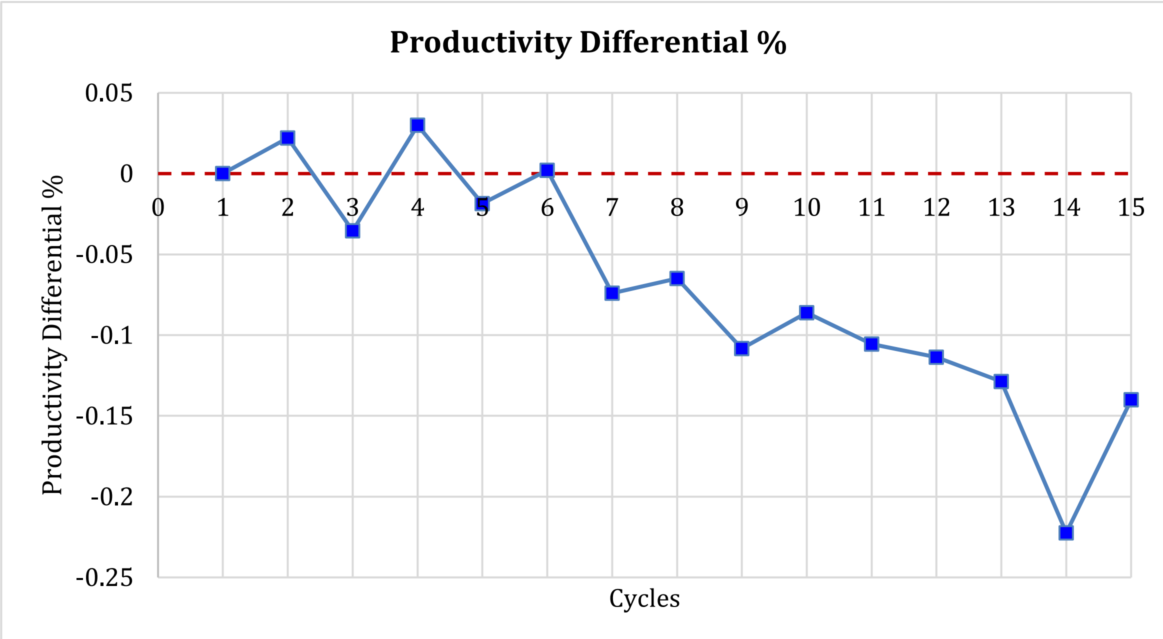


Figure 7-13: Model's calculated percentage of productivity differential for each cycle

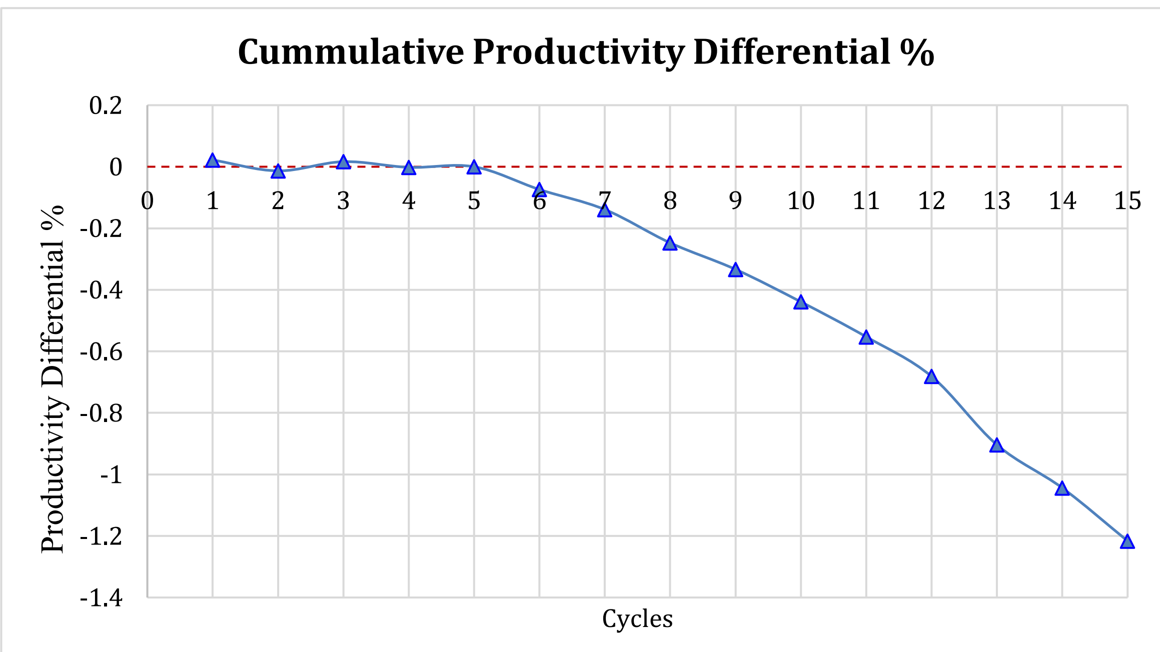


Figure 7-14: Model's calculated cumulative productivity differential for each cycle

7.2 Web-based Near-Real-Time Monitoring

The developed productivity measurement and analysis model guarantees a fully automated application for acquiring and processing raw data to achieve meaningful information. As big as the project as gigantic as the acquired raw data and hence the proposed meaningful information. Tabulation is the common routine for simplifying the representation of the derived information that needed for proper management practice. Since this information has an infinite value and it considers the common denominator in successful delivery of projects, it should be accessible in a stress-free interpreted and timely manner. Therefore, the usual reporting even from an automated model through tabulating the significant outputs; is not the appropriate practice. In other words, a bunch of information in the form of tabulated numerical records could consume considerable time and it is still subjected to misinterpretation. The best practice to avoid these risks is the visualized representation of the required information. Therefore, collaborative productivity measurement and analysis data monitoring, representation and sharing web-based platform was developed.

This model exploits both the power and flexibility of the developed MySQL database in addition to Knowi® representation and analytics abilities. Knowi is an integrated analytics platform built for modern data stacks. Knowi data management and analytics engine is capable of dealing with both structured and unstructured data alike. The developed system is mainly processing the raw data in a developed MySQL in the cloud database. Then, near real-time, monitoring not only measurement and analysis results for each cycle but also road and driving condition analysis can be accessed in Knowi platform through any internet browser. Figure 7-15 depicts the framework of the web-based monitoring system schematically.

Web-based productivity monitoring through Knowi provides an efficient collaborating environment for tracking productivity and causes behind its variations. It also generates a pre-customized timely distribution of productivity and progress reports. Hourly, daily, weekly and to date reports can be sent by emails in a pre-determined time instants to one or more project management team members.

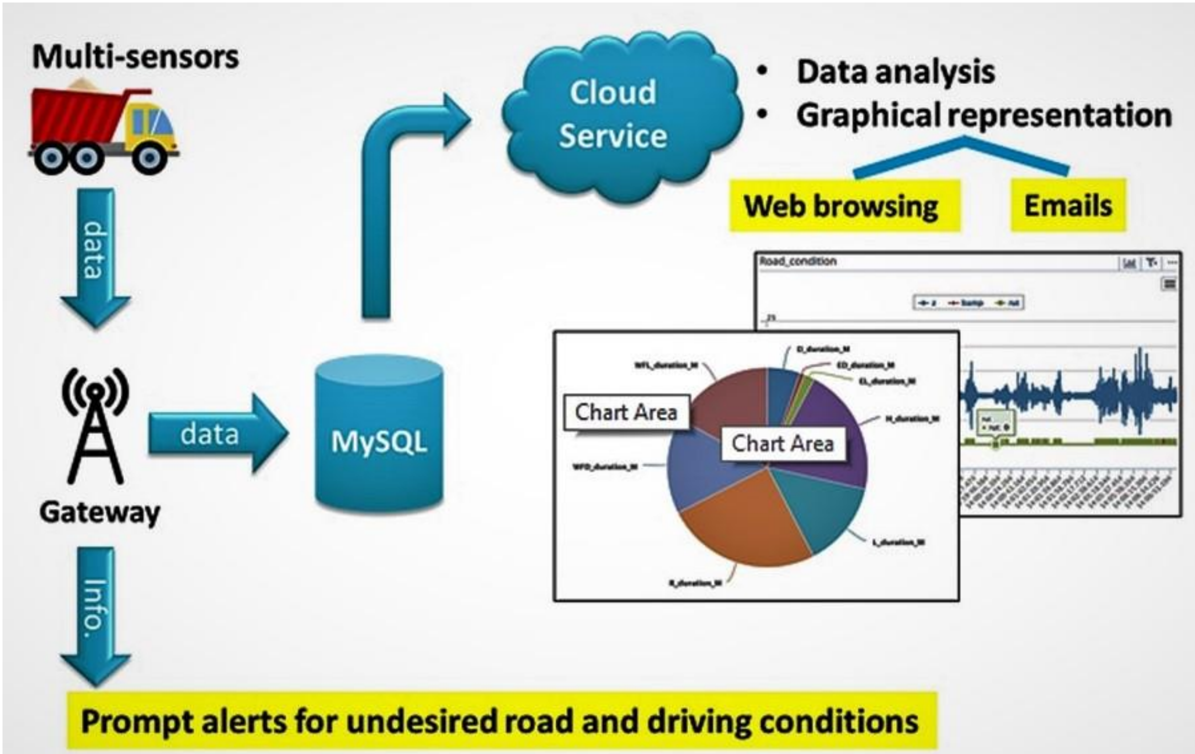


Figure: 7-15: Schematic framework of the web-based monitoring system

7.2.1 Web-based Productivity Monitoring

However, analytics tools in Knowi are customizable to satisfy management needs, it provides artificial intelligence capabilities, i.e. natural language queries. The web-based intelligent engine allows friendly non-programming specialist user's inquiries using natural language. Figure 7-16 shows an example of utilizing natural language queries. In addition, the data analytics and representation platform can generate predesignated trigger notifications; hence, it allows users to set triggers on any data to drive an action including email alerts to trigger actions in downstream applications.

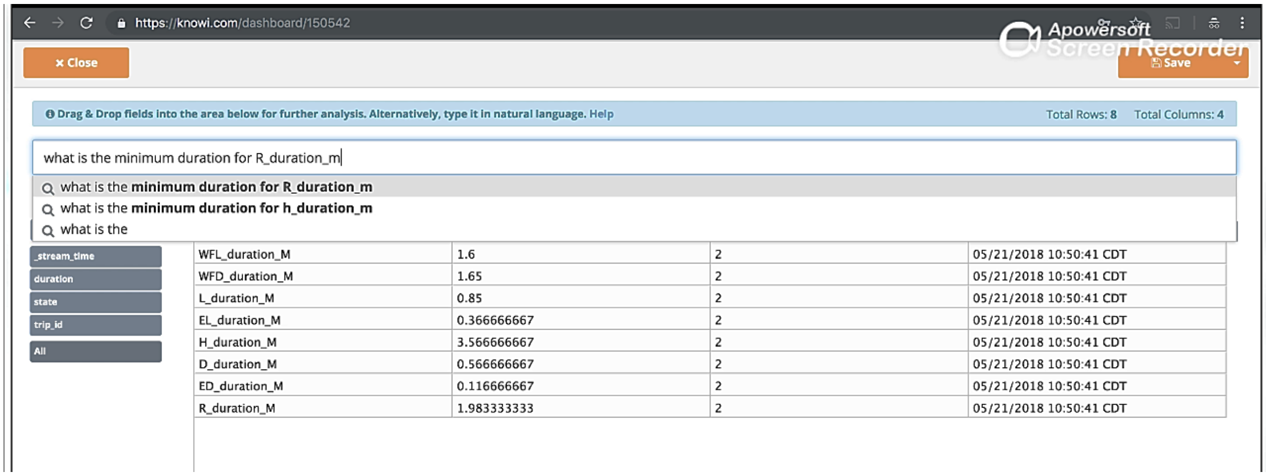
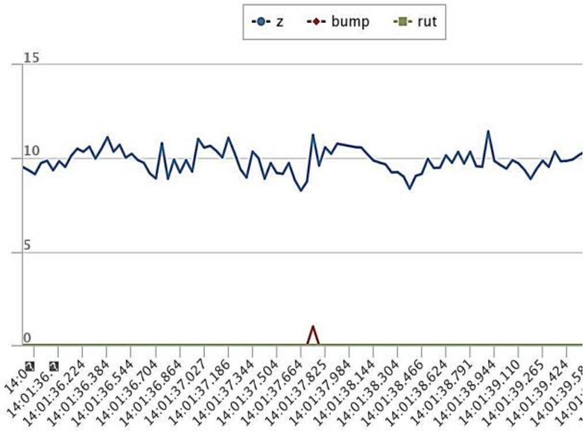


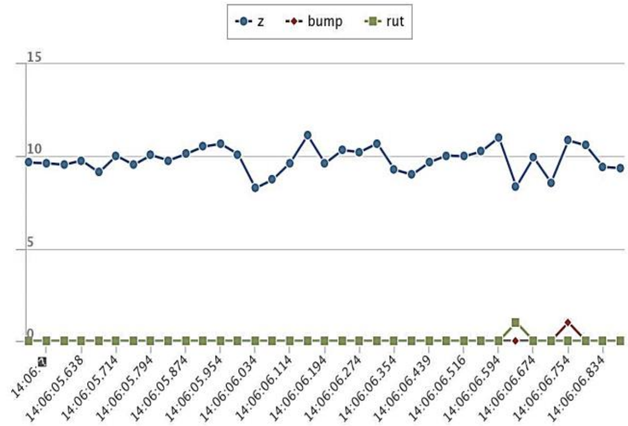
Figure 7-16: Example of utilizing natural language queries in the web-based platform

7.2.2 Web-based Road Conditions Monitoring

Interactive road condition interactive charts in which a computer mouse tick on a recognized road anomaly (bump or rut) that are shown in the chart, directs the user to a geo-spatiotemporal representation of that anomaly. A bump and successive rut and bump are identified in road condition analysis chart as shown in Figure 7-17, a and b respectively. While Figure 7-18, a and b shows the geo-spatiotemporal representation of the identified bump and rut respectively; showing both location and time of detection on the map.

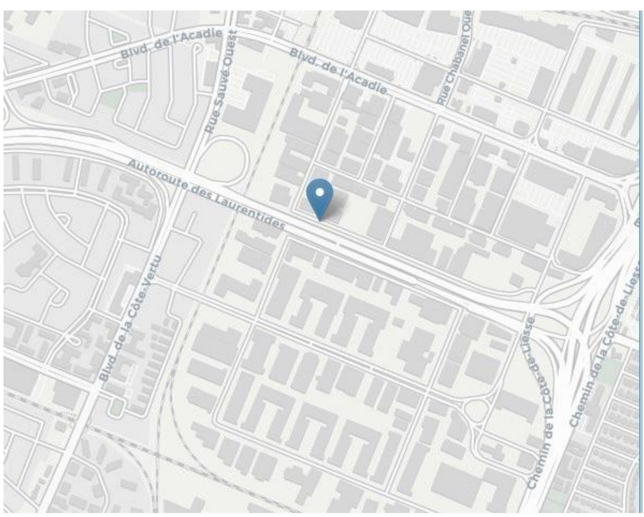


(a) Bump identification

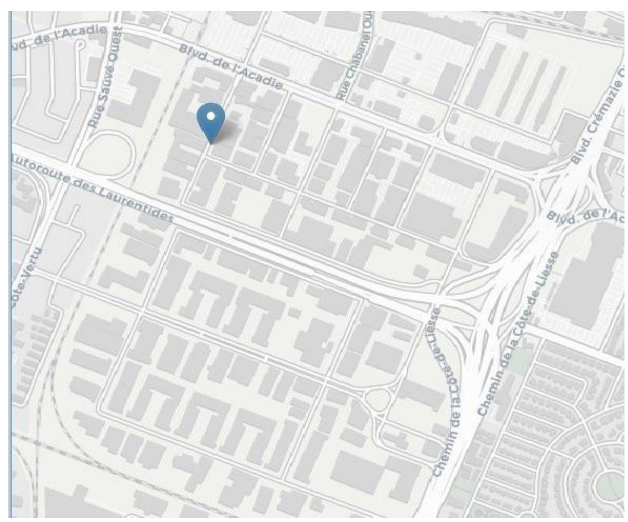


(b) Successive rut and bump identification

Figure 7-17: Web-based identification of bumps and ruts



(a) Bump location representation



(b) Rut location representation

Figure 7-18 : Web-based spatiotemporal representation of bumps and ruts

7.3 Summary

This chapter introduces the validation of the developed model for automated productivity measurement and analysis of earthmoving operations. A pre-designed case study was used to reveal the applicability and accuracy of the developed model in measuring, monitoring and analyzing actual productivity. The model was validated using two integrated phase's case study; the first phase utilized 1:24 loader and dumping truck. The second phase was a field experimental simulation of earthmoving operations. The loading and dumping data were retrieved from the first phase while all the other operational states of the hauling truck were extracted from the second phase. The data from both two phases was processed in the designed MySQL database. Results were drawn and discussed to shed lights on the model's applicability, validity and capabilities . The developed model demonstrated to measure actual productivity in an accurate manner, in addition to the timely recognition of undesired variances in productivity. A web-based platform was utilized to allow near real-time graphical representation of the model's outputs.

8 Chapter 8: Conclusions and Future Work

8.1 Summary and Conclusions

This research incorporating many objectives to automate data acquisition, productivity tracking and monitoring efficiently. These objectives were to study, design and develop a customized data acquisition model with automated measurement and analysis capabilities that satisfy the needs of earthwork projects. This research has a special focus on profiting from the advancement in wireless sensing technologies, artificial intelligence techniques, and the Internet of Things (IoT) to deliver near real-time tracking and monitoring of productivity and performance of earthmoving operations. This research presented three integrated models for cost-effective smart productivity monitoring, measurement, assessment and analysis of earthwork projects. The models were developed sequentially, whereas the utilized data acquisition module was configured in a customized manner to collect the necessary data. Then, the collected data streamed to a designated MySQL database that applies data fusion and mining algorithms in the form of encoding MySQL procedures. It is worthy to mention that the developed data acquisition model was customized to serve earthmoving operations and highway construction projects, while it could serve other construction projects, i.e., dams.

This customized data acquisition module consists of a microcontroller equipped with a several types of selected sensors. The selection of sensors was based on fuzzy-set based analysis of experts' responses to a questionnaire. This questionnaire was designed to poll experts' evaluation of different influencing factors contained in literature and basic references in earthmoving and equipment management i.e., Peuifoy and Schexnayder, Day and Benjamin, and Nunnally. Based on the questionnaire analysis, the selected sensors were GPS module as well as a collection of sensors such as load cell, 3D accelerometer, soil water content, temperature, and humidity sensor. The developed model for customizing the configurations of data acquisition systems overcomes not only limitations of the common utilized standalone GPS but also eliminates the subjectivity associated in customization process. The collected data from the aforementioned model is the input for the automated productivity measurement, driving, and road condition analysis model. This model applies the data fusion algorithm that improves productivity measurement and analysis, as it guarantees the benefit of all the acquired data. The developed model for productivity analysis of earthmoving operations aims at integrating the superior sensing technologies along with artificial intelligence techniques to develop a fully automated productivity analysis model that tracks the adverse factors and flags any productivity deficiency in a timely manner. Also, the developed productivity measurement and analysis models have high potential applicability in various types of construction projects. A web-based monitoring platform was developed using cloud-based integration of the developed database and Knowi® analytics. The developed web-based platform allows near real-time graphical representation of the output from the developed models for productivity measurement and analysis.

8.2 Contributions

The contributions of this research are projected to overcome a number of gaps associated with existing automated site data acquisition systems and current practice in measuring, tracking and analyzing the productivity of earthmoving operations. The research contributions can be concluded as follow:

- Study, identify, evaluate and prioritize factors influencing the productivity of earthmoving operations in order to consider that in customizing the configuration of data acquisition systems.
- Develop a systematic method for customizing the configuration of data acquisition systems for earthmoving operations. This method eliminates the subjectivity associated with customizing the configurations of data acquisition systems.
- Develop a customized, cost-effective automated data acquisition system utilizes cutting-edge, innovative sensing and communication technologies. The developed systematic customization model guarantees flexibility that could serve other applications in construction (e.g., safety and collision detection in job sites).
- Develop a web-based monitoring platform that guarantees appropriate graphical representation for monitoring productivity of earthmoving operations in near real-time. Automate the productivity measurement and analysis process using data mining, fusion algorithms; providing fast, robust and truthful outcomes.
- Consider the uncertainty associated with weather condition sensors reading by integrating weather API calls, which guarantee redundancy through another truthful source of data.

- Examine how embracing the technological revolution can positively impact a vital key activity in construction like earthmoving operations.
- Develop cost-effective machine-based instead of the common conventional expensive human-based to measure and analyze productivity of earthmoving operations.

8.3 Limitations

- The data related to planned quantities and productivity rates have to be provided manually into the developed database.
- The developed models supposed to be applied on adequately planned earthmoving operations only, where a balanced number of trucks that guarantee efficient operations was determined.
- The developed models were validated using a laboratory, scaled and real field experiments.

8.4 Recommendations for Future Work

A methodology and a computational procedure for customized configuration of data acquisition systems in earthmoving operations, and automated productivity measurement and analysis were presented in this study. The developed model and the computational platform are flexible to be applied to other domains of construction projects. However, the expansion of the model's potential applications could benefit from the following recommendations for future research work:

- Validating the model using a real case study.
- Promoting the model's applicability to embrace other applications in the construction industry.
- Linking the productivity analysis model with computerized planned quantities and duration extractor such as BIM 360 Field.
- Integrating machine learning software, i.e., Matlab with the developed MySQL database to permit further automated analysis capabilities.

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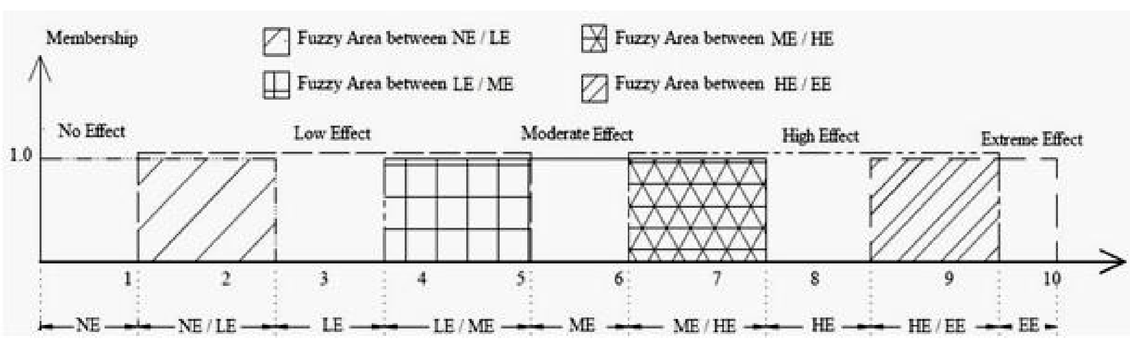
Appendix I

Survey of Major Factors Influencing Earthmoving Operations Productivity

Contractors are routinely utilizing heavy construction equipment in earthmoving operations and road construction. Economical utilization of these equipment has a great impact on the contractor's profitability. Several factors can impact the productivity and cost of earthmoving operations such as the machine utilization, fuel consumption, labor, and soil properties.
This survey aims to examine some of these factors and to identify their impact on earthmoving operation productivity and profitability. In addition, it explores some of the problems contractors can run into and look for early warning signs that can pin points to the underlying issues. The report that is generated from the results of this survey will seek to recommend best practices contractors can adopt in order to maximize their chances of delivering effective and efficient earthmoving projects.
This research is conducted at Concordia University, Montreal, Quebec, Canada. Any data obtained will not be used for either commercial purposes or made available to third party. The results from this study will be available to all participants.

The following scheme explains the utilized scale, please make you respond on each question according to this scale unless otherwise mentioned.



Fuzzy linguistic-Numeric conversion scheme

1. Which of the following best describes your job title?
Mark only one oval.

- ○ Project manager
- ○ Construction manager
- ○ Site engineer
- ○ Foreman
- ◉ Operator
- ○ Academic staff
- ○ Other:

2. How many years of experience do you have in Earthmoving / Highways construction projects?
Mark only one oval.

- Less than 5 years
- 5 - 10 years
- 10 - 15 years
- More than 15 years

3. Where are you located?

4. What is the annual volume of your business in construction projects?
Mark only one oval.

- Less than $100 Million
- $100 - $250 Million
- $2500 - $500 Million
- More than $500 Million

5. With respect to soil properties, Please weigh the influence of the following factors on the productivity of earthmoving operations.
Mark only one oval per row.

	No effect	Minor effect	Moderate effect	High effect	Extreme effect
Loadability (A measure of the difficulty in excavating and loading a soil)					
Moisture Content (Water content in soil)					
Swelling factor (The percentage of increase in the volume)					
Compactability (The ability of soil to be compacted)					

	No effect	Minor effect	Moderate effect	High effect	Extreme effect
Soil weight	○	○	○	○	○
Others (specify below)	○	○	○	○	○

Please enter one response per row

6. The condition of access roads to loading or dumping site can influence the productivity of earth-moving operations, rate on a scale from 1-5 the influence of the following access road conditions:
Mark only one oval per row.

	No effect	Minor effect	Moderate effect	High effect	Extreme effect
Loosely soil road	○	○	○	○	○
Rutty road	○	○	○	○	○
Congested road	○	○	○	○	○
Road with up or downhills	○	○	○	○	○
Muddy road	○	○	○	○	○
Snowy road	○	○	○	○	○
Others (specify below)	○	○	○	○	○

Please enter one response per row

7.Wheel slippage is an undesirable phenomenon which results in loss of traction Please, evaluate the following conditions that could lead to wheel slippage.
Mark only one oval per row.

	No effect	Minor effect	Moderate effect	High effect	Extreme effect
Loosely soil road	○	○	○	○	○
Road with up or downhills	○	○	○	○	○
Muddy road	○	○	○	○	○

	No effect	Minor effect	Moderate effect	High effect	Extreme effect
Snowy road					
Excessive loads					
Operator skills					
Tire pressure					
Others (specify below)					

Please enter one response per row

8. The bucket fill factor significantly affects the productivity of earthmoving operations. Please, in the light of your experience, evaluate the following factors that affect the buck fill factor.
Mark only one oval per row.

	No effect	Minor effect	Moderate effect	High effect	Extreme effect
Soil hardness					
Change of cut depth					
Operator skills					
Excavated soil particle size					
Power of machine					
Others (specify below)					

Please enter one response per row

9. The fuel consumption efficiency of the machine; directly affects the operational cost.Please, based on your experience, evaluate the following factors that could cause low fuel consumption efficiency.
Mark only one oval per row.

	No effect	Minor effect	Moderate effect	High effect	Extreme effect
Tire pressure					
Age of equipment					

	No effect	Minor effect	Moderate effect	High effect	Extreme effect
Operator skills	○	○	○	○	○
Excessive loads	○	○	○	○	○
Wind resistance	○	○	○	○	○
Bad road conditions	○	○	○	○	○
Cold weather	○	○	○	○	○
Frequent short trips	○	○	○	○	○
Wheel slippage and excessive turk	○	○	○	○	○
Engine tuning / maintenace	○	○	○	○	○
Others (specify below)	○	○	○	○	○

Please enter one response per row

There are three operation zones (power zone, slow speed zone and high speed zone), In the power zone, maximum power is required to overcome adverse site such as rough terrain or steep slopes. The slow-speed hauling zone is similar to the power zone since power, more than speed, is the essential factor. Site conditions are slightly better than in the power zone, and the haul distance is short. In the high-speed hauling zone, the ground conditions are good, longer, or well-maintained haul roads are established.

10. In the light of the above mentioned definition of the operating zones and depending on various conditions (e.g. the ground condition, hauling travel distance and grade resistance), the operator have to choose the relevant appropriate gear speed. Please, evaluate the impact of inappropriate choice of operation zones for the following cases
Mark only one oval per row.

	No effect	Minor effect	Moderate effect	High effect	Extreme effect
Using gear speed lower than the appropriate	○	○	○	○	○
Using gear speed higher	○	○	○	○	○

	No effect	Minor effect	Moderate effect	High effect	Extreme effect
than the appropriate					

Please enter one response per row

11. Operation cycle time is the period required to complete one cycle. Weigh the factors that could improve the operation cycle time

Mark only one oval per row.

	No importance	Low importance	Moderate importance	High importance	Extreme importance
Least waiting durations	○	○	○	○	○
Considering equipment balance	○	○	○	○	○
Skilled drivers and operators	○	○	○	○	○
Strict supervision	○	○	○	○	○
Good road conditions	○	○	○	○	○
Others (specify below)	○	○	○	○	○

Please enter one response per row

12. What is the impact of increasing the cycle time on the productivity of Earth-moving operations in case of the following cases?

Mark only one oval per row.

	No impact	Low impact	Moderate impact	High impact	Extreme impact
+5 % of the planned duration	○	○	○	○	○
+10 % of the planned duration	○	○	○	○	○
+15 % of the planned duration	○	○	○	○	○

	No impact	Low impact	Moderate impact	High impact	Extreme impact
+20 % of the planned duration	○	○	○	○	○
+25 % of the planned duration	○	○	○	○	○

Please enter one response per row

13. Please, evaluate the impact of the following weather conditions on the productivity of Earth-moving operations

Mark only one oval per row.

	No effect	Minor effect	Moderate effect	High effect	Extreme effect
Rain	○	○	○	○	○
Humidity	○	○	○	○	○
Wind	○	○	○	○	○
Temperature	○	○	○	○	○
Fog	○	○	○	○	○
Sun shine	○	○	○	○	○
Others (specify below)	○	○	○	○	○

Please enter one response per row

14. Most crafts do not work in the rain, but many do. Up which level of rain quantity the work in different operations may not be stopped?

Mark only one oval per row.

	Up to 5 mm	5 - 10 mm	10 - 15 mm	15 - 20 mm	More than 20 mm
Loading	○	○	○	○	○
Travel / Return	○	○	○	○	○
Dump	○	○	○	○	○

Please enter one response per row

15. Please, assess the influence of rain on the productivity (reduction) for the following rain records.

Mark only one oval per row.

	No effect	Minor effect	Moderate effect	High effect	Extreme effect
Less than 5 mm	○	○	○	○	○
5 - 10 mm	○	○	○	○	○
10 - 15 mm	○	○	○	○	○
15 - 20 mm	○	○	○	○	○
More than 20 mm	○	○	○	○	○
Others (specify below)	○	○	○	○	○

Please enter one response per row

16. Different regions and locations around the world have different amounts of daylight hours, depending on the season. Please, assess the influence of the seasonal daylight duration on the productivity.
Mark only one oval per row.

	No effect	Minor effect	Moderate effect	High effect	Extreme effect
Fall	○	○	○	○	○
Winter	○	○	○	○	○
Spring	○	○	○	○	○
Summer	○	○	○	○	○

Please enter one response per row

17.There are many factors related to labors which may affect the productivity Please, evaluate the impact of the following factors on the productivity of Earth-moving operations
Mark only one oval per row.

	No effect	Minor effect	Moderate effect	High effect	Extreme effect
Over time	○	○	○	○	○
Absenteeism	○	○	○	○	○
Learning curve	○	○	○	○	○
Moral and attitude	○	○	○	○	○

	No effect	Minor effect	Moderate effect	High effect	Extreme effect
Fatigue	○	○	○	○	○
Others (specify below)	○	○	○	○	○

Please enter one response per row

18. What is the usual percentage of workers in Earth-moving operations (e.g. operators) who are motivated to work overtime?
Mark only one oval.

- ○ Less than 25 %
- ○ 25 - 50 %
- ○ 50 - 75 %
- ○ More than 75 %

19. Please, evaluate the impact of overtime on productivity (e.g. reduction in productivity) in the following numbers of overtime hours.
Mark only one oval per row.

	No impact	Minor impact	Moderate impact	High impact	Extreme impact
2 Hrs/day	○	○	○	○	○
4 Hrs/day	○	○	○	○	○
6 Hrs/day	○	○	○	○	○
8 Hrs/day	○	○	○	○	○

Please enter one response per row

20. What are the other factors that might impact the productivity of Earth-moving operations? Please, evaluate these factors on the same shown scale.

Appendix II

Generic databases for weather conditions and forecast

Example of API respond:

```
{"coord":
{"lon":145.77,"lat":-16.92},
"weather":[{"id":803,"main":"Clouds","description":"broken
clouds","icon":"04n"}],
"base":"cmc stations",
"main":{"temp":293.25,"pressure":1019,"humidity":83,"temp_min":289.82,"temp_m
ax":295.37},
"wind":{"speed":5.1,"deg":150},
"clouds":{"all":75},
"rain":{"3h":3},
"dt":1435658272,
"sys":{"type":1,"id":8166,"message":0.0166,"country":"AU","sunrise":143561079
6,"sunset":1435650870},
"id":2172797,
"name":"Cairns",
"cod":200}
```


Parameters:

- `coord`
  - ✓ `coord.lon` City geo location, longitude
  - ✓ `coord.lat` City geo location, latitude
- `weather` (more info Weather condition codes)
  - ✓ `weather.id` Weather condition id
  - ✓ `weather.main` Group of weather parameters (Rain, Snow, Extreme etc.)
  - ✓ `weather.description` Weather condition within the group
  - ✓ `weather.icon` Weather icon id
- `base` Internal parameter
- `main`
  - ✓ `main.temp` Temperature. Unit Default: Kelvin, Metric: Celsius, Imperial: Fahrenheit.
  - ✓ `main.pressure` Atmospheric pressure (on the sea level, if there is no sea_level or grnd_level data), hPa
  - ✓ `main.humidity` Humidity, %
  - ✓ `main.temp_min` Minimum temperature at the moment. This is deviation from current temp that is possible for large cities and megalopolises geographically expanded (use these parameter optionally). Unit Default: Kelvin, Metric: Celsius, Imperial: Fahrenheit.
  - ✓ `main.temp_max` Maximum temperature at the moment. This is deviation from current temp that is possible for large cities and megalopolises geographically expanded (use these parameter optionally). Unit Default: Kelvin, Metric: Celsius, Imperial: Fahrenheit.
  - ✓ `main.sea_level` Atmospheric pressure on the sea level, hPa
  - ✓ `main.grnd_level` Atmospheric pressure on the ground level, hPa
- `wind`
  - ✓ `wind.speed` Wind speed. Unit Default: meter/sec, Metric: meter/sec, Imperial: miles/hour.
  - ✓ `wind.deg` Wind direction, degrees (meteorological)
- `clouds`
  - ✓ `clouds.all` Cloudiness, %

- `rain`
  - ✓ `rain.3h` Rain volume for the last 3 hours
- `snow`
  - ✓ `snow.3h` Snow volume for the last 3 hours
- `dt` Time of data calculation, unix, UTC
- `sys`
  - ✓ `sys.type` Internal parameter
  - ✓ `sys.id` Internal parameter
  - ✓ `sys.message` Internal parameter
  - ✓ `sys.country` Country code (GB, JP etc.)
  - ✓ `sys.sunrise` Sunrise time, unix, UTC
  - ✓ `sys.sunset` Sunset time, unix, UTC
- `id` City ID
- `name` City name
- `cod` Internal parameter

https://openweathermap.org/current

Appendix III

Several programming syntaxes for different utilized sensors

A. Recorddind different sensor data to SD card

```
// variables
float temp = 0.0;
```

```
int light = 0;
i // Put your libraries here (#include ...)
#include <WaspSensorAgr_v20.h>
#include <WaspGPS.h>
// define GPS timeout when connecting to satellites
// this time is defined in seconds (240sec = 4minutes)
#define TIMEOUT 10
// define status variable for GPS connection
bool status;
float value_light;
float value_hum;
float value_temp;
// define file name: MUST be 8.3 SHORT FILE NAME
char filename[]="OUTPUT.csv";
// define variable
uint8_t sd_answer;
void setup() {
   // put your setup code here, to run once:
 // Turn on the USB and print a start message
  USB.ON();
  USB.println(F("start"));
  delay(100);
  // Turn on the sensor board
  SensorAgrv20.ON();
  // Turn on the RTC
  RTC.ON();
  SD.ON();
   // Delete file
  sd_answer = SD.del(filename);
  if( sd_answer == 1 )
  {
   USB.println(F("file deleted"));
  }
  else
  {
   USB.println(F("file NOT deleted"));
  }

  // Create file
  sd_answer = SD.create(filename);

  if( sd_answer == 1 )
  {
   USB.println(F("file created"));
  }
  else
  {
   USB.println(F("file NOT created"));
  }
  // Set GPS ON
  GPS.ON();

}

void loop() {
```

```
  ////////////////////////////////////////////////
 // 1. wait for GPS signal for specific time
 ////////////////////////////////////////////////
 status = GPS.waitForSignal(TIMEOUT);

 if( status == true )
 {
//    USB.println(F("\n----------------------"));
   USB.println(F("Connected"));
//    USB.println(F("----------------------"));
 }
 else
 {
 //   USB.println(F("\n----------------------"));
   USB.println(F("GPS TIMEOUT. NOT connected"));
//    USB.println(F("----------------------"));
 }

 //**********************************
//  USB.print(RTC.getTime());
 // Part 1: Sensor reading
 // Turn on the sensor and wait for stabilization and response time
 SensorAgrv20.setSensorMode(SENS_ON, SENS_AGR_HUMIDITY);
//  delay(1000);

 // Read the humidity sensor
 value_hum = SensorAgrv20.readValue(SENS_AGR_HUMIDITY);

 // Turn off the sensor
 SensorAgrv20.setSensorMode(SENS_OFF, SENS_AGR_HUMIDITY);

 // Part 2: USB printing
 // Print the humidity value through the USB
//  USB.print(F("Humidity: "));
//  USB.print(value_hum);
//  USB.println(F("%RH"));

 // delay(1000);
 //------------
 SensorAgrv20.setSensorMode(SENS_ON, SENS_AGR_LDR);
 // delay(100);

 // Read the LDR sensor
 value_light = SensorAgrv20.readValue(SENS_AGR_LDR);

 // Turn off the sensor
 SensorAgrv20.setSensorMode(SENS_OFF, SENS_AGR_LDR);

 // Part 2: USB printing
 // Print the LDR value through the USB
//  USB.print(F("Luminosity: "));
//  USB.print(value_light);
//  USB.println(F("V"));

//  delay(1000);
 //-----------
```

```
   // Part 1: Sensor reading
  // Turn on the sensor and wait for stabilization and response time
  SensorAgrv20.setSensorMode(SENS_ON, SENS_AGR_TEMPERATURE);
///  delay(100);

  // Read the temperature sensor
  value_temp = SensorAgrv20.readValue(SENS_AGR_TEMPERATURE);

  // Turn off the sensor
  SensorAgrv20.setSensorMode(SENS_OFF, SENS_AGR_TEMPERATURE);

  // Part 2: USB printing
  // Print the temperature value through the USB
//  USB.print(F("Temperature: "));
//  USB.print(value_temp);
//data = RTC.getTime() + "," + value_temp + "," + value_hum + "," + value_light;
//USB.print(RTC.getTime());
//USB.print(F(","));
//USB.print(value_temp);
//USB.print(F(","));
//USB.print(value_hum);
//USB.print(F(","));
//USB.println(value_light);
 // define local buffer for float to string conversion
  char str_value_temp[10];
  char str_value_hum[10];
  char str_value_light[10];
  char NS_ind = GPS.NS_indicator;
  char str_NS_ind[1];
  snprintf( str_NS_ind, sizeof(str_NS_ind),"%c", NS_ind);

  char EW_ind = GPS.EW_indicator;
  char str_EW_ind[1];
  snprintf( str_EW_ind, sizeof(str_EW_ind),"%c", EW_ind);

  // use dtostrf() to convert from float to string:
  // '1' refers to minimum width
  // '3' refers to number of decimals
  dtostrf( value_temp, 1, 3, str_value_temp);
  dtostrf( value_hum, 1, 3, str_value_hum);
  dtostrf( value_light, 1, 3, str_value_light);
// 1 - It appends “he” in file indicating 2-byte length
//  sd_answer = SD.append(filename, RTC.getTime());
if( status == true )
  {
 // sd_answer = SD.append(filename, GPS.dateGPS);
  sd_answer = SD.append(filename, ",");
//  sd_answer = SD.append(filename, GPS.timeGPS);
  sd_answer = SD.append(filename, ",");
//  sd_answer = SD.append(filename, GPS.latitude);
  sd_answer = SD.append(filename, ",");
//  sd_answer = SD.append(filename, str_NS_ind);
  sd_answer = SD.append(filename, ",");
//  sd_answer = SD.append(filename, GPS.longitude);
  sd_answer = SD.append(filename, ",");
 // sd_answer = SD.append(filename, str_EW_ind);
```

```
  sd_answer = SD.append(filename, ",");
 // sd_answer = SD.append(filename, GPS.altitude);
  sd_answer = SD.append(filename, ",");
 // sd_answer = SD.append(filename, GPS.speed);
  sd_answer = SD.append(filename, ",");
 // sd_answer = SD.append(filename, GPS.course);
  sd_answer = SD.append(filename, ",");
}
  sd_answer = SD.append(filename, str_value_temp);
  sd_answer = SD.append(filename, ",");
  sd_answer = SD.append(filename, str_value_hum);
  sd_answer = SD.append(filename, ",");
  sd_answer = SD.append(filename, str_value_light);
  sd_answer = SD.append(filename, "\n");

  if( sd_answer == 1 )
  {
    USB.println(F("\n1 - append \"he\" in file indicating 2-byte length"));
  }
  else
  {
    USB.println(F("\n1 - append error"));
  }

  // show file
  SD.showFile(filename);

//USB.println(F("ºC"));

  delay(1000);
}
```

B. Sending GPS reading to Meshlium gateway via Wi-Fi

```
#include <WaspFrame.h>
#include <WaspGPS.h>
#include <WaspWIFI.h>
// Define GPS timeout when connecting to satellites
// this time is defined in seconds (240sec = 4minutes)
#define TIMEOUT 240
```

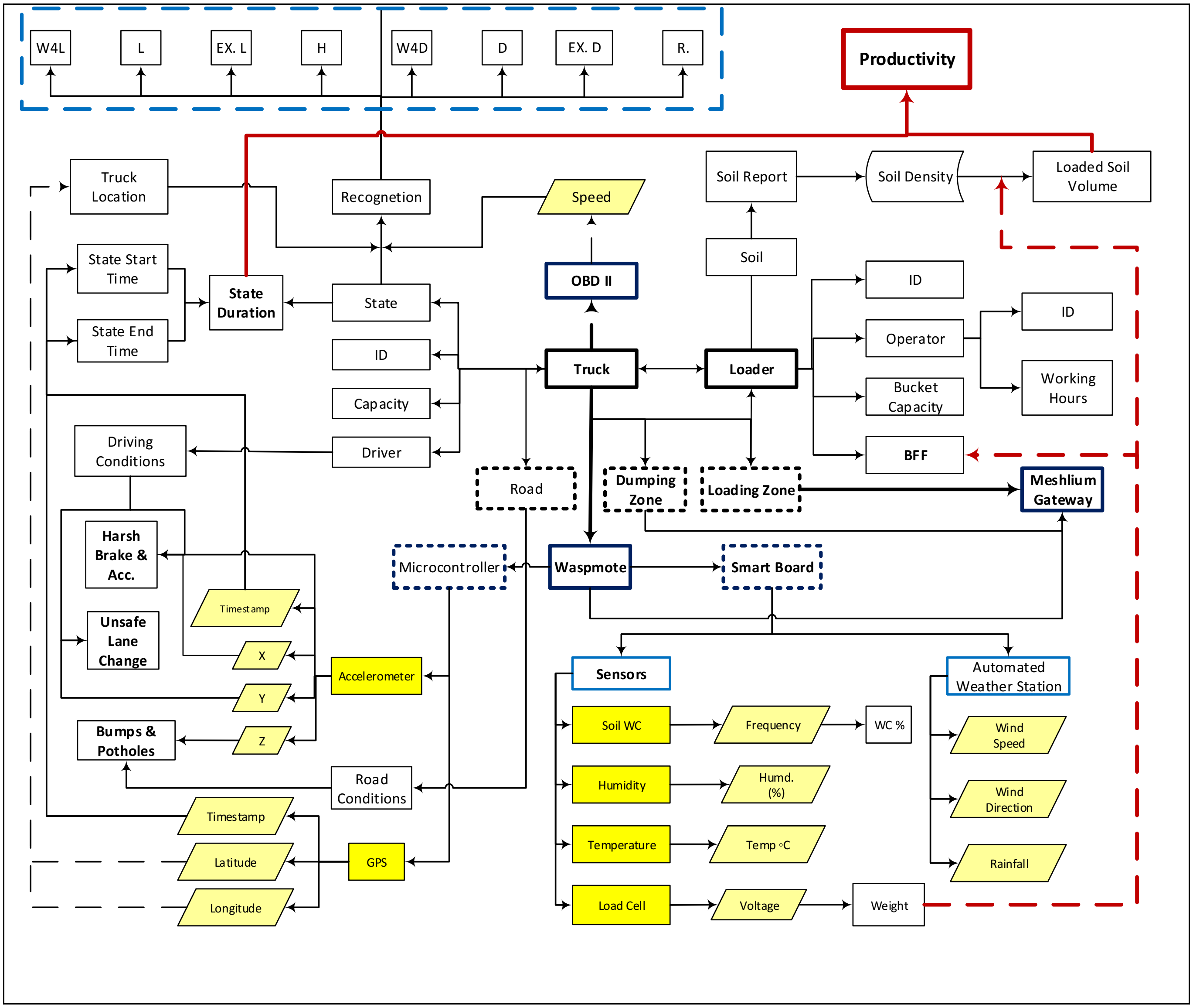
```
// WiFi AP settings (CHANGE TO USER'S AP)
///////////////////////////////////////
char ESSID[] = "libelium_AP";
char AUTHKEY[] = "password";
///////////////////////////////////////
// MESHLIUM settings
///////////////////////////////////////////////////////////////////////////
char ADDRESS[] = "10.10.10.1";
int REMOTE_PORT = 80;
///////////////////////////////////////////////////////////////////////////
// Define status variable for GPS connection
bool status;
// Variable to store sleeping period. Format DD:HH:MM:SS
char sleepTime[] = "00:00:00:10";
// Variable to store data to be sent
char data[200];
void setup()
{
  // 0. Init USB port for debugging
  USB.ON();
  USB.println(F("C_11 Example"));

  ///////////////////////////////////////////////////////
  // 1. Initial message composition
  ///////////////////////////////////////////////////////
  // 1.1 Set mote Identifier (16-Byte max)
  frame.setID("WASPMOTE_001");
  // 1.2 Create new ASCII frame
  frame.createFrame(ASCII);
  // 1.3 Set frame fields (String - char*)
  frame.addSensor(SENSOR_STR, (char*) "C_11 Example");
  // 1.4 Print frame
  frame.showFrame();
  ///////////////////////////////////////////////////////
  // 2. Send initial message
  ///////////////////////////////////////////////////////
  USB.println(F("Turning WIFI module ON"));
  // 2.1 Switch on the WIFI module on the desired socket.
  WIFI.ON(SOCKET0);
  // 2.2 Configure the transport protocol (UDP, TCP, FTP, HTTP...)
  WIFI.setConnectionOptions(HTTP|CLIENT_SERVER);
  // 2.3 Configure the way the modules will resolve the IP address.
  WIFI.setDHCPoptions(DHCP_ON);
  // 2.4 Configure how to connect the AP
  WIFI.setJoinMode(MANUAL);
  // 2.5 Set the AP authentication key
  WIFI.setAuthKey(WPA1, AUTHKEY);
  // 2.6 Save current configuration
  WIFI.storeData();
  // 2.7 Power off WIFI module
  WIFI.OFF();
}

void loop()
{
  ///////////////////////////////////////////////////////
```

```
// 3. Measure corresponding values
///////////////////////////////////////////////
USB.println(F("Obtaining GPS data..."));
// 3.1 Set GPS ON
GPS.ON();
///////////////////////////////////////////////
// 3.2 Wait for GPS signal
///////////////////////////////////////////////
status = GPS.waitForSignal(TIMEOUT);
if( status == true )
{
 USB.println(F("\n----------------------"));
 USB.println(F("Connected"));
 USB.println(F("----------------------"));
}
else
{
 USB.println(F("\n----------------------"));
 USB.println(F("GPS TIMEOUT. NOT connected"));
 USB.println(F("----------------------"));
}
///////////////////////////////////////////////
// 4. Message composition
///////////////////////////////////////////////
// 4.1 Set mote Identifier (16-Byte max)
frame.setID("WASPMOTE_001");
// 4.2 Create new frame
frame.createFrame(ASCII);
// 4.3 if GPS is connected then get position
if( status == true )
{
 // getPosition function gets all basic data
 GPS.getPosition();
 USB.print("Latitude (degrees):");
 USB.println(GPS.convert2Degrees(GPS.latitude, GPS.NS_indicator));
 USB.print("Longitude (degrees):");
 USB.println(GPS.convert2Degrees(GPS.longitude, GPS.EW_indicator));
 // add frame fields
 frame.addSensor(SENSOR_GPS,
 GPS.convert2Degrees(GPS.latitude, GPS.NS_indicator),
 GPS.convert2Degrees(GPS.longitude, GPS.EW_indicator) );
}
else
{
 // add frame fields
 frame.addSensor(SENSOR_STR,"GPS not connected");
}
// 4.4 Print frame
// Example: <=>\0x80\0x03#35689884#WASPMOTE_001#...
frame.showFrame();
///////////////////////////////////////////////
// 5. Send message
///////////////////////////////////////////////
USB.println(F("Turning WIFI module ON"));
// 5.1 Switch on the WIFI module on the desired socket.
WIFI.ON(SOCKET0);
```

```
  if (WIFI.join(ESSID))
  {
   USB.println(F("Joined AP"));
   status = WIFI.sendHTTPframe(IP,ADDRESS, REMOTE_PORT, frame.buffer, frame.length);
   if( status == 1)
   {
    USB.println(F("\nHTTP query OK."));
    USB.print(F("WIFI.answer:"));
    USB.println(WIFI.answer);
    /*
    * At this point, it could be possible
     * to parse the web server information
     */
   }
   else
   {
    USB.println(F("HTTP query ERROR"));
   }
  }
  else
  {
   USB.println(F("NOT joined"));
  }
  // 5.2 Power off WIFI module
  WIFI.OFF();
  ////////////////////////////////////////////////
  // 6. Entering Deep Sleep mode
  ////////////////////////////////////////////////
  USB.println(F("Going to sleep..."));
  USB.println();
  PWR.deepSleep(sleepTime, RTC_OFFSET, RTC_ALM1_MODE1, ALL_OFF);
  USB.ON();
  USB.println(F("wake"));
}
```

Appendix IV

A. Developed MySQL Database Structure Plan



B. Developed MySQL Database Procedures

Procedure Name	FindZone_new
Description	Fill GPS table with the zone from polygons table

DELIMITER $$

```sql
CREATE DEFINER=`root`@`localhost` PROCEDURE `FindZone_new`()
begin
   -- Variables to hold values from the communications table
   declare Latt double;
   declare Longt double;
   declare Pointt varchar(100);
   declare tt varchar(100);
   declare tc integer;
   declare currentzone varchar(4);
   declare previouszone varchar(4);
   declare Zone1 varchar(4);
      declare Zone2 varchar(4);
   -- Variables related to cursor:
--    1. 'done' will be used to check if all the rows in the cursor were read
   --    2. 'curComm' will be the cursor: it will fetch each row
   --    3. The 'continue' handler will update the 'done' variable
   declare done int default false;
   declare curComm cursor for
      select LongitudeD, LatitudeD,Time from gps1;
-- This is the query used by the cursor.
   declare continue handler for not found
-- This handler will be executed if no row is found in the cursor (for example, if all rows were read).
      set done = true;

 -- Open the cursor: This will put the cursor on the first row of its
 -- rowset.
   set tc=1;
   set zone1='X';
   open curComm;

   -- Begin the loop (that 'loop_comm' is a label for the loop)
   loop_comm: loop
      -- When you fetch a row from the cursor, the data from the current
      -- row is read into the variables, and the cursor advances to the
      -- next row. If there's no next row, the 'continue handler for not found'
      -- will set the 'done' variable to 'TRUE'
      fetch curComm into LongT, Latt, tt;
      -- Exit the loop if you're done
      if done then
         leave loop_comm;
      end if;

        SET pointt = CONCAT('POINT(',Latt,' ',LongT,')');
      set zone2= ifnull((SELECT location FROM polygons WHERE
MBRContains(polygon_data,GeomFromText(pointt)) AND
point_inside_polygon(Latt,LongT,ASTEXT(polygon_data))),"R");

      if zone2=zone1 then set currentzone=previouszone;
      elseif concat(zone1,zone2) = 'XL' then set currentzone = concat('L',tc);
      elseif concat(zone1,zone2) = 'LR' then set currentzone = concat('R',tc,'LD');
```

```
        elseif concat(zone1,zone2) = 'RD' then set currentzone = concat('D',tc);
        elseif concat(zone1,zone2) = 'DR' then set currentzone = concat('R',tc,'DL');
        else set currentzone = concat('L',tc+1);
        end if;

            update gps1 set zone = currentzone where time = tt;

             if concat(zone1,zone2) = 'RL' then set tc=tc+1;
                      end if;

   set zone1=zone2;
   set previouszone=currentzone;

     end loop;

    close curComm;
end$$
DELIMITER ;
```

Procedure Name	Fill_Acc_Zones
Description	Fill acceleration table with the missing data due to frequency differences

```
DELIMITER $$
CREATE DEFINER=`root`@`localhost` PROCEDURE `Fill_Acc_zones`()
begin
    -- Variables to hold values from the communications table
    declare Rowid integer;
    declare Zonee varchar(20);
    --    1. 'done' will be used to check if all the rows in the cursor were read
    --    2. 'curComm' will be the cursor: it will fetch each row
    --    3. The 'continue' handler will update the 'done' variable
        declare done int default false;
    declare curComm cursor for
        select Row_id from acceleration where zone_new is null;
-- This is the query used by the cursor.
     declare continue handler for not found
-- This handler will be executed if no row is found in the cursor (for example, if all rows were
read).
        set done = true;

 -- Open the cursor: This will put the cursor on the first row of its
 -- rowset.
    open curComm;
    -- Begin the loop (that 'loop_comm' is a label for the loop)
    loop_comm: loop
        -- When you fetch a row from the cursor, the data from the current
        -- row is read into the variables, and the cursor advances to the
        -- next row. If there's no next row, the 'continue handler for not found'
        -- will set the 'done' variable to 'TRUE'
        fetch curComm into Rowid;
```

```
        -- Exit the loop if you're done
        if done then
           leave loop_comm;
        end if;
                              SELECT zone_new into zonee FROM acceleration  where row_id =
rowid-1;

           update acceleration set zone_new = zonee
        where Row_id=Rowid;
    end loop;
close curComm;
end$$
DELIMITER ;
```

Procedure Name	Fill_OBD_Zones
Description	Fill OBD table with the missing data due to frequency differences

```
DELIMITER $$
CREATE DEFINER=`root`@`localhost` PROCEDURE `Fill_obd_zones`()
begin
    -- Variables to hold values from the communications table
    declare Rowid integer;
    declare Zonee varchar(20);
        --    1. 'done' will be used to check if all the rows in the cursor
    --       were read
    --    2. 'curComm' will be the cursor: it will fetch each row
    --    3. The 'continue' handler will update the 'done' variable
        declare done int default false;
    declare curComm cursor for
        select Row_id from obd where zone_new is null;
-- This is the query used by the cursor.
     declare continue handler for not found
-- This handler will be executed if no row is found in the cursor (for example, if all rows were
read).
        set done = true;

-- Open the cursor: This will put the cursor on the first row of its rowset.
    open curComm;
    -- Begin the loop (that 'loop_comm' is a label for the loop)
    loop_comm: loop
        -- When you fetch a row from the cursor, the data from the current
        -- row is read into the variables, and the cursor advances to the
        -- next row. If there's no next row, the 'continue handler for not found'
        -- will set the 'done' variable to 'TRUE'
        fetch curComm into Rowid;

        if done then
           leave loop_comm;
        end if;

       SELECT zone_new into zonee FROM obd  where row_id = rowid-1;
```

```
          update obd set zone_new = zonee
        where Row_id=Rowid;
    end loop;
close curComm;
end$$
DELIMITER ;
```

Procedure Name	Fill_State
Description	Fill acceleration table with the state using the loadcell, water, and OBD tables data

```
DELIMITER $$
CREATE DEFINER=`root`@`localhost` PROCEDURE `Fill_State`()
begin
    -- Variables to hold values from the communications table
     declare var_time varchar(20);
     declare var_x double;
     declare var_y double;
     declare var_z double;
     declare var_zone varchar(20);
     declare var_rowid varchar(20);
     declare var_speed double;
     declare var_voltage double;
         declare var_frequency double;
     declare var_count double;
     declare var_rowid_before varchar(20);

        declare done int default false;

 -- Get data for only loading zones

    declare curComm1 cursor for
        select substring(time,1,8),truncate(x,6),truncate(y,6),truncate(z,6),zone_new, row_id from
acceleration where zone_new like 'L%' ;

-- Get data for only dumping zones

    declare curComm2 cursor for
        select substring(time,1,8),truncate(x,6),truncate(y,6),truncate(z,6),zone_new, row_id from
acceleration where zone_new like 'D%' ;


-- Get data for only Road zones
        declare curComm3 cursor for
        select substring(time,1,8),truncate(x,6),truncate(y,6),truncate(z,6),zone_new, row_id from
acceleration where zone_new like 'R%' ;


      declare continue handler for not found
```

```
      set done = true;

   open curComm1;
   loop_comm1: loop
      fetch curComm1 into var_Time, var_x, var_y, var_z, var_zone, var_rowid;
      if done then
         leave loop_comm1;
      end if;

-- Get speed data from odb table

      SELECT avg(speed) into var_speed FROM obd  where substring(time,1,8) = var_time;

     select count(*) into var_count from loadcell where substring(time,1,8) = var_time;

    if var_count = 0 then

   begin
       select max(row_id) into var_rowid_before from loadcell where substring(time,1,8)<
var_Time;
       select substring(time,1,8) into var_time from loadcell where row_id = var_rowid_before;
    end;
    end if;


     SELECT voltage into var_voltage FROM loadcell  where substring(time,1,8) = var_time;
     SELECT Frequency into var_Frequency FROM water  where substring(time,1,8) =
var_time;


     -- checking limits to get state

     if ((var_x between -2.212249  and 1.177947) and (var_y between -1.819599 and 1.139649 )
and (var_z between 8.485051 and 11.511329) and (var_speed between 0 and 25) and
(var_voltage between 0 and 0.015) and (var_frequency between 40 and 300)) then
     update acceleration set state = 'WFL' where Row_id=var_rowid;

     elseif ((var_x between -6.608999   and 3.572149 ) and (var_y between -2.288856  and
2.126059 ) and (var_z between 7.249643  and 11.473019) and (var_speed = 0) and
(var_voltage between 0.1 and 0.6) and (var_frequency between 100 and 6500)) then
     update acceleration set state = 'Loading' where Row_id=var_rowid;

     elseif ((var_x between -6.608999   and 3.572149 ) and (var_y between -2.288856  and
2.126059 ) and (var_z between 7.249643  and 11.473019) and (var_speed > 0) and
(var_voltage between 0.1 and 0.6) and (var_frequency between 100 and 6500)) then
     update acceleration set state = 'Exit Load' where Row_id=var_rowid;

     else update acceleration set state = 'LOOR' where Row_id=var_rowid;
     end if;
```

```
    end loop;

    update acceleration set state = 'WFL' where zone_new = 'L3'  and state = 'LOOR';


close curComm1;

    set done = false;

    open curComm2;
    loop_comm2: loop
       fetch curComm2 into var_Time, var_x, var_y, var_z, var_zone, var_rowid;
       if done then
          leave loop_comm2;
       end if;

          SELECT avg(speed) into var_speed FROM obd  where substring(time,1,8) = var_time;

     select count(*) into var_count from loadcell where substring(time,1,8) = var_time;

      if var_count = 0 then

begin
         select max(row_id) into var_rowid_before from loadcell where substring(time,1,8)<
var_Time;
         select substring(time,1,8) into var_time from loadcell where row_id = var_rowid_before;
end;
      end if;


       SELECT voltage into var_voltage FROM loadcell  where substring(time,1,8) = var_time;
       SELECT Frequency into var_Frequency FROM water  where substring(time,1,8) =
var_time;


       if ((var_x between -2.250699 and 2.365471 ) and (var_y between -2.181879  and 1.268371
) and (var_z between 8.207323  and 11.358099) and (var_speed between 0 and 25) and
(var_voltage between 0.3 and 0.6) and (var_frequency between 100 and 6500)) then
       update acceleration set state = 'WFD' where Row_id=var_rowid;

       elseif ((var_x between -8.858559 and 3.552995) and (var_y between -5.746089 and
11.444289) and (var_z between 2.260126 and 13.148969) and (var_speed = 0) and
(var_voltage between 0 and 0.6) and (var_frequency between 97 and 6500)) then
       update acceleration set state = 'Dumping' where Row_id=var_rowid;

       elseif ((var_x between -8.858559 and 3.552995) and (var_y between -5.746089 and
11.444289) and (var_z between 2.260126 and 13.148969) and (var_speed >0) and
(var_voltage between 0 and 0.6) and (var_frequency between 97 and 6500)) then
       update acceleration set state = 'Exit Dump' where Row_id=var_rowid;

       else update acceleration set state = 'DOOR' where Row_id=var_rowid;
```

```
      end if;

   end loop;
   -- Don't forget to close the cursor when you finish
   close curComm2;

      set done = false;

   open curComm3;
   loop_comm3: loop
       fetch curComm3 into var_Time, var_x, var_y, var_z, var_zone, var_rowid;
       if done then
          leave loop_comm3;
       end if;

          SELECT avg(speed) into var_speed FROM obd  where substring(time,1,8) = var_time;

       select count(*) into var_count from loadcell where substring(time,1,8) = var_time;

      if var_count = 0 then

     begin
                  select max(row_id) into var_rowid_before from loadcell where
substring(time,1,8)< var_Time;
                  select substring(time,1,8) into var_time from loadcell where row_id =
var_rowid_before;
      end;
     end if;

      SELECT voltage into var_voltage FROM loadcell  where substring(time,1,8) = var_time;
      SELECT Frequency into var_Frequency FROM water  where substring(time,1,8) =
var_time;

      if ((var_x between -10.448399 and 14.001299) and (var_y between -10.879399 and
9.078813) and (var_z between -4.185079 and 19.613399) and (var_speed between 0 and 100)
and (var_voltage between 0.3 and 0.6) and (var_frequency between 100 and 6500)) then
      update acceleration set state = 'Hauling' where Row_id=var_rowid;

      elseif ((var_x between -6.866579 and 8.044518) and (var_y between -9.940739  and
9.710882) and (var_z between -4.970369 and 19.613399) and (var_speed between 0 and 100)
and (var_voltage between 0 and 0.015) and (var_frequency between 50 and 1000)) then
      update acceleration set state = 'Return' where Row_id=var_rowid;

      else update acceleration set state = 'ROOR' where Row_id=var_rowid;
      end if;

   end loop;
   -- Don't forget to close the cursor when you finish
   close curComm3;

end$$
```

DELIMITER ;

Procedure Name	Fill_Time_Duration
Description	Fill State time duration table with duration of each state per trip

```
DELIMITER $$
CREATE DEFINER=`root`@`localhost` PROCEDURE `Fill_Time_Duration`()
begin
   -- Variables to hold values from the communications table
    declare Trip_count int;
    declare max_trips int;

    -- initiate count number
set trip_count=1;

   -- Get the maximum number of trips

select max(substring(zone_new,2,1)) into max_trips from acceleration where zone_new like
'L%';

   -- Loop to calculate when the trip count is less than maximum trips

  while trip_count < max_trips Do

  begin

   -- Fill the start and end of each state

update State_Time_Duration set WFL_F = (select min(time) from acceleration where state =
'WFL' and zone_new = concat('L',trip_count) ) where trip_id=trip_count;
update State_Time_Duration set WFL_T = (select max(time) from acceleration where state =
'WFL' and zone_new = concat('L',trip_count) ) where trip_id=trip_count;
update State_Time_Duration set L_F = (select min(time) from acceleration where state =
'Loading' and zone_new = concat('L',trip_count) ) where trip_id=trip_count;
update State_Time_Duration set L_T = (select max(time) from acceleration where state =
'Loading' and zone_new = concat('L',trip_count) ) where trip_id=trip_count;
update State_Time_Duration set EL_F = (select min(time) from acceleration where state = 'Exit
Load' and zone_new = concat('L',trip_count) ) where trip_id=trip_count;
update State_Time_Duration set EL_T = (select max(time) from acceleration where state = 'Exit
Load' and zone_new = concat('L',trip_count) ) where trip_id=trip_count;
update State_Time_Duration set H_F = (select min(time) from acceleration where state =
'Hauling' and zone_new = concat('R',trip_count,'LD') ) where trip_id=trip_count;
update State_Time_Duration set H_T = (select max(time) from acceleration where state =
'Hauling' and zone_new = concat('R',trip_count,'LD') ) where trip_id=trip_count;
update State_Time_Duration set WFD_F = (select min(time) from acceleration where state =
'WFD' and zone_new = concat('D',trip_count) ) where trip_id=trip_count;
update State_Time_Duration set WFD_T = (select max(time) from acceleration where state =
'WFD' and zone_new = concat('D',trip_count) ) where trip_id=trip_count;
update State_Time_Duration set D_F = (select min(time) from acceleration where state =
'Dumping' and zone_new = concat('D',trip_count) ) where trip_id=trip_count;
update State_Time_Duration set D_T = (select max(time) from acceleration where state =
'Dumping' and zone_new = concat('D',trip_count) ) where trip_id=trip_count;
```

```
update State_Time_Duration set ED_F = (select min(time) from acceleration where state = 'Exit Dump' and zone_new = concat('D',trip_count) ) where trip_id=trip_count;
update State_Time_Duration set ED_T = (select max(time) from acceleration where state = 'Exit Dump' and zone_new = concat('D',trip_count) ) where trip_id=trip_count;
update State_Time_Duration set R_F = (select min(time) from acceleration where state = 'Return' and zone_new = concat('R',trip_count,'DL') ) where trip_id=trip_count;
update State_Time_Duration set R_T = (select max(time) from acceleration where state = 'Return' and zone_new = concat('R',trip_count,'DL') ) where trip_id=trip_count;
end;

 set trip_count = trip_count+1;

   end while;

    -- Fill the duration of each state

update State_Time_Duration set WFL_duration = timediff(STR_to_date(substring(WFL_T,1,8),'%H:%i:%s'),STR_to_date(substring(WFL_F,1,8),'%H:%i:%s'));
update State_Time_Duration set L_duration = timediff(STR_to_date(substring(L_T,1,8),'%H:%i:%s'),STR_to_date(substring(L_F,1,8),'%H:%i:%s'));
update State_Time_Duration set EL_duration = timediff(STR_to_date(substring(EL_T,1,8),'%H:%i:%s'),STR_to_date(substring(EL_F,1,8),'%H:%i:%s'));
update State_Time_Duration set H_duration = timediff(STR_to_date(substring(H_T,1,8),'%H:%i:%s'),STR_to_date(substring(H_F,1,8),'%H:%i:%s'));

update State_Time_Duration set WFD_duration = timediff(STR_to_date(substring(WFD_T,1,8),'%H:%i:%s'),STR_to_date(substring(WFD_F,1,8),'%H:%i:%s'));
update State_Time_Duration set D_duration = timediff(STR_to_date(substring(D_T,1,8),'%H:%i:%s'),STR_to_date(substring(D_F,1,8),'%H:%i:%s'));
update State_Time_Duration set ED_duration = timediff(STR_to_date(substring(ED_T,1,8),'%H:%i:%s'),STR_to_date(substring(ED_F,1,8),'%H:%i:%s'));
update State_Time_Duration set R_duration = timediff(STR_to_date(substring(R_T,1,8),'%H:%i:%s'),STR_to_date(substring(R_F,1,8),'%H:%i:%s'));
-- Fill the total duration column
update State_Time_Duration set total_duration = addtime(WFL_duration,addtime(WFD_duration,addtime(L_duration,addtime(EL_duration,addtime(H_duration,addtime(D_duration,addtime(ED_duration,R_duration)))))));

-- Fill the duration of each state in minutes format

update State_Time_Duration set WFL_duration_M = substring(WFL_duration,5,1)+(substring(WFL_duration,7,2)/60) ;
update State_Time_Duration set L_duration_M =
```

```
substring(L_duration,5,1)+(substring(L_duration,7,2)/60);
update State_Time_Duration set EL_duration_M =
substring(EL_duration,5,1)+(substring(EL_duration,7,2)/60);
update State_Time_Duration set H_duration_M =
substring(H_duration,5,1)+(substring(H_duration,7,2)/60);

update State_Time_Duration set WFD_duration_M =
substring(WFD_duration,5,1)+(substring(WFD_duration,7,2)/60);
update State_Time_Duration set D_duration_M =
substring(D_duration,5,1)+(substring(D_duration,7,2)/60);
update State_Time_Duration set ED_duration_M =
substring(ED_duration,5,1)+(substring(ED_duration,7,2)/60);
update State_Time_Duration set R_duration_M =
substring(R_duration,5,1)+(substring(R_duration,7,2)/60);

update State_Time_Duration set total_duration_M =
substring(total_duration,4,2)+(substring(total_duration,7,2)/60);

   end$$
DELIMITER ;
```

Procedure Name	Calculate_Productivity
Description	Update the Loadcell, Water and State time duration table with the volume, density, mass, TA, Per_WC

```
DELIMITER $$
CREATE DEFINER=`root`@`localhost` PROCEDURE `Calculate_Productivity`()
begin


declare done int default false;
declare var_Time varchar(25);
declare var_mass double;
declare var_state varchar(25);
declare Latt double;
declare Longt double;
declare Pointt varchar(100);
declare var_density double;
declare Trip_count int;
declare max_trips int;
declare v_rowid varchar(25);

declare curComm1 cursor for
select time,mass,row_id from loadcell order by row_id;
declare continue handler for not found
set done = true;

-- Update loadcell with mass value

update loadcell set mass = 2500 * voltage;

-- Update Water with TA Value
```

```
update water set TA = (150940 - (19.74*Frequency)) / ((2.8875*Frequency) - 137.5) ;

-- Update loadcell with Per_WC value

update water set Per_WC = (- 4.036*(LN (TA))) + 28.342;

open curComm1;
   loop_comm1: loop
      fetch curComm1 into var_Time, var_mass, v_rowid;
      if done then
         leave loop_comm1;
      end if;

      SELECT count(*) into var_state FROM acceleration where substring(time,1,8) = var_time
and state = 'Loading';

if var_state <> 0 then

   begin

select LongitudeD, LatitudeD into LongT, Latt from gps1 where time = var_time;
      SET pointt = CONCAT('POINT(',Latt,' ',LongT,')');
      set var_density= (SELECT density FROM sub_polygons WHERE
MBRContains(polygon_data,GeomFromText(pointt)) AND
point_inside_polygon(Latt,LongT,ASTEXT(polygon_data)));

-- Update loadcell with volume value using density
update loadcell set volume = (mass/var_density) where time = var_time;
      Update loadcell set density = var_density where time = var_time;

      end;
end if;

   end loop;
set done = false;

close curComm1;

set trip_count=1;

select max(substring(zone_new,2,1)) into max_trips from acceleration where zone_new like
'L%';

  while trip_count < max_trips Do

  begin

   -- Update state_time_duration

   update state_time_duration set volume = (select max(volume) from loadcell where zone_new
```

```
= concat('L',trip_count)) where trip_id=trip_count;

    end;

 set trip_count = trip_count+1;

   end while;

update state_time_duration set productivity = volume/(TIME_TO_SEC(total_duration)/60);

end$$
DELIMITER ;
```

Procedure Name	Check_road_condition
Description	Fill road condition table with relevant checks tests

```
DELIMITER $$
CREATE DEFINER=`root`@`localhost` PROCEDURE `Check_Road_Condition`()
begin

declare done int default false;
declare var_Time varchar(25);
declare var_x double;
declare var_y double;
declare var_z double;
declare var_xp double;
declare var_yp double;
declare var_zp double;
declare var_rowid INT;
declare var_count INT;
declare var_long double;
declare var_lat double;

declare curComm1 cursor for
select time,x,y,z,row_id from acceleration where row_id >1 and zone_new like 'R%' order by
row_id;

declare continue handler for not found
set done = true;

delete from road_condition;

open curComm1;
    loop_comm1: loop
        fetch curComm1 into var_Time, var_x, var_y, var_z, var_rowid;
        if done then
            leave loop_comm1;
        end if;

         select count(*) into var_count from gps1 where time = substring(var_Time,1,8);
```

```
 if var_count <> 0 then
        begin
            select LongitudeD, LatitudeD into var_long, var_lat from gps1 where time
= substring(var_Time,1,8);
        end;
    else
        select LongitudeD, LatitudeD into var_long, var_lat from gps1 where time <
substring(var_Time,1,8) order by time desc limit 1;
    end if;

 SELECT x,y,z into var_xp,var_yp, var_zp FROM acceleration where row_id=var_rowid-1;

    if abs(var_x)-abs(var_xp) >= 3 then insert into road_condition values (var_Time,
var_long,var_lat,var_x,var_y, var_z,'1','0','0','0','0','0');
    elseif abs(var_x)-abs(var_xp) <= -3 then insert into road_condition values (var_Time,
var_long,var_lat,var_x,var_y, var_z, '0','1','0','0','0','0');
    elseif abs(var_y)-abs(var_yp) >= 5 then insert into road_condition values (var_Time,
var_long,var_lat,var_x,var_y, var_z,'0','0','1','0','0','0');
    elseif abs(var_y)-abs(var_yp) <= -5 then insert into road_condition values (var_Time,
var_long,var_lat, var_x,var_y, var_z,'0','0','0','1','0','0');
    elseif abs(var_z)-abs(var_zp) >= 2 then insert into road_condition values (var_Time,
var_long,var_lat, var_x,var_y, var_z,'0','0','0','0','1','0');
    elseif abs(var_z)-abs(var_zp) <= -2 then insert into road_condition values (var_Time,
var_long,var_lat, var_x,var_y, var_z,'0','0','0','0','0','1');
    else insert into road_condition values (var_Time, var_long,var_lat, var_x,var_y,
var_z,'0','0','0','0','0','0');

    end if;

   end loop;
set done = false;
close curComm1;

end$$
DELIMITER ;
```