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Earthwork Haul-Truck Cycle-Time Monitoring – A Case Study

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Final Report
March 2016

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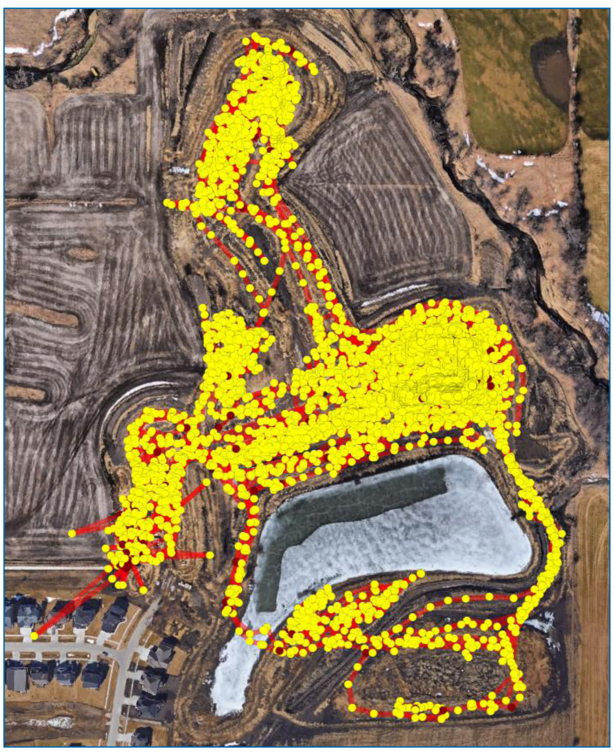

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16. Abstract

Recent developments in autonomous technologies have motivated practitioners to adopt new technologies in highway and earthwork construction projects. This project set out to (1) identify new and emerging autonomous earthwork technologies and (2) set up a field study to monitor site-level equipment operations at an earthmoving project. The results of the first part of this study are described in a separate report (2015 Conference on Autonomous and Robotic Construction of Infrastructure [CARCI]). The information reported herein presents the results of the site-level monitoring of an earthwork project, where the objective was to quantify haul truck cycle time.

The site selected for monitoring was located in Johnston, Iowa, and required grading to build up a residential development. The project involved about 200,000 cubic yards of excavation and placement. Installing a storm sewer and digging a pond were also required for the project. The soils on site were of glacial origin and were generally classified as silty clays. Position tracking devices were installed on the equipment to monitor the time and position of the equipment for several days. Based on statistical analysis (non-parametric) of the haul cycle times for three haul trucks, the results are presented in terms of frequency distributions and accompanying statistical parameters. Recommendations are provided to build on this study so that additional earthwork sites can be evaluated to more broadly quantify the many factors affecting earthwork productivity.

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EARTHWORK HAUL-TRUCK CYCLE-TIME MONITORING – A CASE STUDY

Final Report
March 2016

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The authors would also like to thank McAninch Corporation for allowing the research team access to the project site to carry out the field monitoring phase of this project.

EXECUTIVE SUMMARY

This report presents the results of site-level monitoring of an earthwork project, where the objective was to quantify haul truck cycle time. During the monitoring period, the soil conditions were observed to be wet, and sections of the haul roads were rutting and or pumping under construction traffic, which is a common challenge with earthwork operations in Iowa. Dewatering was needed to excavate the pond area. During the monitoring period, lime was used on a section of the construction site to reduce moisture content and stabilize the wet soils.

GPS tracking devices were attached to three hauling trucks, the excavator, and the bulldozer. All records from the devices were connected to Google Earth using .KMZ* files showing the positions superimposed on a map. Each recorded point contained the x, y, and z global coordinates and the time. In addition to position information, the data files included truck speed and rest time (if not moving). Position monitoring was active from October 17 to October 21, 2014. Cycle time analysis was conducted on all hauling trucks to describe the haul truck activity in terms of statistical parameters to assess the productivity observed on the project.

Cycle times were determined by defining the haul boundary, dump locations, and loading locations. The data were then organized into individual cycle records so that the cycle times could be determined for each piece of equipment. The cycle time analysis process involved defining the location of the excavator and either the nearest stopping point of the hauling truck or the point with the lowest speed. The starting time of the stopping point defines the end of a cycle and the beginning of a new cycle. Accordingly, the cycle time is defined as the difference between the times of two loading points. Within a cycle, it was observed that there were several instances where the equipment stopped for a short period (e.g., two minutes) and then resumed travel. These stoppages were related to the equipment yielding to other equipment and waiting for direction from the bulldozer operator as to where a load was to be dumped.

Cycle times without delays were calculated by removing the stopping times other than the loading times from the cycles. The cycles that included an excavator location change were not included in the analysis.

The results show that the cycle time distributions are positively skewed. It was concluded that none of the distributions are normal and, therefore, proper statistical analysis tools should be used to analyze such distributions. Due to the non-normal distribution, the traditional analysis of variance was not used in favor of non-parametric tests. A median rank scores test was performed to test whether there was a statistically significant difference between the distributions' medians. Understanding the factors leading to a significant change in cycle time is desirable because these factors relate to the potential for improving efficiency.

The production rates of the haul trucks were estimated based on the cycle time analysis. In theory, this analysis would help define the optimal number of hauling trucks. The production rate of the excavator was also estimated; the volume of excavated material was estimated by multiplying the number of loads for all trucks per day by the heaped capacity of the trucks.

This study served to demonstrate a relatively simple approach to cycle time monitoring and statistical analysis. However, more advanced data collection and analysis are needed. Moving forward, a more completely designed monitoring program should be devised to capture the effects of the many factors that can influence productivity. For future site-level monitoring programs, an emphasis needs to be placed on carefully capturing and quantifying the key parameters influencing productivity. There is very limited published information on this topic.

Future studies should consider the following parameters at minimum to build a site-level analysis model:

- Project complexity (i.e., site layout and details)
- Dump truck size
- Number of dump trucks
- Loader size
- Number of loaders
- Excavation rates
- Material transfer rates
- Machines’ paths and traffic (i.e., speed, location, and time)
- Haul road resistance
- Work zone drainage
- Soil condition

INTRODUCTION

Recent developments in autonomous technologies have motivated practitioners to adopt new technologies in highway and earthwork construction projects. Automated machine guidance (AMG) is one example that improves earthwork productivity by linking sophisticated design software with construction equipment to direct the operations of construction machinery with a high level of precision, which improves construction efficiency and quality (Vennapusa et al. 2015). AMG includes various technologies (e.g., GPS guidance, three-dimensional [3D] modeling, and machine control) implemented at both the planning and construction stages.

To identify new and emerging technologies that will go beyond AMG in the construction automation space, the current project set out to (1) identify current research and development efforts by hosting a conference of world-wide experts and (2) set up a field study to monitor site-level equipment operations at an earthmoving project to better identify opportunities for integrating automation into the process. The information reported herein presents the results of the site-level monitoring of an earthwork project. The results of the conference are described in White et al. (2015) and are briefly summarized in the following.

The 2015 Conference on Autonomous and Robotic Construction of Infrastructure (CARCI) (White et al. 2015) was attended by more than 100 participants from academia and industry and showed that new construction applications for autonomous/robotic systems are rapidly emerging. Topics presented at the CARCI conference include mobile robotic operations, advanced visual analysis, terrain modeling, simulation, multi-dimensional modeling, 3D printing/manufacturing, data processing, and 3D point cloud generation from digital imagery and other measurement technologies. Twenty-one papers are published in the proceedings and are available online at http://www.ceer.iastate.edu/CARCI/proceedings/.

The success of the CARCI conference confirmed the wide ranging interest in further automating construction processes and brought attention to the need for detailed site-level monitoring research to better identify opportunities for further advancements in autonomous, robotic, and co-robotic operations for earthwork and infrastructure construction work. The study described herein offers new information about a relatively simple haul truck monitoring program with relatively inexpensive monitoring equipment and further lays the groundwork for more advanced studies in this area, which are necessary because of the rather complex number of parameters involved and the lack of a quantified framework for assessing earthwork productivity problems.

BACKGROUND

AMG applications in earthwork grading operations are now well integrated into practice and represent an excellent example of how new technology has found a market due to the improved productivity and profitability that it offers users.

Hannon (2007) stated that AMG technologies have proven their value in the field but also noted that there is a need for continued standardization to specify the proper use of various AMG and related technologies. Other studies have reported productivity gains and cost savings when utilizing AMG technologies (Aðalsteinsson 2008, Capony et al. 2012, Hammad et al. 2012, Jonasson et al. 2002).

Early developments in manufacturing automation have motivated researchers to identify the difference between automation in the manufacturing and construction industries. Everett and Slocum (1994) indicated that approaches to automation in manufacturing cannot be transferred to construction, and instead construction must develop its own strategies. They also indicated that machines excel at physically intensive basic tasks that require speed, strength, repetitive motions, and operation in hostile environments. Though human craft workers are still more productive and cost effective than machines and computers for basic information-intensive tasks, this situation might be changing with rapid improvements in machine awareness (Steward et al. 2015).

Different construction automation technologies have been developed based on specific activities of interest. Olearczyk et al. (2014) introduced a Crane Lifting Path Planning (CLPP) algorithm that utilizes a piecewise continuous function in terms of the rotation angle and translation (radius) of the boom to reduce the complexity of the system of equations when optimizing the crane path. Liu et al. (2013) developed an automated system to control the watering operations of dam materials according to the volume and type of material carried in a truck. This system facilitates obtaining an optimal moisture content for these materials efficiently, thus ensuring the compaction efficiency of earth-rock dam construction.

Furthermore, new autonomous paving systems have been developed. These systems can increase the efficiency and quality of operations, lead to reductions in overall project costs and time, and enhance pavement life (Krishnamurthy et al. 1998). Krishnamurthy et al. (1998) introduced a new system, named AUTOPAVE (v1.0), that utilizes algorithmic planning and real-time guidance strategies for semi-automated path-planning and real-time guidance.

Earthworks are complex activities in nature due to the variability in site conditions, project designs, and soil conditions, among other variables, all of which requires specialized AMG systems. Santos et al. (2000) developed a framework to control autonomous backhoe-type excavators. In their study, the control structure was divided into low and high levels. The low-level control utilized fuzzy logic to encapsulate expert experience for capturing soil properties in many excavation scenarios. Unified modelling language (UML) statecharts were used at the higher level for mapping environment and machine sensor data to actuator control signals. The mapping was based on a deep understanding of excavation performed by a skillful operator and was coded into rule sets. Cannon and Singh (2000) introduced a composite forward model of the mechanics of a backhoe excavator digging in soil. The model predicts the excavator's trajectory based on estimations of soil properties and predicts contact forces between the excavator and the terrain.

Stentz et al. (1999) developed a system that enables the excavator to decide where to dig in the soil, where to dump the materials carried in the truck, and how to quickly move between points while detecting and stopping for obstacles. The system included two scanning laser rangefinders to recognize and localize the truck, measure the soil face, and detect obstacles and included software capable of analyzing the inputs and controlling the operation. The system was fully implemented and was demonstrated to load trucks as fast as human operators. Capony et al. (2012) reported that the use of GPS-equipped excavators can achieve more accurate earthwork operations and reduce fuel consumption and working time.

AMG requires advanced planning technologies to provide digital plans that are compatible with the control systems during construction. Jayawardane and Harris (1990) utilized linear programming to optimize a comprehensive earthmoving system in road construction by comparing alternative fleets (from among different available fleets) to provide an optimum material distribution and recommend appropriate plant fleets to complete a project within the specified time. Further developments in computer knowledge–based simulations have allowed automated earthmoving project planning (Askew et al. 2002).

Building information modeling (BIM) and multidimensional modeling simulations are more appropriate tools developed for planning and AMG applications. Huang and Bernold (1997) developed a computer-aided design (CAD) integrated with trenching and pipe-laying machines. The system could lay the foundation for safer and more productive trenching operations in the future. Ji et al. (2009) presented a framework to conduct simulations of earthwork operations using a 3D roadway model, 3D surface model, and 3D subsoil model. The simulation was based on the discrete events paradigm, which describes entities such as diggers and trucks, their behavior, and the time required for an atomic process step. The results provided information on the utilization ratio of the employed resources and the time required for completing the entire earthwork project.

Kamat and Martinez (2001, 2003) described the methodology and a first version of a general purpose 3D visualization system (i.e., Dynamic Construction Visualizer), which is a discrete event construction simulation that is independent of CAD software. This system enables spatially and chronologically accurate 3D visualization of modeled construction operations and the resulting products. Miller et al. (2011) utilized 3D models to visualize paving jobs and help understand the relationship between machine operations and hot-mix asphalt (HMA) temperature and the impact of this relationship on HMA compaction.

BIM use has grown rapidly in recent years due to its usefulness for geometric modelling of a building's performance and for its benefits in terms of cost reduction, the control it provides throughout the project's lifecycle, and significant time savings (Barlish and Sullivan 2012, Bryde et al. 2013). Eadie et al. (2013) reported some issues that limit the use of BIM, such as lack of expertise within the project team, cultural resistance (Dawood and Iqbal 2010, Denzer and

Hedges 2008), resistance at the operational level (Bender 2010), lack of immediate benefits from projects delivered to date (Sebastian 2010), legal issues regarding ownership, and insurance (Chynoweth et al. 2007, Olatunji 2011, Race 2012).

Goodrum (2001) discussed an approach to quantifying the effects of construction technology on labor and partial-factor productivity. Other researchers have implemented machine learning approaches to define different factors related to project productivity (AbouRizk et al. 2001, Heravi and Eslamdoost 2015, Hola and Schabowicz 2010). Although many studies have investigated the effects of different parameters on project productivity at the activity level, fewer studies have modeled the relationship between AMG and construction productivity factors and parameters. The present study introduces a case study using AMG-equipped machines. The data provided are limited to GPS monitoring data to investigate the cycle times of hauling trucks during earthwork activities.

PROJECT DETAILS

The site selected for monitoring was located in Johnston, Iowa, and required grading to build up a residential development. The project involved about 200,000 cubic yards of excavation and placement. Installing a storm sewer and digging a pond were also required for the project. The soils on site were of glacial origin and were generally classified as silty clays. Project monitoring occurred in October 2014. Figure 1 shows the simplified site plan and highlights the primary haul road, the primary fill area, and the pond excavation area.

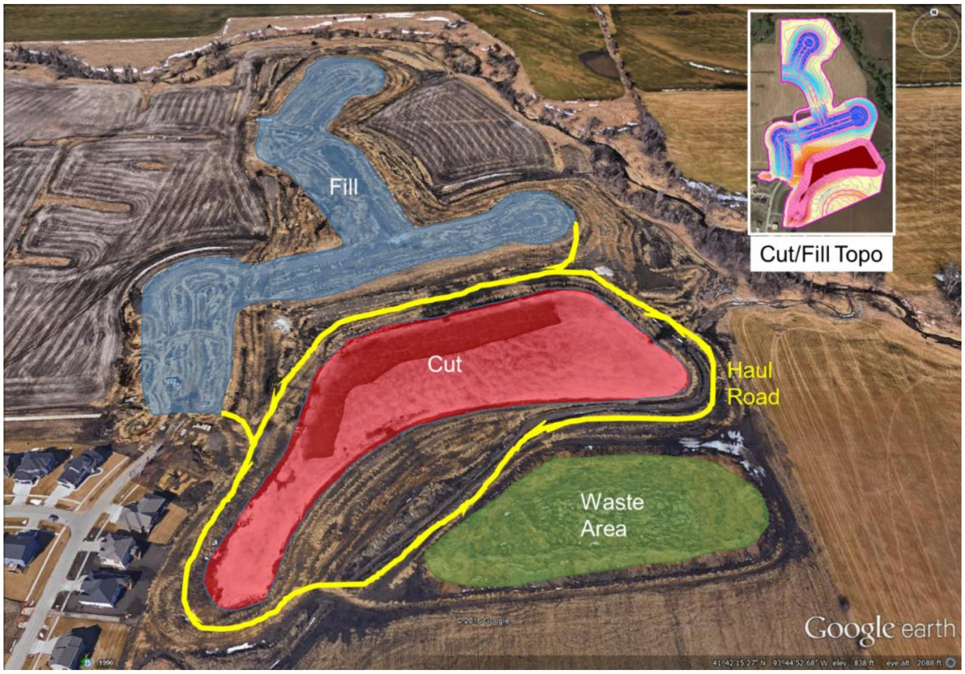


Figure 1. Idealized cut/fill/haul details for the project

Table 1 summarizes the equipment used on site during the monitoring phase of the project.

Table 1. List of equipment monitored on site

Equipment	Model Number	Name	Max. Heaped Capacity (yd^3)
Excavator	Caterpillar (CAT) 375 Hydraulic Excavator	Excavator	7.0
Hauling truck	CAT 740 B	CAT 70073	31.4
Hauling truck	CAT 740 B	CAT 70075	31.4
Hauling truck	Volvo A40F	Volvo	31.4
Bulldozer	CAT D8T	Bulldozer	6.1

Figure 2 shows the equipment.

Figure 2. Equipment monitored on site: CAT D8T bulldozer (top), CAT 375 Hydraulic Excavator and CAT 740 B truck (center), and Volvo A40F truck (bottom)

Position tracking devices were installed on the equipment to monitor the time and position of the equipment for several days. The positional accuracy of the monitoring devices was on the order of about 10 m, and the sampling frequency was set to 0.2 Hz.

Figures 3 through 11 show machine operations and site conditions.

Figure 3. Excavation of the pond (middle left area of image)

Figure 4. Glacial till soil placed in fill area

Figure 5. Wet unstable areas of fill that required lime stabilization

Figure 6. Wet unstable areas of fill that required lime stabilization, and load of lime ready for incorporation into soil

Figure 7. Section of haul road observed to pump and rut under haul truck operations

Figure 8. View from bottom of pond area showing the area being excavated and loaded into haul trucks

Figure 9. Loaded CAT 740B haul truck traveling on haul road to fill area

Figure 10. AMG CAT D8T bulldozer operations to spread fill

Figure 11. Dewatering operation for pond area and loaded haul truck on haul road

During the monitoring period, the soils conditions were observed to be wet, and sections of the haul roads were rutting and or pumping under construction traffic, which is a common challenge with earthwork operations in Iowa. Dewatering was needed to excavate the pond area. During the monitoring period, lime was used on a section of the construction site to reduce moisture content and stabilize the wet soils.

POSITION MONITORING RESULTS

As noted, GPS tracking devices were attached to all hauling trucks, the excavator, and the bulldozer. All records from the devices were connected to Google Earth using .KMZ* files showing the positions superimposed on a map. Each recorded point (the yellow dots in Figures 12 through 35) contained the x, y, and z global coordinates and the time. In addition to position information, the data files included truck speed and rest time (if not moving). Position monitoring was active from October 17 through October 21, 2014. Cycle time analysis was conducted on all hauling trucks to describe the haul truck activity in terms of statistical parameters to assess the productivity observed on the project.

Figures 12 through 17 show the position monitoring results for the bulldozer.

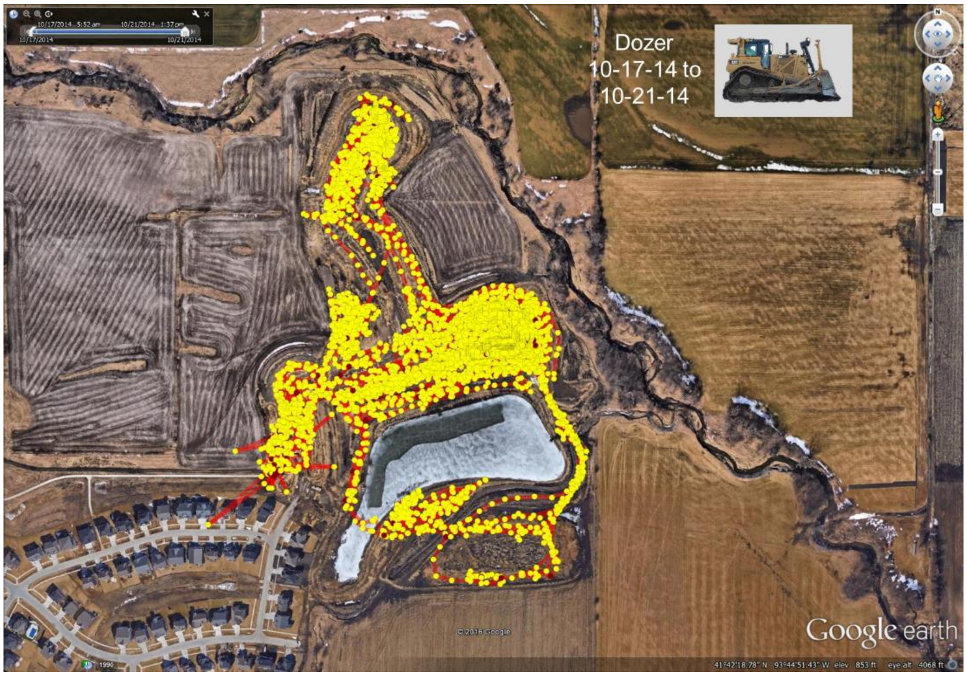


Figure 12. CAT D8T bulldozer operations for October 17 through October 21

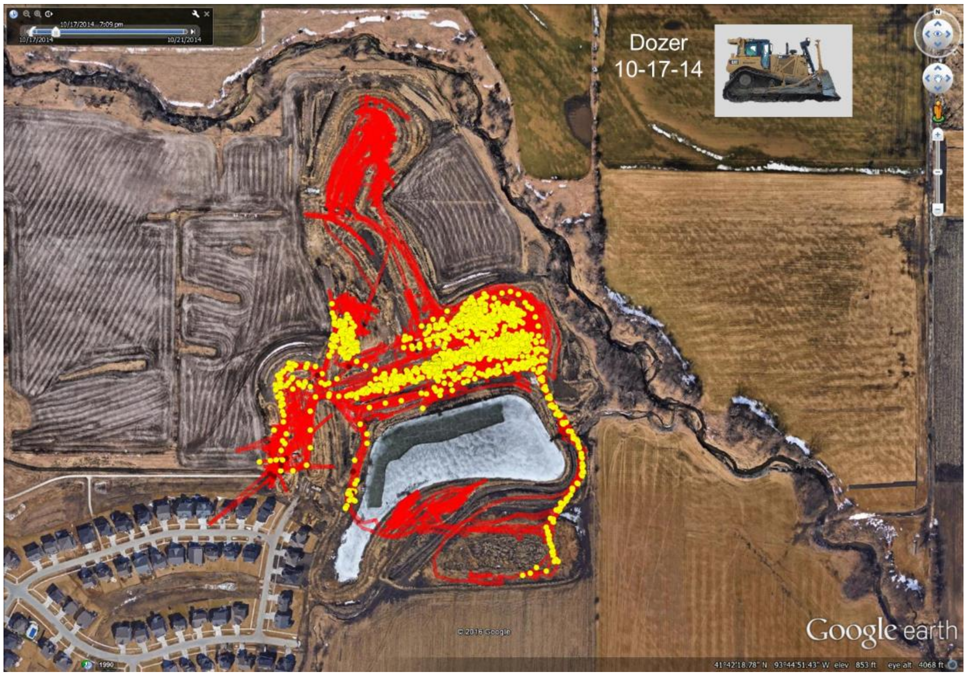


Figure 13. CAT D8T bulldozer operations for October 17

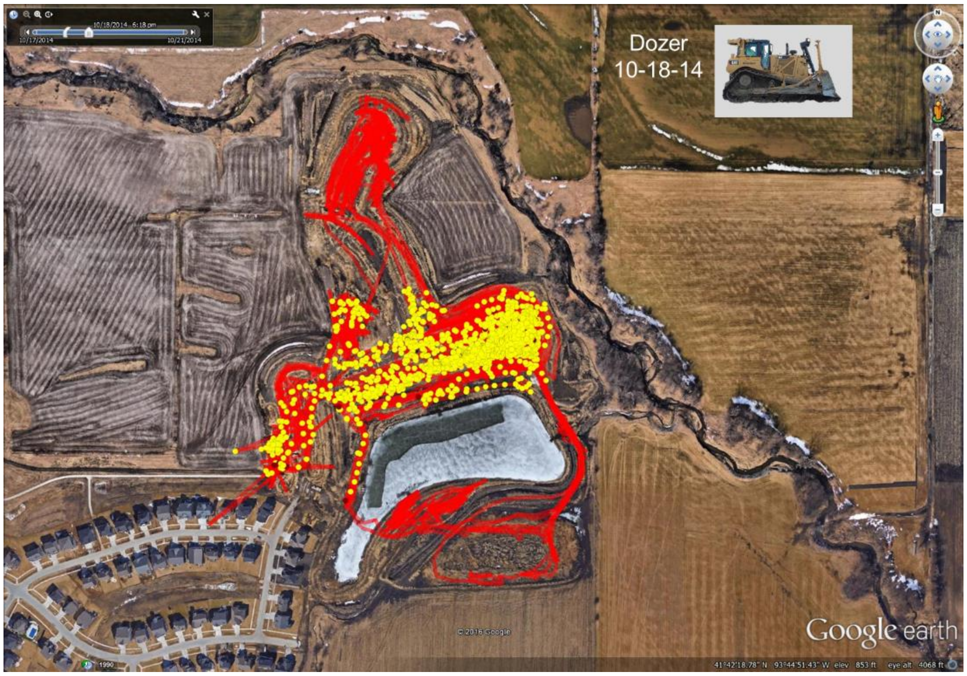


Figure 14. CAT D8T bulldozer operations for October 18

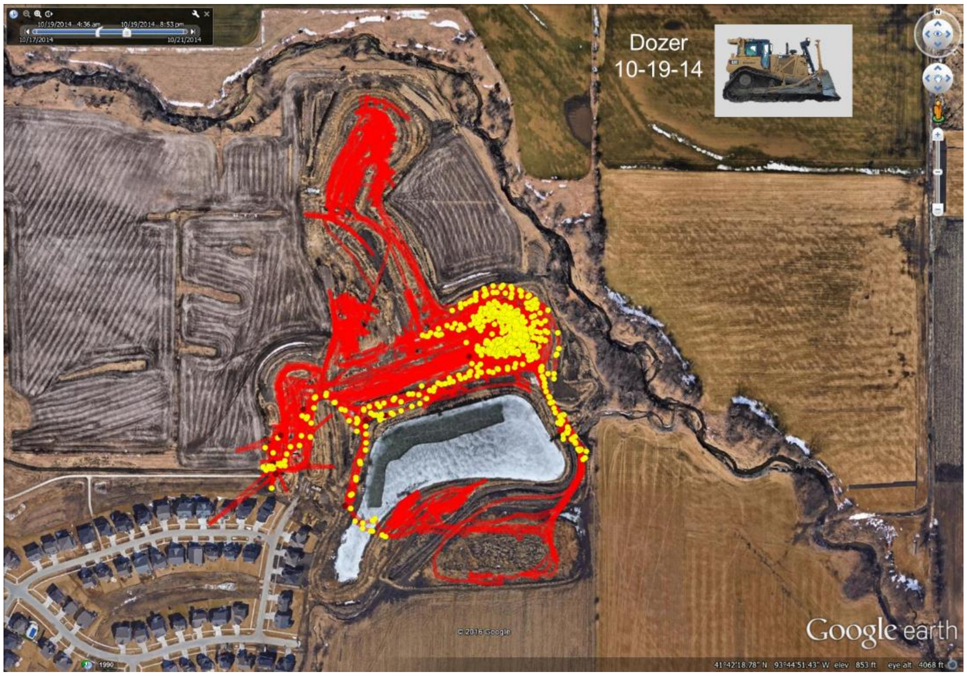


Figure 15. CAT D8T bulldozer operations for October 19

Figure 16. CAT D8T bulldozer operations for October 20

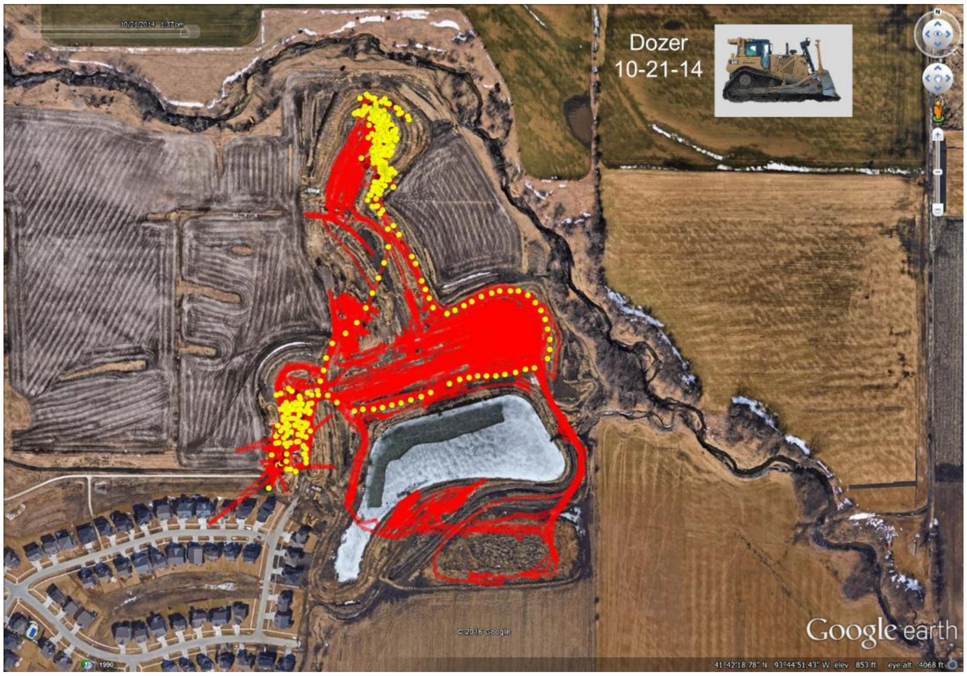


Figure 17. CAT D8T bulldozer operations for October 21

For all position maps in Figures 12 through 35, the red line indicates the travel line for the full evaluation period. The yellow points indicate the position during moving operations, and the red dots indicate periods of no movement (rest).

Figures 18 through 21 show the position monitoring results for the excavator.

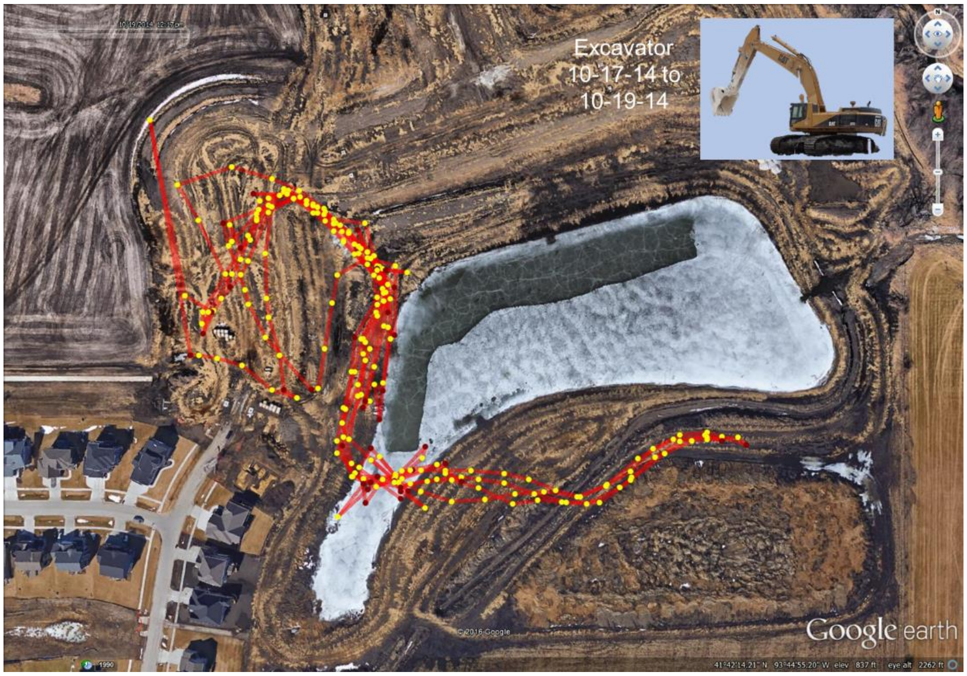


Figure 18. CAT 375 excavator operations for October 17 through October 19

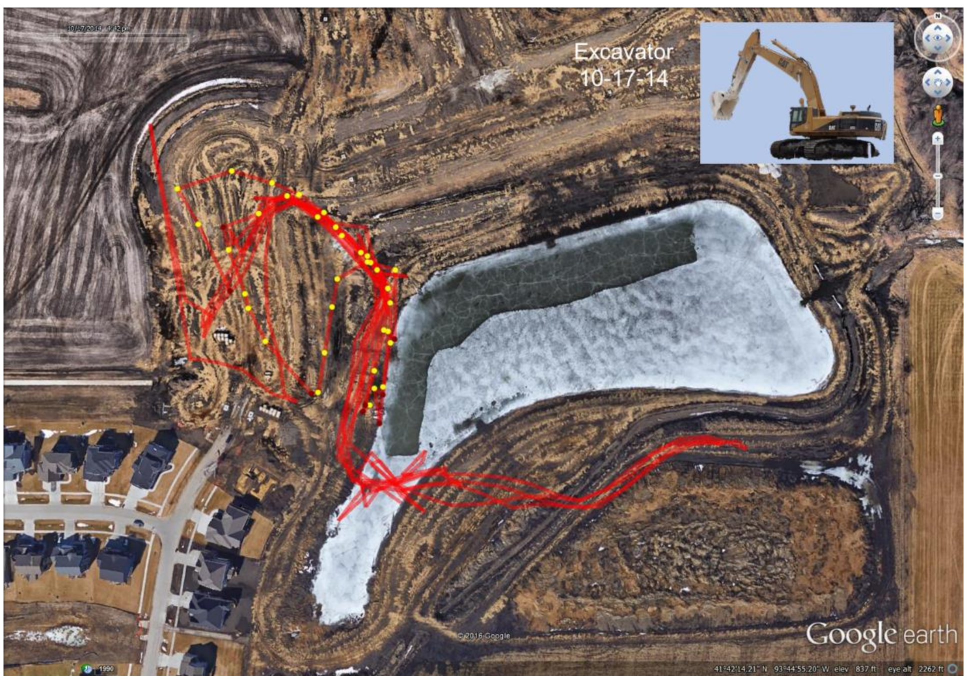


Figure 19. CAT 375 excavator operations for October 17

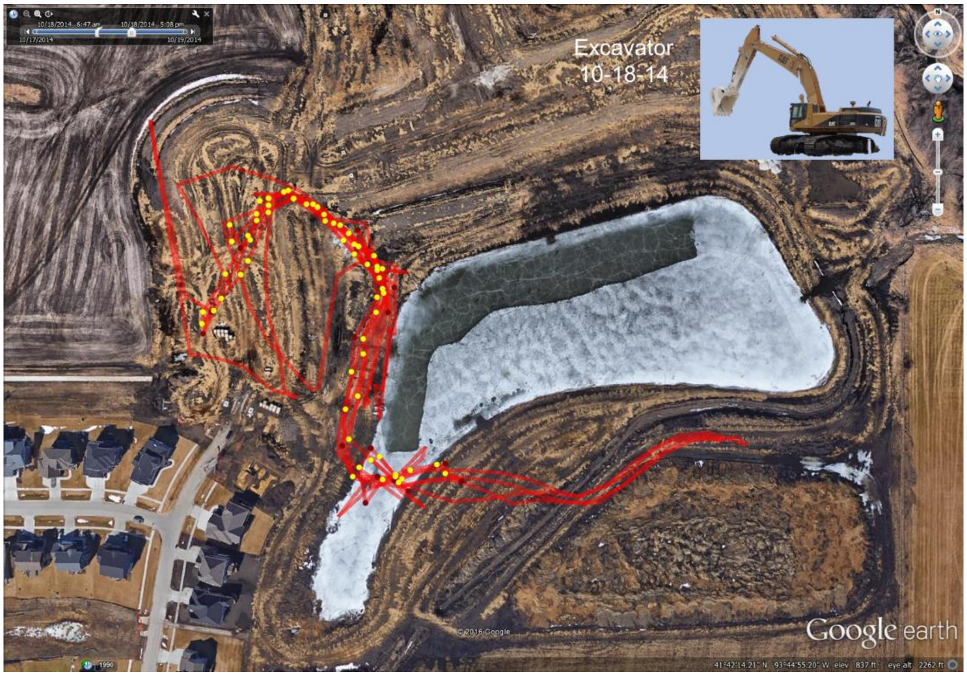


Figure 20. CAT 375 excavator operations for October 18

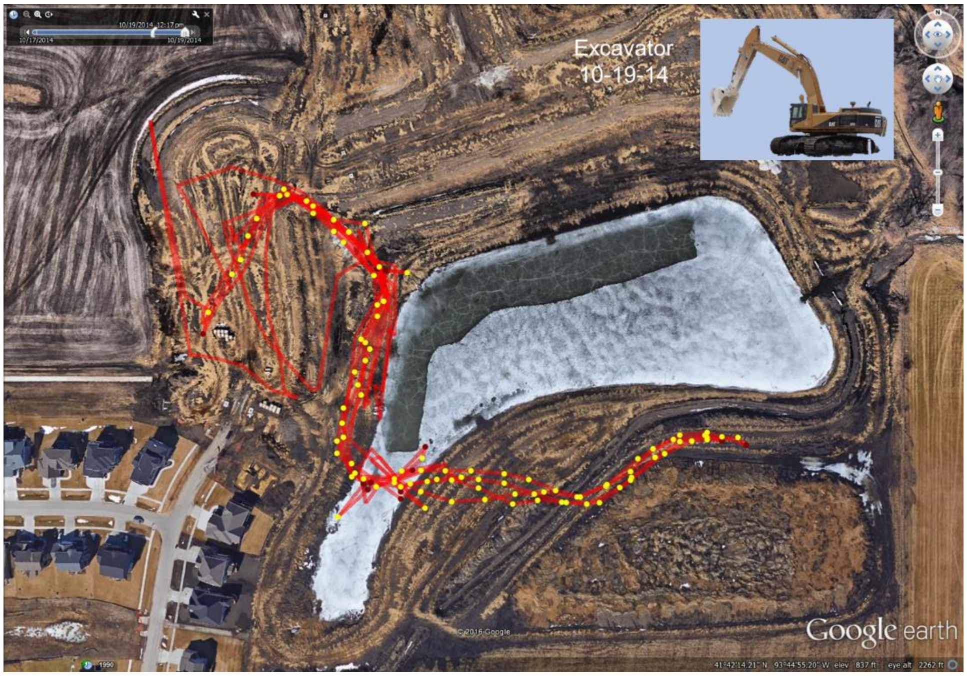


Figure 21. CAT 375 excavator operations for October 19

Figures 22 through 35 show the position monitoring results for the haul trucks. For haul truck #70073, a few of the position measurements were outside of what was realistic and were filtered out of the data.

Figure 22. CAT 740B haul truck (#70075) operations for October 17 through October 20

Figure 23. CAT 740B haul truck (#70075) operations for October 17

Figure 24. CAT 740B haul truck (#70075) operations for October 18

Figure 25. CAT 740B haul truck (#70075) operations for October 19

Figure 26. CAT 740B haul truck (#70075) operations for October 20

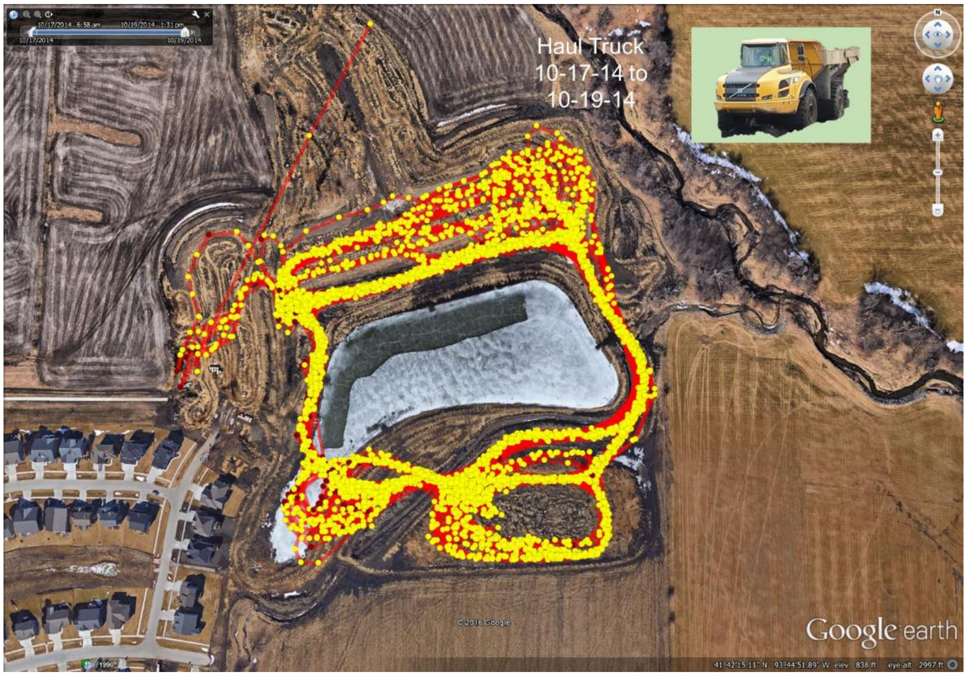


Figure 27. Vovlo A40F haul truck operations for October 17 through October 19

Figure 28. Vovlo A40F haul truck operations for October 17

Figure 29. Vovlo A40F haul truck operations for October 18

Figure 30. Vovlo A40F haul truck operations for October 19

Figure 31. CAT 740B haul truck (#70073) operations for October 17 through October 20

Figure 32. CAT 740B haul truck (#70073) operations for October 17

Figure 33. CAT 740B haul truck (#70073) operations for October 18

Figure 34. CAT 740B haul truck (#70073) operations for October 19

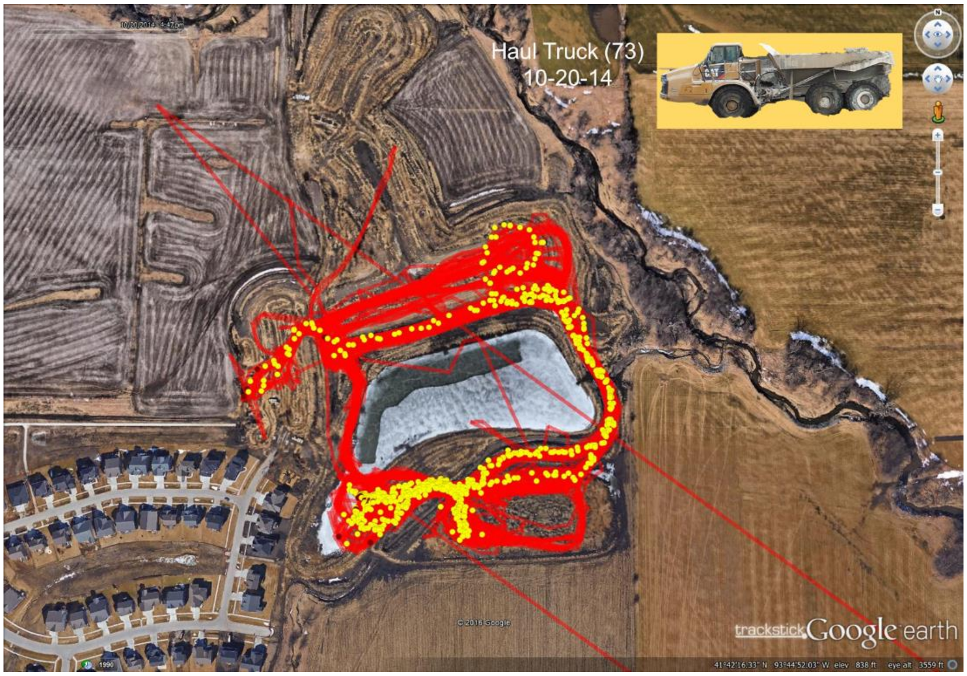


Figure 35. CAT 740B haul truck (#70073) operations for October 20

CYCLE TIME ANALYSIS

One of the goals of this project was to make use of relatively inexpensive GPS positing equipment to generate data for equipment cycle time monitoring and analysis. Cycle times were determined by defining the haul boundary, dump locations, and loading locations. The data were then organized into individual cycle records so that the cycle times could be determined for each piece of equipment.

The cycle time analysis process involved defining the location of the excavator and either the nearest stopping point of the hauling truck or the point with the lowest speed. The starting time of the stopping point defines the end of a cycle and the beginning of a new cycle. Accordingly, the cycle time is defined as the difference between the times of two loading points. Within a cycle, it was observed that there were several instances where the equipment stopped for a short period (e.g., two minutes) and then resumed travel. These stoppages were related to the equipment yielding to other equipment and waiting for direction from the bulldozer operator as to where a load was to be dumped.

Cycle times without delays were calculated by removing the stopping times other than the loading times from the cycles. The cycles that included an excavator location change were not included in the analysis.

Figure 36 shows a histogram of the cycle times for one of the haul trucks during the monitoring period.

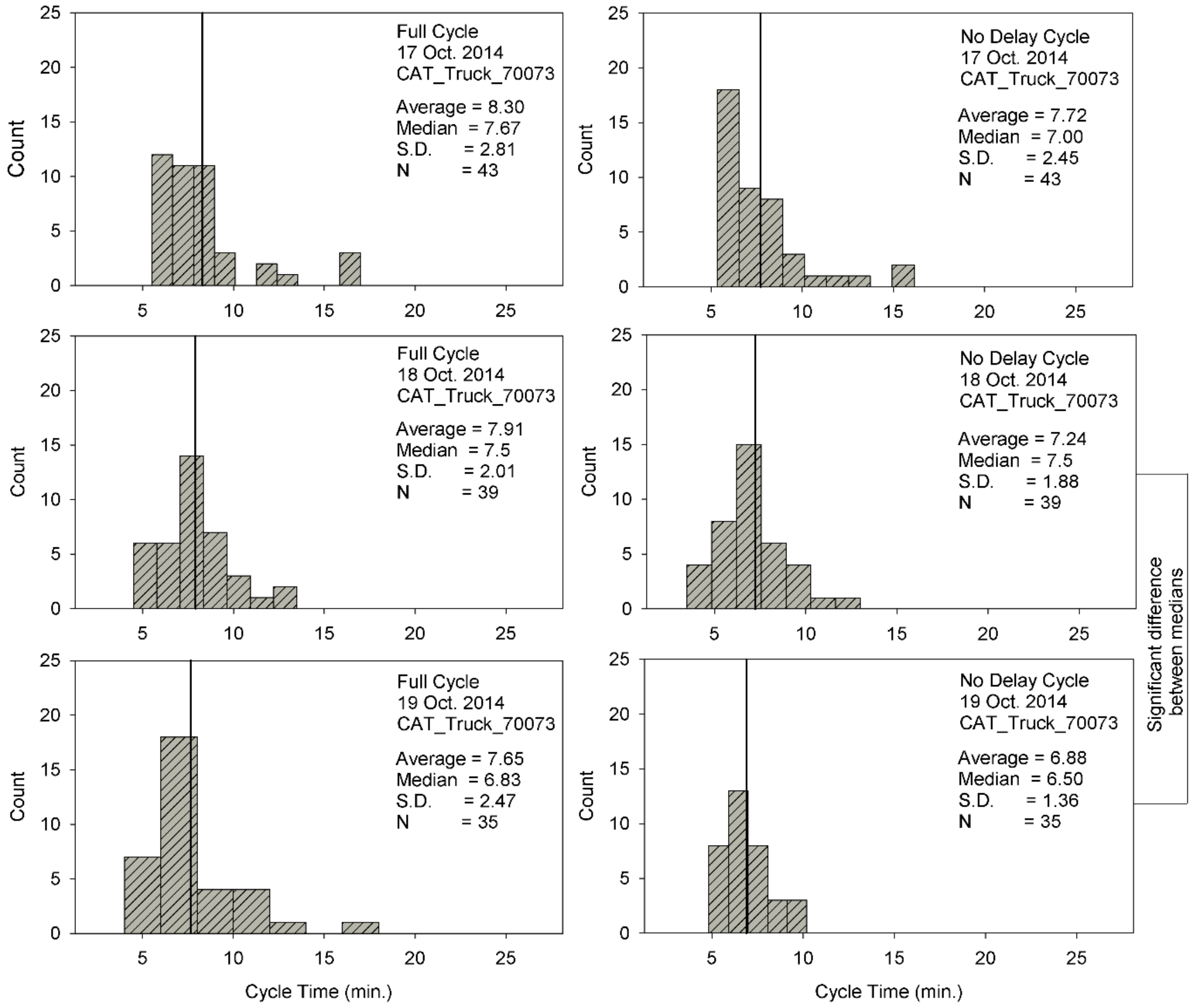


Figure 36. Distribution of cycle times with and without stoppage delays for CAT 740B haul truck (#70073)

It can be seen that the cycle time distributions are positively skewed. The distributions appear non-normal. However, further testing was conducted to verify the distributions' normality using the Shapiro-Wilk test of normality (Royston 1982, Royston 1995). It was concluded that none of the distributions are normal and, therefore, proper statistical analysis tools should be used to analyze such distributions.

Due to the non-normal distribution, the traditional analysis of variance (ANOVA) is not appropriate for comparing the mean performance over time. Non-parametric tests are more suitable for such comparisons. The median rank scores test was performed to test whether there is a statistically significant difference between the distributions' medians. In Figure 36, the connecting lines between the histograms indicate a significant difference between the medians. Thus, it can be concluded that there is a difference between the median cycle times of CAT 740B haul truck 70073 between October 18 and 19. Understanding the factors leading to a significant change in cycle time is desirable because these factors relate to the potential for improving efficiency.

Figure 37 shows that there is a significant difference between the median cycle times on October 17 and 18 and on October 17 and 19 for CAT 740B haul truck 70075.

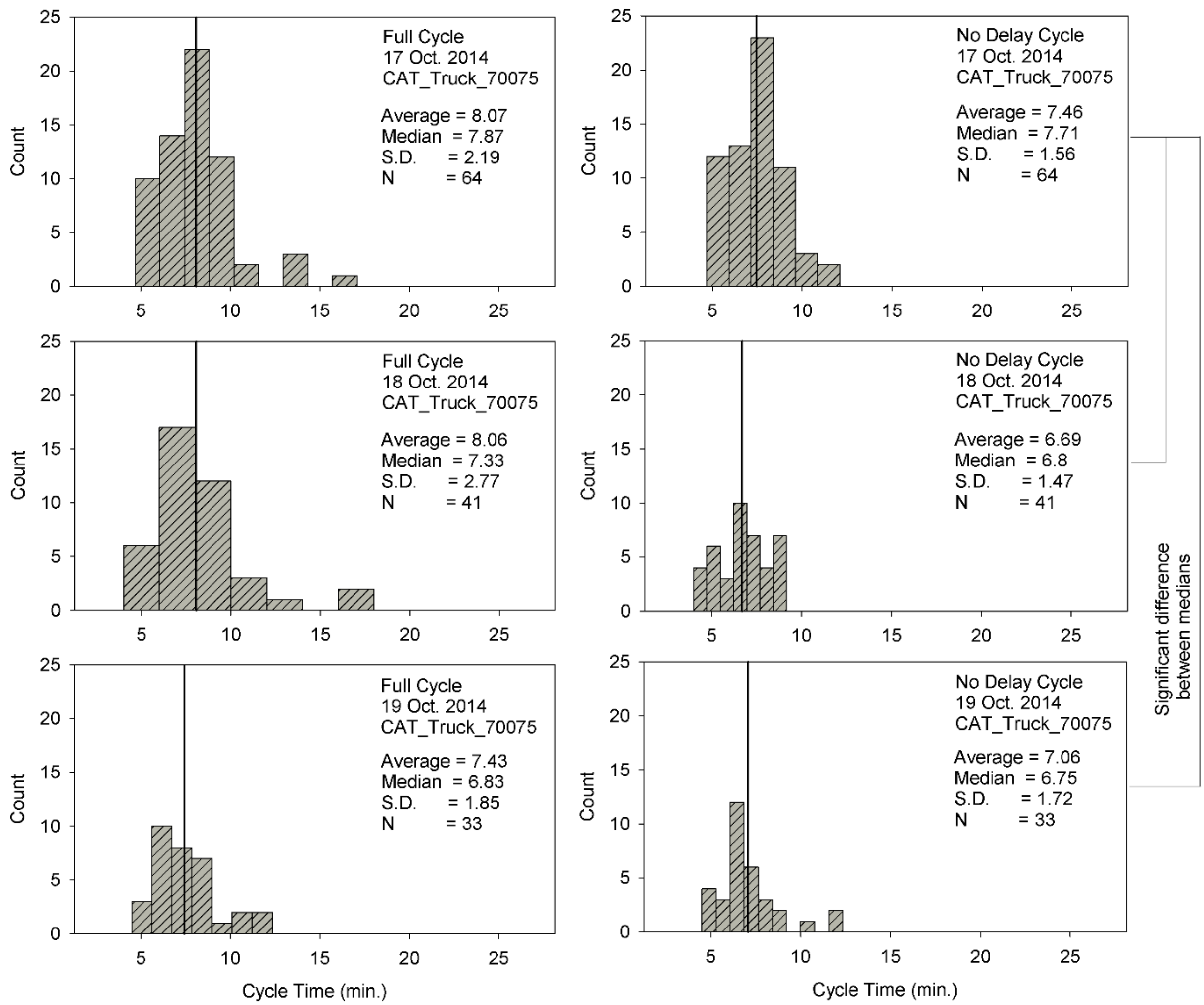


Figure 37. Distribution of cycle times with and without stoppage delays for CAT 740B haul truck (#70075)

Figure 38 shows that there is significant difference between the median cycle times on October 17 and 19 for the Volvo A40F haul truck.

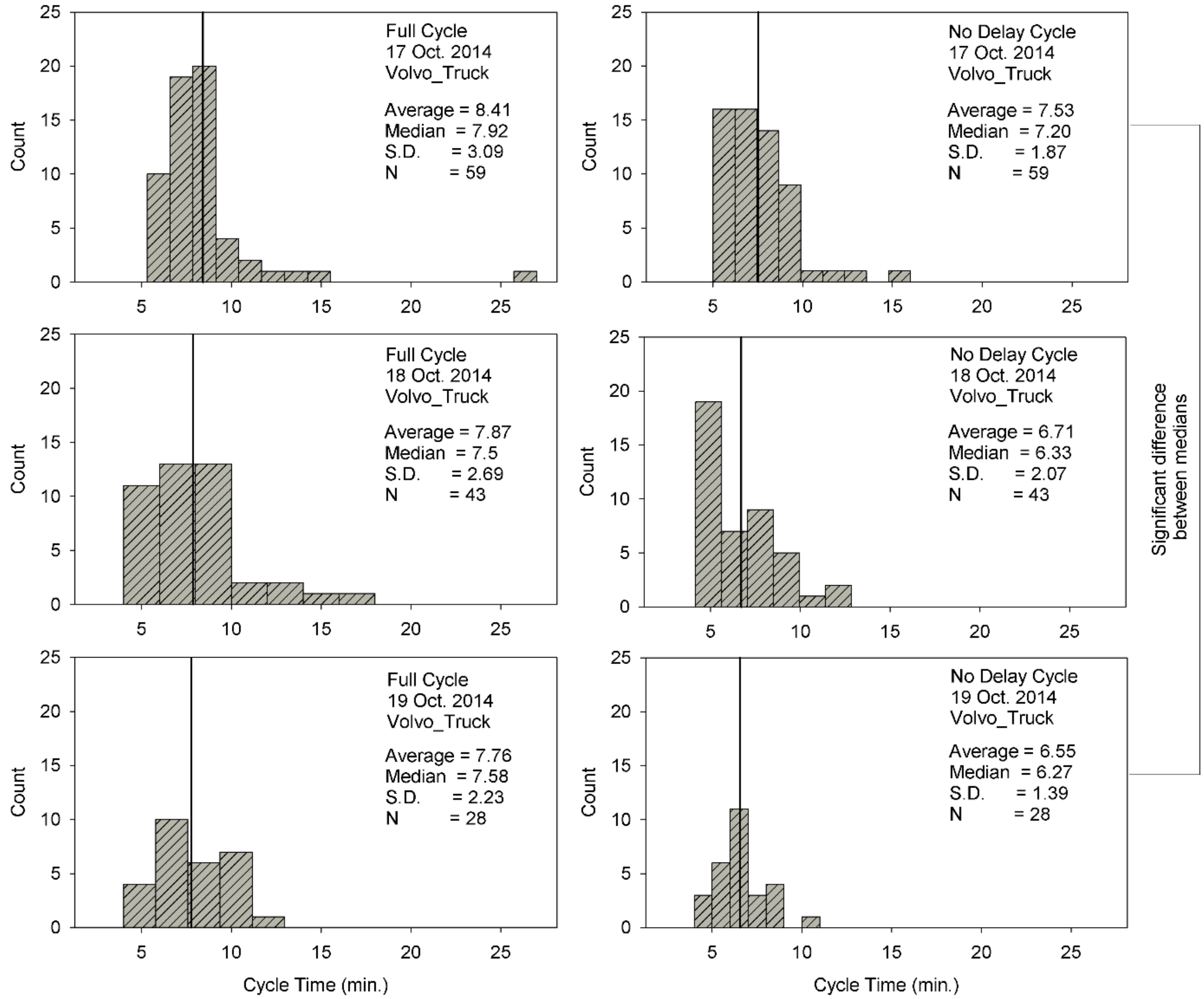


Figure 38. Distribution of cycle times with and without stoppage delays for Volvo A40F haul truck

Based on the statistical analysis conducted on the cycle time distributions, it can be stated that the cycle times were improved (i.e., made shorter) as the monitoring period progressed. This improvement might be due to the operator's increasing familiarity with the nature of the site nature or other factors.

Further median score tests were performed to compare the three trucks' cycle times on each day from October 17 to 19. The results are presented in Figures 39 through 41.

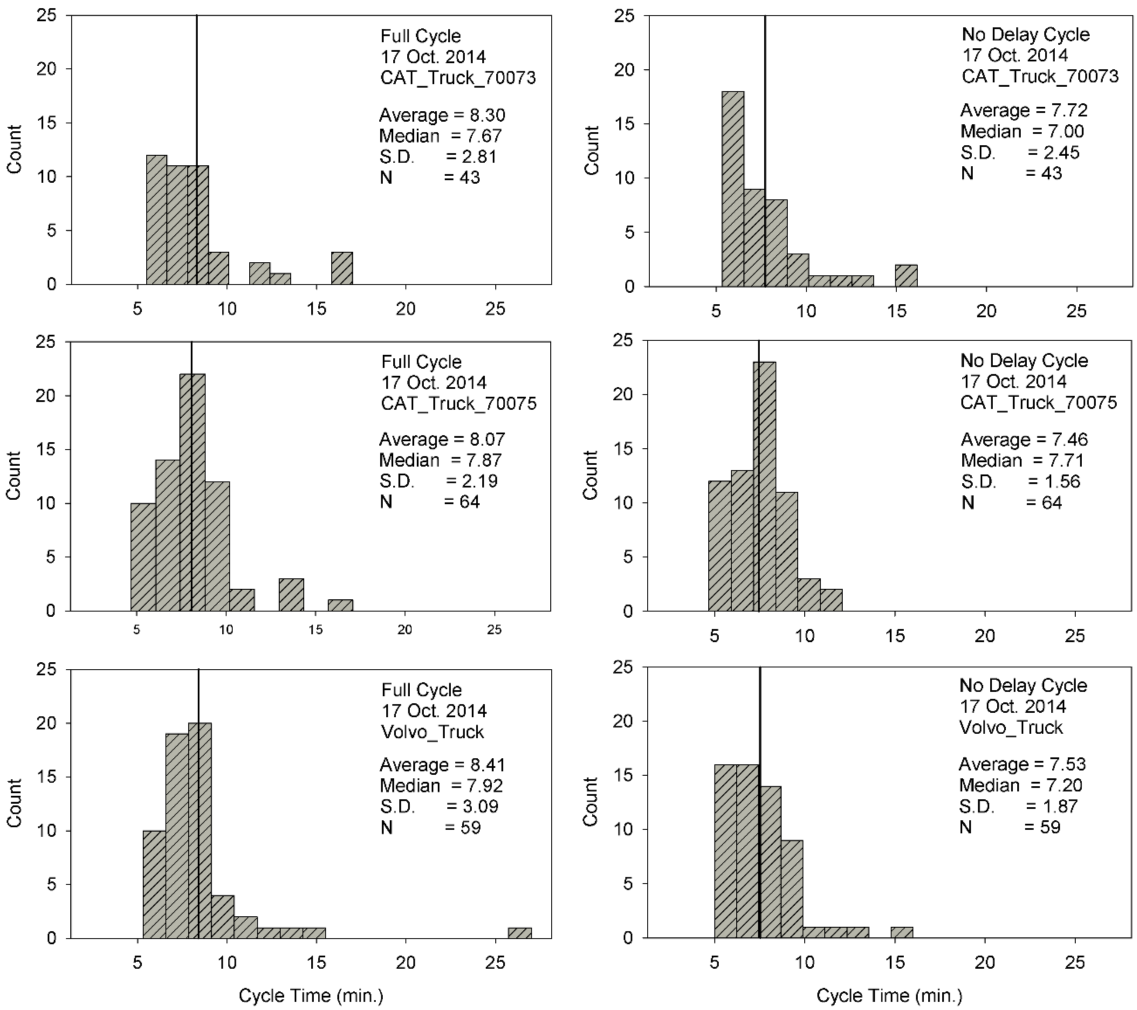


Figure 39. Comparison of cycle times with and without stoppage delays for all three trucks on October 17

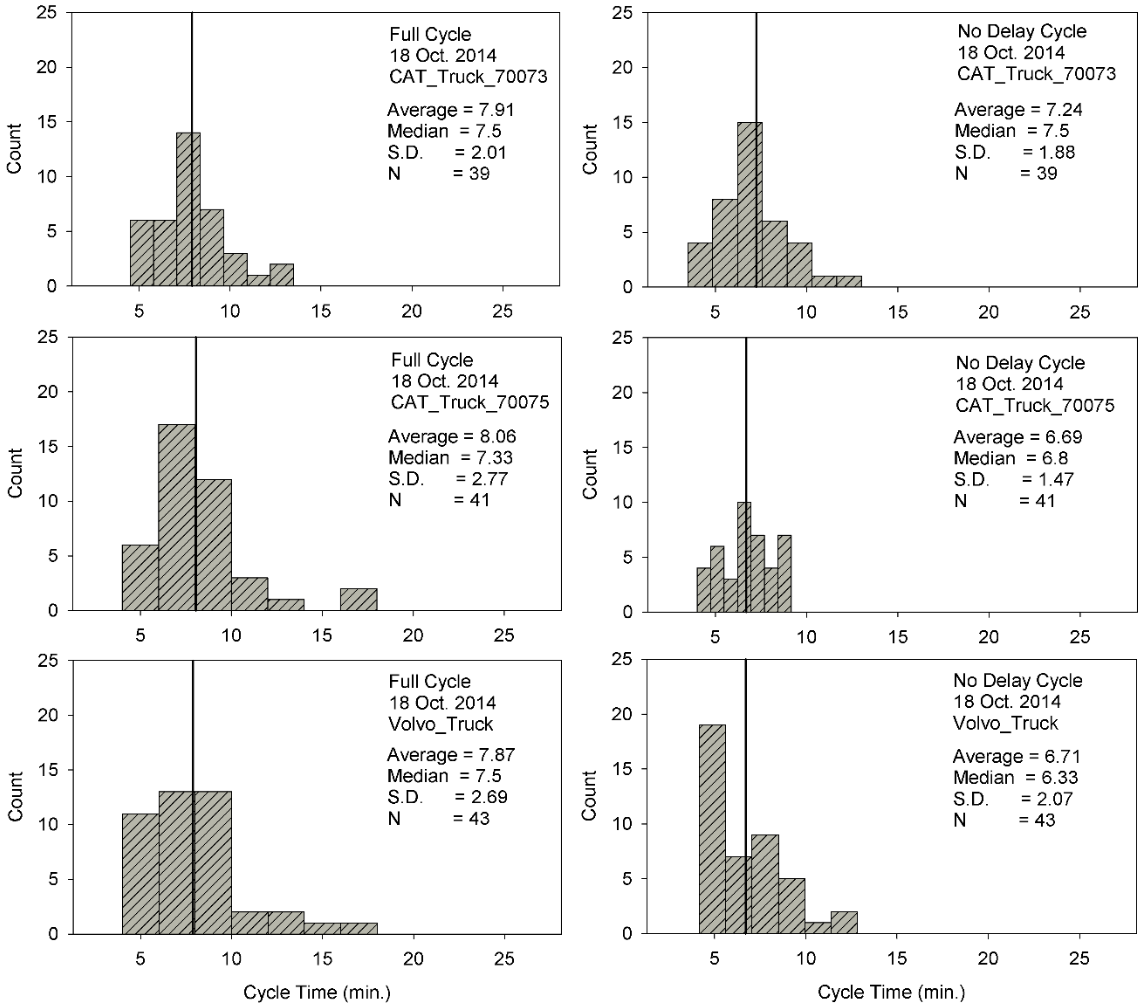


Figure 40. Comparison of cycle times with and without stoppage delays for all three trucks on October 18

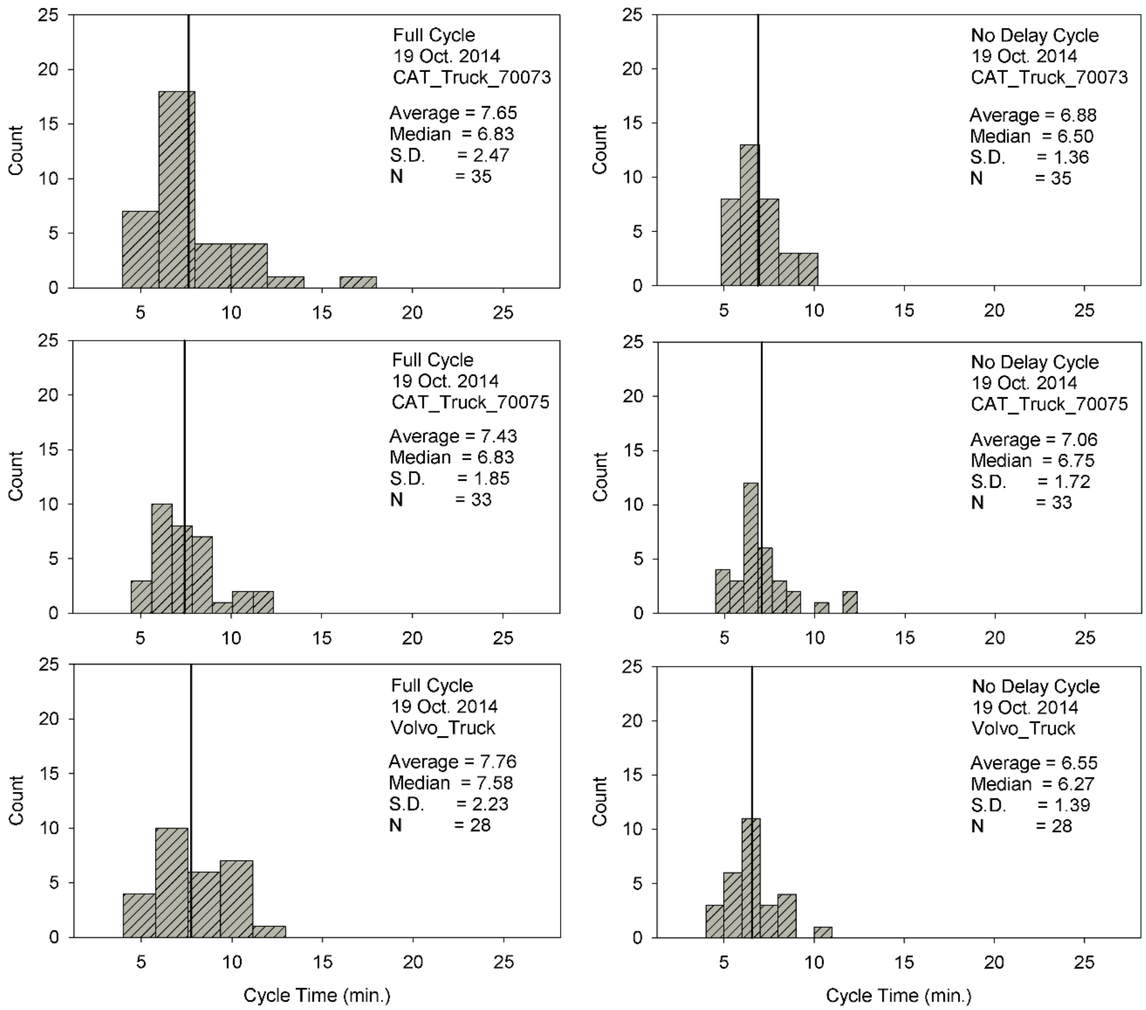


Figure 41. Comparison of cycle times with and without stoppage delays for all three trucks on October 19

It was concluded that there are no significant differences between the median cycle times for all hauling trucks on a given day. This is not unexpected because the cycle times for each truck are heavily dependent upon the cycle times of the other trucks.

The production rate of a truck can be estimated based on the cycle time, as shown in Equation (1).

$$\text{Production rate } (yd^3/hour) = \text{Heaped truck load } (yd^3) \times \frac{60\ (min.)}{Truck\ full\ cycle\ time\ (min.)} \qquad \textbf{(1)}$$

The production rate was calculated for each truck based on a single cycle, which allowed multiple production rates per day to be estimated. To estimate the production rate of the excavator, further data are needed to measure the loading time for the excavator. The optimal number of hauling trucks can be then estimated by dividing the truck cycle time by the loading cycle time. One of the two integer values is then assigned as the optimal number based on the cost.

Figures 42 through 44 show histograms for the trucks' production rates during the monitoring period.

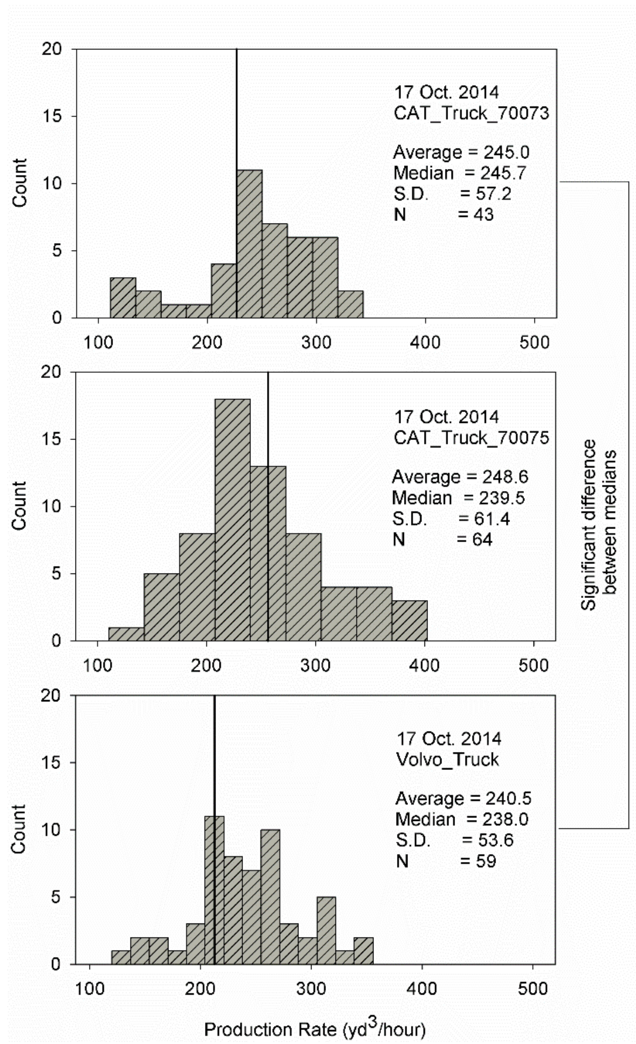


Figure 42. Comparison of estimated production rates of three haul trucks, October 17

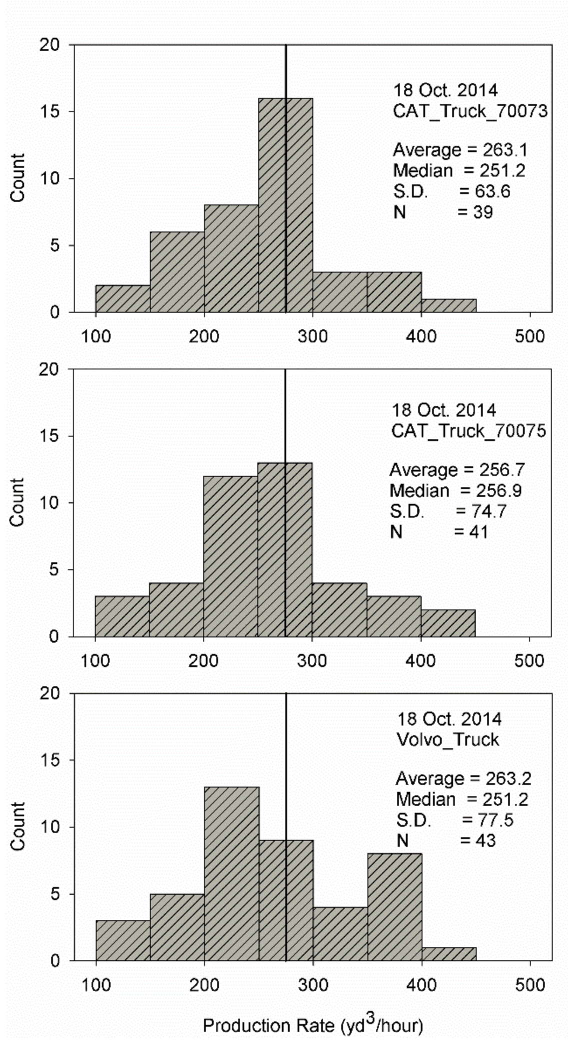


Figure 43. Comparison of estimated production rates of three haul trucks, October 18

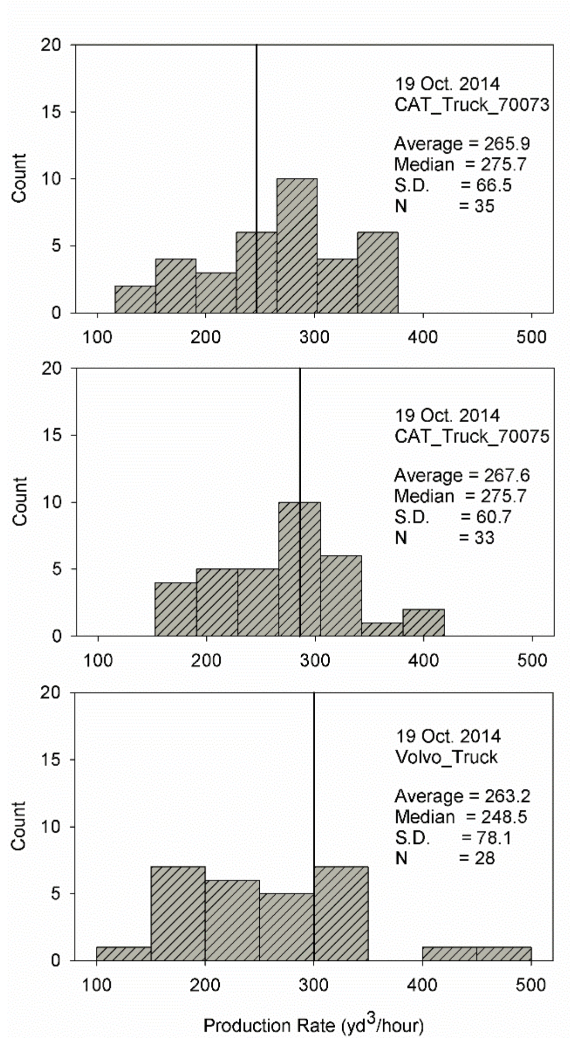


Figure 44. Comparison of estimated production rates of three haul trucks, October 19

There is no significant difference between the production rates for the different trucks. However, when the production rates are compared over time, there is a slight improvement in production for CAT 740B haul truck 70073 between October 17 and 19.

The production rate of the excavator was estimated based on Equation (2).

$$\text{Excavator production rate } (yd^3/hour) = \frac{\text{Total number of truck cycles} \times \text{Heaped truck load } (yd^3)}{Excavating\ time\ (hour)} \qquad \textbf{(2)}$$

The volume of excavated material can be estimated by multiplying the number of loads for all trucks per day by the heaped capacity of the trucks. The work time can be estimated as the sum of stopping times for the excavator, which corresponds to the time spent digging by the excavator. Based on these calculations, the approximate production rates of the excavator were 550.4, 598.7, and 731.1 yd^3/hour for October 17, 18 and 19, respectively. It can be seen that the average excavation rate improved over time, especially on October 19. However, for more realistic production rates, additional details on the number of cycles for the excavator should be recorded.

SUMMARY

The study of site-level earthwork project monitoring described in this report quantifies haul truck cycle times. GPS tracking devices were attached to three hauling trucks, the excavator, and the bulldozer. Each recorded point contained the x, y, and z global coordinates and the time. In addition to position information, the data files included truck speed and rest time (if not moving). Cycle time analysis was then conducted to describe the haul truck activity in terms of statistical parameters. The key findings from this study are as follows:

- Cycle times were determined by defining the haul boundary, dump locations, and loading locations. The data were then organized into individual cycle records so that the cycle times could be determined for each piece of equipment. The cycle time analysis process involved defining the location of the excavator and either the nearest stopping point of the hauling truck or the point with the lowest speed. The starting time of the stopping point defines the end of a cycle and the beginning of a new cycle. Accordingly, the cycle time is defined as the difference between the times of two loading points.

- Within a cycle, it was observed that there were several instances where the equipment stopped for a short period (e.g., two minutes) and then resumed travel. These stoppages were related to the equipment yielding to other equipment and waiting for direction from the bulldozer operator as to where a load was to be dumped.

- Cycle times without delays were calculated by removing the stopping times other than the loading times from the cycles. The cycles that included an excavator location change were not included in the analysis.

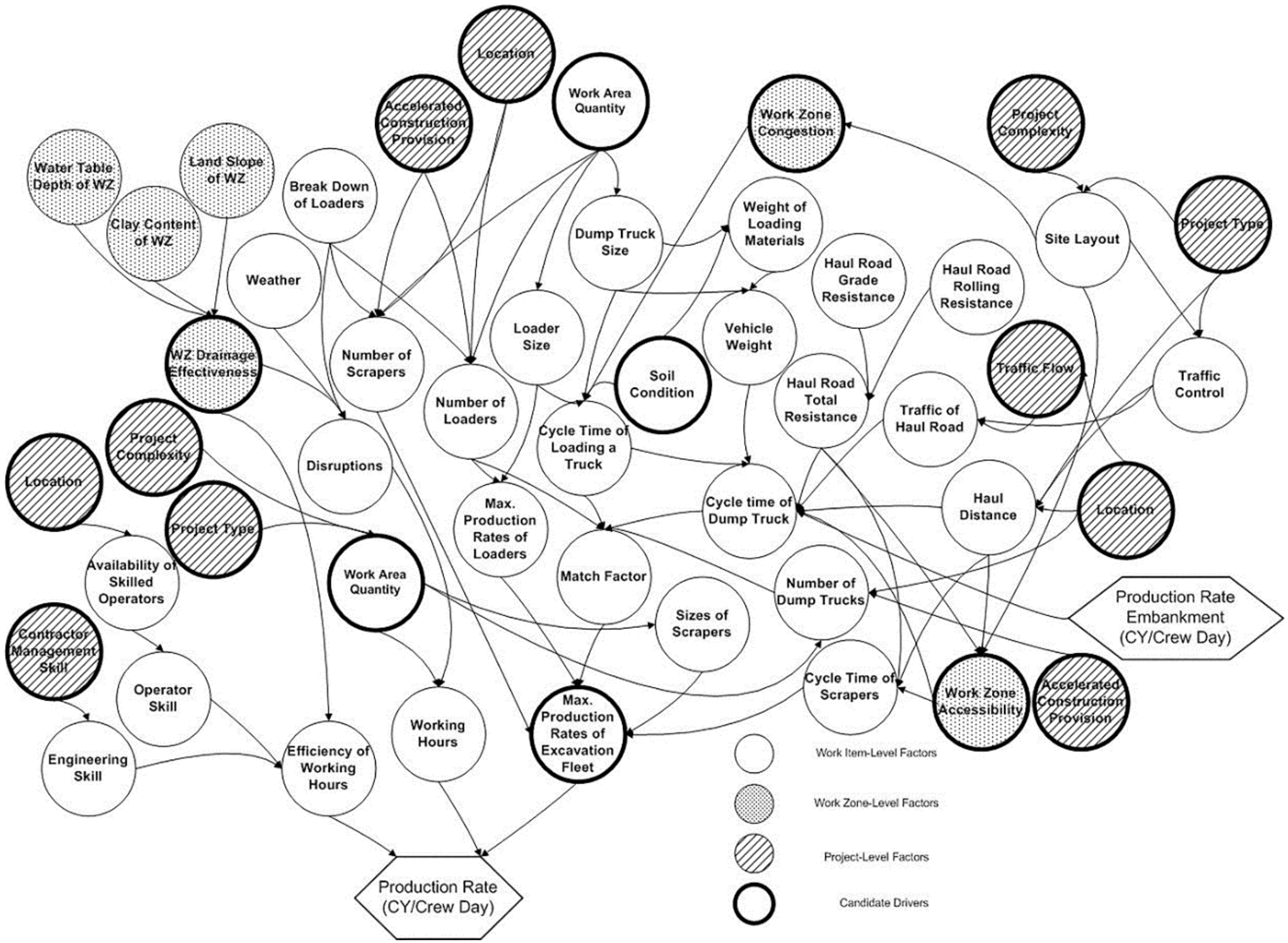
- The results show that the cycle time distributions are positively skewed. It was concluded that none of the distributions are normal and, therefore, proper statistical analysis tools should be used to analyze such distributions. Due to the non-normal distribution, the traditional analysis of variance was not used in favor of non-parametric tests. A median rank scores test was performed to test whether there was a statistically significant difference between the distributions' medians.

- Understanding the factors leading to a significant change in cycle time is desirable because these factors relate to the potential for improving efficiency.

- The production rates of the haul trucks were estimated based on the cycle time analysis. In theory, this analysis would help define the optimal number of hauling trucks. The production rate of the excavator was also estimated; the volume of excavated material was estimated by multiplying the number of loads for all trucks per day by the heaped capacity of the trucks.

RECOMMENDATIONS FOR FUTURE RESEARCH

This study served to demonstrate a relatively simple approach to cycle time monitoring and statistical analysis. However, more advanced data collection and analysis are needed. Moving forward, a more completely designed monitoring program should be devised to capture the effects of the many factors that can influence productivity. Kuo (2004) identified multiple parameters that might affect the production rate (Figure 45) and used regression analysis and ANOVA to quantify the effects of parameters that are known at the design stage. However, no technological factors were incorporated into the model. The major challenge in defining the effect of technology is deriving quantifiable statistics to measure that effect.



Kuo 2004

Figure 45. Parameters and interconnectivity of parameters that relate to earthwork productivity

For future site-level monitoring programs, an emphasis needs to be placed on carefully capturing and quantifying the key parameters influencing productivity. There is very limited published information on this topic.

Goodrum (2001) developed a technology index that includes a linear combination of five factors that describe the ways technology changes productivity: changes in control, energy, functional range, information processing, and ergonomics. Through ANOVA and regression analyses, Goodrum (2001) found that changes in equipment technology have played a substantial role in changes in labor and partial factor productivity. This approach could be useful for further studies to demonstrate how equipment or technology influences productivity.

The studies conducted by Kuo (2004) and Goodrum (2001) were based on project-level monitoring and did not examine the effects of technology on construction. Modeling the effects of technology continuously for a given activity can provide greater detail on the positive and negative effects of technology on the activity and can predict the effects of technology on other projects in the planning stage. It is proposed that other approaches such as machine learning and time series analysis should be implemented to model the various technology-related factors.

AbouRizk et al. (2001) developed an artificial neural network (ANN) based on 33 factors in 9 categories to predict labor production rates for pipe installation with high accuracy. Heravi et al. (2015) developed an ANN to study the factors affecting labor production rates for the work involved in installing the concrete foundations of gas, steam, and combined-cycle power plants in Iran. Hola and Schabowicz (2010) have also used ANN to predict productivity for selected sets of machines and to calculate the execution time and cost of tasks.

All regression analysis and ANN techniques can predict production rates given inputs that are within the range of the data used to devise the model. However, to forecast the production rates outside the range of the original parameters, especially in the future, time series analysis should be implemented. Abdelhamid and Everett (1999) presented a brief overview of time series analysis and demonstrated its application of autoregressive (AR) and autoregressive moving average (ARMA) models using previously published data for a series of experiments involving crane lift cycle durations. Hwang (2011) used ARMA and multivariate autoregressive models to accurately predict construction cost indexes.

In the time series studies cited above, all models are based on previous productivity data. However, they do not account for site parameters and effects. Based on the results of the present study and the literature review, a further investigation is suggested to devise a dynamic regression model with stochastic inputs to measure the effects of various technologies on earthwork productivity. The model might include several of the following parameters:

- Project complexity (i.e., site layout and details)
- Dump truck size
- Number of dump trucks
- Loader size

- Number of loaders
- Excavation rates
- Material transfer rates
- Machines' paths and traffic (i.e., speed, location, and time)
- Haul road resistance
- Work zone drainage
- Soil condition

Figure 46 presents a simple schematic of the suggested dynamic regression model. The model describes the prediction y_t at time t based on two types of information: (1) independent variables at time t and historical independent variables at an earlier time and (2) historical dependent variables n_t at an earlier time. The filter U(B) relates the independent stochastic "innovations" with independent stochastic realizations. This filter is further divided in two parts: $\Psi_x(B)$, which converts the random residuals of a fit (i.e., innovations) into independent variables, and $\nu(B)$, which describes the relationship between the historical independent variables and the independent variable at time t (i.e., realizations). $\Psi_x(B)$ can be omitted if direct measurements are used in the model as independent variables. The filter $\Psi(B)$ relates historical measurements of the observable y with the prediction y_t.

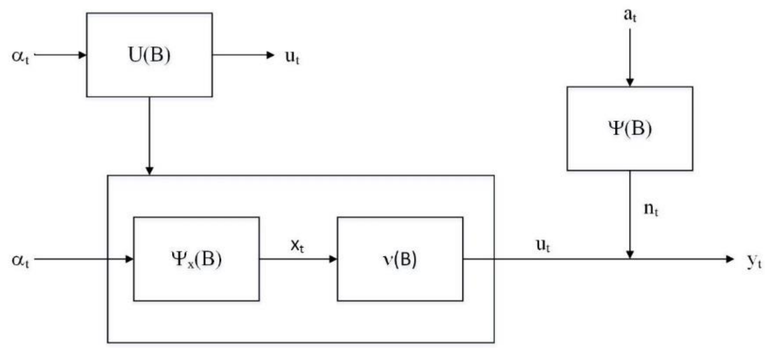


Figure 46. Schematic of the dynamic regression model for future productivity analysis

Future site-level monitoring should thus incorporate a detailed plan to identify which parameters are to be measured, how the parameter values are to be quantified, and the analysis methods to be used to conclusively assess productivity and the associated parameters influencing productivity.

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