CONSTRUCTION EQUIPMENT ACTIVITY RECOGNITION FROM ACCELEROMETER DATA FOR MONITORING OPERATIONAL EFFICIENCY AND ENVIRONMENTAL PERFORMANCE

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ABSTRACT: Construction operations generate a significant amount of air pollutant emissions, including carbon emissions. The environmental performance of construction operations is closely relevant to the operational efficiency of each resource employed, which indicates how efficiently each resource (e.g., construction equipment) is utilized. In this context, monitoring the operational efficiency of construction equipment provides key information in managing and improving the environmental performance and productivity of construction operations. In this paper, we report our efforts to measure the operational efficiency of construction equipment, using low-cost accelerometers. An experimental study and real-world case studies are conducted to demonstrate the feasibility of the proposed approach. The results have shown the potential of this approach as an economically feasible means of monitoring the environmental performance of construction operations.

Keywords: Equipment monitoring; Operational efficiency; Environmental Performance; Sustainable Construction

1. INTRODUCTION

The environmental impact from construction operations has largely been underestimated, even though these operations constitute significant economic activity. They account for a substantial amount of Greenhouse Gases (GHGs) and other diesel emissions, such as nitrogen oxide (NOx) and particulate matter (PM). There has been extensive research on assessing the energy use and emissions from each single source utilized in construction operations [1-4]. Data on energy use and emissions at the project level is limited, however [5-6]. The assessment of energy use and emissions at the project level in the planning phase always has a great deal of uncertainty due to unexpected deviations between as-planned and as-built conditions. The continuous monitoring of the environmental performance is therefore essential for taking timely corrective actions to eliminate the causes of a discrepancy between the planned and actual level of energy use and emissions.

Currently, the only available data to check the environmental performance of a construction project is the daily report on the use of equipment, which tracks how many pieces of equipment are deployed on a jobsite in daily operations. This data is used to quantify the environmental impact of equipment in most LCA research on construction processes [7-8]. However, two key pieces of information for environmental performance monitoring are missing in these reports: actual usage (operation hours) and operational efficiency of construction equipment. In particular, the operational efficiency, which indicates how efficiently a resource (e.g., construction equipment) is utilized, greatly affects the environmental performance of construction operations, considering its great variability therein. Ahn and Lee [9] thus formulated the relationship between environmental performance and operational efficiency, and presented a methodology for incorporating the analysis of operational efficiency into the assessment of the environmental performance of construction operations. They defined the Operating Equipment Efficiency (OEE) as a measurable metric for the operational efficiency of each resource, as the ratio of valuable (non-idle) operating time to total operating time. The OEE of construction equipment in typical construction operations is not that high. For example, the average OEEs of all Komatsu excavators in Colorado and Wyoming are reported to be approximately 65%, which means that the excavators spend 35% of their operating time idling [10]. This indicates that the monitoring of OEE is also essential for productivity improvement.

Several emerging technologies exist that allow for the accurate monitoring of equipment use, but they are still not practical due to economic infeasibility and technological incompatibility. The application of low-cost accelerometers has the potential to address the challenges of existing technologies by providing a low-cost and non-intrusive monitoring system of the equipment operation. To this end, this paper presents a system to measure the operational efficiency of construction equipment using accelerometers, and evaluates the system's feasibility in a real-world application. The paper begins with a review of the emerging technologies for monitoring environmental performance and operational efficiency. Then, the remaining sections of the paper describe the experiment and case studies that were conducted to evaluate the approach used in this paper.

2. BACKGROUND

2.1 Enabling Technologies for Environmental Monitoring

Portable Emission Measurement Systems (PEMS), which are designed to test or assess mobile source emissions for internal-combustion engine vehicles under real-world conditions, are widely used to verify the emission rate of construction equipment, since they can provide very accurate data on the amount of exhaust emissions. PEMS are, however, too costly to be employed for the simultaneous monitoring of a number of energy/emission sources in a project, so their use is limited to the measurement of engine emissions for research purposes. On the other hand, construction equipment has on-board diagnostics (OBD) systems (e.g., OBD-II, EOBD, JOBD, and CAN bus), which allow for the continuous monitoring and recording of engine operational status (e.g., RPM, fuel consumption rate, axle speed, coolant temperature, and engine load). The recorded data can be accessible via on-board diagnostic software (in recently manufactured models) or off-board diagnostic tools [11]. However, there is a compatibility issue between different manufacturers due to a lack of standardized protocol. Moreover, old equipment—which is the majority of equipment in use—does not have OBD supports, and even a piece of equipment with OBD supports requires extensive modification or the installation of additional devices.

2.2 The application of accelerometers in construction

An accelerometer is an electromechanical device that measures acceleration force. With the recent advent of small-sized and low-cost microelectromechanical (MEMS) accelerometers, accelerometers are widely used for various applications. For example, MEMs accelerometers are embedded in most smartphones in order to sense the movements of smartphone users.

The construction industry is no exception. MEMS accelerometers have been widely used for the health monitoring of structures by sensing the structures' vibrations [12]. Joshua and Varghese [13] attempted activity recognition of construction workers from accelerometer data. Accelerometers have also been used for control and condition monitoring of internal combustion (IC) engines in vehicles, including construction machines [14]. The basic underlying idea of such applications is that every moving component or physical process involved in the operation of an engine produces its own unique vibration signal, which is referred to as the vibration signature. Vibration signatures are assumed to exhibit the same features when created by the same engine operating under the same conditions. For conditioning monitoring of IC engines, expensive conventional accelerometers are generally used, since condition monitoring requires a high level of precision in sensing vibrations [15].

Compared to conditioning monitoring, measuring equipment operational efficiency by detecting the activity modes of equipment (e.g., engine off, idle, working) is assumed to be a simpler application that can be achievable with MEMS accelerometers. This is because different activity modes exhibit a clear difference in vibration signatures, while condition monitoring of IC engines (e.g., engine fault) relies on a more subtle difference. In this context, this paper evaluates the feasibility of using MEMS accelerometers as a monitor of the operational efficiency.

3. RESEARCH OBJECTIVE AND METHODOLOGY

The objective of this research is to test the hypothesis that signals captured by MEMS accelerometers that are installed to construction equipment can be used to analyze the operating equipment efficiency of that equipment, which indicates the ratio of the valuable operating time (non-idling) to the total operating time of the equipment. More specifically, the research aims to demonstrate the feasibility of the classification of the operation of construction equipment into three activity modes—such as working, idling, and engine-off—based on signals captured by a sensor. The underlying idea of the hypothesis is twofold: first, any non-stationary operating of construction equipment (e.g. driving) will create a notable level of acceleration that can be detected by a sensor; second, any stationary operating of construction equipment (e.g. controlling excavators' boom) will generate distinguishable patterns of vibration signals compared to the idling and engine-off modes. The former idea has already been demonstrated by the application of accelerometers to detect passenger vehicle motion [15], but the latter idea needs to be demonstrated due to limited previous studies on the vibration of construction vehicles.

In this context, the initial experiment is designed to measure and analyze vibration signals captured during the stationary operating of construction equipment. The experimental result is analyzed in the time domain, and the effect of equipment activity modes on vibration signals is tested using analysis of variance (ANOVA). Next, case studies are conducted in order to evaluate the feasibility of the proposed approach in the real-world applications that involves the stationary and non-stationary operating of equipment. The effect of equipment activity modes on vibration signals is also statistically analyzed, and the feasibility of detecting operational efficiency using signals from an accelerometer is evaluated based on an overall error rate.

Acceleration signals from construction vehicles under the study were measured using a sensor (accelerometer) mounted inside the cabin of vehicles, and the operation of construction vehicles during the study was videotaped. The sensor used was the one embedded in a smartphone, which can sense acceleration in the x-, y-, and z-directions. The sensitivity of the sensor was 16.2 mg (milli-g)/digit, and its measurement range was ±2g. The signals acquired by an accelerometer are sampled at a rate of 100 Hz. The mounting location of a sensor varies by vehicles, but it is generally mounted on a rigid block around the control system within the cabin of vehicles. Video recordings of vehicle operations are used to label actual operational modes of second-by-second vehicle operation; a vehicle is determined to be idling if it does not show any physical movement for more than three seconds, regardless of its engine status.

4. EXPERIMENTAL ANALYSIS

The experiment is designed and conducted to analyze signals from a stationary operating of construction equipment. The goal of the experiment design is to provide conditions that would generate the greatest difficulty in detecting the difference of vibration signals among stationary operating, idling, and engine-off modes. For this purpose, a recently manufactured excavator is chosen, as newer vehicle models usually generate a lower level of vibration due to the advance of vibration control technologies. Then, the operator is asked to idle for several seconds after turning on the excavator, then very slowly swing up and down the boom of the excavator without moving the body during the experiment.

The signals are captured for around 87 seconds. Figure 1 shows vibration signals in three axes after detrending; detrending is a preprocessing step to subtract the mean value from time-series signal data. The signal patterns in the three axes are found to be identical in terms of increasing and decreasing trends, but the levels of amplitudes in the three axes are different. The operational mode of each time segment was determined based on a video recording. The excavator was in engine-off mode from 0 ~ 20 sec and 82 ~ 82 sec, in idling mode from 21 ~ 33 sec and 71~ 81 sec, and in stationary working mode from 34 ~ 70 sec. Different activity modes are observed to have different levels of amplitude variability. When the engine is turned on and off, spikes in the signal are observed. The spikes at around 85 seconds are assumed to be caused by external noise (most likely from the operator unintentionally hitting the accelerometer).

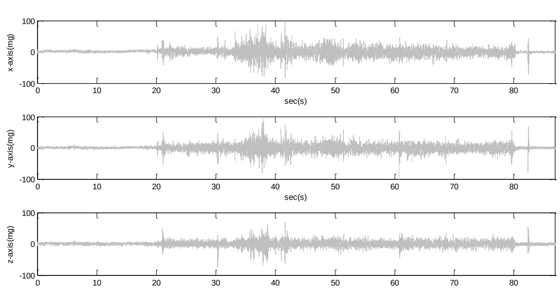

Figure 1. Acceleration time histories in the Experiment

Different levels of amplitude variability by activity modes inspire a comparison of the root mean square (RMS) value of signals between different activity modes. The RMS value of a vibration signal is a time analysis feature that represents the power content in the vibration signature [16]. Although RMS is not an inherent signal processing technique, it is a widely used feature in signal processing and classification due to its simplicity. The RMS value for the x-axis is calculated as:

$$x_{RMS_k} = \sqrt{\frac{1}{M}\sum_{i=1}^{M}\left(x_{(k-1)M+i}\right)^2} \qquad k = 1,2,\ldots,\left\lfloor \frac{N}{M} \right\rfloor.$$

where N is the total number of points in a time series and M is the number of points in time series interval used in analysis. The RMS values for the y- and z-axis data can be combined to form the RMS acceleration vector magnitude, as follows:

$$accel_{RMS_k} = \sqrt{x_{RMS_k}{}^2 + y_{RMS_k}{}^2 + z_{RMS_k}{}^2}$$

Figure 2 shows the RMS values in regular time intervals (1 second). The RMS values are classified into three groups based on the activity mode of their time frame. In this procedure, 2 time frames that include signal spikes due to the engine turning on and off are discarded. Figure 3 shows a box plot of the distribution of three groups; the data points are drawn as outliners if they are larger than the 75th percentile or smaller than the 25th percentile by 1.5 times of the interquartile range. The RMS value of the engine-off group indicates the level of noise, and it is observed that any operation of the equipment including idling generates a distinguishable level of the vibration amplitude compared to the noise. Also, idling and stationary operating groups have different ranges of the value, although the lower boundary of the stationary operating group (between the smallest value and the 25th percentile) overlaps with the idling group; it is thought that the data points in the overlapped range represent the time frames in transient mode between stationary operating and idle modes.

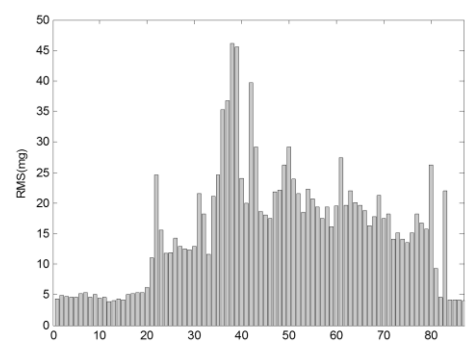

Figure 2. RMS value of a time series in the Experiment

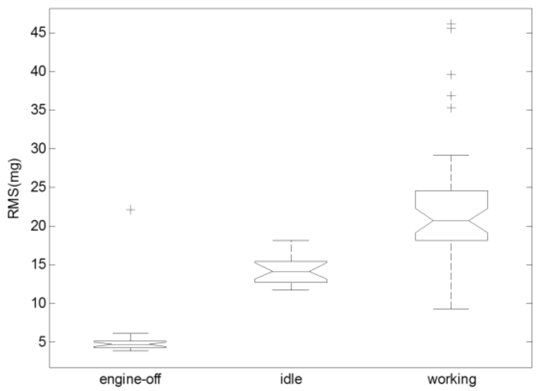

Figure 3. Box-plot of RMS values of different activity modes in the Experiment

The data shown in Figure 3 were further employed for ANOVA to confirm that each group has statistically significantly different distribution of RMS values from others. The results of ANOVA are listed in Table 1. It is clear from Table 1 that the RMS value of the signals, which represents the vibration amplitude, is influenced by the activity mode of the excavator. This result demonstrates that engine-off, idling, and stationary operating of an excavator generates distinguishable patterns of vibration signals, and that the RMS value of vibration signals is a good signal feature in classifying the time frames of construction vehicle operating into different activity modes. One challenging issue is the uncertainty of the boundary estimate, which arises due to the transient mode of equipment between working and idle modes.

Table 1. Analysis of variation in the Experiment

Source	Sum Square	Degree of freedom	Mean square	F ratio	P value
Activity mode	4891.17	2	2445.59	66.97	0
Error	3067.55	84	36.52		
Total	7958.73	86			

5. CASE STUDIES

This section describes the case studies conducted in order to evaluate the feasibility of monitoring the operational efficiency of construction vehicles in real-world operational settings using the signals captured by an accelerometer. The main focus is how reliably the idling can be detected in a real-world operation of construction vehicles that involves the various types of the stationary and non-stationary operation of equipment. Three different excavators that perform various real-world work tasks are chosen for the case studies.

The RMS value is selected as a feature for classifying the signals, based on the result of the previous experimental analysis. Each time frame in case studies is classified into working and idle modes, based on the RMS value. The classification errors are then identified based on the comparison with visual observations. There are two types of errors, working errors and idling errors. The former error indicates that the time frames known to contain working are not classified as working modes. The latter error indicates that the time frames known to contain idling are not classified as idling modes. An overall classification error rate, a working error rate, and an idling error rate are then calculated as:

$$Err = \frac{N_{Err_w} + N_{Err_i}}{N_w + N_i}, \quad Err_w = \frac{N_{Err_w}}{N_w}, \quad Err_i = \frac{N_{Err_i}}{N_i}$$

where E_{rr}, E_{rrw}, and E_{rri} are an overall classification error rate, a working error rate, and an idling error rate, respectively. N_w and N_i are the total number of time frames that are known as working and idling. N_{Errw} and N_{Erri} are the number of working error and idling error time frames.

The possible minimum value of an overall classification error rate in each case study is assessed as a mean of evaluating the feasibility of the proposed approach. A minimum error rate is determined as follows: each RMS value existing in a range between the 75th percentile value of the idling RMS distribution and the 25th percentile value of the working RMS distribution in each case study is chosen as a threshold RMS value that works as a classifier to distinguish working and idling time frames; overall classification error rates using each threshold value are calculated, and a minimum value among them is reported.

5.1 Case study 1

The first case study is conducted for a medium-sized crawler excavator that was analyzed in the previous experiment. The excavator is performing real-world utility work that involves digging a trench and placing wooden trench boxes. The observation ran for around 30 minutes, during which time the excavator was kept running and was not turned off. While digging a trench required quite tumultuous actions of the excavator, placing wooden trench boxes involved relatively modest actions.

The clear difference of the RMS distribution between working and idle time frames is found; the statistical analysis using t-test ($P<0.01$) confirms that the activity mode of the excavator affected the RMS values of time frames. The RMS threshold value that generates a minimum error rate is determined to be 11.5 mg, based on the previously described algorithm. Figure 4 shows the result of the classification using this RMS threshold value. The time frames that have lower RMS values than the threshold are marked as dark gray bars and the time frames that are truly in an idling mode are marked with dotted-line boxes. The overall error rate is assessed as 8%, while the working error rate is assessed as 3%, and the idling error rate is assessed as 25%.

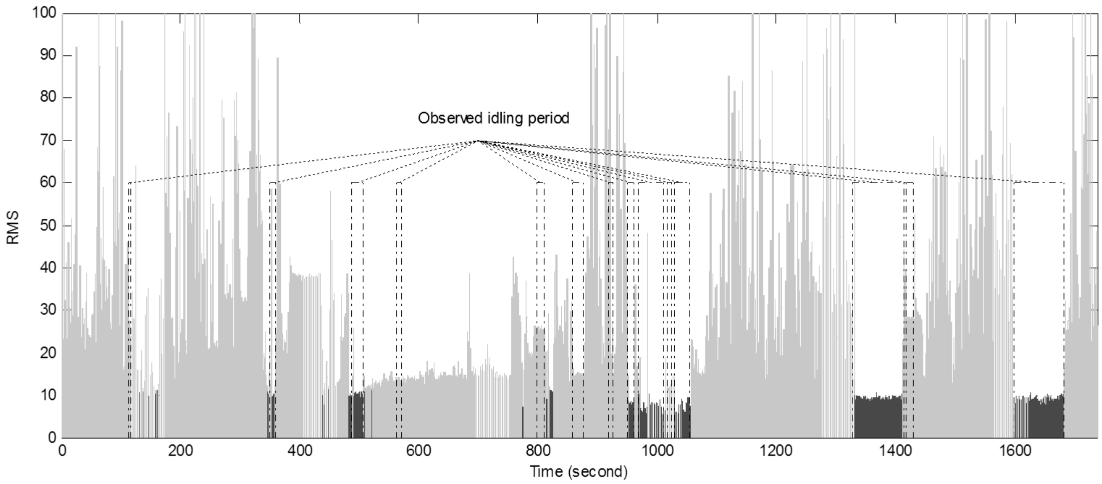

Figure 4. Comparison of idling periods between the observation (dotted-line box) and the energy analysis of vibration signals (dark gray bars) in Case Study 1

5.2 Case study 2

The second case study analyzed a medium-sized wheeled excavator that performs debris-clearing and destroys existing pavement. The difference of the undercarriage type is expected to affect vibration patterns and amplitude. In addition, the wheeled excavator is equipped with stabilizers to provide better lifting performance during stationary operating, and the use of the stabilizers would affect vibration patterns and amplitude. Two independent observations are made; one lasting around 30 minutes, the other around 60 minutes. During the first observation, the excavator mainly cleared and moved waste, and processed debris with another bobcat. During the second observation, the excavator mainly demolished existing ground pavement, with its stabilizers down. The sensor was installed for each observation, so the mounting location and orientation changed.

The statistical analysis using t-test (P<0.01) confirms the difference of the RMS values between working and idle time frames in both observations. Another point of interest in this case study is whether and to what extent the change of mounting conditions (location and orientation) of the sensor affects the vibration amplitude (RMS values) of the idling time frames and the RMS threshold value for the classification. The first observation is found to have a difference in the RMS distribution of the idling time frames compared to the second observation, in terms of the interquartile range. However, they have a similar level of mean values and RMS threshold values that generate a minimum error rate. This indicates that a possible deviation of sensor mounting conditions may not significantly impact the accuracy of the classification.

The RMS threshold value that generates a minimum error rate is determined to be 35 mg and 36.5 mg in the first and second observations, respectively. Figure 5 shows the result of the classification using these RMS threshold values. The overall error rates in the first and second observations are assessed to be 9% and 4%, respectively, while the working error rates are assessed to be 9% and 2%, and the idling error rates 11% and 9%. The type of work that the equipment performs is found to affect the classification error rate. In this case study, the demolition work that involved actions with high engine torque and power output resulted in a better accuracy in the classification.

5.3. Case study 3

A large-sized excavator that bored holes for dewatering using a vibratory pile driver is chosen for the third case study. The performed work repeated the working cycle that consisted of moving, locating the pile driver, driving the pile, and pulling out the pile. While driving the pile generated an excessive level of vibration, moving and locating the pile driver involved a very modest level of vibration.

The difference of the RMS values between working and idle time frames is confirmed through a t-test (P<0.01). The RMS threshold value that generates a minimum error rate is determined to be 73 mg, based on the previously described algorithm. Figure 6 shows the result of the classification using this RMS threshold value. The overall error rate is assessed to be 7%, while the working error rate is assessed to be 6%, and the idling error rate 10%. Locating and calibrating the pile driver at the start of each production cycle involves sporadic pauses of the excavator motion that caused a difficulty in the classification even with the visual observation. Those time frames were found to be error-prone.

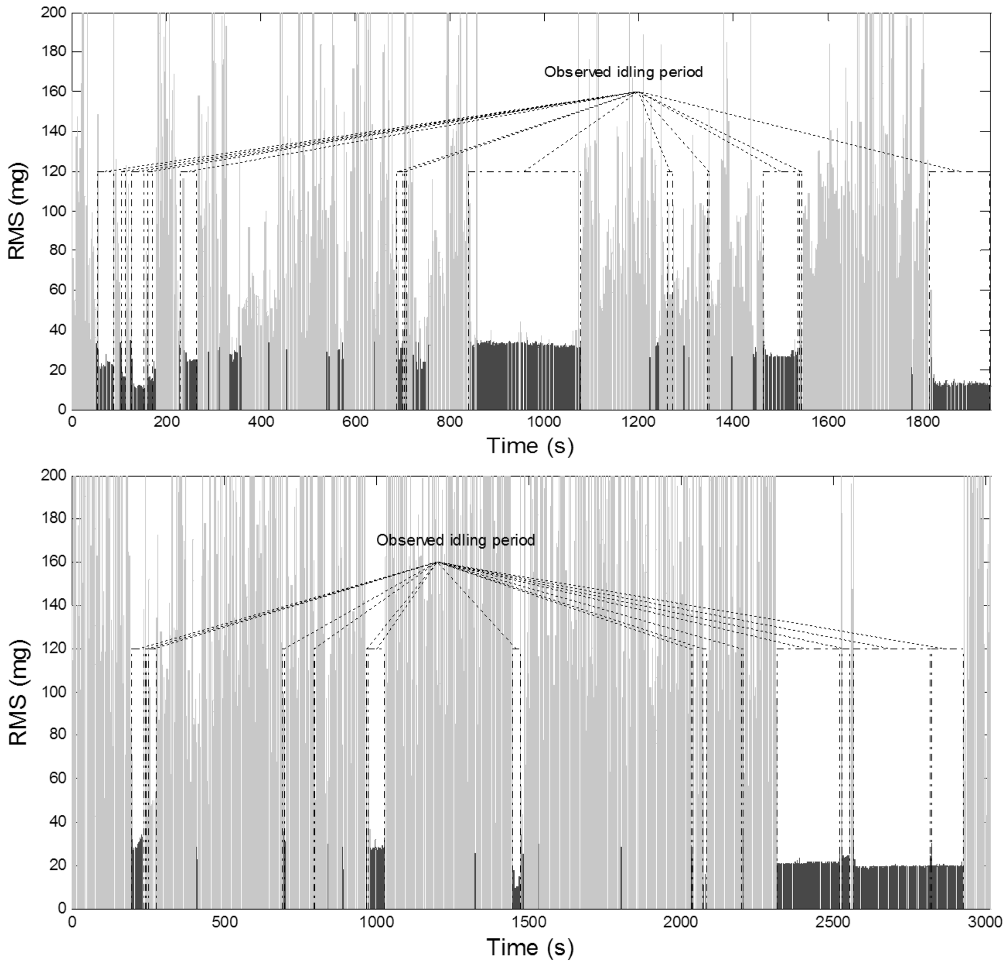

Figure 5. Comparison of idling periods between the observation (dotted-line box) and the energy analysis of vibration signals (dark gray bars) in Case Study 2 - (top) 1st observation; (bottom) 2nd observation

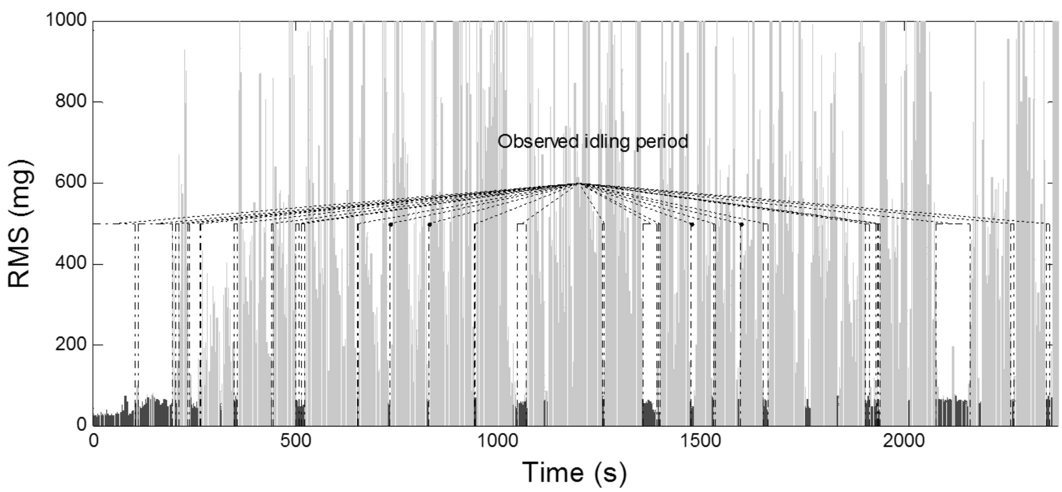

Figure 6. Comparison of idling periods between the observation (dotted-line box) and the energy analysis of vibration signals (dark gray bars) in Case Study 3.

5.4. Results and Analyses

The primary focus of the case studies is on the detecting accuracy of the actual versus measured values of the operating equipment efficiency, which is the ratio of valuable operating time to total operating time. Table 2 summarizes the actual and measured operating equipment efficiency values of the case studies. The classification errors in the case studies created a deviation between the actual and measured operating equipment efficiency. However, such deviations are found to be quite small (within ±3) compared to the classification error rates, because working errors and idling errors somewhat offset each other in the assessment of the operating equipment efficiency.

In addition, the classification errors can be greatly alleviated with a more practical definition of the idling period. In the case study, the manual observation determined that the excavator was idling if it did not show any physical movement for more than three seconds, regardless of its engine status. During idling, however, excavators' engines typically go through four sub-modes: low idle, transient between low and high idle, high idle, and transient between high idle and non-idle [17]. When the operator is ready to start using the bucket, he/she increases the engine idle speed to a high idle mode, which is run at a higher engine revolutions per minute (RPM) than a low idle mode. Therefore, during short idling periods, the excavator may have run at high idle or transient modes, rather than at a low idle mode, whereas it may have run mostly at a low idle mode during long idling periods. This would explain a high error rate in detecting short idling periods, and a low error rate in detecting long idling periods. In a real-world operation, a three-second-long pause of the equipment motion often occurs between the change of motion (body direction or initiating boom use). In the case that we regard such short pauses as the continuation of the valuable operating, and define idling with a longer period of continuous motion pause, the accuracy of the classification would greatly improve, by allowing the discard of idle errors in short idling periods. For example, when we regard short pauses (less than 10 seconds) of the excavator as the valuable operating time, the classification error in Case Study 1 reduces to 5%.

The signal produced by the accelerometer is dependent on the relative orientation of the accelerometer based on the direction of Earth's gravity. Integrating signals from three axes was expected to minimize the effect of the mounting orientation of the accelerometer, but failed to completely disregard such effect, since the detrend process of raw data and data floating limits creates a difference of steady state RMS values by the mounting orientation. Therefore, in the case that the equipment body tilts slightly during its operation, the baseline of vibration signals was affected and sometimes classification errors occurred. This type of error will be addressed with the use of another signal feature for the classification (e.g. kurtosis, crest factor) or the adoption of advanced signal processing techniques (e.g. spectral analysis). On the other hand, external noises (e.g. unintended knock on the sensor) created a spike in the signals and sometimes caused classification errors. This type of error can also be addressed with the use of filtering techniques, which can smooth out short-term fluctuations and highlight longer-term trends.

In summary, the level of classification errors found in the case studies is acceptable for an environmental monitoring application, since (1) the effects of this level of classification errors on the accuracy of measuring the operating equipment efficiency are not significant, and (2) the classification errors would be greatly reduced with the practical definition of equipment idling.

Table 2. Summary of case study results

	Equip. Specs. (HP, model year)	Performed Work	Classification Error (%)	Operating Equipment Efficiency		
				Actual	Measured	Deviation
Case 1	Crawler type, (148 hp, 2010)	Trench and install utility	8%	79%	81%	+2
Case 2	Wheeled type (160 hp, 2006)	1st - Clear debris 2nd - Demolition	10% 4%	69% 74%	66% 75%	-3 +1
Case 3	Crawler type, (270 hp, 2004)	Drill dewatering holes	7%	80%	77%	-3

6. CONCLUSIONS AND FUTURE DIRECTIONS

This paper presented a system to measure the operational efficiency of equipment. Its feasibility in a real-world operation was demonstrated by assessing the accuracy in case studies. Case studies represented diverse equipment configuration (e.g. different gear types, engine sizes, and model year) and various duty cycles that an excavator can have. It is thus envisioned that the results from case studies can be generalized to most types of excavators.

The presented approach has significant advantages over other emerging technologies in terms of economic feasibility. In addition, it ensures technological compatibility with any equipment by providing a non-intrusive measure that does not require any connection with a legacy engine system. Also, this method has an advantage over Global Positioning System (GPS)-based equipment tracking system that is prevalent in the construction industry, in that it can detect the operation of construction equipment in a stationary mode. The presented approach will potentially offer a significant contribution to the enhancement of productivity monitoring, as well as environmental performance monitoring.

However, many challenges exist for the implementation of the presented approach. For example, the method of data transfer and synthesis from accelerometers that are installed to each piece of equipment needs to be investigated. In addition, the expansion of emission factor database that will allow converting measured OEE from the presented approach to emission amounts. The future direction of this research will focus on tackling those challenges. Furthermore, future research will apply machine learning techniques to improve the accuracy and minimize the subjectivity in determining the classifier value. The current approach in the classification of second-by-second equipment operation depends mainly on one feature of the signals for the purpose of testing the approach's feasibility. However, utilizing multiple features of signals could greatly improve the accuracy of the classification. In addition, the current approach is based on supervised learning that requires a training process, and this would require the calibration process for each piece of construction equipment. The development of a classification algorithm based on unsupervised learning has the potential to minimize the training process of the monitoring system.

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