A CASE STUDY OF THE IMPLEMENTATION AND EVALUATION OF ON-BOARD COMPUTERS IN FOREST OPERATIONS IN NORTHERN ONTARIO

By

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ABSTRACT

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Keywords: On-Board Computers (OBC), forest operations, supply chain, northern Ontario, forestry, heavy equipment

In the Canadian forest industry, there are many challenges. One of these challenges is obtaining basic operational information from heavy forest equipment. Acquiring this information can lead to various opportunities including developing best practices, identifying operational issues and monitoring costs/operations. The development of Key Performance Indicators (KPI), a data collection/transmission system and customized reports are some of the challenges associated with collecting this information. One tool that may be used to collect this information is On-Board Computers (OBC).

The main objective of this study is to implement and evaluate the use of a data collection system to monitor the performance of forest operations. An OBC system was planned and integrated into forest operations in northern Ontario, Canada. These OBCs were installed in feller-bunchers, skidders, roadside single-grip processors, excavators and dump trucks. Basic KPIs were developed in order to monitor forest operations. These KPIs were: Approximate Available Machine Hours (~AMH), Approximate Productive Machine Hours (~PMH), Efficiency ((~PMH/~AMH)*100%) and productivity count. In order to determine the effect of KPI information and report usage, two separate intensity reporting periods were created. The High Intensity Reporting Period presented weekly KPI reports to staff. The Low Intensity Reporting Period did not present weekly reports to staff. Parametric and nonparametric statistical tests were used to determine if there were significant differences in KPI values between the two intensity periods. ~AMH, ~PMH, Efficiency and Count KPIs all proved to have significant differences between reporting intensity periods. The significance of these differences varied between machine types and individual machines. Feller-bunchers proved to have the greatest significant differences in KPI values between intensity reporting periods. After identifying significant differences in the ~PMH KPI, an ROI was used to estimate the return on OBC investment. During a three year period, an ROI of 105% was estimated when considering the implementation of these OBCs in 10 feller-bunchers.

Recommendations and methods for the implementation of OBCs in forestry are also presented. This includes the development of KPIs, OBC system installation and report creation.

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1. INTRODUCTION

There are many challenges in the Canadian forest industry. These challenges have a considerable range of subjects and can be quite complex.

This introduction will begin by focusing on some of the challenges in the forest industry, specifically outlining how they can be rooted to a general lack of operational information. A discussion on Supply Chain Management and the important link to operational information will follow. Subsequently, an expression of importance to data collection systems and their applicability will be reviewed. On-Board Computers (OBC) and reference to past applications will introduce the opportunities and some potential uses. The introduction will conclude with a discussion of objectives and the scope of the study.

1.1 CHALLENGES AND LACK OF INFORMATION

One challenge put forth by D'Amours *et al.* (2007) and Chauhan *et al.* (2009) is the need to plan on short and long term bases (1second to 100+years). This can include deciding which trees to cut in a stand to the long-term decision making for silvicultural programs. These decisions require information. Obtaining this information can be difficult and costly due to the size and variability of the work. This variability stems from the heterogeneous nature and variability of forests and its fibre. This, in turn, provides considerable uncertainty and variability in decision making (Frayret *et al.* 2004).

To make matters more challenging, Beaudoin *et al.* (2007) emphasize added complexity in planning within a multi-firm environment. This is due to the involvement of multiple businesses and product sources within supply chains. Acquiring, analysis and reporting of data can be difficult if a system is not automated and operating in a “cloud” type atmosphere. In addition, multiple stakeholders have many different goals and values which may clash when collecting, analysing and disseminating information.

Roscher *et al.* (2004) suggest that although minimizing cost is still one of the primary goals of wood supply organisations, there are other objectives that are gaining importance. They suggest that the achievement of these new objectives requires greater attention to system control and adaptability. Consequently, this requires access to more information (IUFRO 2005).

Product diversification also adds an element of complication to data collection (IUFRO 2005). The diversification of products leads to additional challenges due to changing needs and values. This may require the development and collection of alternate sources of information that were not previously required or wanted. An example of product diversification would be the harvest and transport of woody biomass for fuels on a large scale (Sikanen *et al.* 2005).

Although there is a series of different Decision Support Tools (DST) that have been created or suggested (Karlsson *et al.* 2004, Beaudoin *et al.* 2007, Chauhan *et al.* 2009), they are not used (if at all) to their full potential. In order to use DSTs in forestry, there is a constant need to collect and analyse basic information on rolling time horizons.

1.2 SUPPLY CHAIN MANAGEMENT AND INFORMATION

Supply Chain Management (SCM) has become of significant interest in the Canadian forest industry. The main focus of SCM is on order fulfilment processes, financial and informational flows (Stadtler 2005). The quick and accurate collection, analysis and distribution of information will be one of the determining factors that will make or break the success of the system; the ability to collect real-time information is a core component of SCM. Real-time information keeps managers up-to-date and able to better react to events and make decisions (Frayret *et al.* 2004). Frayret *et al.* (2004) and Sikanen *et al.* (2005) suggest that the integration of an automated, open access web-based system would provide grounds for the collaboration of all organisations. Therefore, matching production with customer requirements grows the need for improved integration among different actors in the supply chain (IUFRO 2005). It is clear that the quality of forest management and operations has a direct impact on the performance of wood fibre supply chains (D'Amours *et al.* 2007; D'Amours *et al.* 2008).

1.3 IMPORTANCE OF DATA COLLECTION SYSTEMS

After reviewing challenges faced by the Canadian forest industry, it is apparent that a data collection system(s) is important. One section of the industry which can greatly profit from the use of a well-developed data collection system is forest operations. This is because data recording and analysis is a very basic component of any business strategy in forestry (Holzleitner *et al.* 2012). The collection of this basic information could be used for refining Rate Determination Models, monitoring operations and developing best practices.

When considering the implementation of a data collection system in forest operations, there are key requirements that must be considered. Johansson (1997) suggested a few major components to the creation and operation of such a system:

- Road network database
- Operations analysis with optimizing function
- Providing follow-up/control in real-time
- Internal and external computer network
- Mobile data system consisting of hardware and software for mobile data communication, production control and navigation

It is important that the data collection system contain mobile components. This is because mobile components suit decentralized organisations, which are often found in forest operations (IUFRO 2005). The 24/7 online access of information can also be valuable since it is easily used to share data amongst different parties (IUFRO 2005). One must also consider that with the collection and analysis of a large amount of data, there is a need to have a robust automated system which is capable of collecting, managing and storing all information (Cordero *et al.* 2006). Furthermore, it is of crucial importance to have a good data transmission network between the field and central database (Emeyriat and Bigot 2006). The ability for the data collection system to adapt to different and changing environments is the key to its successful implementation in forest operations (Davis and Kellogg 2005).

With this being said, there is a clear need for an automated data collection system which is capable of collecting, analysing and disseminating information to all members of the supply chain in order to manage operations (IUFRO 2005).

1.4 ON-BOARD COMPUTERS (OBC)

Tools which can be used to collect information are OBCs specifically designed for the forest industry. The history of OBCs in forestry can be considered by their inclusion within International Precision Forestry (PF) Symposia papers. At the first PF symposium in 2001, there were approximately three studies which discussed the use of OBCs for data collection and analysis (Anonymous 2001). At the 2003 symposium, a new plenary session was added and dedicated to precision operations and equipment, of which OBCs were a large component (Anonymous 2003). In 2006, there was an even more specialized session which centred on equipment monitoring and management, followed by the Decision Support System, data and information requirements session which also contained studies with OBCs (Ackerman *et al.* 2006). At the last PF symposium in 2010, the second largest session was strictly dedicated to equipment monitoring and management. This session contained a series of projects which utilised OBCs and considered their current and future use (Ackerman *et al.* 2010).

Considering this expansion in knowledge and use of OBCs, it is clear that equipment and monitoring tools found in PF are being increasingly implemented within the forest industry. OBCs are beginning to gain considerable value and importance throughout the industry, and their applicability is becoming proven internationally; an example of this is found in the Irish forestry sector, where the technology has been introduced into timber haulage (Devlin and McDonnell 2009).

Information and Communications Technology (ICT) found within PF can help both cost leaders and quality/value leaders (IUFRO 2005). There are opportunities for improvements and major changes in logistical systems that would lead to considerable gains. The implementation rate has been slow and additional research is needed to develop better methods and to utilise incoming information (IUFRO 2005). Since it is a relatively new tool, its implementation and use involves the development of change within an organisation. This change can be difficult to achieve if it is not undertaken properly. One way to implement these changes is for management to understand and value the impact of these changes and effectively communicate this to stakeholders (Grover *et al.* 1995).

The progress in PF is strengthened by the growing capabilities and advancements in information and communication technology (hardware, software and sensors) experienced by the entire Information Technologies (IT) industry. The utilisation of these tools can lead to the development of major advantages in the forest industry. Roscher *et al.* (2004) cited a document by Svanberg (2000), which listed three main advantages to using mobile data systems in round wood transport: 1) better communication; 2) improved navigation; and 3) faster reporting.

1.5 WHATS BEEN DONE?

There are very few peer-reviewed journal articles which discuss or provide a case study on the implementation of OBCs in forest operations. Only two articles were found to match these criteria; these were McDonald *et al.* (2002) and McDonald and Fulton (2005). The bulk of the information found on implementation and use of OBCs and even GPS systems in forest operations is mostly restricted to non-peer-reviewed publications (Johansson 1997, Thor *et al.* 1997, Carter 1999, Taylor *et al.* 2001, Thompson 2001, Davis and Kellog 2005, Cordero *et al.* 2006, Thompson and Klepac 2010, Strandgard 2011). This lack of peer-reviewed publications on OBCs and data collection systems for forest operations is odd, since there are a large number of publications in forest planning and supply chain management that emphasize importance of developing a reliable, accurate and efficient data collection system. An article which has recently stressed this is Brown *et al.* (2012). They suggest that being able to effectively measure and understand machine performance is critical to having efficient mechanised forest operations.

This lack of publication and data sharing are attributed to certain factors. One reason being the limited amount of literature and experience that looks at ICT in the forest sector. Studies regarding ICT solutions in procurement are still often regarded as immature (IUFRO 2005). Another reason for the deficiency in implementation and publication is the lack of development of a fast, easily implemented and utilised solution which is consistent over time. Time-constrained managers and contractors have difficulty implementing, troubleshooting and learning new systems. When a need arises for machine evaluation to support important management decisions, understanding and maintaining basic skills and a consistent approach is difficult (Brown *et al.* 2012). Additional reasoning for the lack of publications on successful implementation of OBC technologies is that attempting to track productivity in forestry operations can be frustrating and expensive (IUFRO 2005, Holzleitner *et al.* 2012). In addition, determining the impact of a change in operations and its influence on productivity is difficult and thus has led to a limited number of reports describing productivity gains in forestry (IUFRO 2005).

However, when these obstacles are overcome, international experience in forest harvesting and in related industries has shown significant savings can be made by using onboard computers to get expensive equipment working more effectively (Strandgard 2011). MultiDATs can be used to identify machines with poor utilisation and, when combined with knowledge of the operation, can be used to make corrections to improve utilisation and to monitor the impact of the changes over time (Strandgard 2011).

1.6 OBJECTIVES

There are many challenges within the forest industry. One particular problem, which will be the focus of this case study, is the lack of detailed operational information which can lead to uncertainty in forest operations control. The collection and use of detailed performance information should create opportunities for operations improvement. Some of these improvements would include the development of best practices and the refining of economic calculations.

The main objective of this study is to determine whether there are significant differences in KPIs between two different reporting intensity periods. Attaining this objective will rely on achieving the following secondary objectives:

- The identification of needs and resources
- System design and integration
- Data analysis and reporting

- Evaluation of the Return On Investment

This study will also contain an implementation guide, review errors in system implementation, discuss alternative methods to system implementation and discuss future research opportunities.

The Null Hypothesis (H_0) of this study is that there is no significant difference in KPI values between periods when detailed data from the OBCs is not utilised by supervisors and when utilised (i.e., between data reporting intensity periods). The Alternative Hypothesis (H_A) is that KPI values will be higher in periods where data from OBCs is consistently used by staff.

1.7 SCOPE

The field work for this study took place from May 2011 to January 2012. All field data collection took place during this period. This was due to time and budget restrictions.

The data system was installed in a contractor's operations. One contractor owned all of the forestry equipment and this equipment was operated by unionized workers. Machine types studied were feller-bunchers, grapple skidders, dangle head processors operated at roadside (subsequently referred to as "processor"), excavators, gravel trucks and belly-dumps.

The study was designed to be a broad level study of forest operations. Data used for all calculations were based on shift level information. Some shifts were lost due to technical difficulties associated with the machine or the datalogging equipment. Because of this, some shift data were not collected and could therefore not be considered in data analysis.

Site and stand conditions or specific shift details were not monitored for each shift. These conditions may have had some effect on logged machine information. In addition, the scheduling of operators on machines was not monitored. Operators were regularly scheduled according to the contractor's scheduling method and were regularly cycled between shifts and some machines. Very few machines tended to retain the same operator throughout the study. In summary, this study is applied to an actual working forest harvesting operation in real-life operating conditions.

2.0 MATERIALS AND METHODS

2.1 SITE SELECTION AND TIME PERIOD

This study took place in a logging operation in Northern Ontario. All operations were located in the Boreal forest. The field data collection began May 2011 and was completed in January 2012. For the purpose of confidentiality, detailed information is limited to only the logging equipment and not given about the overall logging operation.

2.2 MACHINES STUDIED

In this study, multiple machine types were studied (Table 1). This included feller-bunchers, grapple skidders, processors, excavators, gravel trucks and belly-dumps. Each machine type varied in number of units studied and each machine is an independent unit. There was some variability found in equipment such as make, model and year. The units listed in Table 1 were specified for this study since they were the most readily available for OBC equipment installation.

Table 1. List of machines.

Machine type	Make	Model	Year
Feller-buncher	Tigercat	870C	2007
Feller-buncher	Tigercat	845S	2009
Feller-buncher	Tigercat	845S	2010
Feller-buncher	Tigercat	845S	2010
Feller-buncher	Tigercat	845S	2011
Skidder	J.Deere	748H	2008
Skidder	J.Deere	748H	2009
Skidder	Tigercat	E630D	2010
Skidder	J.Deere	848H	2010
Processor	Hitachi	ZX250	2006
Processor	Hitachi	ZX250	2006
Excavator	Hitachi	EX270	2001
Excavator	Hitachi	ZX250	N/A
Excavator	Hyundai	290LC	2007
Excavator	J.Deere	2554	2003
Excavator	J.Deere	2554	2005
Gravel truck	W.Star	N/A	1996
Gravel truck	W.Star	N/A	1995
Gravel truck	W.Star	N/A	1995
Gravel truck	W.Star	N/A	1999
Gravel truck	Intl	N/A	2006
Gravel truck	J. Deere	250D	N/A
Belly-dump	W.Star	N/A	2006
Belly-dump	W.Star	N/A	1996
Belly-dump	W.Star	N/A	2002

2.3 MULTIDAT

MultiDAT is a data logging system designed to meet the needs of owners and managers of heavy equipment (FPInnovation 2010). Its main components are an OBC, software and a shuttle for data transfer. Davis and Kellogg (2005) reported that the multiDAT OBC and software provides a good analysis tool at the contract level for monitoring production efficiencies and can aid in determining limiting aspects of the operations. It is a comparably simple, well-established OBC which is purpose built as a third party

OBC for the forest industry. One major advantage of this system is its ability to identify long term trends by smoothing short term fluctuations (Strandgard 2011).

2.3.1 OBC

In its most basic form, the OBC has the ability to sense motion and four different "channels" (Figure 1). Each "channel" is one wire. These wires can be connected to an electronic impulse between 5 and 28V. Activities for each of these channels will be logged.

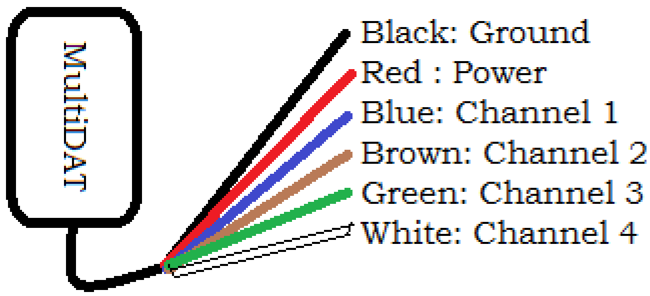

Figure 1. MultiDAT and connections.

As an example, channel 1 can be connected to the electronic impulse for the saw of a processor. Every time there is an electronic impulse on this wire, it is recorded in the multiDAT. The period length or count of this impulse can be logged. This can provide a total number of activations within a set amount of time, or provide the number of times a signal was sensed in the channel. Another example would be connecting a channel to the machine work lights switch. Whenever the lights are engaged, it can log the number of times and/or when the lights are activated.

There is a motion sensor built into the OBC. This motion sensor will constantly be tracking the velocity of motion. The user can set a certain threshold to determine when there is enough velocity to log this motion. This is done to eliminate unwanted noise in data. An example of this would be setting the velocity of motion to be higher than that of the vibrations from machine idling. This would provide a better idea of when the machine is having more pronounced motion as opposed to just small vibrations.

2.3.2 Data shuttle

Since this system was developed in the late 1990s, data shuttles (also known as PDAs) were used to transfer information from the multiDAT to a database. In this study, a wireless download system was used to transfer data from the multiDAT to a database. Each multiDAT was connected to a Radio Frequency (RF) modem. This modem would transfer information from the multiDAT to a custom made computer in the supervisor's pick-up truck. This computer would then transfer the information via cellular modem to a File Transfer Protocol (ftp) site. Data would then transfer from the ftp site to the multiDAT database for data reporting and analysis. Figure 2 illustrates this data transfer.

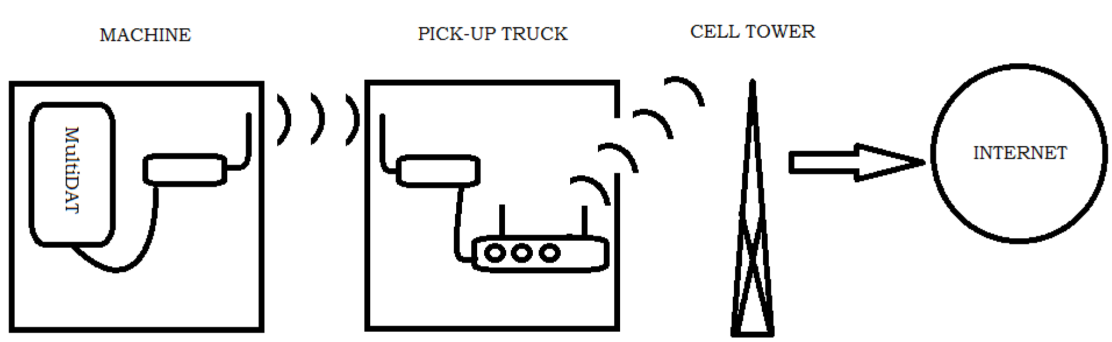

Figure 2. MultiDAT dataflow.

2.3.3 Software

Once data were accessible, the software would take the log files and add them to the database. Once transferred, this data can be reported and viewed graphically. In a graphical representation, the data are presented on a timeline. Figure 3 is a screenshot of actual data from the study graphically represented in the program.

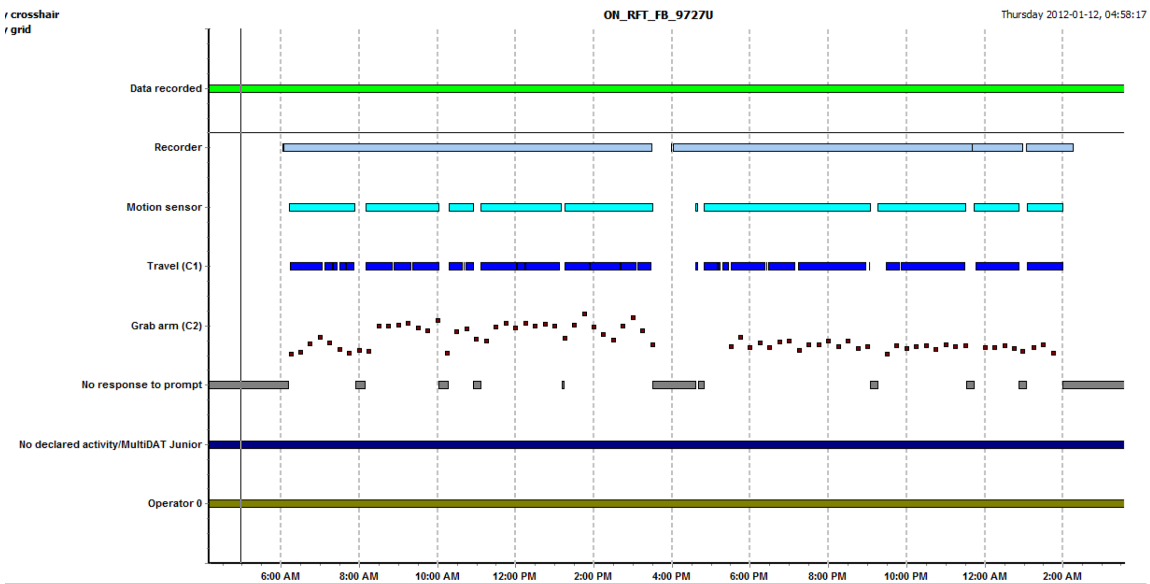

Figure 3. Screenshot of graphical dataview in the multiDAT software.

This view allows the user to graphically review and evaluate logged data. This can be used to look at specific windows in time to determine what actions happened and when. In this case, this is a graphical representation of two 10 h feller-buncher work shifts. The day began at approximately 6:00 a.m. and was completed at 2:00 a.m. the next day. The shift change took place at 4:00 p.m.. The first bar from the top (data recorded) indicates that there are available data for this time period. The second bar from the top (Recorder) indicates when the ~AMH (master) switch was turned on. The third bar from the top (Motion Sensor) indicates when motion was sensed. The fourth bar from the top (Travel) indicates when the machine engaged its tracks. The small dots are 15 min totals of grab arm counts. The remaining bars are not used in this particular study. With this information, the user can efficiently and graphically view work shifts.

The software was also used to create custom reports. Custom reports can be created by the user to show exactly what data he/she would like and how it should be displayed. Examples of this will be shown after KPIs have been discussed.

2.4 KEY PERFORMANCE INDICATOR (KPI) DEVELOPMENT

Study KPIs were developed by the staff and the researcher. Early discussions were based on the establishment of basic KPI requirements. It was agreed that KPIs have to be:

- Easy to track, understand and report
- Somewhat similar between all machine types
- Provide an indication of machine performance
- KPI electronic signal easily connected to the OBC

After some deliberation, the basic KPIs were decided to be Master switch on (h), Motion sensor (h), Efficiency (%) and a Count.

2.4.1 Master switch for estimating Available Machine Hours (~AMH)

This KPI is used as a proxy for machine availability. The master switch is a physical switch on the machine which activates machine power. Machine power is deactivated when it is not used. The multiDAT logs information on the activation of this power switch. When the power is engaged, it tracks its activation in hours. This gives an estimation of when the machine is available for use within its scheduled time. Since it is not quite an accurate measure of Available Machine Hours (AMH) and only an estimate, this KPI will be referred to as ~AMH for the remainder of the text.

2.4.2 Motion sensor for estimating Productive Machine Hours (~PMH)

This KPI provides an estimate of how much the machine is moving and is used as a proxy for utilisation. It is assumed that the machine is moving when the accelerometer (or motion sensor) gets above a certain motion velocity threshold. This KPI has been used as a proxy for utilisation in other studies (e.g., Strandgard 2011). It is important to track utilisation since forest machinery utilisation rates are one of the most important factors influencing machine cost calculations (Holzleitner *et al.* 2012). Since this is only an estimate of machine utilisation or Productive Machine Hours (PMH), it will be referred to as ~PMH for the remainder of the text.

2.4.3 Efficiency

This KPI gives a measure of "presence" at the machine. It is a function of dividing ~PMH by ~AMH and is reported as a percentage. This gives a measure of percent of the time the machine was moving (~PMH) while it was turned on (~AMH). This gives the supervisors an idea of how "efficient" the machine may be while it is active (i.e., time available actually utilised).

2.4.4 Count

This KPI is a count of specific machine actions. There are only two machine types which had this KPI: feller-bunchers and processors. For feller-bunchers, it was measuring a count of grab arm activations on the saw head. For processors, it counted the activation of the bottom saw. Both of these give a measure of machine direct production activity (i.e., main work time (Rickards *et al*. 1995)). It is not intended to provide an accurate measure of tree count or log count. There are, however, some correlations which can be drawn that can help estimate this.

2.4.5 Track monitoring

This KPI was intended to monitor the amount of time machine tracks were engaged. It was to only be used for feller-bunchers and processors. After some deliberation and testing, this KPI was removed from the study. This KPI was determined to be unimportant since the Motion KPI was giving very similar results. Furthermore, the OBC's memory was being challenged due to the frequency of the start and stop of the tracks.

2.4.6 Skidder Count

This was chosen to be the production Count KPI for skidders. It was thought that there would be a relatively common ratio between back-ups and bundles. After installation and initial study, it was determined that this KPI would not be a good proxy to represent skidder productivity. The engagement of the reverse gears had no relation to productivity. Therefore, it was removed from the study.

2.5 INSTALLATION

Once KPIs were determined, installations could take place. The installation of these OBCs took place when both machine and mechanic were available (May 17, 2011 to August 11, 2011). Table 2 indicates when each multiDAT was installed, when reports were generated and the start dates for on-site trips. These trips varied in length from 4 to 6 days. Trip 1 was a preliminary trip completed in March and is not listed in Table 2.

Table 2. MultiDAT installation, reporting and trip dates.

Machine	Machine #	Data collection start	Report #	Report date	Trip #	Trip
May						
Gravel truck	1002	17/05/2011			Trip 2	15/05/2011
Gravel truck	1004	17/05/2011				
Hoe	1301	17/05/2011				
Rock truck	1401	18/05/2011				
Hoe	1304	24/05/2011				
Gravel truck	1003	30/05/2011				
Gravel truck	1001	30/05/2011				
June						
Buncher	1201	08/06/2011	Report 1	08/06/2011	Trip 3	06/06/2011
Gravel truck	1005	08/06/2011				
Buncher	1202	10/06/2011				
Processor	1501	10/06/2011				
Belly-dump	1101	12/06/2011				
Hoe	1302	14/06/2011				
Belly-dump	1102	20/06/2011			Trip 4	19/06/2011
Belly-dump	1103	20/06/2011	Report 2	21/06/2011		
Buncher	1203	24/06/2011				
Hoe	1303	27/06/2011	Report 3	27/06/2011	Trip 5	26/06/2011
Grapple skidder	1601	29/06/2011	Report 4	30/06/2011		
Grapple skidder	1602	29/06/2011				
July						
Processor	1502	04/07/2011	Report 5	04/07/2011	Trip 6	03/07/2011
Buncher	1204	09/07/2011	Report 6	09/07/2011		
Grapple skidder	1604	19/07/2011	Report 7	18/07/2011	Trip 7	17/07/2011
Hoe	1305	20/07/2011	Report 8	22/07/2011	Trip 8	23/07/2011
Grapple skidder	1603	25/07/2011	Report 9	26/07/2011		
August						
Buncher	1205	11/08/2011	Report 10	08/08/2011	Trip 9	07/08/2011
			Report 11	11/08/2011	Trip 10	14/08/2011
September						
			Report 12	05/09/2011	Trip 11	03/09/2011
			Report 13	21/09/2011	Trip 12	19/09/2011

Table 2. MultiDAT installation, reporting and trip dates.

Machine	Machine #	Data collection start	Report #	Report date	Trip #	Trip
October						
			Report 14	26/10/2011	Trip 13	11/10/2011
					Trip 14	24/10/2011
November						
			Report 15	02/11/2011	Trip 15	04/11/2011
			Report 16	08/11/2011	Trip 16	12/11/2011
			Report 17	14/11/2011	Trip 17	28/11/2011
			Report 18	29/11/2011		
December						
			Report 19	06/12/2011		
			Report 20	13/12/2011	Trip 18	11/12/2011
			Report 21	20/12/2011		
			Report 22	26/12/2011	Trip 19	28/12/2011
January						
			Report 23	01/01/2011		
			Report 24	01/10/2011		
			Report 25	24/01/2011		

2.6 DATA REPORTING

Data would be collected throughout the week and reported every following Tuesday for a supervisor meeting. Data were presented in three different reports. These reports are referred to as the “glance”, “weekly” and “detailed” reports. Each report was reporting information in different styles and was intended for different audiences.

2.6.1 Glance report

This report was designed to provide weekly information for each machine at a quick glance. This report was most often used by higher level supervisors and managers to get a weekly snapshot of each machine's work. Table 3 illustrates a small piece of this report.

Table 3. Glance report examples.

	~AMH	~PMH	~PMH/ ~AMH
Bellydumps	(h)	(h)	(%)
Belly dump 1			
	49.35	19.07	38.64
Belly dump 2			
	2.04		
Sub-total for Belly dumps			
	51.40	19.07	37.10
Feller-bunchers	(h)	(h)	(%)
Feller-buncher 1			
	0.04		
Feller-buncher 2			
	72.16	59.07	81.86
Feller-buncher 3			
	95.55	78.70	82.36
Feller-buncher 4			
	54.70	49.35	90.21
Sub-total Feller-bunchers			
	222.45	187.11	84.11

The first column indicates the machine name. The second column indicates the ~AMH in hours. The third column indicates the ~PMH in hours. The third column is a percentage score of Efficiency [~PMH/~AMH].

2.6.2 Weekly report

This report was used by managers and supervisors to quickly identify subtotals between different shifts per machine. This was used to monitor activity for each individual shift. An example of this report is shown as Table 4.

Table 4. Weekly report example.

	SMH	~AMH	~PMH	~Availability [~AMH/ SMH]	~Utilisation [~PMH/ SMH]	Efficiency [~PMH/ ~AMH]
Feller-bunchers	(h)	(h)	(h)	(%)	(%)	(%)
Feller-buncher 1						
Day shift	40.00	34.18	26.93	85.44	67.33	78.80
Night shift	40.00	13.96	11.89	34.89	29.71	85.17
Split shift	40.00	24.02	20.25	60.06	50.62	84.29
Sub-total / FB 1	120.00	72.16	59.07	60.13	49.22	81.86
Feller-buncher 2						
Day shift	40.00	34.78	27.42	86.95	68.55	78.84
Night shift	40.00	22.93	18.87	57.32	47.17	82.29
Split shift	40.00	37.85	32.41	94.61	81.02	85.63
Sub-total / FB 2	120.00	95.55	78.70	79.63	65.58	82.36
Feller-buncher 3						
Day shift	40.00	35.66	33.03	89.15	82.57	92.62
Night shift	40.00	0.82	0.79	2.05	1.97	96.04
Split shift	40.00	18.22	15.53	45.56	38.83	85.22
Sub-total / FB 3	120.00	54.70	49.35	45.59	41.12	90.21
Sub-total FB						
	480.00	222.45	187.11	46.34	38.98	84.11

The SMH column states the Scheduled Machine Hours for each shift. The ~AMH column reports the master switch activation in hours. The ~PMH column reports the amount of motion sensed in hours. The ~Availability column is a percentage of the ~AMH value divided by the SMH value. The ~Utilisation column is a percentage of the

~PMH value divided by the SMH value. The "efficiency" column is the ~PMH value divided by the ~AMH value.

2.6.3 Detailed report

This report was used in order to view specific results for each individual shift. Shifts are listed in chronological order for each shift type. The three shift types within a work week are Dayshifts, Splitshifts and Nightshifts. A typical shift rotation for a worker would be composed of 4 Nightshifts, followed by 4 Splitshifts and finished with four dayshifts. After these dayshifts, workers were given a five day rest before restarting the rotation.

Nightshifts were 10 h shifts scheduled to be completed between 4:30 p.m. to 4:30 a.m. This means that shifts could start as early as 4:30 p.m. and be completed at 2:30 a.m., or could start as late as 6:30 p.m. and finish at 4:30 a.m. Nightshifts would occur on Wednesday, Thursday, Friday and Saturday nights. Splitshifts were the pivot point between nightshifts and dayshifts. Therefore, the first two shifts were at night and the following two were during the day. The first two splitshifts are comparable to nightshifts where 10 h shifts are scheduled to be completed between 4:30 p.m. to 4:30 a.m. These two took place on Monday and Tuesday nights. After a two day break, operators would work a 10 h shift between 4:30 a.m. to 4:30 p.m.. These shifts would take place on Friday and Saturday. Dayshifts were 10 h shifts scheduled to take place between 4:30 a.m. to 4:30 p.m. on Monday, Tuesday, Wednesday and Thursday.

When considering a complete 6 day work week, this schedule provides 20 SMH daily from Monday to Saturday night. Table 5 is an example section of this report.

Table 5. Examples of a detailed report.

	SMH (h)	~AMH (h)	~PMH (h)	Walking time (h)	Production indicator shift total (count)	Production indicator/~PMH (count/h)	~Availability [~AMH /SMH] (%)	~Utilisation [~PMH/SMH] (%)
Feller-buncher 1								
A - Monday Dayshift	10.00	9.73	7.64	6.82	1036	135.54	97.31	76.44
B - Tuesday Dayshift	10.00	9.62	8.16	7.31	1018	124.70	96.21	81.64
C - Wednesday Dayshift	10.00	8.52	7.87	7.08	1053	133.87	85.23	78.66
D - Thursday Dayshift	10.00	6.90	3.75	3.16	274	73.10	69.04	37.48
E - Monday Splitshift	10.00	9.75	8.41	8.21	2439	290.17	97.45	84.06
F - Tuesday Splitshift	10.00	9.37	8.31	7.91	2508	301.79	93.74	83.10
G- Friday Splitshift	10.00	9.18	7.57	7.04	1947	257.27	91.83	75.68
H - Saturday Splitshift	10.00	9.54	8.12	7.67	2478	305.02	95.43	81.24
I - Wednesday Nightshift	10.00	4.85	3.82	3.75	701	183.41	48.51	38.22
J - Thursday Nightshift	10.00	9.26	7.42	7.33	1853	249.79	92.59	74.18
K - Friday Nightshift	10.00	8.82	7.63	7.36	1746	228.92	88.19	76.27
L - Saturday Nightshift	10.00							
Sub-total / Feller-buncher 1	120.00	95.55	78.70	73.63	17053	216.69	79.63	65.58
Feller-buncher 2								
A - Monday Dayshift	10.00	9.90	9.30	8.82	2871	308.77	98.99	92.98
B - Tuesday Dayshift	10.00	9.99	9.59	9.25	2913	303.80	99.94	95.89
C - Wednesday Dayshift	10.00	7.91	7.17	6.91	1711	238.76	79.11	71.66
D - Thursday Dayshift	10.00	7.86	6.97	5.08	2301	329.93	78.55	69.74
E - Monday Splitshift	10.00	10.01	8.31	8.11	2400	288.78	100.08	83.11
F - Tuesday Splitshift	10.00							
G- Friday Splitshift	10.00	4.91	4.14	3.95	1155	279.14	49.14	41.38
H - Saturday Splitshift	10.00	3.30	3.08	2.94	818	265.42	33.01	30.82
I - Wednesday Nightshift	10.00	0.02					0.24	
J - Thursday Nightshift	10.00	0.80	0.79	0.69	71	90.06	7.97	7.88
K - Friday Nightshift	10.00							
L - Saturday Nightshift	10.00							
Sub-total / Feller-buncher 2	120.00	54.70	49.35	45.74	14240	288.58	45.59	41.12

The SMH, ~AMH and ~PMH values are reported as stated for the Weekly report. The "walking time" column indicates how long the tracks were engaged in hours. Once again, "walking time" was reported but was not used in this case study. The "production indicator shift total" indicates how many times the "signal" (i.e., counter) was activated throughout the shift. The "production indicator/~PMH" column is the "production indicator shift total" divided by the "~PMH" value. It indicates how many times the "signal" was activated per ~PMH on average. The ~Availability and ~Utilisation column are identical to those explained in the previous report.

Data from the detailed report were used as the experimental units for analysis. This gave KPI values for each individual shift by machine.

2.7 DATABASES

Data were separated into four different databases. Each database was created in order to best represent individual KPIs by reducing errors and categorizing data. Table 6 illustrates these databases and associated rules. The number of rows can also be interpreted as the number of shifts in each database.

Table 6. Database rules.

Database	Rule	Number of rows
~AMH 1	Remove belly-dumps Remove excavator and gravel truck nightshift Remove rows with 0 ~PMH hours Remove May Remove > 11 h ~AMH	3465
~PMH 1	Remove belly-dumps Remove excavator and gravel truck nightshift Remove rows with 0 ~PMH Remove May	3768
Efficiency	~AMH switch 1 Remove < 1 hour ~AMH	3191
FB count	Feller-buncher shifts only Remove count < 100 Remove count/~PMH > 1000	534
RP count	Processor shifts only Remove count < 100 Remove bottom saw for Processor 1 before 13/07	232

Note: there are less shifts for ~AMH 1 than ~PMH 1 because there were a number of shifts when the master switch was accidentally left on and thus the ~AMH was >11 h.

2.7.1 ~AMH 1

This dataset was used in order to statistically test the ~AMH KPI. To do so, some data had to be removed to reduce possible errors. All belly-dump data were removed from the dataset because these units did not have regular tasks. They were used as all-purpose tractor-trailers for floating other machines, and hauling chips and roundwood amongst other tasks. Nightshift data for excavators and gravel trucks were also removed since these machines were never scheduled to work at night. Any data collected during a nightshift would be attributed to a non-normal shift event. Items such as activating the machine for mechanical repair, floating, etc., could have recorded data as a work shift. Since these shifts were not truly for work, this would be an error. Shifts which had 0 h of ~PMH were also removed. This would not be considered a work shift and should therefore not be recorded. Shifts recorded in the month of May were also removed since it was a troubleshooting period to test the OBCs and set motion sensor thresholds. Shifts which had a ~AMH value of greater than 11 h were removed since the master switch was occasionally accidentally left on between shifts. Since the master switch would have been turned on for a longer period of time than the operator was actually present, this would be a misrepresentation of machine availability. Eleven hours was decided as the threshold value since there were some occasions where the operator went over the scheduled time to finish a job. Anything over 11 h was determined too high.

2.7.2 ~PMH 1

This database was used to test the ~PMH KPI. Once again, some data were removed. Belly-dumps, excavator and gravel truck night shifts, and data from the month of May were removed. Shifts with ~AMH >11 h were not removed since the ~PMH would not be greater than 11 h since the machine would not be active and/or moving. This resulted in data for more ~PMH than ~AMH shifts.

2.7.3 FB count

This database was used to test the Feller-Buncher Count KPI. Only shifts with a feller-buncher machine type were used. Shifts which had a total count of less than 100 were removed. This was done in an effort to eliminate shifts which were thought to have no trees harvested. This can be because the machine was being repaired, floated, etc. Shifts with a count/~PMH greater than 1000 were removed. This would be attributed to repairs where the grab arms would have been activated many times in a short period of time.

2.7.4 RP count

This database was used to test the Processor Count KPI. Only shifts with a Processor machine type were used. Shifts with a count of less than 100 were removed. Also, shifts before July 13, 2011 for machine number 9732 were removed. The cause of this was an improper connection of the voltage input for channel 2.

2.8 DATA ANALYSIS

The goal of the data analysis was to determine if the utilisation of KPI information being collected from OBCs would have a positive impact on forest operations. This impact would be determined by comparing KPI values between two user groups. These groups were based on the intensity at which reports and data were released to the staff. There were a series of months where KPI data were not released or poorly released to supervisors (Low intensity). There were other months where KPI data were released weekly to supervisors (High intensity).

2.8.1 High intensity

This intensity was designed to reflect a higher intensity of data use by supervisors. The High intensity group was established in the fourth week of July. This was the first week in which the detailed reports were generated and reported to supervisors and staff. The same took place in August, November, December and January.

2.8.2 Low intensity

This intensity was designed to reflect poor or no use of data by supervisors. Reports were being generated in June, but were only used to help develop future report templates. They were not specifically generated for reporting KPIs to supervisors and staff. Data were also not released or poorly released to supervisors and staff in September and October.

If a difference in KPI values is found between these groups, it would indicate that the use of KPI information from OBCs would have an impact on forest operations. This would help determine if an investment in OBCs would prove to be beneficial.

Some of the strengths of this data analysis would be the use of actual operational information and the use of equipment in real-world applications. Some weaknesses associated with this analysis are seasonal operational effects, time constraints and the specific use and interpretation of KPI information by individuals. Additional strengths and weaknesses are further reviewed in the discussion section.

2.9 STATISTICAL TESTS

Parametric and non-parametric tests were used in order to find significant differences between data release intensity periods. In some cases, non-parametric tests had to be used since the data did not meet parametric test assumptions.

Histograms were generated for each database. These histograms gave an indication of data distribution for each KPI. In addition to this, tests of normality were generated to indicate if the data are distributed normally. This would indicate if non-parametric or parametric tests were necessary.

2.9.1 Parametric tests

The Single-Factor Between-Subjects Analysis of Variance (or ANOVA) was used as the main parametric test. In this test, each sample mean is used to estimate the mean of the population it represents. A test statistic is generated for each sample. If the test statistic for this sample is found to be significant, there is a significant difference between at least two of the sample means in the population (Sheskin 1997). The acceptable level of significance is determined by the researcher. In order for this test to be run, the data must meet certain assumptions. According to Sheskin (1997), these assumptions must meet the following criteria:

- Each sample is selected randomly from the population
- The underlying population of the sample is normally distributed
- Variance between the sample and the underlying population is equal

A General Linear Model Univariate procedure was used as a test to determine the presence of significant differences between factors and their interactions. These tests were used when comparing the effect of reporting intensity periods for different machines within the same machine type.

2.9.2 Nonparametric tests

Kruskal-Wallis One-Way Analysis of Variance by Ranks was used as the nonparametric test. This test ranks the ratio/interval data according to their values. It then uses these ranks in order to run a One-Way Analysis of Variance to determine if there is a significant difference between populations. This nonparametric test was run in databases which violated one of the parametric test assumptions (i.e., normal distribution).

2.10 NORMAL SHIFTS

The OBC was collecting data every time it was powered. Some shifts were subject to unforeseen events that prevented the machine from working (e.g., breakdowns, floating the machine, etc.) Shifts with unforeseen interruptions, are referred to as “non-normal shifts”. Shifts that are not part of this category are referred to as “normal shifts” The definition of normal shifts changed between databases. For the ~AMH 1 database, a normal shift was assumed to be a shift which had between 5 and 11 h of the ~AMH. For the ~PMH 1 database, a normal shift was assumed to be a shift which had greater than 5 h of ~PMH. Data were categorised in this manner for two major reasons; the first reason being the additional interest in testing differences between normal shifts by the contractor. The second reason being that additional information was not available to accurately categorise shifts which recorded 0 h of activity. Shifts with 0 h of activity would fall within one of three categories:

- 0 h because it is not scheduled (further explained below)

- 0 h because there was an unforeseen event that prohibited the machine to work (e.g., mechanical breakdown, operator missing).
- 0 h because the multiDAT OBC was unplugged and could not collect shift information.

Scheduling conflicts are the most difficult to identify when additional shift information is not being collected during a broad-scale time study. An example of this would be the scheduling of excavator shifts. Excavators are scheduled to work four days a week. The specific scheduling of these shifts (specific day) is weather dependent. If the weather is cooperative, machines would work four days that week. If it is uncooperative, they may only work two or three. The remaining scheduled days would then be completed the following week. When determining broad scale availability, it is impossible to know why machines did not complete all of their shifts during that specific week without additional information. For this reason, shifts which had 0 ~AMH were eliminated from the analysis. Because of this, it is important to note that results from this study may prove to be conservative since they do not consider the gain of reducing the number of non-normal shifts.

2.11 OBSERVATIONS BY MACHINE

There was interest in verifying significant differences between reporting intensity periods for individual machine types. The logic being that if there is more of a significant difference found in one specific machine type, it would be worth targeting these machines for further study or OBC implementation. Furthermore, there was additional interest in testing if there were significant differences between individual machines within a machine type. This would help determine if there were possibilities in random errors attributed to machine, operator or differences in operations from working in neighbouring Sustainable Forest Licenses.

2.12 DATA FLOW EXPRESSED VISUALLY

Figure 4 was generated in order to show how data were categorize and sourced. Furthermore, it illustrates which tests were used for data analysis.

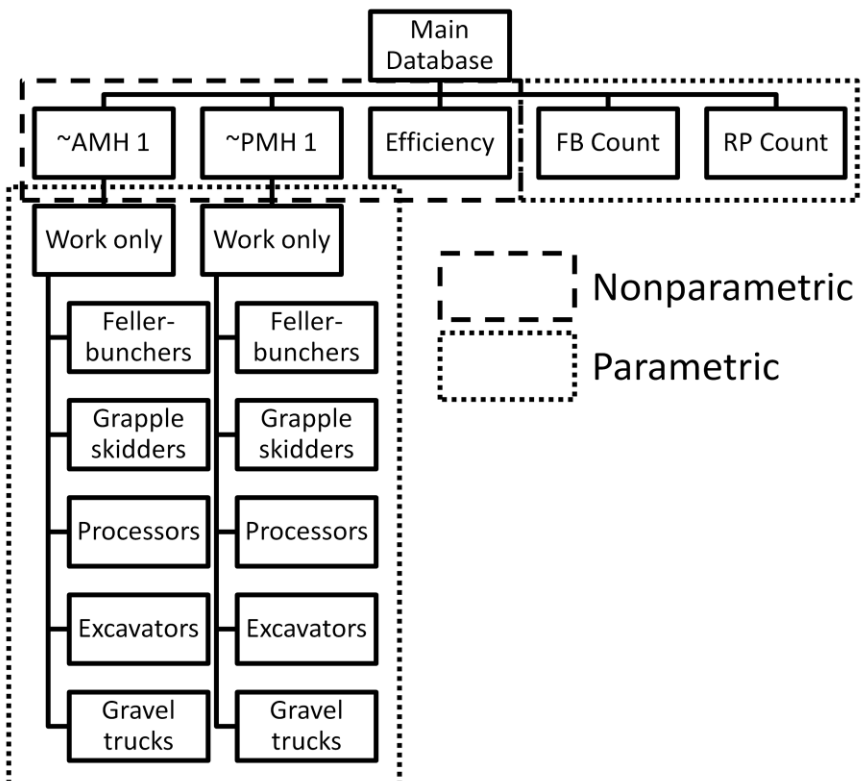

Figure 4. Dataflow and tests.

2.13 COUNT KPI ACCURACY

Field tests were conducted to verify the accuracy and validity of the Count KPI for feller-bunchers, processors and skidders. These field tests were restricted to the availability of the machine, the field observer, and the accurate connection and reporting of the count.

After initial observations, the Count KPI for skidders was removed due to its ineffectiveness and difficulty to connect. The original Count KPI for skidders was totalling of the number of times the machine would reverse. This was to give an estimate of how many bundles would be picked up. The machines were found to have no specific reverse patterns which varied depending on site and operator.

Two feller-bunchers and two processors were observed. Each individual machine was observed for one complete 10 h shift. During the observation period for one processor, it was found that an improper connection was made to the OBC. Therefore, data from only one of the two processors was utilised. This shift was restricted to day operations. The observer would arrive on site before the shift start. The multiDAT would be downloaded and its clock would be synchronized to the observer's time keeping equipment. Throughout the shift, the observer would record three items:

- The tree count (feller-bunchers) or log count (processors)
- The visual activation count (grab arm activation for feller-bunchers and bottom saw activation for processor)
- The OBC count

These were recorded by a manual tally. The observer would mark each item occurrence through a dot tally. These were totalled every five minutes.

The "tree (or log) count" was the number of trees (or logs) processed by a machine every 15 min. The observer would be on site visually counting every tree (or log) that was produced. For the feller-bunchers, it was the number of trees cut. For the processor, it was the number of logs produced.

The "visual activation count" is the observer's visual count of the hydraulic activation of a machine component. For the feller-buncher, this was a visual count of grab arm activations. For the processor, this was a visual count of the bottom saw activation. These were also totalled every 15 min.

The "OBC count" is the registered count of electronic pulses from a channel being monitored by the OBC. In the case of the processor, the channel being monitored is the activation of a certain pump on the processing head. This pump is normally engaged when the bottom saw is activated to produce a log. For the feller-buncher, this is the hydraulic cylinder which moves the grab-arm.

Each of these counts were monitored individually and compared in order to compare one another. One reason being that tree or log counts may differ from the visual activation count due to variations between sites and operators. In some cases, operators may grab multiple trees with one reach of the feller-buncher since tree density was found to be high. This would require the operator to only engage the grab arm once in order to cut multiple trees.

The second reason for doing this would be to match the visual activation count to the OBC count. This is done to verify if the electronic impulse (or channel) monitored by the OBC equates to the visual activation count of component activations. In some cases, this may vary. An example of this would be the connection of the OBC to the bottom saw pump on the processor's machine head. This pump may engage most of the time to activate the bottom saw on the processor, however, it may occasionally not engage since there is already adequate pressure in the lines. This would lead to the activation of the bottom saw twice, while it is only registered once in the OBC's memory.

In order to compare these items, ratios were developed between different counts. These ratios are:

- OBC count / visual activation count
- OBC count / tree (or log) count

The Pearson product-moment correlation coefficient was used to test and measure data correlation. It estimates the degree to which a linear relationship exists between the variables (Sheskin 1997). Predictor and criterion variables were compared in order to determine the presence and strength of data relationship. In this test, the strength of a relationship between variables is indicated by the significance value. The closer this value is to 1.0, the stronger the relationship between the variables. In order for this test to be valid, data must respect specific assumptions (Sheskin 1997):

- Sample subjects are randomly selected from the population it represents
- The variables are interval or ratio type data
- Both variables have a bivariate normal distribution

2.14 RETURN ON INVESTMENT

A Rate Determination Model (RDM) was used to estimate possible gains from the use of OBC systems. In this case, the ~PMH value was used as the "utilisation" input in the model. ~PMH values found to be significantly different between data release intensity periods were used in the RDM. Two different scenarios were generated with the RDM. One representing the values obtained during the High intensity reporting period, the other representing the values obtained during Low intensity reporting period. The resulting costs ($\$/m^3$) were compared. The difference between the two was established as profit. Figure 5 is a screenshot of the RDM and the highlighted red cell was the only item which was modified. The yellow cells found in Figure 5 are the input cells which can be modified by the user. These are only estimations and do not represent the actual costs of this operation.

EQUIPMENT COSTING MODEL	
Machine/system name:	Feller-buncher
No. of working days/year:	280
No. of scheduled hour/shift (SMH/shift):	10
No. of shifts/day	2
Machine utilisation (%):	76.6
Productivity, m3/PMH	40
Installed or purchase price (P) ($):	650000
Future salvage value ($):	65000
Expected economic life (years):	5.0
Interest rate (%):	5.0
Fuel consumption (litre/PMH):	20.0
Fuel cost ($/litre):	1.00
Oil, lubricants and hydraulic oil cost (% of fuel cost):	15.0
Annual repair & maint. cost (% of P)	25.0
Operator wage ($/SMH):	25.00
Overtime wage rate (% of op. wage)	0
Paid travelling time for operator (hours/day)	0.0
Fringe benefits & employment expense (% of op. wage):	50
Number of operators required per shift:	1
Insurance cost per year (% of P):	3.20
License cost ($/year):	0.00
Contractor profit margin (% of annual cost)	5

EQUIPMENT COST SUMMARY	
SMH/year	5600.0
PMH/year	4290.2
Annual production (m3/year)	171606.4
m3 produced per SMH:	30.64
m3 produced per PMH:	40.00
PV of salvage value ($):	50929.20
Annual capital cost (depeciation & interest) ($/year):	140916.72
Capital cost ($/PMH):	32.85
Number of regular working hours per day	8.0
Number of overtime working hours per day	2.0
Number of travel hours per day	0.0
Annual operator cost ($/year):	168000.0
Operator cost ($/shift):	300.00
Operator cost ($/PMH)	39.16
Fuel cost ($/PMH)	20.00
Engine oil, lubes and hydraulic oil cost ($/PMH)	3.00
Repair & maintenance cost ($/year):	162500.00
Insurance cost ($/year):	20800.00
License cost ($/year):	0.00
Total operating cost ($/year):	590890.40
Contractor profit ($/year):	29544.52
Total cost (operating + profit) ($/year):	620434.92
Operating cost ($/SMH):	110.79
Operating cost ($/PMH):	144.62
Production unit cost ($/m3)	3.62

Figure 5. Screenshot of the Interface Express RDM.

The ROI was calculated using a standard ROI equation (Equation 1).

$$ROI = \frac{(Gains\ from\ investment - Cost\ of\ investment)}{Cost\ of\ investment} \qquad [1]$$

This calculation is based on a three year period (assumed technical life of the equipment). The “cost of investment” includes installation and annual operation costs. Installation costs include equipment, installation, software and management costs. The annual operation cost includes maintenance, management and data transfer costs. The “gains from investment” are the annual savings from increased equipment utilisation for each of the three years of OBC use. The input values used to calculate the “gains from investment” are based on average estimates for the area. These include items such as operating time, worker salaries, etc. Evidently, these values will vary between contractors and can be modified for additional accuracy.

3.0 RESULTS

3.1 NON-PARAMETRIC TEST RESULTS

Tests of normality indicated that the distribution of the ~AMH, ~PMH and Efficiency KPIs were not normal. Shifts are scheduled to be 10 h in length. Since there were occasionally unintended interruptions throughout the shift, work activity may not last an entire scheduled shift. These interruptions caused a longer tail to form on the Left Hand Side (LHS) of the mean. This, in turn, created a non-normal distribution. Figures 6 to 8 are histograms which illustrate the distribution of all KPI results per reporting intensity period for logged shifts in a database. A normality curve is drawn on the histogram to illustrate how a normal distribution would fit the data. Figure 6 is a histogram of the ~AMH value for all shifts in the ~AMH 1 database. The x axis categorizes ~AMH values within intervals of 0.25 h. The Y axis demonstrates the frequency of these categories. It is clear that the bulk of the shifts (~70%) range from 8 to 10.5 h. These are considered as shifts which had very minimal or no interruptions. There is also a tail which is found between 0 and 5 h. These are considered shifts which have suffered some sort of interruption. The distributions of these shifts are demonstrated in Table 7.

Table 7. Distribution of shifts per database by High and Low reporting intensity periods.

	~AMH 1		~PMH 1	
Treatment	High	Low	High	Low
<2 h	8.3%	12.0%	10.0%	14.0%
2 h to 5 h	5.2%	4.7%	7.5%	6.3%
5 h +	86.5%	83.3%	82.5%	79.7%
N	2047	1417	2292	1476

Another population of shifts can be found between 0 and 2 h in Figures 6 and 7. These are shifts in which a machine was most likely not expected to work, and was subject to repair or other activities which rendered it unavailable. Another cause may be an operator was not available to operate the machine. These shifts are most pronounced in Figure 7 which shows the data distribution of the ~PMH in the ~PMH 1 database.

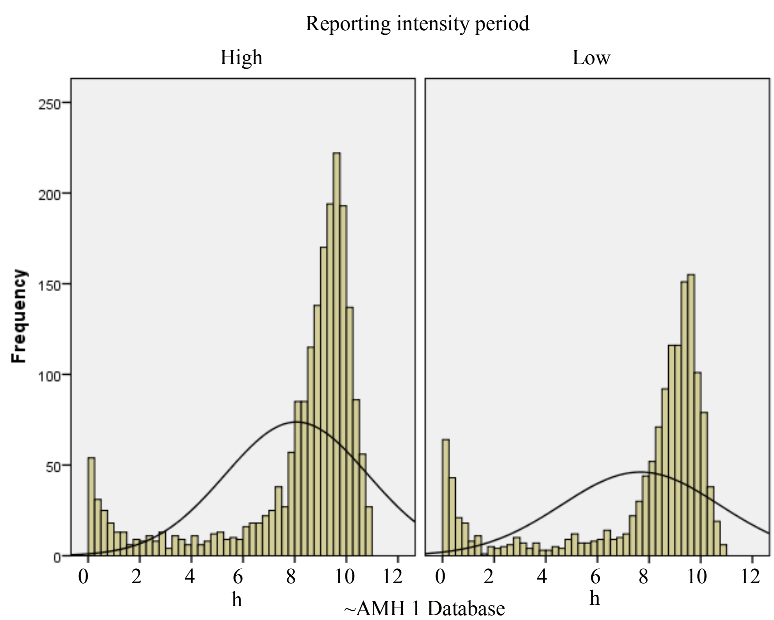

Figure 6. Histogram per reporting intensity period of the ~AMH KPI in the ~AMH 1 database; black solid line indicates normally distributed data.

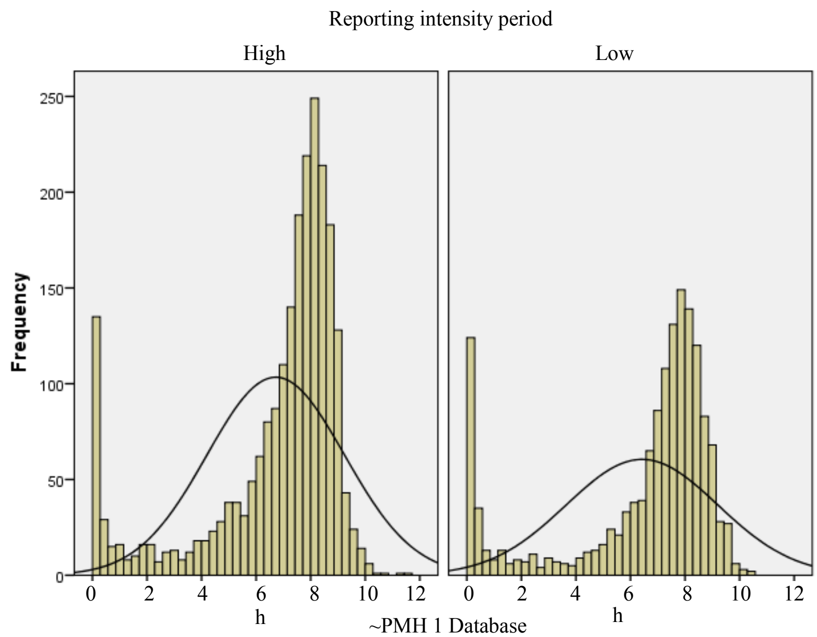

Figure 7. Histogram per reporting intensity period of the ~PMH KPI in the ~PMH 1 database; black solid line indicates normally distributed data.

For the Efficiency KPI, the Efficiency database was used. This helped eliminate shifts which may have recorded ~AMH activity, but no ~PMH on the extreme LHS of the mean. As shown in Figure 8, the efficiency KPI was also found to have a non-normal distribution. Since the ~PMH KPI value will always be lower than or equal to the ~AMH KPI value, the Efficiency KPI cannot surpass 100%. The majority of shifts were found to operate without much interruption and were found in the range of 70% to 100%. Like previous distributions, a tail was found on the LHS of the mean. These were shifts which were found to have a higher ~AMH KPI and lower ~PMH KPI value. Once again, this can most likely be attributed to events such as mechanical failures and servicing.

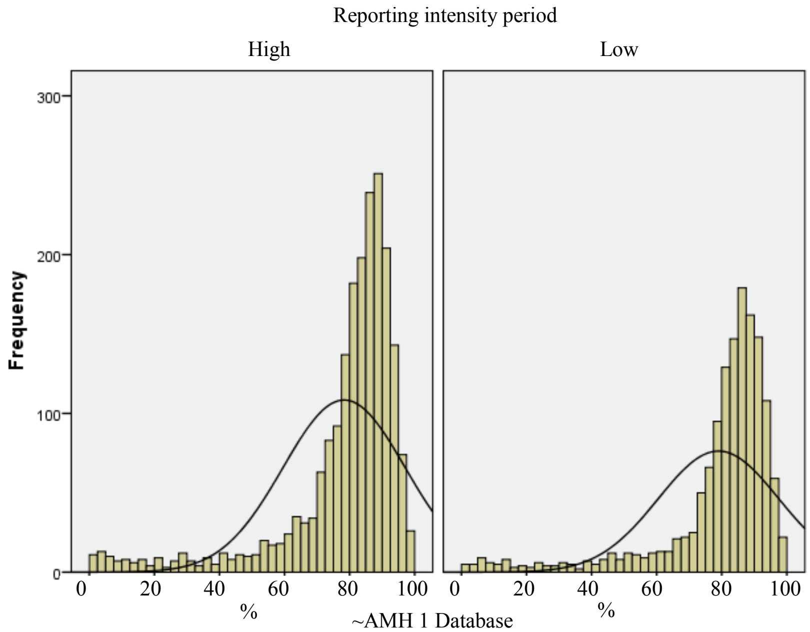

Figure 8. Histogram per reporting intensity period of the Effciency KPI in the Efficiency database; black solid line indicates normally distributed data.

Due to this non-normality, Kruskal-Wallis rank-order ANOVA tests were run for each KPI to test for the presence of significant differences between reporting intensity periods. In the case of the ~AMH 1 database, a significant difference ($p < 0.000$) between reporting intensity periods was estimated (Table 8).

Table 8. Kruskal-Wallis Rank-order test for the ~AMH KPI in ~AMH 1 database

Test Statistics[a,b]

	~AMH
Chi-Square	21.273
df	1
Asymp. Sig.	.000***

a. Kruskal Wallis Test
b. Grouping Variable: intensity

Since this test indicates a significant difference between reporting intensity periods, one would conclude that the level at which OBC data are utilised will have an effect on the ~AMH KPI. This outcome would therefore reject H_0.

When interpreting descriptive statistics for this test, one should only consider mean ranks and not mean values (Sheskin 1997). This is because the K-W rank order test assigns ranks to the ratio level data in order to run the test. Therefore, the mean rank of each reporting intensity period would provide a more accurate statistic than the mean value of the data. Interpreting the mean rank, however, can be more challenging since the rank is not measured in units. Table 9 was generated in order to list mean ranks along with mean values for each database per Low and High reporting intensity periods. Mean values could be interpreted as a guideline for the value of the K-W rank, but it may not reflect the actual value of the mean rank.

Table 9. Mean rank and values of nonparametric tests for ~AMH, ~PMH and Efficiency KPIs during High and Low intensity reporting periods.

	Mean K-W Rank		Mean values		
Database	High Intensity	Low intensity	High Intensity	Low intensity	Sig. difference
~AMH 1	1797.75	1638.36	8.07 (h)	7.66 (h)	***
~PMH 1	1929.25	1813.77	6.72 (h)	6.42 (h)	**
Efficiency	1710.19	1764.69	78.29 (%)	79 (%)	Ns

*** = significant at $\alpha \leq 0.001$
** = significant at $\alpha \leq 0.01$
* = significant at $\alpha \leq 0.05$
ns = not significant

For the ~AMH 1 database, the mean rank and value for the High intensity reporting period was greater than for the Low intensity period. Therefore, a significant increase in the ~AMH KPI was observed for the High intensity reporting period overall.

For the ~PMH 1 database, nonparametric tests yielded a significant difference between reporting intensity periods for the ~PMH KPI. The asymptotic significance value was found to be 0.001 (Table 10). This indicates that H_0 has been rejected for this database. When considering the Mean K-W rank and Mean values for the ~PMH 1 database in Table 10, one would determine that the High intensity period has a higher ~PMH KPI value than the Low intensity period. This would indicate that H_A has failed to be rejected. Therefore, a higher intensity use of data from OBCs would have a significantly positive impact on the ~PMH KPI for all machines.

Table 10. Kruskal-Wallis Rank-order test for the ~PMH KPI in ~PMH 1 database

Test Statistics[a,b]

	~PMH
Chi-Square	10.121
df	1
Asymp. Sig.	.001**

a. Kruskal Wallis Test
b. Grouping Variable: intensity

For the Efficiency KPI, the Kruskal-Wallis Rank-order test resulted in an asymptotic significance value of 0.115 (Table 11). This indicates that a significant difference in efficiency was not observed between reporting intensity periods when considering all shifts for all machines at $\alpha = 0.05$. Therefore, increasing the intensity of data use from OBCs has no significant impact on the Efficiency KPI. This indicates that even though the ~AMH or ~PMH KPI may increase, the Efficiency of a shift will remain comparable between reporting intensity periods. Therefore, the H_0 has failed to be rejected for the Efficiency KPI.

Table 11. Kruskal-Wallis Rank-order test for the Efficiency KPI in the Efficiency database

Test Statistics[a,b]

	Efficiency
Chi-Square	2.487
df	1
Asymp. Sig.	.115[ns]

a. Kruskal Wallis Test
b. Grouping Variable: intensity

3.2 PARAMETRIC TESTS RESULTS

Parametric tests were run on data which were normally distributed.

Feller-buncher and processor Count KPIs were the first to be tested with parametric tests. Values from this KPI were compared between reporting intensity periods for each machine. Figure 9 is a histogram which illustrates data distribution of the Count KPI for feller-bunchers between the two reporting intensity periods. The *x* axis lists the Count/~PMH. The *y* axis indicates frequencies. The x-axis is categorized in intervals of 20. The LHS panel illustrates Count KPI data for the High intensity reporting period. The Right Hand Side (RHS) panel illustrates Count KPI data for the Low intensity reporting period. A normality curve is set in black to illustrate how the data fits to a normal distribution.

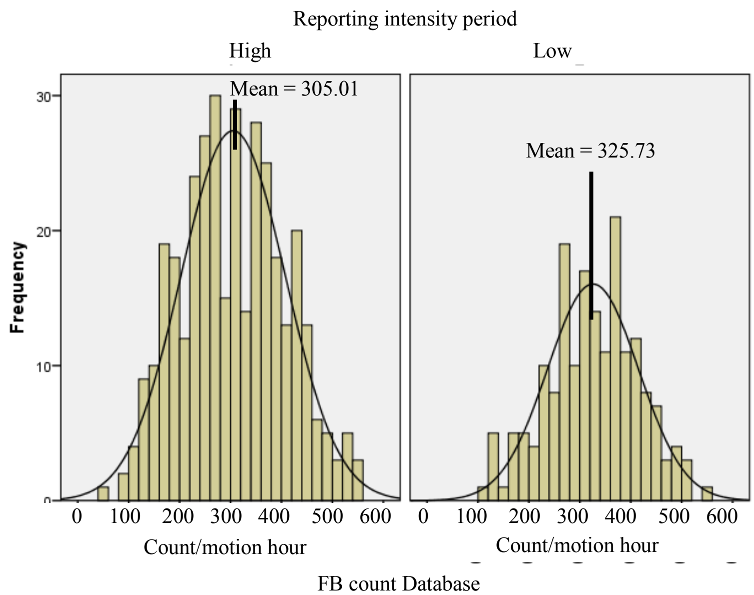

Figure 9. FB count KPI in FB count database histogram per reporting intensity period; black solid line indicates normally distributed data.

Table 12 is the associated ANOVA results for the feller-buncher Count KPI. Since p = 0.022, there is a significant difference between reporting intensity periods and thus the H_0 is rejected.

Table 12. ANOVA table for Count KPI for Feller-bunchers

		Sum of Squares	df	Mean Square	F	Sig.
Countper~PMH	Between Groups	51181.104	1	51181.104	5.273	0.022*
	Within Groups	5154467.154	531	9707.094		
	Total	5205648.259	532			

In order to determine H_A, one must consider the mean FB Count KPI values for both reporting intensity periods. The mean FB Count KPI for the High intensity reporting period is 305.01, while the value for the Low intensity reporting period it is 325.73. Since the FB Count KPI is found to be greater in the Low intensity reporting period, H_A can also be rejected. This is because H_A stipulated that the FB Count KPI would be greater in the High intensity reporting period. This outcome indicates that the more intensive use of data may have a negative effect on the FB Count, however no explanation could be found for this.

Figure 10 is a histogram of the Count KPI values for processors. Data are found to be normally distributed for both reporting intensity periods. There is a difference in "*n*" between reporting intensity periods. This is due to mechanical complications and scheduling difficulties experienced during the Low intensity reporting period, resulting in less normal shifts. Data are displayed in the same manner as Figure 9, except KPI values for processors are shown.

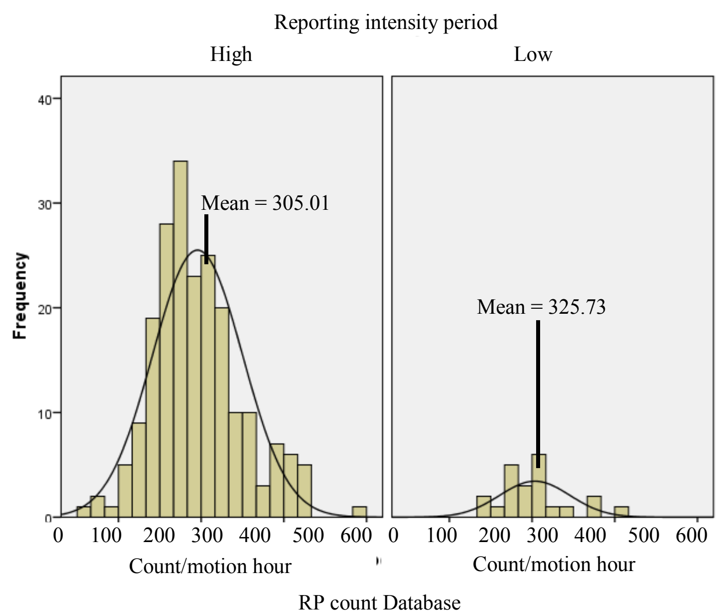

Figure 10. RP count KPI in RP count data base histogram by reporting intensity period; black solid line indicates normally distributed data.

Table 13 is the associated ANOVA results for the Processor Count KPI. No significant difference ($p=0.526$) was found between the High and Low intensity reporting periods and H_0 can be rejected. Therefore, more intensive use of OBC data are not found to have an effect on the RP Count KPI.

Table 13. ANOVA table for Count KPI for processors

		Sum of Squares	df	Mean Square	F	Sig.
countper~PMH	Between Groups	4605.686	1	4605.686	0.402	0.526^{ns}
	Within Groups	2620973.969	229	11445.301		
	Total	2625579.655	230			

3.3 NORMAL AND NON-NORMALWORK

Figure 11 illustrates data distribution for the ~AMH KPI normal shifts for both reporting intensity periods. The top panel illustrates data distribution for the High intensity reporting period. The bottom panel illustrate data distribution for the Low intensity reporting period. A normal distribution curve is fitted as a black line to both panels in order to show how the data fits as compared to a normal distribution. Once again, data seems skewed to the right. This is due to the nature of time series data and work interruptions as previously explained.

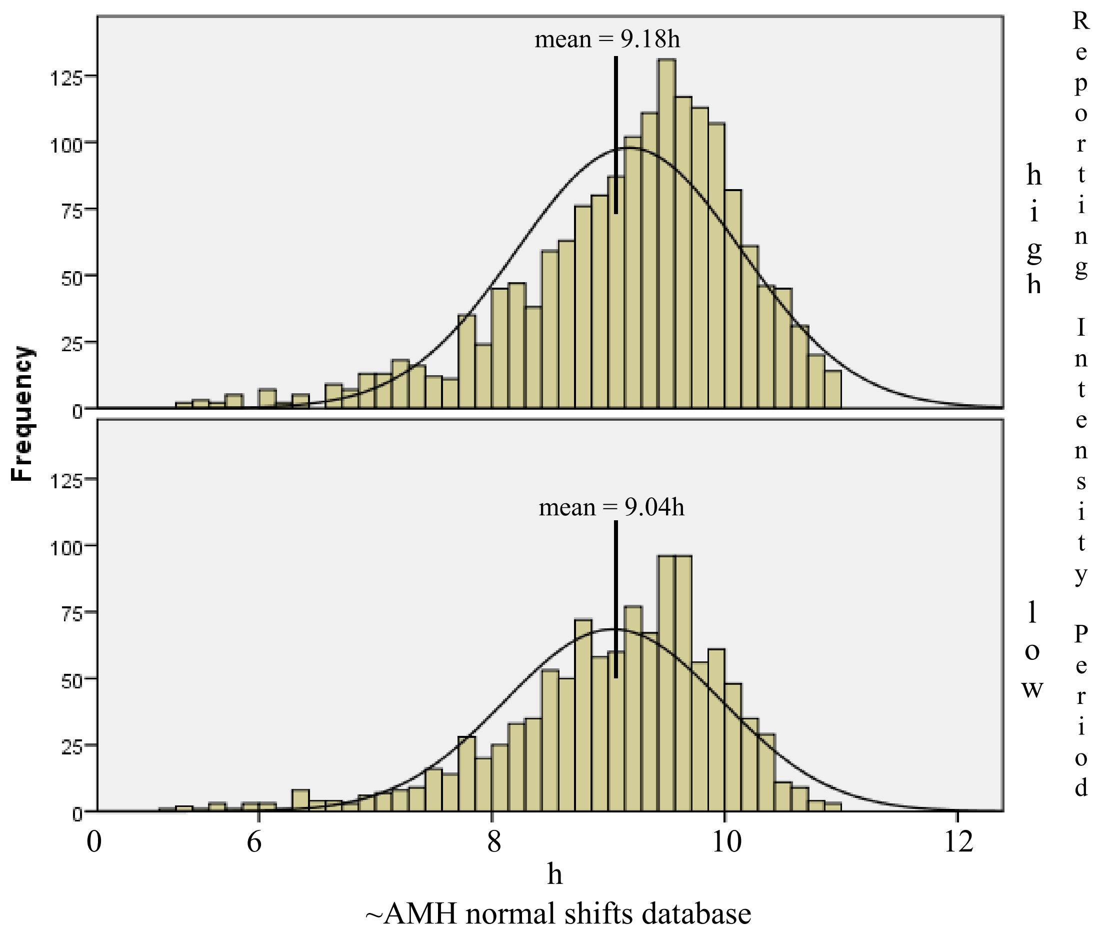

Figure 11. ~AMH KPI (normal shifts) in the ~AMH 1 database histogram by reporting intensity periods; black solid line indicates normally distributed data.

After testing data normality for both reporting intensity periods, ANOVA tests were run. This was to help indicate the presence of any significant differences observed for the ~AMH KPI between reporting intensity periods for normal shifts. A highly significant difference ($p < 0.000$) was found between the two reporting intensity periods and H_0 is rejected. The mean ~AMH KPI value for the High intensity reporting period for normal shifts was 9.18 h, while the same value for the Low intensity reporting period was 9.04 h.

~PMH KPI data were also categorized between normal and non-normal shifts. Normality tests were performed on ~PMH KPI normal shifts. Figure 12 illustrates the data distribution of normal shifts for both reporting intensity periods. The figure illustrates this data in the same manner as Figure 11. It is interesting to note that the High intensity reporting period ~PMH KPI values are slightly more skewed to the right. This could indicate that shifts in this reporting intensity period would tend to be of longer duration and have less interruptions.

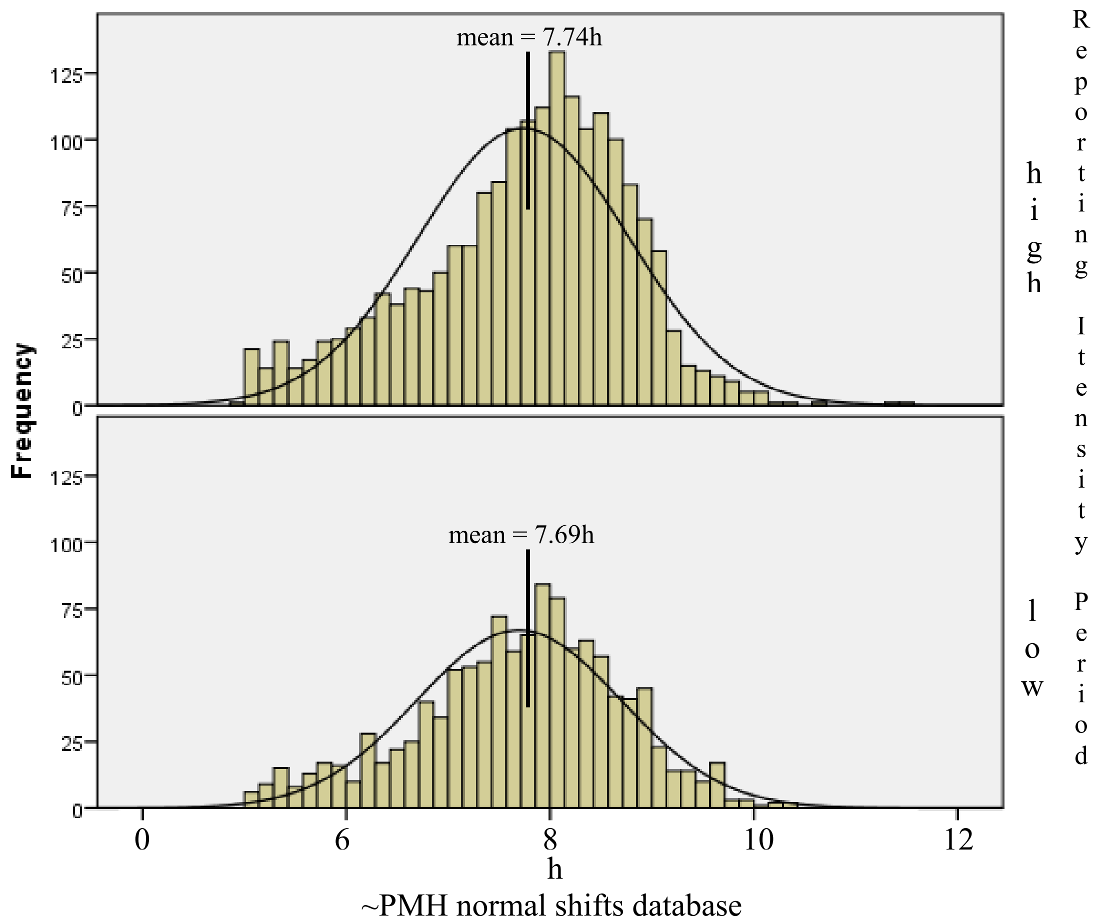

Figure 12. ~PMH KPI (normal shifts) in the ~PMH 1 data base histogram by reporting intensity period; black solid line indicates normally distributed data.

ANOVA tests were completed to test whether there was a significant difference in ~PMH KPI values between reporting intensity periods. No significant difference ($p=0.246$) was found between reporting intensity periods for the ~PMH KPI. Therefore, the more intensive use of OBC data has no significant effect on the ~PMH KPI when considering normal shifts for all machines.

For the Efficiency KPI, values were derived from the ~AMH normal shift database. This was done in order to eliminate data from the non-normal shifts, thus eliminating the tails on the LHS of the mean. Even though these shifts were eliminated, a tail is still visible for this KPI (Figure 13). Data were still found to be normally distributed. The bulk of data for this KPI is found between 75 and 100%. Once again, the High intensity reporting period seems to have a slight skew to the right.

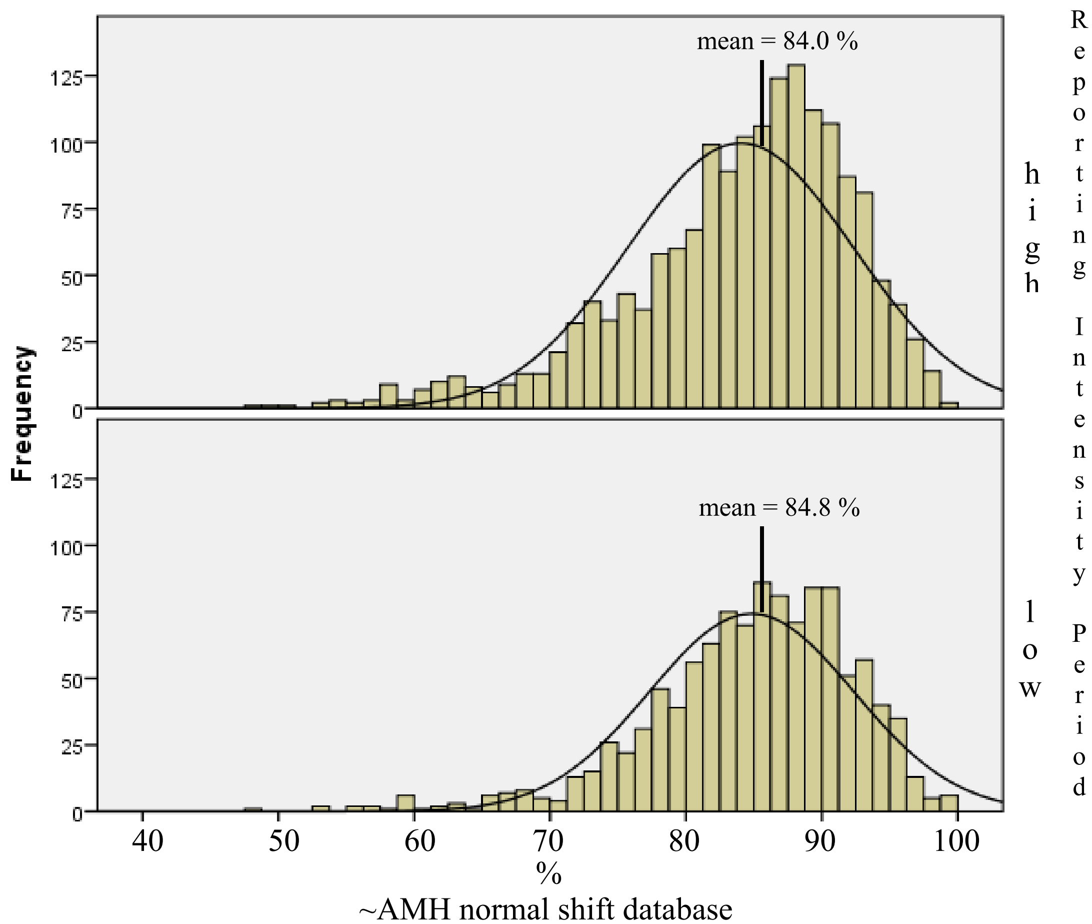

Figure 13. Efficiency KPI (normal shifts) in the ~AMH 1 data base histogram by reporting intensity period; black solid line indicates normally distributed data.

The ANOVA test run on the Efficiency KPI found a highly significant difference (p=0.009) between reporting intensity periods. Therefore, one can reject the null hypothesis and conclude that different reporting intensity periods had an effect on the Efficiency KPI. The High intensity reporting period had an Efficiency KPI value of 84.0%, while for the and Low intensity reporting period, it was 84.8%. This indicates that a higher efficiency is found in the Low intensity reporting period. The reason for this discrepancy is further reviewed in the results discussion.

3.3.1 Normal shifts by machine

After testing if there was a significant difference between reporting intensity periods for the ~AMH, ~PMH and Efficiency KPIs during normal shifts, ANOVA tests were conducted on normal shifts for individual machine types. This was done in order to identify if there would be more pronounced significant differences between reporting intensity periods for certain machine types. Each KPI was reviewed independently and thus reported in the three separate sections below.

3.3.1.1 ANOVA

~AMH ANOVA

In Table 15, ~AMH KPI averages have been changed to percentages. This was done to ease interpretation when considering targets. It is also a more common way to display machine availability. When considering machine availability, the goal is to have 100%. This percentage is calculated by dividing the ~AMH KPI value by the scheduled time (SMH) for each shift. In this study, a scheduled shift was always 10 h. Furthermore, displaying this value in a percentage is also more intuitive when considering its possible use in the ROI section. Coded texts are used in the remainder of the results section (Table 14).

Table 14. Coded values for machine types

Code	Machine Type
FB	Feller-buncher
SK	Skidder
RP	Processor
BH	Excavator
GT	Gravel truck

When categorizing different machine types, there were significant differences between reporting intensity periods for feller-bunchers ($p < 0.000$), skidders ($p = 0.033$) and gravel trucks ($p=0.044$). For this reason, H_0 can be rejected for these machines. On average, feller-bunchers and skidders were found to have a higher ~AMH KPI. A percentage point difference of 2.2% for feller-bunchers and 1.7% for skidders were found between High and Low reporting intensity periods, respectively. For gravel trucks, a greater ~AMH KPI was found in the Low intensity reporting period (lower by 1.4%) (Table 15).

Table 15. Summarized ANOVA results and means between individual machines types for the ~AMH KPI.

	High intensity reporting period availability	Low intensity reporting period availability	sig
FB normal shifts	90.1%	87.9%	0.000***
SK normal shifts	94.5%	92.8%	0.033*
RP normal shifts	91.0%	88.2%	0.084^{ns}
BH normal shifts	91.8%	91.0%	0.360^{ns}
GT normal shifts	90.1%	91.5%	0.044^{*}

*** = significant at $\alpha \leq 0.001$
** = significant at $\alpha \leq 0.01$
* = significant at $\alpha \leq 0.05$
ns = not significant

<u>~PMH ANOVA</u>

After categorizing data to normal shifts and running ANOVA tests on individual machine types, Table 16 was generated to summarize findings. Feller-bunchers were the only machine type found to have a significant difference ($p = 0.04$) between reporting intensity periods for the ~PMH KPI; hence, H_0 is rejected. There is a greater ~PMH KPI value found in the High intensity reporting period as compared to the Low intensity reporting period.

Table 16. Summarized ANOVA results and means between individual machines per machine type for the ~PMH KPI.

	High intensity reporting period utilisation	Low intensity reporting period utilisation	sig
FB normal shifts	76.6%	74.5%	0.04*
SK normal shifts	77.7%	77.0%	0.387^{ns}
RP normal shifts	76.4%	75.8%	0.74^{ns}
BH normal shifts	77.8%	79.3%	0.598^{ns}
GT normal shifts	78.3%	78.0%	0.67^{ns}

*** = significant at $\alpha \leq 0.001$
** = significant at $\alpha \leq 0.01$
* = significant at $\alpha \leq 0.05$
ns = not significant

Efficiency ANOVA

In the ANOVA tests for individual machine types, there was a significant difference in Efficiency KPI values between reporting intensity periods for processors ($p = 0.01$), excavators ($p < 0.000$) and gravel trucks ($p = 0.004$). To that end, the H_0 has been rejected. When considering Efficiency KPI means for each machine type, they were higher in the Low intensity reporting period for processors and excavators, and higher in the High intensity reporting period for gravel trucks.

Table 17. Summarized ANOVA results and means between individual machines per machine type for the Efficiency KPI

	High intensity reporting period efficiency	Low intensity reporting period efficiency	Sig
FB normal shifts	84.4%	84.6%	0.746^{ns}
SK normal shifts	81.4%	81.7%	0.769^{ns}
RP normal shifts	83.4%	85.9%	0.010*
BH normal shifts	84.7%	87.2%	0.000***
GT normal shifts	86.9%	85.3%	0.004**

*** = significant at α ≤ 0.001
** = significant at α ≤ 0.01
* = significant at α ≤ 0.05
ns = not significant

3.3.1.2 Univariate

Equation (2) was used for the GLM univariate procedure after data normality was confirmed:

$y = a + b + ab + \varepsilon$ [2]

Where:

a = Reporting intensity period effect
b = Machine effect
ab = Reporting intensity period * Machine interaction
ε = Error

~AMH univariate

The GLM univariate procedure results for the ~AMH KPI are illustrated in Table 18. This model was run independently for each machine type. In this table, "High intensity availability" and "Low intensity availability" are mean percentage values for the ~AMH KPI for each reporting intensity period. The "sig intensity" column is the significance value which only considers the machine effect (*a* in Equation 2). The "sig machine" column is the significance value which states the difference between machines within the machine type (*b* in Equation 2). The "Sig interaction" column illustrates the significance value which helps determine whether there were any significant differences in KPI values when considering machine-reporting intensity period interactions (*ab* in Equation 2).

When considering the reporting intensity period effect, the only significant difference was found for feller-bunchers (p = 0.013) and H_0 is rejected. When considering the machine-reporting intensity period interaction, significant differences for excavators (p = 0.008) and gravel trucks (p = 0.018) were observed and H_0 is rejected. Hence, individual machines within the excavator and gravel truck machine types were found to react with significant difference to the two different reporting intensity periods. This machine-reporting intensity period interaction will be further discussed when viewing Tables 24 and 25 since individual machine results are presented individually.

Table 18. Summarized Univariate results between individual machines per machine type for the ~AMH KPI.

Machine type	High intensity availability	Low intensity availability	sig intensity	sig machine	sig interaction
FB normal shifts	90.1%	87.9%	0.013*	0.000***	0.245^{ns}
SK normal shifts	94.5%	92.8%	0.095^{ns}	0.407^{ns}	0.055^{ns}
RP normal shifts	91.0%	88.2%	0.289^{ns}	0.741^{ns}	0.505^{ns}
BH normal shifts	91.8%	91.0%	0.851^{ns}	0.000***	0.008**
GT normal shifts	90.1%	91.5%	0.055^{ns}	0.000***	0.018*

*** = significant at α ≤ 0.001
** = significant at α ≤ 0.01
* = significant at α ≤ 0.05
ns = not significant

~PMH univariate

When considering the ~PMH GLM univariate procedure results for each machine type, only feller-bunchers (p = 0.004) were found to have a significant difference between reporting intensity periods and H_0 is rejected (Table 19). So, even when considering the additional effect of individual machine interactions with reporting intensity periods, feller-bunchers are still found to have a significant difference between reporting intensity periods. Machines are found to have a higher ~PMH KPI value in the High intensity reporting period versus the Low intensity reporting period.

The machine-reporting intensity period interaction yielded a significant difference only for excavators (p = 0.018); therefore H_0 can be rejected. This indicates that even though excavators were found to have no significant difference between reporting intensity periods as a machine type, individual machine ~PMH KPI values were found to be significantly different between reporting intensity periods from one another. Therefore, when considering the use of data in different reporting intensity periods for excavators, the ~PMH KPI values were significantly different between machines. Individual machine results will be discussed with Table 24.

Table 19. Summarized Univariate results between individual machines per machine type for the ~PMH KPI

Machine type	High intensity utilisation	Low intensity utilisation	sig intensity	sig machine	sig interaction
FB normal shifts	76.6%	74.5%	0.004**	0.000***	0.196^{ns}
SK normal shifts	77.7%	77.0%	0.501^{ns}	0.002**	0.643^{ns}
RP normal shifts	76.3%	75.8%	0.719^{ns}	0.897^{ns}	0.866^{ns}
BH normal shifts	77.8%	79.3%	0.075^{ns}	0.000***	0.018*
GT normal shifts	78.3%	78.0%	0.737^{ns}	0.000***	0.667^{ns}

*** = significant at $\alpha \leq 0.001$
** = significant at $\alpha \leq 0.01$
* = significant at $\alpha \leq 0.05$
ns = not significant

Efficiency univariate

For the Efficiency KPI, the GLM univariate procedure estimated a highly significant difference for excavators ($p < 0.000$) and gravel trucks ($p=0.006$) and therefore H_0 is rejected (Table 20). Efficiencies were greater in the High intensity reporting period for gravel trucks and greater in the Low intensity reporting period for excavators. The machine-reporting intensity period interactions were found to be significant for the feller-bunchers ($p = 0.013$) and skidders ($p = 0.021$) and H_0 is rejected (Table 21). This indicates that the effect of reporting intensity periods on Efficiency KPI values for individual feller-bunchers and skidders were significantly different between machines. Individual machine observations will be continued in Tables 21 and 22 since individual machine KPI results are discussed and displayed clearly.

Table 20. Summarized Univariate results between individual machines per machine type for the Efficiency KPI.

Machine type	High intensity efficiency	Low intensity efficiency	sig intensity	sig machine	sig interaction
FB normal shifts	84.4%	84.6%	0.100^{ns}	0.000***	0.013*
SK normal shifts	81.4%	81.6%	0.477^{ns}	0.000***	0.021*
RP normal shifts	83.4%	85.9%	0.168^{ns}	0.444^{ns}	0.166^{ns}
BH normal shifts	84.7%	87.1%	0.000***	0.000***	0.338^{ns}
GT normal shifts	86.9%	85.3%	0.006**	0.000***	0.069^{ns}

*** = significant at $\alpha \leq 0.001$
** = significant at $\alpha \leq 0.01$
* = significant at $\alpha \leq 0.05$
ns = not significant

Feller-Buncher

Feller-bunchers were the machine type with the most significant differences in KPI values between reporting intensity periods. This indicates that feller-buncher KPIs were affected by varying reporting intensity periods. Both the ~PMH (p = 0.004) and ~AMH (p = 0.013) KPI were significantly different between reporting intensity periods. It was found that all but one machine had a higher average ~PMH KPI in the High intensity reporting period. For the ~AMH KPI, nearly all machines were found to have a higher ~AMH KPI average in the High intensity reporting period. The only exception was feller-buncher 5, which had a slightly larger increase in the ~AMH KPI during the Low intensity reporting period. The Efficiency KPI was the only one which had a significant intensity-machine interaction for feller-bunchers (p = 0.013). The average Efficiency KPI value was greater in the High intensity reporting period for feller-bunchers 1, 2 and 5, and greater in the Low intensity reporting period for feller-bunchers 3 and 4.

Table 21. Summarized Univariate results for ~AMH, ~PMH and Efficiency KPI between individual machines for Feller-bunchers.

Machine #	Univariate ~PMH		Univariate ~AMH		Univariate Efficiency	
	High intensity utilisation	Low intensity utilisation	High intensity availability	Low intensity availability	High Intensity efficiency	Low Intensity efficiency
FB 1	75.6%	70.9%	84.3%	81.9%	89.7%	86.5%
FB 2	76.5%	73.1%	88.5%	86.6%	86.4%	84.5%
FB 3	74.7%	75.4%	91.5%	90.9%	81.6%	83.1%
FB 4	76.4%	73.5%	91.3%	87.0%	83.5%	84.5%
FB 5	79.5%	78.3%	90.9%	90.6%	87.3%	85.4%

Skidder

For skidders, H_0 failed to be rejected for the ~AMH and ~PMH KPIs. However, H_0 was rejected for the Efficiency KPI (p = 0.021). A higher average efficiency in the High intensity reporting period was observed for skidder 1, while a greater average efficiency in the Low intensity reporting period was found for skidders 2, 3 and 4 (Table 22).

Table 22. Summarized Univariate results for ~AMH, ~PMH and Efficiency KPI between individual machines for Skidders.

Machine #	Univariate ~PMH High intensity utilisation	Univariate ~PMH Low intensity utilisation	Univariate ~AMH High intensity availability	Univariate ~AMH Low intensity availability	Univariate Efficiency High intensity efficiency	Univariate Efficiency Low intensity efficiency
SK 1	78.9%	76.7%	93.7%	94.9%	82.5%	79.5%
SK 2	75.2%	74.6%	95.7%	90.8%	75.7%	80.4%
SK 3	77.9%	79.0%	94.9%	94.8%	81.6%	83.3%
SK 4	78.6%	78.5%	94.2%	92.5%	83.8%	83.0%

Processor

For the Univariate GLM procedure, processors were found to have no significant difference for any KPI. Therefore, H_0 is not rejected for the processor machine type for all KPIs. This indicates that none of the processor's KPI values are affected by varying intensities of data usage. Average values for each reporting intensity period of the ~AMH, ~PMH and Efficiency KPI are displayed in Table 23.

Table 23. Summarized Univariate results for ~AMH, ~PMH and Efficiency KPI between individual machines for processors.

Machine #	Univariate ~PMH High intensity utilisation	Univariate ~PMH Low intensity utilisation	Univariate ~AMH High intensity availability	Univariate ~AMH Low intensity availability	Univariate Efficiency High intensity efficiency	Univariate Efficiency Low intensity efficiency
RP 1	76.3%	75.9%	91.4%	87.9%	83.0%	86.30%
RP 2	76.4%	75.2%	90.8%	89.9%	83.7%	83.7%

Excavator

Excavators were found to have the most significant machine-reporting intensity period interaction for the ~AMH and ~PMH KPIs. For the ~AMH KPI, excavators 1, 2 and 3 had a higher average value in the High intensity reporting period. Excavators 4 and 5 had a higher average ~AMH KPI in the Low intensity reporting period. In terms of the

~PMH KPI, it was found that excavators 1 and 2 had a higher value in the High intensity reporting period. Excavators 3, 4 and 5 had a higher value in the Low intensity reporting period. Excavators were also found to have an overall higher efficiency in the Low intensity reporting period over the High intensity reporting period. In this case, the machine-reporting intensity period interaction indicates that the effect of varying reporting intensity periods on the Efficiency KPI varies per machine. They all, however, were found to have a higher average Efficiency in the Low intensity reporting period (Table 24).

Table 24. Summarized Univariate results for ~AMH, ~PMH and Efficiency KPI between individual machines for Excavators.

Machine #	Univariate ~PMH		Univariate ~AMH		Univariate Efficiency	
	High intensity utilisation	Low intensity utilisation	High intensity availability	Low intensity availability	High intensity efficiency	Low intensity efficiency
BH 1	77.9%	77.8%	92.1%	89.5%	84.4%	86.9%
BH 2	75.7%	73.4%	92.6%	88.4%	81.6%	83.5%
BH 3	80.0%	80.1%	93.3%	93.1%	85.8%	85.9%
BH 4	75.4%	79.6%	86.0%	87.6%	87.5%	90.9%
BH 5	78.7%	84.6%	91.2%	95.6%	86.3%	88.4%

Gravel trucks

Gravel trucks were found to have a significant machine-reporting intensity period interaction for the ~AMH KPI ($p = 0.018$) and H_0 was rejected. Gravel trucks 3 and 4 had a higher ~AMH KPI in the High intensity reporting period while gravel trucks 1, 2, 5 and 6 had a greater ~AMH KPI in the Low intensity reporting period. A significant difference was found between reporting intensity periods for the Efficiency KPI ($p = 0.006$); 5 out of 6 gravel trucks were found to have a higher efficiency in the High intensity reporting period (Table 25).

Table 25. Summarized Univariate results for ~AMH, ~PMH and Efficiency KPI between individual machines for Gravel trucks.

Machine #	Univariate ~PMH		Univariate ~AMH		Univariate Efficiency	
	High intensity utilisation	Low intensity utilisation	High intensity availability	Low intensity availability	High intensity efficiency	Low intensity efficiency
GT 1	80.3%	79.7%	94.0%	95.1%	85.3%	83.8%
GT 2	78.7%	78.0%	88.9%	91.6%	88.2%	85.0%
GT 3	78.4%	77.2%	88.9%	85.3%	88.4%	90.6%
GT 4	76.0%	73.9%	90.1%	90.1%	84.3%	81.7%
GT 5	77.5%	78.9%	89.2%	92.2%	87.2%	85.8%
GT 6	79.4%	81.1%	88.8%	93.5%	89.4%	86.8%

3.4 COUNT KPI ACCURACY

3.4.1 Feller-buncher Count

In order to help determine the accuracy of the Count KPI, additional tests and correlations were generated. Table 26 summarizes descriptive statistics for the feller-buncher count data. "N" lists the total number of samples. "Mean" lists the average value for the sample. "Mean Std. Error" lists the standard error of the mean.

The mean value of 0.97 for the OBC/visual activation ratio is quite good. This indicates that overall, the number of grab arm activations counted by the observer corresponds closely to the electronic count found in the OBC's memory. This suggests that the multiDAT is correctly connected to the proper electronic impulse to monitor grab arm activations. A mean ratio value of 0.99 of OBC count to tree count was found. This indicates that the OBC count of grab arm activations is closely related to the number of trees harvested.

Table 26. Feller-buncher summarized descriptive statistics for the count accuracy ratios.

Ratio	N	Mean	
		Value	Std. Error
OBC /visual activation	46	0.97	0.02
OBC/tree	46	0.99	0.02

Table 27 shows the Pearson Product-Moment Correlation Coefficient results. The first column lists the variables which were compared; in this case, OBC count and visual activation count. Each variable from the first column is tested against each variable in the first row. The “Pearson Correlation” value for each variable interaction is displayed, along with 2-tailed significance value “Sig. (2-tailed)” and the total sample population, “N”.

When testing two different variables, the closer the Pearson Correlation value is to 1.0, the better the relationship between the variables. When comparing the “OBC” to “visual activation” values for feller-bunchers, the Pearson Correlation is 0.912. This correlation is significantly high. This indicates that the number of grab arm activations counted by the observer is closely related to the OBC count of grab arm activations by the multiDAT OBC.

Table 27. Correlation results from OBC and visual activation data for feller-bunchers.

	OBC	Visual Activation
OBC	1	0.912 ***
Visual Activation	0.912 ***	1
n	46	46

*** = significant at α ≤ 0.001
** = significant at α ≤ 0.01
* = significant at α ≤ 0.05
ns = not significant

A Pearson Product-Moment Correlation Coefficient was also generated for the OBC and tree count variables (Table 28). The Pearson Correlation between the OBC and tree count variables for feller-bunchers was found to be 0.923. This indicated a strong correlation between the number of grab arm activations counted by the OBC and the number of trees harvested.

Table 28. Correlation results from OBC and Tree count data for feller-bunchers.

	OBC	Tree count
OBC	1	0.923 **
Tree count	0.923 **	1
n	46	46

*** = significant at α ≤ 0.001
** = significant at α ≤ 0.01
* = significant at α ≤ 0.05
ns = not significant

ANOVA tests were generated in order to identify whether machines would have an effect on OBC/tree count ratios (Table 29). The tree count/OBC significance value was calculated as 0.000. This indicated a significant difference in tree count/OBC ratios between machines. Therefore, individual machines may have varying ratios between the number of tree counts and OBC counts. The null hypothesis of no changes in the ratios was rejected.

Table 29. ANOVA test for testing significant differences between OBC to tree count ratios between machines.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.172	1	.172	18.506	***
Within Groups	.409	44	.009		
Total	.581	45			

*** = significant at $\alpha \leq 0.001$
** = significant at $\alpha \leq 0.01$
* = significant at $\alpha \leq 0.05$
ns = not significant

3.4.2 Processor Count

Descriptive statistics for the OBC/visual activation and OBC/log count ratios are illustrated in Table 30. With a total sample of 62, the mean value for OBC/visual activation and OBC/log count ratios are 1.08 and 0.91, respectively. This indicates a slight disconnect between the number of visual activations counted by the observer and by the OBC. This also indicates a small difference between the number of logs produced (log count) and the number of bottom saw activations (visual activation Count).

Table 30. Processor summarized descriptive statistics for the count accuracy ratios.

	N	Mean	
		Value	Std. Error
OBC /Visual activation	62	1.08	0.02
OBC/Log Count	62	0.91	0.02

Table 31 illustrates the Pearson Correlation value for processors. After completing this test, a correlation of 0.88 is calculated for the OBC and visual activation count variables. This indicates that the OBC counts are slightly different than the visual activation counts. Even though there is a difference, a correlation of 0.88 is still quite close and could be considered a good value.

Table 31. Correlation results from OBC and visual activation count data for processors.

	OBC	Visual Activation
OBC	1	0.88 **
Visual Activation	0.88 **	1
n	62	62

*** = significant at $\alpha \leq 0.001$
** = significant at $\alpha \leq 0.01$
* = significant at $\alpha \leq 0.05$
ns = not significant

Table 32 illustrates the Pearson Correlation results for the OBC and log count variables. In this case, OBC and log count variables are found to have a correlation of 0.87. Even though there is a slightly lower correlation, it can still be considered quite accurate.

Table 32. Correlation results from OBC and log count data for processors.

	OBC	Log count
OBC	1	0.87 (0.00)**
Log count	0.87 (0.00)**	1
n	62	62

*** = significant at $\alpha \leq 0.001$
** = significant at $\alpha \leq 0.01$
* = significant at $\alpha \leq 0.05$
ns = not significant

3.5 ROI RESULTS

In this case study, the only ~PMH KPI found to be significantly different between reporting intensity periods for normal shifts was for the feller-buncher machine type. Since this was the only machine type found to have these differences, it was the only one to have ROI estimates computed. As described in the methods, the total cost per cubic metre ($\$/m^3$) was calculated for two scenarios. The difference between scenarios was the utilisation value input to the RDM; one scenario had the ~PMH KPI value in the Low intensity reporting period and the other scenario had the ~PMH KPI value for the High intensity reporting period. All other inputs remained untouched. The following table illustrates the estimated cost in $\$/m^3$ when comparing the different ~PMH KPI rates in the RDM (Table 33).

Table 33. Feller-buncher RDM results for the ~PMH KPI.

Reporting intensity periods	Utilisation rate used	$\$/m^3$
High intensity	76.61%	3.62
Low intensity	74.48%	3.70

The High intensity reporting period was found to have a greater utilisation rate during normal shifts. This eventually led to a reduction of 0.08$\$/m^3$. If considering H_0 as no change in the final cost/m^3 between reporting intensity periods, this hypothesis can be rejected. When considering the alternative hypothesis as the High intensity reporting period having a greater cost savings (lower cost per m^3) than the Low intensity reporting period, the H_A has failed to be rejected.

In order to calculate ROI, costs must be determined. In this case study, approximate costs were calculated for the implementation of OBCs in 10 feller-bunchers. This would estimate the cost of retrofitting a large contracting firm with multiple OBCs. Table 34 is an estimated cost of initial implementation for an OBC system.

Table 34. Initial cost estimates of OBC system installation

Initial cost		Initial cost per machine		Total
Download box	$ 2,750	multiDAT	$ 1,000	
Software	$ 400	Modem	$ 275	
System Installation	$ 2,000	Installation	$ 500	
Management	$ 2,000	Management	$ 1,000	
Subtotal	$ 7,150		$ 2,775	
Number of machines			10	
Total initial cost	$ 7,150		$ 27,750	$ 34,900

"Initial costs" are items which are required for the initial installation of the system. This includes the purchase and installation of the download box in a pick-up, the initial software purchase and the management of these activities. "Initial cost per machine" includes initial costs per individual machine such as the purchase of the OBC and accessories, its installation and the management of these activities. Once initial costs have been estimated, annual costs of maintaining the system were also estimated. The subsequent table illustrates the annual cost of utilising this equipment (Table 35).

Table 35. Annual estimated cost of OBC system

Annual cost per machine		Annual cost		Total
Maintenance	$ 1,000	System maintenance	$ 2,000	
Management	$ 1,000	Cell download	$ 400	
		Management	$ 5,000	
Subtotal	$ 2,000		$ 7,400	
Number of machines	10.00			
Total annual cost	$ 20,000		$ 7,400	$ 27,400

"Annual cost per machine" includes the annual cost of maintenance and management per machine. Maintenance issues may include the replacement of damaged equipment, re-connection of wiring and other maintenance issues. Management includes the additional cost of managing associated issues that may arise with the equipment. "Annual cost" includes maintenance of the entire system, cellular data collection fees, and overall management of the system as a whole.

Totalling the Initial and Annual costs gives an estimate of total system cost. Table 36 illustrates the average cost per year for year 1, 2 and beyond for retrofitting 10 feller-bunchers with this equipment.

Table 36. Estimated yearly costs of OBC system

Year	Initial cost	Annual cost	Total cost
Year 1	$34,900	$27,400	$62,300
Year 2	$ -	$27,400	$27,400
Year 3	$ -	$27,400	$27,400
Total	$34,900	$82,200	$117,100

Additional maintenance costs could be applied in subsequent years due to aging equipment and additional maintenance. However, maintenance costs may decrease due to experience gained with equipment installation and maintenance. Management costs may also change through time due to evolving uses, implementation style, and data use, as examples of possible changes. Also, the user may intend to change the equipment after three years due to the possibility of newer and improved OBCs.

Based on these values, an ROI over a 3-year period can be estimated (Table 37). The total cost is the initial and annual cost for outfitting 10 feller-bunchers for three years. In this case study, 10 feller-bunchers are assumed to cut 1 million m^3 in one year. In reality, feller-bunchers may be more productive (10-15% more). However, for easy interpretation and calculations, 1 million m3 has been deemed appropriate. A total savings of 0.08$/$m^3$ is assumed for 1 million m^3 per year for three years.

Table 37. ROI for 10 feller-bunchers over a 3-year period

Year	Total cost	Total savings	ROI	Payback period (years)
3	$117,100.00	$240,000.00	105%	1.46

4.0 DISCUSSION

The discussion has been subdivided into two major sections. The first section discusses the implementation of an OBC system with experience gained in this study, while the second section discusses KPI results from this case study. The first section provides valuable background information on the installation of this system. It also discusses challenges associated with the implementation of these systems along with the value and limitations of individual KPIs. The second section delves into specific details of the results and their interpretation.

4.1 SECTION I: IMPLEMENTATION OF ON-BOARD COMPUTERS

After this study, one could suggest that there are seven major steps to the implementation of OBC systems in forest operations. They can be considered as:

1) Identify problems and set goals
2) Study local forest operations
3) Identify KPIs
4) Design and implement OBC system
5) Collect information
6) Analyse, report and identify opportunities
7) Constantly re-evaluate

4.1.1 Identify problems and set goals

The first step to implementing an OBC system is to identify problems and set goals. The identification and definition of these problems/goals will vary in each situation according to the need of individuals. Since each implementation situation is unique, it is obvious that external applications cannot be used without extra developments within a new environment (Emeyriat and Bigot 2006). This suggests that each system must be "custom fit" to individual companies; there is no definite solution for all of them.

Defining goals will also help identify information timelines; which is the rate at which information must be available to reach those goals. An example of this is looking at the use of OBCs for incentive programs versus coordination improvements. The first can work with longer timelines, whereas the second usually requires shorter, more immediate access to data (Hubbard 2000). Therefore, the collection, communication, access, analysis and reporting will be determined by the end goal.

In this case study, the goal was to develop and implement a simple system which would be applicable to all machine types and easy to use over the long term. The core problem was the lack of accurately determining machine utilisation, availability and productivity. More specifically, the items of interest were:

- What basic data is most important and how do we track it?
- Can there be a single data collection template across all machines?

4.1.2. Study local forest operations

The first step is to take a holistic approach to problem solving by considering all components of the forest supply chain. These components will then be broken down to smaller elements or activities and be critically observed and analysed. Sundberg and Silversides (1988) suggest identifying and critically observing the components of a system by asking such questions as “what are the technical means for doing the job” and “which factors have influence on the performance”. The answers to these questions will help understand and outline the factors which can affect work. In addition to this, they suggest that one should consider both physical and human variables as different. This is because physical variables tend to have a much more linear and predictive effect than human variables, due to the stochastic behaviour and unpredictability of human activity.

In this case study, a forest harvest supply chain and some road building equipment were studied. Each machine type is a unique component of the supply chain. Therefore, each machine type has to be critically analysed and observed. Moreover, some of the road building equipment may have a greater variety of applications than forest harvesting equipment (i.e., an excavator may build road, dig a pit, load trucks, etc.) which would mean that additional machine observation and study would be necessary to understand all tasks.

4.1.3 Identify KPIs

Once the supply chain is understood, there is a need for developing key measurable metrics to report and evaluate performance. There are several ways to undertake this, one of which is by working under the principles of governing the control function by Urwick (1947). These principles provide guidance to aid in the identification of data metrics that provide the best opportunity to enhance control and include the principles of uniformity, comparison, utility and exception. These principles outline the major considerations when collecting, analysing and reporting data to increase the user's ability to control operations.

According to Silversides and Sundberg (1989), the first principle states the importance of choosing data which can be directly affected or controlled. This will ensure that this metric can be improved. The second principle declares the importance of being able to compare past, present and future data. This allows for performance tracking and monitoring. The third principle simply stresses the importance that only data which are useful should be collected and used. The last principle suggests the importance of being able to identify outliers and exceptions to provide better control. The idea is to have an automated identification of special cases in order to improve or modify them.

The importance of an operator's ability to affect KPIs is important; especially when considering any incentive payment system. Hubbard (2000) provides one example that when basing a driver's performance on arrival time only, it does not account for items out of a driver's control (i.e., mechanical breakdowns and traffic). This provides inaccuracies in the data and may render some values as skewed or invalid. Some examples of KPIs found in relevant literature are given below:

- traffic intensity, degree of intensity (Carter *et al.*1999);
- utilisation time, harvesting time, productivity (m^3/day), fuel consumption based on topography, shift progress, location of wood piles, compliance with harvest prescription, GPS signal quality (Cordero *et al.* 2006);

- % area covered, operational delays, type of delay, skidder cycle time, cycle time elements (Davis and Kellogg 2005).

In this case study, the development of KPIs followed Urwick's principles. A total of four KPIs were used in this study.

4.1.3.1 ~AMH

In order for a machine to operate, the master switch must be engaged since this switch activates power for the machine. Without this power, the machine is unable to run. In order for this switch to be activated, it must be physically turned on and off by an operator. Operators are instructed to activate this switch when they arrive on site for their shift and deactivate it when they depart. Therefore, measuring the activation time of this switch can be interpreted as a measure of performance. If a machine is scheduled to work for 10 h, it should theoretically have the master switch activated for 10 h. Therefore, when considering Urwick's first principle, the ~AMH KPI can be directly controlled.

However, there are exceptions to this hypothesis. Within 10 h of scheduled time, the machine can be powered down to do preventive and regular maintenance. For some machines, this regular maintenance can take as little as 10 min. For others, it may be as much as 30 min. Other items which may be out of the operator's control are when the machine must be moved to another location, or if the machine breaks down. A scheduled machine move or sporadic machine failures are not monitored or catalogued electronically. This can lead to misrepresentation when attempting to compare different work shifts over a short period of time.

Another challenge to this KPI is that there are times where the master switch is left on by the operator. This phenomenon was only observed for some of the skidders.

This is because the master switch is a little less accessible as compared to other machine types. This would lead to the switch being left on between shifts. When considering and measuring performance, one must consider that some of the results for these skidders may be a misrepresentation of the ~AMH KPI.

With these exceptions in mind, it is important to identify outliers and exceptions (Urwick's fourth principle). When the Master switch is left on, it will record a shift time often greater than the scheduled time. On very rare occasions does the operator work over a designated 10 h shift. However, this overtime must be tracked. Therefore, one can make an assumption or rule that any shift which has over a certain number of the ~AMH KPI, the master switch was left on and this should therefore not be considered in data analysis.

When a machine gets moved or breaks, a large portion of the shift is generally defunct. Generally, one can assume that shifts which have less than a certain number of ~AMH were subject to one of these events. Once data have been generated, ~AMH values can be filtered to eliminate these exceptions if it is required. However, when an overall value for the ~AMH KPI is required, it is best to include these exceptions and outliers since it should remain as part of the machine history and data.

Based on Urwick's second principle, these data can be compared to past, present and future values, especially when considering broad timelines. However, considering the comparison of this KPI over short periods of time may be considered imperfect. Once again, the lack of knowledge pertaining to breaks and machine moves may misrepresent unfiltered data over the short term. If there was additional field knowledge of individual machine and shift events, these data can be used as a tool for comparison over the short term.

An example of using these data would be comparing the ~AMH KPI between newer machine models and older models. A difference in this KPI may indicate that the older model may not have as high of a KPI value due to its age. The machine may be prone to more mechanical breaks and additional maintenance.

4.1.3.2 ~PMH

The use of ~PMH as a KPI can be very valuable. In order for most machines to complete work tasks they will have some sort of movement. Feller-bunchers will be moving to trees, processors will be picking up logs, skidders will be transporting bundles, etc. These activities provide differing levels of ~PMH which are evaluated and logged by the OBC. Therefore, when tracking ~PMH, one can assume that any movement above a certain threshold can relate to the machine doing a work task. For the most part, this would respect Urwick's first principle since this data can be directly affected or controlled.

The only limitation of this assumption is that a machine could be recording ~PMH activities but may not be doing any work. In most scenarios any case of false information would be related to the deliberate attempt by operators to falsify data by having the machine move without completing any work tasks. This, however, has not been observed or suspected in this study. Nevertheless, incidence of false information must be considered when analysing this information. It is important to pair the ~PMH KPI with other KPIs and on-site information to ensure that information being recorded matches the work which was done on site. Other weaknesses to these data are very similar to those of the ~AMH KPI. If a machine moves to a new site or breaks, ~PMH cannot be logged since it is unavailable and unable to complete its work tasks. This is because it is mostly out of the control of management or an operator. There are different factors which can affect machine utilisation; these can include technical reliability of the machines, weather and road conditions, logistics, proportion of set-up time and workers. (Holzleitner *et al.* 2012)

The ~PMH KPI also applies to Urwick's second principle; comparisons can be made to past, present and future data with some restrictions similar to those for the ~AMH KPI. That is, when considering short term comparisons, detailed field information can be applied to enhance data analysis and interpretation.

With these exceptions in mind, outliers and exceptions can be identified through data filtering. However, some assumptions have to be made in order to best estimate KPIs.

The ~PMH KPI can be used in many ways. An example of this would be to help determine the accuracy of machine rates. Having a better estimate of machine utilisation can help determine how machine costs and profits are determined. This can provide a firm with more accurate costs and help improve the achievement of financial targets.

Thompson (2001) considered the use of OBCs as long term solutions to calculating utilisation rates for grapple skidders. MultiDATs were installed in four grapple skidders for approximately 44 working days. In this case, a motion sensor was tracking when the machine was moving, assuming that this movement was considered to be "work".

4.1.3.3 Efficiency

The Efficiency KPI is a ratio of both the ~AMH and ~PMH KPI. It is a percentage of ~AMH when the machine is utilised ((~PMH/~AMH)*100). This KPI is designed to give a sort of "efficiency" rating. It gives an estimate of how the machine is used within its "available" time.

This is arguably the KPI with the most control. For a machine to move, it requires power. Since the ~AMH KPI tracks the activation of power, the number of ~PMH will never surpass that of the ~AMH. The goal would be to achieve the highest Efficiency KPI; since it would indicate the machine is moving as long as it is powered. This would indicate a sort of “job dedication” or “efficiency” within a designated amount of time (i.e., 1 shift).

There would tend to be less error in the interpretation of this KPI. For one, it is less affected by machine breakdowns and moves, as compared to the others since the power is normally shut off when there is an issue. As an example, if a machine is available to work for 3 h in a shift because of a breakdown, the master switch may be on for 3 h and have 2.75 h of ~PMH. When the machine stops due to a predicted or unpredicted event, it still reflects the amount of “work” which was completed that day.

However, there may be exceptions to this “lack of error”. If a machine was set to move, it may only be activated when it is loaded and unloaded from a float trailer. Potentially, the machine would be quickly powered up and moving for a very small amount of time. This may give the Efficiency KPI a high value. When interpreting this data, it is important to pair this value with the total amount of ~AMH and ~PMH which took place. Thus, this helps one consider ~AMH and ~PMH in relation to SMH.

When considering Urwick’s second principle, it is simpler to compare past, present and future data for this KPI as compared to others. This would be because there is more direct control, less potential errors and less effect from external noise. For instance, the reason a ~AMH KPI for a particular shift would be lower may be because it took more time to start up a machine (possibly because of weather or road travel). The Efficiency KPI would provide an opportunity to show that the machine may still be productive for the amount of time that was "available". Therefore, it provides a unique KPI which can be very valuable and different from the two KPIs which are used to generate it.

In terms of Urwick's fourth principle, it is a little more difficult to identify outliers and exceptions. In order to identify these, one would have to compare the Efficiency KPI to the ~AMH and ~PMH KPIs. Outliers from these two other KPIs would be the source of errors for the Efficiency KPI. An example of these errors would be leaving the master switch on after a shift was completed (as mentioned in the ~AMH KPI section). The amount of ~PMH that would have taken place during one of these shifts would be accurate, however, the Efficiency KPI would give a false ratio since the ~AMH KPI is incorrect. The filtering of these outliers could take place when filtering outliers for the ~AMH and ~PMH KPI.

4.1.3.4 Count

Productivity can be very difficult to track in forest operations due to variability in site and stand conditions and stochastic events. Furthermore, the operating environment can be harsh for any type of production measuring equipment (e.g., weather, vibrations, dust, etc.) Therefore, there is not much automated productivity tracking hardware and equipment in use in Canada. Certain machine types (mainly harvesters) are equipped with some form of production monitoring equipment, but this equipment is often not used to its full potential in Canada. This is mostly due to the technical challenges of implementing, maintaining and operating this new equipment.

The count KPI is designed to provide an alternate measure of productivity. It is not to be interpreted as a perfect measure, but instead a proxy that can give supplemental information to staff as per how much production may have occurred. It can also be used as another metric for machine utilisation and monitoring.

The interpretation of this KPI can be difficult. When evaluating this KPI's value, one must consider the various factors which may have affected its outcome. Therefore, when referring to Urwick's principle of uniformity, this KPI must be evaluated carefully and critically. This also applies to the principle of comparison. When attempting to compare KPI values between shifts, work factors must be considered. When comparing KPI values over longer periods (years), values may be more comparable, since variability would be considered more normalized.

When considering the principle of utility, this KPI would be valuable for various reasons. For one, it can be used as a verification tool for other KPIs. If the integrity of the ~AMH and ~PMH KPI is questioned, the Count KPI can be compared to these values. A high ~PMH and ~AMH KPI coupled with a lower Count KPI may indicate poor practices, a lack of training, or the active intention to affect the ~AMH and ~PMH KPI. A higher Count compared to ~PMH and ~AMH KPI may indicate some technical or interpretive errors and should entice further evaluation and verification of the equipment. As previously mentioned, this KPI could be used as a loose proxy for measuring productivity. The OBC count can help estimate how many trees or logs have been modified over time.

4.1.2 Design and implement OBC system

Once goals and key metrics are identified, the design of an OBC system can take place. At this stage, the best-fit solution for the user is to be explored; this includes a series of considerations including hardware, software and communications. Once again, the user's problems, goals, limitations and needs are to be considered to make an educated decision to ensure the desired outcome. Once this has been completed, an implementation procedure should be developed to ensure its smooth integration within forest operations. This includes plans for hardware installation, IT integration and data collection, analysis and reporting. Involvement of all stakeholders would prove to be beneficial throughout the research and implementation process.

In this case study, this included the installation of a multiDAT and RF modem in each machine, and a receiving unit in two pick-up trucks. The idea was to have two pick-up trucks download each multiDAT while completing their regular day-to-day operations. Doing this would save time and money since the process is automated and requires little or no maintenance.

There were considerable challenges which arose that made the system difficult to maintain and not work as originally envisioned. This data collection system was based on the assumption that machines would tend to remain in the same groups and that a supervisor would visit each machine once a week. It also assumed that no real maintenance would be required since these units tend to have minimal manufacturing defects and would be monitored daily for any issues.

There were two download pick-ups. Each pick-up was designed to interface with specific machines. Since machines tend to stay in the same groups and areas, this arrangement was thought to be acceptable. However, after further study it was found that machines tend to move between groups more frequently than originally thought. This led to some machines being unable to get downloaded for long periods of time since they were now working in different areas and groups. If a machine changed groups, it would have to come back to its original group to get downloaded by the associated pick-up. This led to gaps in data collection and reporting.

Another problem was that supervisors would not necessarily visit each machine once a week. Machines were being moved to different areas, put to different tasks, were at inaccessible parts of the harvest block, etc. Therefore, a pick-up might not have the opportunity to download each individual machine once per week. If this were to take place a few weeks in a row, there would be gaps in reporting and data. These gaps in data reporting and collection were seen as a nuisance since not all machines would be reported weekly.

The largest issue is that physical damage was recorded to some of the equipment. Some of the hardware components (datalogger, wiring, RF modem, antenna) were found to be damaged or disabled. This was partially due to the harsh work environment and the sabotaging of equipment. This damage can be attributed to a few items. Stadler (2005) stated that the culture of mistrust and "learn on the job" history requires that frontline forestry workers must be approached carefully when implementing new ideas. Furthermore, scepticism of IT and lack of information sharing has led to a greater need for care in implementation and application (Stadler 2005). In this case study, workers may not have been approached with enough care and involvement. One may speculate that fear of new technology and mistrust of management was the largest contributor to sabotage. The physical sabotaging of this equipment would mostly be minor instances limited to only a few machines and areas. For the most part, most OBCs were not damaged and this was not an issue in this case study.

In addition to this damage, some of the RF modems would occasionally be turned off. This could be a form of sabotage, but it would not affect data collection, only data transfer. With the wireless transmitter powered off, machine data could not be transmitted to an awaiting receiver in the pick-up. Since data could not be transferred, it could not be reported on a timely basis.

4.1.3 Collect information

In order to make changes and improve operations, there is a need for benchmark information. This step is dedicated to the collection of base information for initial data analysis. It will provide a baseline for current operations that will subsequently be analysed for further improvement. This will also provide an opportunity for testing the equipment and ensure reliable/accurate data collection.

In this case study, data were collected from the last week of May 2011 to the end of January 2012. All KPIs were collected through this period. Data were reported in two different reporting intensity periods. Benchmark data were not developed and reported. This was because releasing benchmark information may have affected the outcome on different reporting intensity periods. However, once the field work was complete, benchmark information was released.

4.1.4 Analyse, report and identify opportunities

This step focuses on data collection, analysis and reporting following baseline data collection. At this stage, data are critically analysed in order to identify opportunities and develop improvement plans. The development of data reporting and information dissemination methods also takes place in this step. New data are analysed and reported to be used and compared to past events. These data are also used to monitor the effect of changes in forest operations. Examples of this are new harvesting methods, systems, personnel or best practices. This is where data treatment and heavy analysis takes place in order to improve operations.

After initial data collection, report customization began. The development of these reports took place from late May to the third week of July. It took seven rounds of report building and customization to arrive at an agreeable and legible template. Each round of report building would answer the following questions:

- Who will receive the results and how is it disseminated?
- What is the data frame? 1 week? 2 weeks?
- When will the report be released? Weekly? Specific days?
- How will data be organised? By machine? By day?
- What unit of time will form the rows? Daily, weekly or shift results?

Furthermore, reports had to be easy to interpret and generate.

Once these main questions were answered, reports were created and evaluated to determine whether they needed further refinement. The final result of the report customization period yielded three different reports released on a weekly basis to staff only.

Once the reports were released to the staff, data were used at each staff member's discretion. Since this was designed to be a broad scaled study between reporting intensity periods, specific tracking of data use was not logged.

After completing the study, it was felt that there should have been a different data utilisation structure. The lack of experience in data analysis and reporting led to the under-utilisation of information. The following are suggestions which could have been used during the high intensity data reporting period.

- KPI targets could have been set and compared to incoming weekly data. The comparison and review of weekly results to target KPIs would have led to more reflection and use of data. This is because staff would have to respond to weak or strong KPI values. This would lead to more involvement by enticing the staff to further review and analyse what resulted in the past week's values. This would lead to the identification of problems or strengths and subsequently develop better practices.
- A template to log data use should have been developed and implemented. This additional information would have provided insight as to how each individual staff member utilised the data. This information could have been used to further refine reports, develop additional KPIs, report best practices and identify weak points amongst many other uses. The only issue with implementing this would be the lack of involvement by staff due to time constraints. It is felt that most staff are already overloaded with work and additional forms would further increase the workload.
- Additional site information could have been used to further refine and analyse results. This additional information would have to be collected and reported in one of two ways: 1) Written daily logs of machine activities and location; and 2) Availability of daily GPS information and additional GIS accessibility with the use of mulitDAT stop codes. This would have provided additional information to track KPI values. Written

logs would provide shift specific detail which could be considered during data analysis and interpretation of KPIs. Unfortunately, the amount of additional data management, involvement of staff and operators, and the development of an activity log would be major hurdles that would have to be overcome. A simpler way to address this would be the use of stop codes. Operators would have to choose one of up to 10 categories to define why a machine was stopped for a prolonged period of time. This could help identify why a machine was stopped, and thus why some KPIs are lower. This, however, may prove to be challenging since operators would have to be trained on these functions and subsequently use them. It is felt that some operators would not participate in this due to the additional interaction with this equipment. This resistance would be due to general resistance to the use of this equipment, but also because of the additional noise which comes from the OBC when a stop code is not used. The use of GPS information is an alternative. However, this would require additional training and data management with third party software to generate valuable reports and maps. Furthermore, additional hardware requirements would be necessary, such as the addition of hardware components in the multiDAT itself and the addition of an antenna.

- Further involvement of operators could have been valuable. Operator involvement during KPI creation and reporting may have led to more comprehensive reports, additional data analysis and more successful hardware implementation. However, this would have most likely made the KPI and report creation process much longer. This would be due to the additional time required by stakeholders to review reports and KPIs. Furthermore, unrestricted report and data interpretation by operators could have led to new challenges which could include:

- Operators scrutinizing other operators
- Operators unwilling to accept the resulting KPIs
- Operators speculating on the use of this information

The additional success of hardware implementation is also debatable. On one hand, operators may feel that they are directly participating in a major program and want to succeed by improving KPIs and maintaining equipment. On the other hand, operators may feel they are being scrutinized and further damage equipment since they do not agree with the results.

4.1.5 Re-evaluate

Once all of these steps have been completed (and even over the course of implementation) constant re-evaluation is necessary for continual improvement. A system can always be improved and status quo will only lead to lagging behind competitors. Everything from the identification of new KPIs, data systems, measurement methods and improvement opportunities should be reviewed or introduced. This will lead to the improvement of the overall supply chain, and sustain or improve competitiveness.

Re-evaluation was taking place during this study. For one, data collection methods had to be re-evaluated for more consistency. Wireless equipment was occasionally being tampered and damaged intentionally and unintentionally. A few operators would power off or damage equipment to restrict data transmission. Some cables were loosening through time by vibration and regular wear; this equipment had to be re-connected and fixed in order to transfer data. To resolve this challenge, a few options could have been discussed. One option would be to have operators more involved in the datalogging process. This additional involvement may have led to additional care of the equipment. Another option would be to have supervisors actively monitoring equipment health and ensuring their operation. A final option would be to dedicate specialized staff that would ensure the system is working as a whole and perform regular maintenance. In this case study, a specialized staff was assigned to download and monitor equipment on a weekly basis to ensure data retrieval, equipment monitoring and maintenance.

The accuracy of the "count" KPI was evaluated. This included field studies which matched the OBC count of machine component activations to a visual count (visual activation count) of component activations. This was done for feller-bunchers, processors and skidders.

The "count" KPI data was found to be unusable for skidders. The field evaluation showed no correlation between the number of back-ups to bunches delivered to a landing. This was because there was too much site and operator variability to achieve a comparable and accurate metric through time. A new metric to measure a form of productivity for skidders would be required. One of the metrics of interest would be loaded time. This would require a signal to activate when the skidder is loaded and skidding bunches. Unfortunately, a connection for this signal is not available. There are no signals which currently measure when the skidder is loaded and skidding. One option would be to connect a weight sensor to the grapple which would sense when trees are in the grapple. This could in turn be logged and reported.

The feller-buncher Count KPI produced interesting results. The OBC/visual activation and OBC/tree count ratio means were both close to 1.0. This indicates that the use of the OBC count provides a good estimate of the number of trees cut. A bivariate correlation between OBC/visual activation and OBC/tree count was also completed. A correlation between OBC and visual activation count of 0.912 indicates no error found between the visual activation count and the OBC count of grab arm activations. This can be due to error from the observer's visual count of the activations or from and incorrect connection to the machine signal for activation. In this case, the observer's count would most likely be the sources of these errors. Counting grab arm activations can prove to be challenging due to safety concerns and visual obstructions. The observer had to be outside of the machine's operating zone (which is approximately 150 m) while still maintaining visual contact with the head's grab arms. Since the machine would be constantly turning, moving and occasionally facing away from the observer, some errors most likely occurred. Even though small discrepancies are possible, the correlation is still quite high. The correlation between OBC and tree count is found to be even higher with a value of 0.923. This indicates that there is a strong correlation between the number of grab arm counts (OBC count) and the number of trees harvested (tree count).

There are also considerable limitations to these observations. For one, an ANOVA test was generated to test whether there were significant differences in accuracy ratios between machines. A significant result from this test indicates that machines would have a significant effect on these ratios. This effect can result from many sources. This can be related to the actual machine operation, the operator, weather, site conditions (tree DBH, tree density, slope, obstacles, etc.) amongst other items. Additional tests and field observations would need to take place in order to test the accuracy of this KPI.

The processor Count KPI also produced interesting results. The OBC to visual activation count ratio mean was 0.878. A correlation between the OBC and log count was 0.871. This indicates a strong correlation between the two. Therefore, one can assume that the OBC count can be an estimate of log production. However, there are limitations to this.

There were some discrepancies between the observer's visual count of activations (visual activation Count) and the OBC count of activations. The OBC/visual activation count accuracy ratio mean was 1.08. In theory, this mean should be approximately 1.0. Also, a correlation of 0.878 was observed between the OBC and visual activation count. The source of this error would most likely be attributed to the OBC count. The signal for the saw comes from the activation of an electronic impulse which controls a pump on the machine head. This pump engages when the bottom saw is activated. Occasionally, there would be enough pressure left in the line to activate the saw without actually engaging the pump. This can often take place when the bottom saw is engaged in quick succession.

An additional processor was studied to determine the accuracy of the Count KPI to the number of logs produced. After the collection of field data and its analysis, it was discovered that the signal for the OBC count was attached to a different pump which had a more sporadic operation, thus resulting in a lower log count to OBC count accuracy. Subsequently, this connection had to be modified and was connected to the same terminal as the other processor. Much like the feller-buncher limitations, additional studies would have to take place to determine the effect of different machine, site and operator conditions.

Re-evaluation of the Count KPIs proved to be valuable to verify its validity and accuracy. Additional Count KPIs would have to be developed for other machines such as skidders, excavators and gravel trucks. A Count KPI for gravel trucks could prove to be fairly simple. One option would be to count the number of dumps the truck would make in a shift. A Count KPI for excavators would prove to be much more challenging. This is due to the varied work that an excavator may perform and the different operating style for each operator. Furthermore, these styles will vary according to site conditions, available aggregates, type of road, and so forth.

4.1.6 Examples of implementation

There are studies which have implemented multidats in order to track certain performance indicators. As previously mentioned in the introduction, there are a very limited number of peer reviewed studies published even though there are thousands of multiDATs and other OBC types used in the forest industry.

The use of GPS tracking for monitoring forest operations has been successfully tested for the study of forest operations traffic (Carter *et al.* 1999) and soil disturbance (Taylor *et al.* 2001; Veal *et al.* 2001; MacDonald *et al.* 2002; Davis and Kellogg 2005; MacDonald and Fulton 2005). Taylor *et al.* (2001) and Husband (2010) suggest using a machine's GPS information to report on treated areas for compliance.

Davis and Kellogg (2005) also state the OBCs could be used to help determine limiting aspects of the operation, which if corrected, leads to gains in efficiency.

Strandgard (2011) installed multiDATs in a feller-buncher, a skidder and an excavator in a study in Australia. The goal was to identify machine utilisation rates and how they can be improved. Based on the results, work practices were modified in order to improve machine utilisation.

4.2 SECTION II: RESULTS DISCUSSION

The objective of the study was to determine whether there were significant differences in KPI values between different data reporting intensity periods. Significant differences between these reporting intensity periods may indicate that the reporting and use of data from OBCs can have a measurable effect on performance indicators. These indicators can in turn indicate an improvement in forest operations.

4.2.1 ~AMH

Overall, the ~AMH KPI seemed to be higher in the High intensity reporting period with some minor exceptions. When considering all machines within the ~AMH 1 database, there was an improvement of this KPI.

In Nonparametric tests, the ~AMH KPI was found to be significantly different between reporting intensity periods for the ~AMH 1 databases. This indicates that when considering all data collected, the data have a positive influence on the ~AMH KPI. Therefore, the null hypothesis (H_0) that there were no significant changes in KPIs between reporting intensity periods is rejected.

In the normal shift ~AMH 1 database ANOVA tests resulted in a significant difference between High and Low intensity reporting periods and led to the rejection of H_0. The means of High and Low intensity reporting periods are found to be 9.18 h and 9.04 h, respectively. This indicates that the more intensive use of OBC data may have a positive influence on the ~AMH KPI since it has changed by approximately 1.6%.

The effect of reporting intensity periods for individual machine types was tested. Feller-bunchers, skidders and gravel trucks were found to have a significant difference between reporting intensity periods. Feller-bunchers and skidders were found to have a higher ~AMH KPI in the High intensity reporting period by 2.5% and 1.8%, respectively, while the gravel trucks had a 1.5% lower ~AMH KPI during the High intensity reporting period. A lower ~AMH KPI for gravel trucks is attributed to site and job variability and morning mustering point.

Throughout this study, gravel trucks were usually on longer-term jobs which had site specific challenges. An example of this would be differences in waiting time for loading and unloading. This difference in waiting could result in trucks shutting off their engines for short periods of time when the waiting is too long. Since the length of these jobs would vary over time, it is possible that jobs in High intensity reporting period were found to have more waiting time than the Low intensity reporting period. Better documentation of these jobs and associated wait times should have been completed in order to better track the effects of these wait times.

The morning mustering point for trucks may also have an effect on this KPI. For some jobs, trucks may be left on a site which required travel time in the morning. On other jobs, the trucks were parked at the workshop. When trucks are parked at the workshop, operators are more likely to start the machine at its scheduled time due to its ease of accessibility. A lower KPI in the High intensity reporting period may be attributed to having the mustering site further away than for the Low intensity reporting period. Unfortunately, the morning mustering sites were not tracked through time and this hypothesis cannot be tested. As previously explained, a log of additional information would be required in order to track this effect.

Therefore, when considering individual machine types, H_0 was rejected for feller-bunchers, skidders and gravel trucks but not rejected for excavators and processors. Also, H_A has been rejected for feller-bunchers and skidders but not rejected for gravel trucks.

The Univariate GLM procedure only yielded significant differences between reporting intensity periods for feller-bunchers. The High intensity reporting period had a 2.5% higher ~AMH KPI. When considering the previous test, this suggests that when considering the effect of individual machines within a machine type, skidders did not have enough of a significant difference overall. This indicates that individual machines react differently to the data reporting intensity period treatments when considered individually. This leads to the rejection of H_0 only for Feller-bunchers.

The machine-reporting intensity period interaction found a significant difference in excavators and gravel trucks. Excavators 1,2 and 3 had a higher ~AMH KPI in the High intensity reporting period while excavators 4 and 5 had a higher ~AMH KPI in the Low intensity reporting period. As for gravel trucks, the ~AMH is higher in the High intensity reporting period for only trucks 3 and 4, and higher in the Low intensity reporting period for trucks 1, 2, 5 and 6. The reasoning for this lack of consistency may be attributed to the more variable nature of road building. Gravel trucks and excavators may be assigned to very different jobs for more extensive periods of time (such as working in a gravel pit for one month, then building road the next) However, when considering the machine-reporting intensity period interaction, there are significant differences between individual machines within the machine type. This indicates that individual machines KPIs within a machine type will be significantly different between reporting intensity periods from one another. This may be the result of less scheduling rotations for operators on those machines. Excavators and gravel trucks tended to be operated by the same operators, and only on day shift. This may affect the machine's KPI's between reporting intensity periods, since the same operator may react differently to the information being forwarded to him via the staff.

Excavator 4 was found to have a higher ~AMH KPI in the Low intensity reporting period. This may be due to its difference in job types between High and Low intensity reporting periods. During the Low intensity reporting period, it was mostly restricted to working in a pit instead of building roads. When working in the pit, the machine tended to break less and have better availability due to its accessibility. This would result in additional running time. When building road, the machine may be less accessible and may tend to have more mechanical breaks and complications due to the nature of the work. Excavator 5 was also found to have a higher ~AMH KPI in the Low intensity reporting period. This may be attributed to its difference in work locations. The mustering point in the Low intensity reporting period tended to be closer than that found in High intensity reporting period. For a considerable part of the Low intensity reporting period, this machine was working in a less accessible region which had longer travel times for operators. This may in turn result in less machine availability due to delays associated with travel and departures.

4.2.1.1 ~AMH summary

With some minor exceptions, the ~AMH KPI was higher in the High intensity reporting period than the Low intensity reporting period. This can indicate that the use of these reports can improve this KPI. These improvements may be resulting from additional worker motivation, work modifications, technical modifications, additional maintenance and other items. This has led to the rejection of H_0 and the failure to reject H_A for a majority of the tests.

4.2.2 ~PMH

In nonparametric tests, significant differences between both reporting intensity periods were observed for the ~PMH 1 database. This indicates there is a significant difference in the ~PMH KPI. Therefore, a higher intensity of reporting may have a positive influence on the ~PMH KPI. To that end, H_0 can be rejected.

In the ANOVA test for the normal data, there was no significant difference ($p = 0.246$) in the ~PMH KPI between reporting intensity periods. This may indicate that overall, the use of OBC reports did not have an effect on the ~PMH KPI value. Therefore, H_0 could not be rejected. However, it is interesting to note the distribution of data in Figure 12. The data distribution in the High intensity reporting period seems to be less normal than that of the Low intensity reporting period; there is more of a skew to the right. This could be attributed to the use of data from OBCs. More shifts would be bunched near the end of the scheduled time since additional monitoring would be taking place.

When further categorizing the data into individual machine types, the ~PMH KPI was found to be significantly different between reporting intensity periods for feller-bunchers. A difference of 2.8% was observed from the High intensity reporting period to the Low intensity reporting period. This indicates a more pronounced difference for the feller-buncher machine type as compared to other machine types. Therefore, H_0 was rejected for the feller-buncher machine type.

This significant difference may be associated to additional attention given to the improvement of feller-buncher KPIs. During installations, there was particular attention and willingness to quickly implement OBCs in feller-bunchers. This was most likely done since it was believed that these OBCs had particular potential for operational improvement. The source of this additional interest may be from its high capital cost, high maintenance cost, lack of staff supervision due to solitary work and its ability to set the pace for subsequent operations. Because of this, the improvement of feller-buncher KPI's was thought to have the greatest return as opposed to the improvement of other machine types.

With a GLM univariate procedure, a significant difference between reporting intensity periods was found for feller-bunchers. When considering the machine-reporting intensity period interaction, only a significant difference was found for excavators. Excavators 1, 2 and 3 had a similar or higher ~PMH KPI in the High intensity reporting period while excavators 4 and 5 had a higher ~PMH KPI in the Low intensity reporting period. The difference in the ~PMH KPI for excavators 4 and 5 was much more pronounced than that of excavators 1, 2 and 3. As previously mentioned in the ~AMH KPI discussion, this may be the result of differences in job types and morning mustering points for these machines. These results have led to the rejection of

H_0 and H_A for the excavator machine type. H_0 fails to be rejected for feller-bunchers, skidders, processors and gravel trucks.

4.2.2.1 ~PMH summary

Overall, there was very little or no significant difference for the ~PMH KPI between reporting intensity periods except for feller-bunchers and some excavators. This can indicate that using data from OBCs can improve the ~PMH KPI for Feller-bunchers and have a sporadic effect on some excavators. This KPI, however, was not found to be significantly different for other machine types. To this end, H_0 count not be rejected for skidders, processors and gravel trucks. H_0 is rejected for feller-bunchers and excavators.

4.2.3 Efficiency

A non-parametric test for efficiency yielded an insignificant difference between reporting intensity periods ($p = 0.115$). This indicates that an overall change in efficiency was not observed when considering all shifts for all machines. Therefore, H_0 could not be rejected.

An ANOVA test for the ~AMH 1 normal database yielded a significant difference for the Efficiency KPI ($p = 0.009$) between reporting intensity periods. The efficiency KPI was found to be 0.8% higher in the Low intensity reporting period. This leads to the rejection of H_0, since the Efficiency KPI is higher in the Low intensity reporting period. Since the efficiency KPI is the product of a division between the ~PMH KPI and ~AMH KPI, a change in either would affect the outcome of the Efficiency KPI. In this case, efficiency is found to be significantly higher in the Low intensity reporting period most likely due to the significant increase in the ~AMH KPI and the insignificant increase of the ~PMH KPI.

In the ANOVA tests for individual machine types, there was a significant difference between Efficiency KPIs for processors, excavators and gravel trucks. This led to the rejection of H_0 for these three machine types, but the failure to reject H_0 for feller-bunchers and skidders. These differences were a higher efficiency in the Low intensity reporting period for processors and excavators, and a higher efficiency in the High intensity reporting period for gravel trucks. A lower efficiency for excavators and processors in the High intensity reporting period may be related to seasonal effects. The High intensity reporting period has a larger component of winter months. Machines may be idling for longer periods of time during these months to keep warm. Also, additional maintenance in these months may require longer and more frequent stops.

For the GLM univariate procedure, significant differences between reporting intensity periods were found for excavators and gravel trucks. Therefore, the null hypothesis of no significant difference has been rejected for these two machine types. Efficiencies were higher in the High intensity reporting period for gravel trucks and higher in the Low intensity reporting period for excavators. The machine-reporting intensity period interactions were found to be significant for the feller-bunchers and skidders. Efficiencies were significantly higher in the High intensity reporting period for feller-bunchers 1, 2 and 5 and for skidder 1. Efficiencies were significantly lower in High intensity reporting period for skidder 2. Therefore, H_0 has been rejected for these two machine types when considering the machine-reporting intensity period interaction. The rejection of H_A varies between machines and reporting intensity periods. This indicates that individual machine Efficiency KPI values within a machine type will react differently between reporting intensity periods.

4.2.3.1 Efficiency summary

The efficiency KPI is a percentage of the ~PMH KPI divided by the ~AMH KPI. This KPI indicates how long the machine was moving per how long the machine was powered. This KPI helps provide an approximate measure of "machine efficiency" and verification. In terms of "machine efficiency", a shift may still be perceived as "efficient" if it was logging ~PMH for a large amount of time that it was powered. This leads to the collection of valuable information which can be used on its own or as verification for other KPIs. If you consider the ~AMH KPI individually, the machine may be powered up for the entire shift, but not have any movement. If you consider the ~PMH KPI individually, there may be only 6 h ~PMH but the machine was powered for 6.5 h. This KPI can provide validity to other KPIs while producing valuable information on its own.

4.2.4 Count

As previously discussed in the "re-evaluate" section, Count KPI values were tested for correlations between visual activation, OBC and tree (or log) count. This correlation was found to be relatively strong for both feller-bunchers and processors. This correlation helps indicate that the Count KPI could be used as an approximate measure of productivity in terms of tree or log count.

This KPI is only a log of electronic impulses. If it is meant to be a proxy of productivity, it will most likely be affected by the same factors that can impact productivity.

For feller-bunchers, items which can affect productivity are slope, tree size, ground firmness, operators and weather, just to name a few (Gingras 1988). For processors, items such as sorting, tree size, tree form, branchiness and tree piling method amongst other items may affect productivity.

Because of these effects, it is the most difficult KPI to track and compare through time. The comparison of Count KPI results would partly hinge on site and stand information from every shift. Shifts which have similar conditions could be compared.

In this study, Count KPI data were collected for feller-bunchers and processors. ANOVA tests were run to test the presence of significant differences between the two reporting intensity periods. Significant differences between reporting intensity periods were found for feller-bunchers, but not for processors.

Significant differences in reporting intensity periods for feller-bunchers, or lack thereof for processors, may be the result of differing site and stand conditions. Additional logging information for each shift would be necessary in order to compare Count KPI values over longer periods of time.

Currently, this KPI may prove to have its best use over short periods of time by on-site supervisors. If information is promptly reviewed by on-site personnel, who have some site specific exposure and knowledge of what may have affected KPI values, this information may be interpreted and compared more effectively.

Even though there are factors which can affect productivity, “soft” Count KPI targets could be established and monitored for each shift. This would provide additional motivation to employees to be more productive. This, however, would have to be closely monitored to ensure that signals are not being activated for the specific purpose of improving the Count KPI.

4.3 RETURN ON INVESTMENT (ROI)

ROI is always considered when making an investment. In order to invest in OBCs, there must be confidence in its return. In this case study, a very simple ROI was estimated in order to determine ROI for the use of OBCs and its associated data.

A Rate Determination Model (RDM) was used as a vehicle to compare KPI results from the two different reporting intensity periods. Basic inputs were entered into the RDM; these inputs included items such as purchase price, fuel cost, fuel consumption and estimated productivity. Data from both reporting intensity periods were compared using the same RDM and inputs, with only one modification. Utilisation rates between the models were modified. In this case study, the ~PMH KPI was serving as a proxy to estimate utilisation. The difference in utilisation resulted in different cost outputs. The costs ($\$/m^3$) of both RDMs were compared.

The use of this RDM was only to provide an estimate of gains. It does not represent the actual costs or inputs of the operation. Productivity values are estimated based on information built-in to the model.

RDMs were only generated for machine types which were found to have significantly different ~PMH KPI values between reporting intensity periods during “normal” shifts. Normal shifts were used since they would provide the best estimate of a normal, minimally interrupted work shift. This would provide a more accurate estimate of productive shifts. Feller-bunchers were the only machine type found to have significant differences between reporting intensity periods.

For feller-bunchers, outputs from RDMs estimated costs of 3.62$/m^3 for High intensity reporting period and 3.70$/m^3 for the Low intensity reporting period (Table 33). This indicates a cost difference of 0.08$/m^3. If one were to consider an annual harvest of 1 million m^3, this would yield a cost difference of 80,000$/year.

Evidently, there are major limitations to this output. For one, all inputs in the model are only estimates. Inputs, such as costs, will vary between machines and through time. Productivity will vary between different site and stand conditions, and per operator. The price of fuel will most likely fluctuate throughout the year.

The use of ~PMH KPI values as utilisation inputs in the RDMs is only a proxy. ~PMH may not adequately represent utilisation, and may in fact be an over estimation. One may still argue, however, that a change in the ~PMH KPI would most likely have a high correlation with the actual utilisation of the machine.

When estimating ROI, one must consider the costs. In this case study, costs were divided into Initial Costs and Annual Costs. These costs assume the purchase and use of OBCs for 10 feller-bunchers.

When comparing estimated cost reductions of 80,000$/year for feller-bunchers with the use of OBCs, returns for 10 machines would prove to be a considerable return (105%) with a payback period of 1.46 years. This does not consider inflation rates or Net Present Value.

4.3.1 Other Possible Returns

ROI was only estimated based on the change of the ~PMH KPI for “normal” shifts between two reporting intensity periods. Other sources of return which were not monitored or calculated are possible. An example of this would be utilising the information collected to accordingly test or modify machine rates.

KPIs can also be used in tandem with financial values to further estimate operational costs.” Such information can support strategic and operational decision making processes within a company, especially accurate costing for new investments” (Holzleitner *et al.* 2012). KPI values can be used to review or monitor costs efficiently. Forecast model could also be developed with past information in order to help determine future costs more accurately.

KPIs could also be used for additional tests. The effects of changes in operations can be monitored and evaluated. As an example, a change from 10 to 12 h shifts can be attempted. The value of KPIs can be collected and compared between the two different shift types. This can help determine the justification for changing shift lengths and any gains in certain KPIs.

OBCs are capable of monitoring operator hours. The OBCs can be used as a “punch clock” to help track operator hours. If this function was used, it may reduce operational expenses for tracking operator work time. It may also increase the accuracy of these work times.

OBCs are also capable of tracking and categorizing stops. If this function was used, one could determine why machines stop and help reduce these stops. An example of this would be discovering that not enough regular maintenance happens on a daily basis which leads to longer shut downs. Improving the amount or frequency of regular maintenance may help this.

It is possible that there are KPI gains from simply installing the OBCs in the machine. These gains were not evaluated since KPIs could not be collected before the OBCs were installed. The estimation and evaluation of these gains is very difficult since it would mean OBCs would have to be installed as a blind test.

5.0 CONCLUSION

The objective of the study was to determine whether there were significant differences in KPIs between two different reporting intensity periods. The Null Hypothesis (H_0) stated that KPIs were to have no significant differences between reporting intensity periods. The Alternative Hypothesis (H_A) stated that the High intensity reporting period was to have higher KPI values (on average) than Low intensity reporting period. Overall, significant differences between reporting intensity periods were found for the ~AMH and ~PMH KPIs. KPIs were usually found to be higher in the High intensity reporting period than the Low intensity reporting period. This indicates that data usage from OBCs may increase KPIs.

Count KPIs were thought to have too much variability due to site and stand conditions. The OBC count, however, was found to be highly correlated to the tree (or log) count. This indicates that an approximate measure of productivity between the two can be established. This measure still requires additional field testing to determine the various work factors which may affect this correlation.

ANOVA tests were generated to test whether significant differences were found between reporting intensity periods for “normal” shifts. These are shifts which have between 5 and 11 h of KPI activity. The ~AMH KPI was found to be significantly higher in the High intensity reporting period. This indicates that using data from OBC systems would improve the ~AMH KPI, a proxy for machine availability. The ~PMH

KPI was found to have no significant difference between reporting intensity periods. This would indicate that the use of data from OBC systems would have no significant effect on the ~PMH KPI. The Efficiency KPI was found to be significantly higher in the Low intensity reporting period. Since efficiency is a function of both the ~AMH and ~PMH KPI, the higher value in the Low intensity reporting period would be the result of having a significantly higher ~AMH KPI and an insignificant change in the ~PMH KPI.

Reporting intensity periods were found to have less of an effect on KPIs than anticipated. This may be because there was not enough of an effort to improve KPIs as opposed to simply reporting them. The development and implementation of strategies to improve KPIs may have led to a more pronounced difference between reporting intensity periods. Additional data sharing and more widespread reporting may have also led to an overall improvement of KPIs.

Additional data collection of work factors, such as site and stand conditions, would have been valuable. This would have helped categorize data in order to compare shifts with similar characteristics between reporting intensity periods. Also, additional data regarding operator tracking would have been valuable to determine whether there were any additional effects from different operators.

KPIs may also be affected by seasonal effects. Additional data collection over multiple seasons would prove to be valuable in order to determine these effects (if any).

Return On Investment was done by comparing RDM results. Utilisation inputs were modified according to the values for the ~PMH KPI in normal shifts. Only feller-bunchers were found to have a significant difference in ~PMH KPI values between reporting intensity periods. Because of this, only the ROI for feller-bunchers was calculated. According to the estimated cost savings ($\$/m^3$) of operating the machine at the average ~PMH KPI for the High intensity reporting period, it would prove to be valuable for a medium to large sized contracting firm to implement this OBC system in feller-bunchers. ROI was found to be 105% after three years with a 1.46 year payback period.

Since there was no significant difference in ~PMH KPI values in normal shifts for other machine types, additional research is required to determine the ROI. This can be in the form of additional data collection or further data categorization.

5.1 LIMITATIONS OF THE STUDY

This study was designed to be a broad level evaluation of the installation and use of OBCs and associated data. Since this was a broad level study, individual work details and issues for each machine were not catalogued. The cataloguing and review of this information would have proven to be extremely valuable. This, however, was unattainable due to time, budget and personnel restrictions. To this end, it is possible that KPI improvements were not the result of KPI reporting. Other activities or sources of error may have positively influenced KPIs. Some possible error sources are discussed in the discussion such as morning muster point, site and stand conditions and operator cycling.

Some of the machinery may have been in a state of repair for extended periods of time. There is some equipment which was unavailable for multiple weeks due to mechanical failure and wait times for repairs. The collection of data during this time was not considered.

There are cases where OBCs were damaged or disconnected. During this time, data were not being collected. A lack of power to the OBC would have led it to cease operations. OBCs were being re-connected and fixed throughout the study. These damaged or disconnected OBCs normally happened on specific machines and were not found to occur in the greater majority of machines.

Reports being generated in June up to the third week of July were intended for report design and interpretation purposes only. Information on these reports may have been used to make operational modifications. This may have affected KPIs in the Low intensity reporting period.

The High intensity reporting period contained more winter months than the Low intensity reporting period. The Low intensity reporting period contained more Fall and Summer data than the High intensity reporting period. This may have caused some seasonal effects on KPIs. The staggering of these months through both reporting intensity periods would have helped reduce this, however unknown seasonal variances may be present.

KPI results would have been interpreted and used differently by staff members. Since staff members were normally restricted to working with specific machines, this may have had an effect on KPI values through time.

Count data were not connected in time for certain machines. This was due to the inability to connect these signals or the lack of availability of the machine or the mechanic.

Operators were cycling through different shifts and machines. There were some machines, however, that were found to have the same operators quite frequently. These instances were mostly confined to excavators. Machines usually being used by the same operator may lead to additional errors in data interpretations. Tracking operators would have proven valuable since data could have been categorised to test whether there were significant differences in KPIs between operators and through time.

Site and stand conditions were not monitored throughout the study. For most equipment, its operations may be affected by changes in these conditions. Additional monitoring and categorization of KPI data according to work/site conditions would have proven to be valuable.

Data were only collected for a period of eight months. These months were mid to end of summer, Fall and early Winter. Additional data collection through time would have been preferred to identify possible seasonal variation. This would have been further effective if there were repetitions of seasons.

5.2 FUTURE RESEARCH

In future research, there are a few specific items which should be considered:

1) KPI baselines and targets should be developed to compare weekly results
2) Additional KPIs could be developed (i.e. ignition time to determine idling)
3) Stop codes with broad categories can identify and track stops/delays. This information can be used to help develop strategies which reduce the delays.
4) Activity codes could be used to help identify site and stand conditions to further categorize data.
5) Operator codes could be used in order to track operators and help rate their performance.

6) OBCs could also be upgraded to collect GPS data. This data could subsequently be used for additional monitoring and site reporting.

Additional correlation studies could be done for the count KPI. Comparing the log count to the product count with different factors would help determine the accuracy of this KPI. Factors which could be tested would be machines, operators, and site and stand conditions (tree size, slope, and season). If the count KPI accuracy can be determined, it can be used as a more accurate measure of performance. Furthermore, it can be used to help determine more accurate rates when coupled with additional site information such as piece size.

The implementation guide should be reviewed prior to the installation of an OBC system. It will provide examples of challenges encountered during system implementation as well as suggest steps for a smoother project execution. The greatest efforts should be made in employee inclusion, IT integration, data flow and KPI development.

A double blind experimental design could be done in order to determine whether the visual exposure of OBC equipment would affect KPI results. OBCs could be installed out of site while collecting data. Once enough data are collected, OBCs can be installed so it is visible to staff and operators. KPIs from pre- and post-visual placement of the OBC could be compared and tested for significant differences.

Reports should be developed before OBCs are installed. This can be difficult since every operation and staff will have different criteria by which performance is measured. This, however, can lead to greater efficiency.

There should be equal involvement from managers, staff, operators and mechanics. This would provide the best input for preparing and implementing an OBC system. Goals should be developed as a group and agreements should be determined to ensure data are not misused.

An effective data sharing method should be established by this group. This would develop the most effective and acceptable way to distribute data between groups. This will provide a sense of inclusion and teamwork in the project which would ultimately lead to more success.

Data reporting and release should be established in 2 month alternating periods. This would provide even exposure to both data reporting intensity period and OBC use periods. Absolute full retention of information during the “non data use” period should be in effect.

The weekly posting and review of KPIs should take place for staff. Reasoning for KPI values in relation to targets should be discussed. The improvement of these KPIs should be established. This would help determine the value of this system more effectively. Better operator tracking would be required in order to help determine any operator effect on KPIs. KPIs should be field tested before the study begins. This would ensure their successful installation and operation.

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