Skills development of mechanised softwood sawtimber cut-to-length harvester operators on the Highveld of South Africa

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DECLARATION

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Abstract

In this study, a South African pine sawtimber mechanised cut-to-length harvesting operation – comprising felling, debarking, debranching and cross cutting of log assortments – was analysed using .stm-files from StanForD software. The objective of the analysis was to describe and model productivity development learning curves of beginner harvester operators in both clear-felling and thinning operations. A cohort of trainee operators were selected based on the results of a comprehensive battery of psychometric tests that assessed their aptitude for the complex array of decision-making required of harvester operators. These trainees subsequently completed several sequential tests on a harvester simulator. Following the simulator training, operators commenced with work on machines (harvesters) themselves until they were considered capable of working unsupervised. Within the framework of this progression of operator selection, simulator training and in-field operations, it was possible to model a potential learning curve of a typical beginner harvester operator in softwood sawtimber in both clear-felling and thinning operations.

With regards to simulator training, the results of this study show that, on average, a trainee operator will start at a performance level (PL) of 60% lower than the population's performance level (PPL) and end with a PL of 24% higher than the PPL. Furthermore, when the PL of an average simulator trainee was measured over a period of 9.2 days or 27 tests (three tests per day), it was evident that his PL improved with 269% following the efficient simulator training. Once in-field, thinning operators worked with an average tree size of 0.18m^3 where they started at a productivity of 13.71 $m^3 \cdot PMH^{-1}$ (cubic meter per productive machine hour) at month one and managed to increase their productivity to 38.96 $m^3 \cdot PMH^{-1}$ (overall average = 28.8 $m^3 \cdot PMH^{-1}$) at the end of month 12. Clear-felling operators' felling productivity level on an average tree volume of 0.54m^3 started at 27.5 $m^3 \cdot PMH^{-1}$ in month one and increased to 43.75 $m^3 \cdot PMH^{-1}$ (overall average = 41.9 $m^3 \cdot PMH^{-1}$) at the end of month 12. Finally, on average, a thinning operator can reach the end of the learning phase after nine months. The two clear-fell operators reached the end of their learning curve after five and eight months respectively. On average, thinning operators increased their performances by 218%, while clear-fell operators increased theirs by 104%. These findings suggest acceptable learning periods and performance increases for beginner harvester operators.

Key concepts: psychometric abilities, operator selection, simulator training, operator learning curve, productivity development, skills development.

Opsomming

In hierdie studie is 'n Suid-Afrikaanse gemeganiseerde sny-na-lengte oesoperasie van denneboom saaghout wat uit sloping, ontbasting en dwarssnitte van verkeie produkte bestaan, ontleed. Die ontleding is gedoen met die doel om produktiwiteitsontwikkeling leerkurwes van beginner-oesoperateurs in beide kaalkap- en verdunningsoperasies te ontwikkel en verduidelik met behulp van .stm-lêers van die sogenoemde StanForD-sagteware. 'n Groep leerder-operateurs is op grond van ʼn omvattende reeks psigometriese toetse gekies om hulle bekwaamheid te evalueer ten opsigte van ‘n komplekse verskeidenheid besluite wat vereis word van die oesoperateurs. Hierdie leerlinge het gevolglik verskeie sekwensiële toetse op die simulator voltooi. Na afloop van die simulatoropleiding het die operateurs met die fisiese masjiene begin werk totdat hulle bevoeg beskou is om onbegeleid te werk. Binne die raamwerk van hierdie vordering van operateur-seleksie, simulatoropleiding en in-veld-produksie-ontwikkeling, is dit moontlik om 'n potensiële leerkurwe van 'n tipiese beginner-oesoperateur in beide kaalkap- en verdunnings van saaghout operasies te modelleer.

Wat simulatoropleiding aanbetref het die resultate van hierdie studie gewys dat simulator-leerder-operateurs se prestasievlak (PV) van 60% laer as dié van die populasie se gemiddelde prestasievlak (PPV) sal wees en dat hy met 'n PV van 24% hoër as die PPV sal eindig. Verder sal 'n gemiddelde simulator-leerder oor 'n tydperk van 9,2 dae of 27 toetse (drie toetse per dag) van doeltreffende simulatoropleiding sy prestasie met 269% verhoog met betrekking tot sy aanvanklike PV. Tydens werk in die veld het verdunnings-operateurs gedurende die 12 maande-studietydperk met 'n gemiddelde boomgrootte van 0.18 m^3 gewerk, waar hulle met 'n produktiwiteit van 13.71 $m^3 \cdot PMU^{-1}$ (kubiekemeter per produktiewe masjien uur) (maand 1) begin het en verder daarin geslaag het om hul produktiwiteit na 38,96 $m^3 \cdot PMU^{-1}$ (algehele gemiddelde = 28.8 $m^3 \cdot PMU^{-1}$) aan die einde van maand 12 te verhoog. Die kaalkap-operateurs se produktiwiteitsvlak gedurende die 12 maande studietydperk op 'n gemiddelde boomgrootte van 0.54 m^3 het by 27.5 $m^3 \cdot PMU^{-1}$ (maand 1) begin en het aan die einde van maand 12 tot 43.75 $m^3 \cdot PMU^{-1}$ (gemiddelde van 41.9 $m^3 \cdot PMU^{-1}$ algeheel) verhoog. Op die ou-end kan 'n gemiddelde verdunningsoperateur die einde van sy leerkurwe na nege maande bereik. Die twee kaalkap-operateurs het onderskeidelik na vyf en agt maande die einde van hul leerkurwes bereik. Oor die algemeen het die verdunning- en kaalkap-operateur hulle prestasies onderskeidelik met 218% en 104% verhoog. Hierdie bevindings suggereer aanvaarbare leertydperke en prestasieverhogings vir beginner-oesoperateurs.

Sleutelbegrippe: psigometriese vermoëns, operateurseleksie, simulatorleer, leerkurve van operateur, produkontwikkeling, vaardigheidsontwikkeling.

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COFE	Council on Forest Engineering
CTL	Cut-to-Length
FMH	Fully mechanised harvesting
GNSS	Global navigation satellite systems
MAP	Mean annual precipitation
MAT	Mean annual temperature
MH	Mechanised harvesting
MHS	Mechanised harvesting systems
MTO	Mountain to ocean
PL	Performance level
PPL	Population’s performance level
PPV	Populasie se gemiddelde prestasievlak
PV	Prestasievlak
ST	Sawtimber

1 Introduction

The total land use area for industrial plantation forestry in South Africa is relatively small (only 1.23 million ha). This comprises only 1% of the total land mass of South Africa (FSA, 2017). Nonetheless, the forestry industry is highly regarded internationally in terms of plantation forestry management.

Historically, motor-manual and semi-mechanised harvesting systems have dominated harvesting operations in South Africa, with manual operations, semi-mechanised operations and mechanised systems contributing 9.5%, 19.5% and 6.4% respectively (Längin & Ackerman, 2007). Studies over the last decade have shown that the South African forestry industry is following the international trend of employing more fully mechanised harvesting systems (Krieg *et al.*, 2010; Hogg *et al.*, 2011; Van der Merwe *et al.*, 2013; Ackerman *et al.*, 2017). Apart from ergonomic factors, this move is mainly being made to ensure the health and safety of forest workers and to compensate for a lack of suitable manpower in traditional forestry areas (Hogg *et al*., 2011). Formal operator selection and subsequent training are required to gain the full benefit of employing mechanised cut-to-length (CTL) systems (Nurminen *et al.*, 2006). Mechanised CTL systems comprise a harvester and forwarder, where the harvester fells, debranches and processes logs into assortments for subsequent forwarder extraction of logs from the stump site to a roadside landing (Kellog & Bettinger, 1994).

The costs related to companies not selecting an appropriate operator with the skills to work productively and ability to adapt techniques to become safer and more productive are significant (Kirk *et al*., 1997). By being able to formally select harvester machine operators according to their psychometric, cognitive and skills ability, companies could reduce unproductive downtimes, repair times and machine maintenance costs (Kirk *et al*., 1997). In addition, a consistent and competent operator will achieve a more consistent flow of wood (Kirk *et al*., 1997). In a South African context, the impact of structured operator selection and efficient simulator training on the eventual success of beginner machine operators and their respective learning curves are largely unknown. This includes the importance of defining what the duration of the learning curve is (or should be) and how this relates back to individual operator character traits. The learning curve of an beginner harvester operator is defined as the relation between productivity ($m^3 \cdot PMH^{-1}$) and experience (months of work) (Purfürst, 2010).

It is well known that productivity levels and time influencing factors (such as the type of machine, the tree species, the slope, the terrain roughness and the tree size) can be measured. For this reason, a real learning curve is defined as the relation between productivity and time per work cycle (Purfürst, 2010). It is assumed that the more time operators spend on an activity, either on a simulator or in-field work on a machine, the more familiar they will become with the controls and the environment. This will eventually lead to an enhancement of performance as their skills increase over time (Purfürst, 2010).

Operators who have prolonged learning curves (relative to fellow trainees) will incur cost penalties on employers. Kirk *et al*., (1997) stated that structured training, such as simulator training, of an operator prior to using a harvester is essential to shorten the learning curve. Simulator training allows potential operators to get used to a single influencing factor (such as machine controls) rather than having to deal with all influencing factors (environment, operational instructions, fear of risks, machine controls and movement) at once (Kirk *et al*., 1997). In this study, a rare opportunity (not only in South Africa but also internationally) to study operator productivity development in newly installed, fully mechanised CTL harvester operations from inception to potential maturity presented itself. A sawtimber company made a strategic decision to develop in-house mechanised CTL capacity with the purchase of new Ponsse harvesters and forwarders and a simulator for their pine sawtimber operation on the Mpumalanga Highveld of South Africa. Part of the strategic decision was to recruit and train operators with no previous experience. A cohort of trainee operators were selected after a comprehensive battery of psychometric tests was administered to assess their aptitude for the complex array of decision-making required of harvester and forwarder operators. These trainees were exposed to the simulator and subsequently completed several coordinated tests. Following the simulator training, operators commenced with work on the machines themselves until they were considered capable of working unsupervised. Within the framework of this progression of operator selection, simulator training and in-field operations, it is possible to model a potential learning curve of a typical harvester operator in softwood sawtimber in both clear-felling and thinning operations.

Objectives:

The primary objective of this study was to describe and model productivity development learning curves of beginner harvester operators in softwood sawtimber in both clear-felling and thinning operations.

The following were sub-objectives:

- Which operator skills and abilities need to be included in structured operator selection when selecting productive beginner operators?
- How long should operators spend on simulator training before they move to the machine?
- What are acceptable productivity ranges within particular operational and structural parameters?
- What is an acceptable learning period for beginner harvester operators?

Answers to these questions will be helpful in managing fully mechanised operations that are associated with large capital expenditures and that therefore need operators to produce timber effectively and efficiently in the shortest possible time; i.e. shortening the so-called “learning curve”. By being able to track operators’ performance over time, from their initial selection to being fully operational, an understanding of this productivity learning curve is facilitated. This insight will furthermore uncover which factors (cognitive and others) contribute to the success of operators and may be invaluable to the South African forestry industry.

2 Literature review

2.1 The South African forestry industry

In 2015 it was reported that South Africa's total commercial timber plantation area comprised 1 268 000 ha (FSA, 2017). Of this total plantation area, pine was planted on 49.8%, *eucalyptus* on 42.7%, black wattle on 7.1% and others on 0.4% (FSA, 2017). On average, 60% of the total planted *eucalyptus* area is used for pulpwood production, 16% for sawtimber production and 23% for other purposes such as mining timber and poles. Furthermore, 72% of the total planted softwood area is used for sawtimber production and 28% for pulpwood production (FSA, 2017), the majority of which stems from the Mpumalanga forestry region.

In terms of the total planted areas of the seven largest commercial forestry companies (Sappi, Mondi, PG Bison, MTO, York timbers, Hans Merensky and KLF): a total of 357 725 ha is planted for the purpose of sawtimber production and 292 950 ha is planted for the purpose of pulpwood production.

2.2 Fully mechanised CTL harvesting systems

During the recent past, international commercial forestry has seen an increase in the use of mechanised harvesting systems due to its potential to increase productivity and improve health and safety of operators, and due to a continual decrease in labourers' willingness to work in forests (Holtzscher & Bossy, 1997). Although motor-manual and semi-mechanised systems are still prevalent in pulp and sawtimber harvesting operations of both pine and *eucalyptus* management regimes in South Africa, mechanised CTL systems will probably become the preferred method over time (Strandgard *et al.*, 2013). In North America, modern mechanised harvesting operations have been employed since the 1870s due to increases in labour costs and timber demand, and changes in timber management (Ince, 2012). European countries such as Sweden, Ireland and Finland have increased the usage of mechanised CTL harvesting systems by 98%, 95% and 91% respectively (Karjalainen *et al.*, 2001) due to labour shortage and the need for economical wood production (Schaeffer *et al.*, 2001).

A CTL harvesting system is defined as a method in which trees are felled, debranched and processed into different log assortments at the stump. The assortments are then subsequently transported to the roadside, pending secondary transport (Krieg *et al*., 2010). A typical, fully mechanised CTL harvesting system will involve at least a harvester (to fell, debranch and cross-cut), a forwarder (to load, extract and stack) and a loader at roadside (Krieg *et al.*, 2010).

2.3 Mechanised harvesting operations in South Africa

The South African forest industry has slowly moved to becoming fully mechanised during harvesting operations over the last decade (Krieg *et al.*, 2010; Hogg *et al.*, 2011; Van der Merwe *et al.*, 2013; Ackerman *et al.*, 2017). Apart from ergonomic factors, this move was mainly motivated by health and safety concerns about more traditional systems, but also resulted from the lack of suitable manpower in traditional forestry areas and poor wood quality (Shackleton *et al.*, 2007; Pogue, 2008; Hogg *et al*., 2011; Van der Merwe *et al.*, 2013).

According to McEwan and Steenkamp (2014), the availability of manual labour and labour productivity in South Africa are negatively affected by the following factors:

- Rural to urban migration of labour
- Increased social welfare payments by government
- Low social status of manual labour
- Improved secondary school education system
- Health (HIV and AIDS) and safety

Due to the increased use of mechanised harvesting systems, it has become important in a South African context to determine which interventions are necessary for the holistic optimisation of operations. One such intervention is to select and train appropriate operators for these machine (Purfürst, 2010). This emphasises the importance of studying 1) the factors that affect a harvester operator’s productivity; 2) a beginner harvester operator’s psychometric abilities; and 3) the effect of simulator and field training on the success of the operators.

2.4 Operators

Studies by Purfürst, (2007); Purfürst & Erler, (2011); Palander *et al.*, (2012) and Häggström, (2015) have shown that a machine operator is the most significant source of variation influencing harvester productivity. This source of variation is usually disregarded when considering mechanical harvesting work performance (Purfürst & Erler, 2011; Strandgard, Alam & Mitchell, 2014). However, when comparing equally experienced operators, different outputs are found, depending on a variety of personal (skill) and career-related (education) traits (Purfürst & Erler, 2011). Strandgard *et al.* (2014) and Hogg *et al.* (2011) found a 40% variation in productivity of equally experienced machine operators in two different studies. Therefore, the cost, productivity and utilisation of a machine will be significantly influenced by a single machine operator (Hogg *et al.*, 2011). By knowing the differences between operators' inherent intelligence, skills and personality (as assessed by psychometric tests) and how these different abilities influence productivity, the importance of selecting operators based on these abilities is emphasised.

2.4.1 Operator selection

Several studies have indicated that there are numerous factors that affect the success of a harvester operator, including memory functions, non-verbal deduction, spatial perception, coordination, concentration, motivation, decision-making, pattern recognition, planning capacity and logic reasoning (Parise, 2004; Ovaskainen, 2009; Tervo, Palmroth *et al.*, 2010; Häggström, 2015).

Productivity is a good measure of skill since skilled operators work efficiently and are very productive, which will furthermore contribute to low fuel consumption amongst others (Ovaskainen, 2009; Purfürst, 2010; Purfürst & Erler, 2011; Palander *et al.*, 2012; Alejandro, 2016). Heavy workloads will cause the operator to become stressed as soon as the demand exceeds his ability to produce (Häggström, 2015). Therefore, not only should an operator be formally selected according to the required operators' inherent intelligence, skills and personality, but operators should also be trained in a controlled environment (where the workload can be controlled by an instructor) and receive simulator training to reduce the stress of the workload and potentially increase the operator's psychometric skills.

2.4.2 Simulator training

As a modern learning alternative, simulator-based training is more efficient than in-field training on a machine (Häggström, 2015) and has become an important part of a comprehensive international training development programme (Ranta, 2004a). Research has shown that simulator-trained students cut 15% more wood and that machine repair costs decreased by 30% when compared to non-simulator-trained operators (Lapointe & Robert, 2000; Ovaskainen, 2009). This can be explained by the control that can be exerted on the environment, personal safety and standards when simulators are used. They also offer a very consistent tool for managing and monitoring forestry education (Ranta, 2004a; Häggström, 2015). Simulator training can furthermore enable beginner harvester operators to become familiar with timber harvesting process planning; forest machine management; working methods; control and measurement systems; cooperation between the felling machine and forwarder; and timber harvesting on different types of felling sites (Ranta, 2004b). Furthermore, simulators are used for refresher courses (where operators move back from the harvester onto the simulator) for experienced operators to eliminate bad habits that an operator learned during field work (Ranta, 2004b).

The success of simulator training depends on how the simulator is actually used during the training phase (Ovaskainen *et al.*, 2004; Ranta, 2004a; Alam *et al.*, 2014). One important factor to bear in mind is that there are limitations (e.g., limited risk of damage to the system resulting in reckless behavior on the simulator) associated with simulator training. If bad habits developed by reckless behavior are developed while training on the simulator these will be passed on to actual machine training phase (Ovaskainen, 2009). Ovaskainen's (2009) study showed that simulator-based training has a direct and positive impact on the learning curve of operators working in-field on harvesters. In other words, their learning curves are shortened. The main objective of an operator working on a simulator is to reduce the amount of time per repetitive simulator test, thereby demonstrating an increase in experience and skill (Purfürst, 2007). An operator is defined as experienced as soon as his experience (time per test) starts to stagnate or stay constant (Purfürst, 2007, 2010).

2.5 Learning curve of individual operators

A learning curve is the result of an improvement of performance, as an operator becomes more experienced on a machine over time (Björheden, 2000; Purfürst, 2010; Purfürst & Erler, 2011). In a study by Purfürst (2010), a harvester operator's learning curve is described as a graphical representation of the relationship between productivity and skill (vertical axis) and experience (horizontal axis). Skills and productivity development is an essential goal of an individual harvester operator seeking to work efficiently and productively (Björheden, 2000; Purfürst, 2010; Purfürst & Erler, 2011).

According to Björheden (2000), Ranta (2004a), Purfürst (2010) and Gellerstedt (2013), there are two phases involved in the learning period of operators. The first phase is characterized by a rapid learning period in the beginning because there is much to learn at this stage (in terms of controls, movement, planning, technique, etc.). In the second phase, the learning slows down, but still constantly increases. This phase, leading to full productivity, can last up to five years for an average harvester operator. This is supported by Purfürst (2010), who conducted a three-year study of harvester operator productivity. However, Purfürst's (2010) findings varied, depending on the particular operator. He found that, on average, it will take a harvester operator eight months (due to the factors as mentioned above) to reach his full potential, but that it can last between 155 to 488 days (Purfürst, 2010). It is important to note the number of years of experience and/or specialized machine education varied greatly among the operators.

There are many ways to describe a learning curve statistically. These different forms of learning curves include exponential, sigmoidal and linear and these learning curve forms can be found when comparing operators (Figure 1) (Purfürst, 2007). Each operator's experience on a machine is unique; therefore, the form of each one's learning curve will differ (Purfürst, 2007). Some operators will have a linear experience (slightly linear development of productivity over time) (Figure 1, bottom left), where others will have a logarithmic experience (Figure 1, top right) since their natural skills and ability differ (Purfürst, 2007; Purfürst & Erler, 2011).

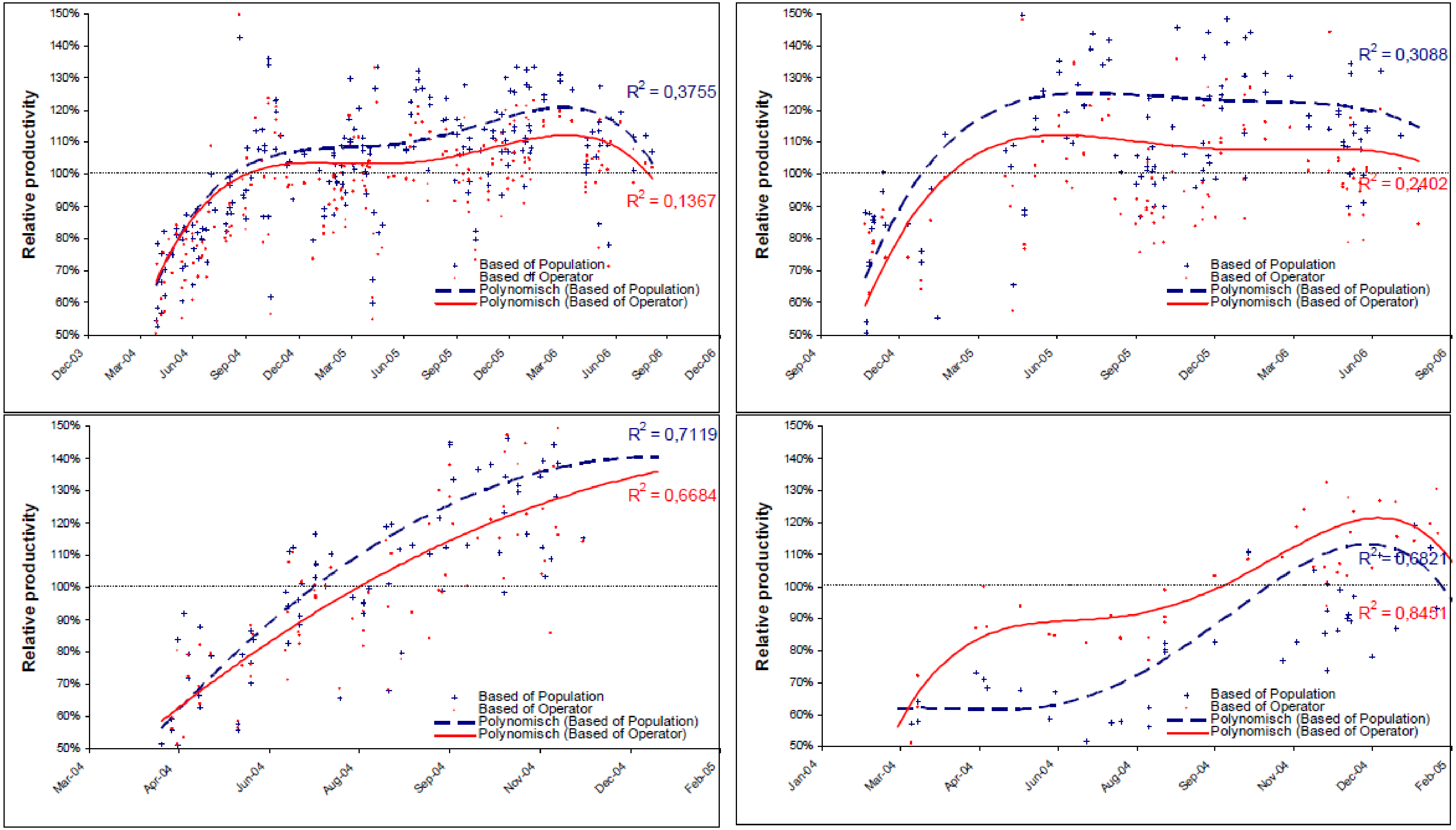

Figure 1: Learning curves of four different operators (Purfürst, 2007)

An operator's performance level (PL), is best described and expressed in percentage, it provides an indication of the productivity levels of a particular operator relative to the population's (a group of beginner operators) mean productivity levels (Purfürst, 2010; Purfürst & Erler, 2011). Calculating PLs of operators is an effective method of comparing the skills and abilities of operators with equal experience (Purfürst, 2010; Purfürst & Erler, 2011). For example, a skilled operator can work at a PL of 140% relative to the population, while others (less skilled operators) will work at 50% relative to the population.

Figure 1 shows the progressive learning curves of four different operators. Many beginner operators begin their PL at 50% to 60% compared to the relative mean of experienced operators. The reason for this is that operators are selected according to their personal skillset to work on a machine. They will start at a PL of 50% due to their inability to use the controls effectively , not using the optimum working technique and not being able to plan ahead (Björheden, 2000; Ranta, 2004a; Purfürst, 2010; Gellerstedt, 2013).

Fluctuations in performance exist within learning curves (Figure 1, top left and bottom right). The reasons for these fluctuations are difficult to explain as they can be either environmental factors (weather), operator factors (motivation) or machine factors (breakdowns) (Purfürst, 2007). In Figure 1, most of the graphs show that the operators' performance drops as time passes (Purfürst, 2007).

Purfürst (2010) found that, to replace an experienced operator with an inexperienced operator can result in a productivity loss of up to 45 000 Euros. This cost does not include the cost of training or machine damage, which could add up to an additional 15 000 Euros (Gellerstedt, 2013). Replacing an experienced operator with an inexperienced one, the cost of repair and maintenance will also increase and be added to the cost related to a learner operator (Gellerstedt, 2013).

2.5.1 Learning curve per month over different volume classes

As demonstrated by Purfürst (2007), each operator's monthly increase in productivity as a function of volume is plotted on a graph to describe the learning curve for each operator (Figure 2). To do so, a model for productivity as a function of volume needs to be calculated for each individual month of E5 time (effective work time, including delays shorter than five minutes). By doing so, an understanding of how an operator increases his productivity over different tree volumes per month is created.

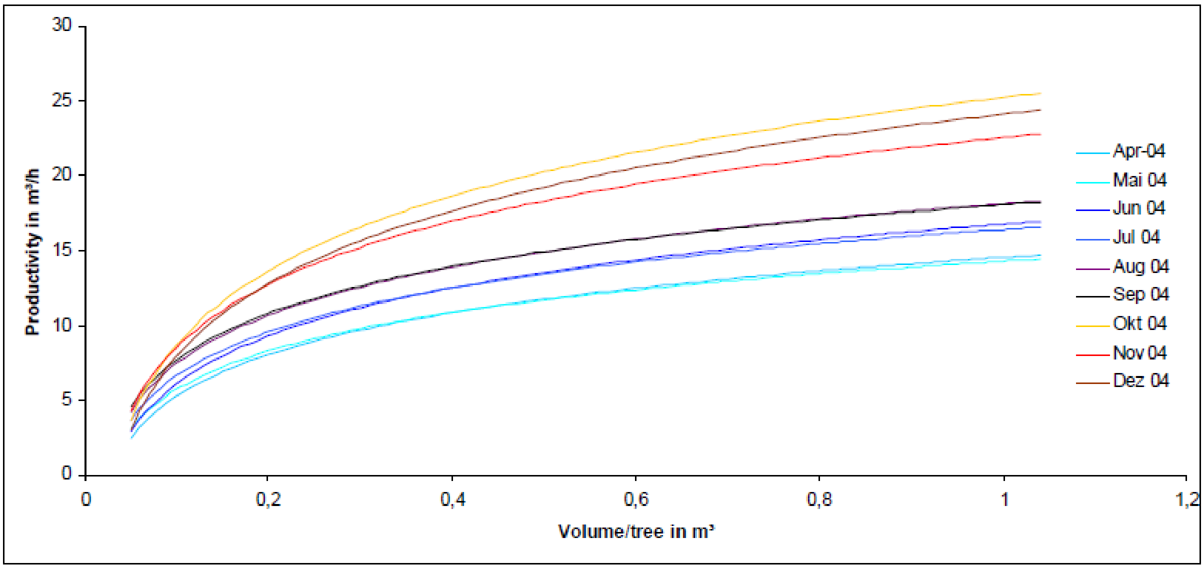

Figure 2: Learning curve of an operator working for nine months on a harvester on different tree volumes

[Source: Purfürst, 2010]

To compare the results of the learning curves of the operators, the increase in productivity (%) between month one and 12 is calculated at different tree volumes. By doing so, the difference between each individual operator's increase (%) in productivity per tree size is explained.

2.5.2 Operator performance

An operator's PL, expressed as a percentage, is a measure that describes the productivity relative to a population's mean productivity levels (Equation 1) (Purfürst, 2010; Purfürst & Erler, 2011). To compare the operators with one another, it is necessary to find a reference performance point such as the mean of the population's performance (Purfürst, 2010; Purfürst & Erler, 2011). The value of 100% is equivalent to the mean performance of the population.

$$Performance = \frac{Observed\ productivity}{Mean\ population\ productivity}\ X\ 100\% \qquad (1)$$

Purfürst (2010) and Purfürst and Erler (2011) used long-term logging data from stems, times and harvested volume to create performance information for each harvester operator for specific dates. The study by Purfürst (2010) used one logarithmic regression to calculate the relative mean performance of the population and only considered tree volume as an influential factor of productivity, as shown in Equation 2.

$$\mathrm{P}r = \frac{Po}{Pm} = \frac{Po}{e^{0.684 * in(tvol) + 3.543}} \qquad (2)$$

Where:

$\mathrm{P}r$ = Relative productivity, $m^3\ h^{-1}$;

P_o = Actually observed productivity, m^3 PMH^{-1};

P_m = Model productivity, m^3 pmh^{-1}; and

tvol = m^3 $tree^{-1}$, solid cubic meter.

Operator performance and experience are highly influential in achieving the maximum potential of the machine (Hogg *et al.*, 2011; Purfürst & Erler, 2011). Mechanised CTL harvesting machines are expensive and have high associated operating costs; therefore, it is important for these machines to produce as much timber as possible in the shortest times to make the operation financially feasible (Purfürst, 2010). Operator performance is influenced by factors such as motivation (financial incentives), energy levels, experience, job satisfaction and machine ergonomics (Hogg *et al.*, 2011).

2.6 Factors affecting productivity in harvester work

In order to run a financially sound harvesting operation and to be highly productive, the key factors affecting harvester productivity need to be identified and understood. A number of international studies have been aimed at predicting productivity and determining what factors influence the success of mechanised CTL systems (Spinelli *et al.*, 2002; Spinelli & Magagnotti, 2010, 2013; Alam *et al.*, 2012; Ghaffariyan *et al.*, 2012; Ramantswana *et al.*, 2012; Ramantswana *et al.*, 2013; Ackerman *et al*., 2014). The majority of the literature does, however, not specifically relate to South African operations but rather focuses on European conditions. Generally, research on this topic has found that productivity is affected by operator experience and motivation; the work objective (tree form and volume); the slope and terrain conditions; the use of shift work; and machine maintenance practices (Spinelli *et al.*, 2002; Spinelli & Magagnotti, 2010, 2013; Alam *et al.*, 2012; Ghaffariyan *et al.*, 2012; Ramantswana *et al.*, 2012; Ramantswana *et al.*, 2013; Ackerman *et al*., 2014). Of these studies, the single most influencial factor has been found to be tree size (Diameter at Breast Height (DBH) and/or tree volume), assuming operators are trained and have an acceptable attitude to the work they have to do. In addition, Väätäinen *et al.* (2004) found that training can improve operators' control during tree felling and processing between 20% to 30%. This includes felling direction, efficient boom movement control and work planning decisions. These factors will be elaborated on in the next sections.

2.6.1 Tree size

Tree size can explain about 60%–70% of the variability in productivity and is the single most determining variable when predicting a harvester's productivity (Krieg *et al.*, 2010). The reason for this is because the times involved in felling and processing of different tree volumes differ (Kellog & Bettinger, 1994; McNeel & Rutherford, 1994; Jiroušek *et al.*, 2007; Ramantswana *et al.,* 2012; Eriksson & Lindroos, 2014; Williams & Ackerman, 2016). Therefore, as tree size increases, so will productivity to some extent (Krieg *et al.*, 2010). This has been shown in many studies in the Nordic countries (Brunberg *et al.*, 1989; Brunberg, 1991, 1997; Kuitto *et al.*, 1994; Eliasson, 1998; Glöde, 1999; Hånell *et al.*, 2000) and also in Northern America (Tufts & Brinker, 1993; Kellog & Bettinger, 1994; McNeel & Rutherford, 1994; Landford & Stokes, 1995, 1996; Tufts, 1997).

In a South African context, Williams and Ackerman (2016) calculated the mean productivity of harvester work in *P. elliottii* compartments of 33.6 $m^3 \cdot PMH^{-1}$ that is within the array of values reported by other researchers, which range from 13.5 $m^3 \cdot PMH^{-1}$ (Jiroušek *et al.*, 2007) to 60.5 $m^3 \cdot PMH^{-1}$ under various conditions (Kellog & Bettinger, 1994; McNeel & Rutherford, 1994; Jiroušek *et al.*, 2007; Eriksson & Lindroos, 2014). As such, these values are deemed representative of typical conditions for mechanised CTL sawtimber harvesters in South Africa. In addition, Ramantswana *et al.* (2012) found that the productivity of a harvester in a wattle plantation varies between 5.5 $m^3 \cdot PMH^{-1}$ to 16.9 $m^3 \cdot PMH^{-1}$, depending on the tree volume, as shown in Figure 3.

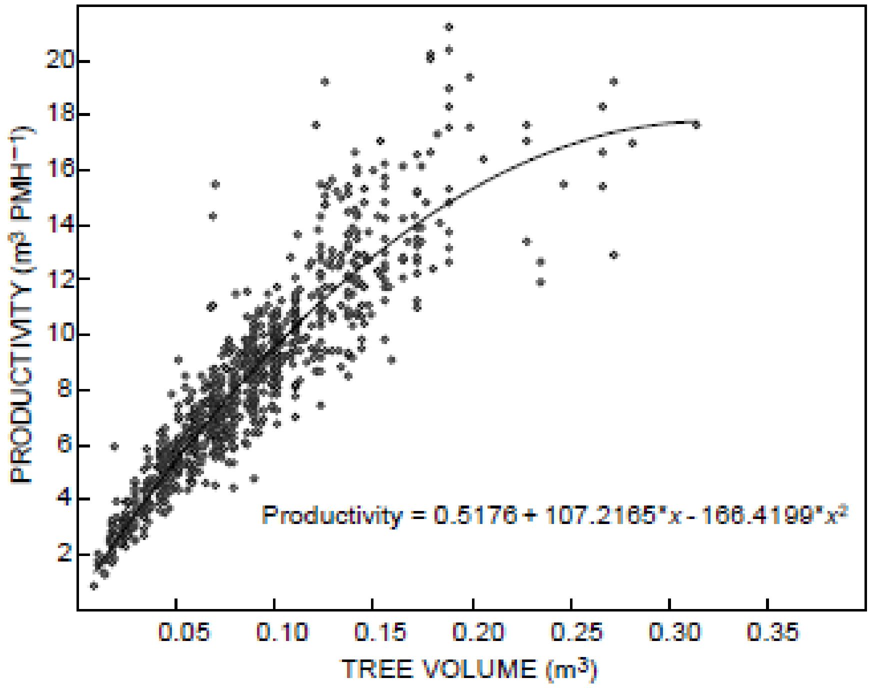

Figure 3: Effect of wattle tree size on productivity (Ramantswana *et al.*, 2012)

2.6.2 Slope

A number of studies have researched the effect of the slope on harvester productivity under different conditions, producing a range of different results. Due to safety and cost effective reasons, wheeled-harvesters are limited to slopes not exceeding 40% (Krieg *et al.,* 2010). Brown *et al.* (2013) compared the productivity of a harvester on steep slopes (33%–51%) to moderate slopes (19%–33%) and found a reduction in productivity of 24% on steep slopes. Based on modelled results from a number of different feller-buncher studies, FPInnovations (2008) found a 30% reduction in productivity of slopes of 10%–19% compared to 19%–33% slopes. This, however, is contradictory to the findings of Olivera *et al.* (2015) who found that the slope does not have a significant effect on productivity in a study area with slopes of up to 12%. However, the general assumption, shown in many studies, is that the slope has a significant effect on productivity, mainly due to machine capabilities and safety, and the ease with which the operator operates the machine (Davis & Reisinger, 1990; Spinelli *et al.*, 2002; Acuna & Kellogg, 2009).

2.6.3 Shift work

Shift rotation, in general, is the tempo at which workers rotate between different shifts of a certain activity (Mitchell *et al.*, 2008). Mitchell *et al.* (2008) conducted a study on the effect of the duration of a shift on a worker, which showed that when working two to three consecutive days on 12-hour shifts, workers would recover after the first day. However, as soon as workers work 12-hour shifts for more than three consecutive days, some workers needed more than three days to recover. In addition, when comparing a 12-hour shift to an 8-hour shift, a worker would simply have four more hours to sleep, commute to and from work, eat, and engage in other domestic activities.

Operator performance will deteriorate after nine to 10 hours of shift work (Nicholls *et al.*, 2004; Murphy & Vanderburg, 2007; Gallis, 2013; Passicot & Murphy, 2013). By allowing breaks every three to four hours to rest, eat, or conduct routine maintenance, and an additional five minutes break for every hour operating equipment, while a second operator continues with the shift, is important to maintain production levels and prevent operator fatigue. The negative side of “overlapping” shifts (two operators work together on a single machine) was that this proved to be financially unfeasible for most contractors and resulted in moving back to straight (nine hour) shifts (Persson *et al.*, 2003; Ager, 2014). Nevertheless, shift work that allows the machine to work longer hours reduces machine fixed costs and therefore makes it financially more feasible than overlapping shifts (Mitchell *et al.*, 2008).

In Sweden during the 1980's-1990’s shifts were designed to include more pauses (shorter rest breaks of 10 minutes each) in a harvester operator’s work schedule. This practice resulted in improved operator health and improved productivity levels (Synwoldt & Gellerstedt, 2003; Ager, 2014). Day shifts were found to be more productive. However, it is difficult to determine if natural variation in cardiac rhythm, better visibility during daylight or other benefits of single shift work has an effect on variation between day and night work times (Persson *et al.*, 2003; Synwoldt & Gellerstedt, 2003; Nicholls *et al.*, 2004; Mitchell *et al.*, 2008; Lebel *et al.*, 2010; Gallis, 2013).

2.6.4 Species

In most South African CTL studies, tree species are seen as a constant when predicting productivity. Nonetheless, a South African based study conducted by Norihiro *et al*. (2018), found that *Eucalyptus grandis x camaldulensis’s* and *Eucalyptus grandis x urophylla’s* effects on productivity differed significantly. These findings were similar to those of Olivera *et al.* (2015) who found significant differences between the four *eucalyptus* species' effects on the productivity of a harvester. When comparing Scots pine to Norway spruce species in Switzerland, it was evident that the use of Scots pine increases productivity to about 1 m^{3}·PMH^{-1} when compared to that of Norway spruce (Heinimann, 2001a). The shape, DBH, health of trees, amount of bark and size of branches can be factors that explain the differences in productivity between species (Olivera *et al.*, 2015).

2.6.5 Terrain

Eriksson and Lindroos (2014) found that a harvester's productivity will decrease when working in more difficult terrain (more rocky and uneven terrain) conditions. This is due to the soil condition, soil moisture, soil depth, ground roughness and stumps limiting the movement of a machine, resulting in a significant reduction in productivity. Furthermore, terrain is the most influential factor when deciding on the selection of an appropriate harvesting system (McEwan *et al.*, 2013). For example, ground based harvesting machines, such as harvesters, cannot fell trees when the terrain is too rough, resulting in a less productive motor-manual felling as alternative (Ministary Of Forests, 1999).

2.7 Using StanForD as an automated data collection tool for learning curves and productivity models

Developed in Scandinavia in 1998, StanForD (standard for forest data and communication) is a data collection tool and system communications programme installed on most on-board computers of modern CTL equipment (Olivera, *et al.*, 2015). The standard for these on-board computers is StanForD software, which produces various file types for data logging (Skogforsk, 2010). The StanForD-standard produces various defined production file types such as .prd, .pri, .drf and .stm (Table 1). However, this study focusses on production and productivity development and therefore only uses .prd and .stm files for data analysis.

Table 1: Descriptions of production file types

File type	Name
.prd	Production (primarily harvesting production data)
.pri	Production-individual, harvesting data concerning each individual log and stem is registered
.drf	Operational monitoring data, covers both time (tid) and repair (rep) data
.stm	Stem values – measured length and diameter values

Stem files (.stm)

Stem (.stm) files are logging files that include compressed tree level data for each individual processed stem (tree). The logging system creates one .stm-file per site (working areas such as compartments in South Africa).

According to Skogforsk (2007) and Olivera *et al.* (2015), .stm files include the following stem values:

- Stem identification number
- Site (compartment name)
- Machine identification
- Operator identification
- Species
- DBH (small end and large end)
- Total tree height
- Diameter sections measured at 10 cm intervals
- Stem utilisable volume
- Produced log assortment volume
- Products (ply wood, different sawtimber assortments, pulp logs)
- Time stamps (year, month, day, hour, minute and second)
- Shifts (using time stamps)
- GPS coordinates for each tree (latitude, longitude and altitude)
- Single tree cycle time by subtraction of consecutive tree records (includes felling, moving the stem, debarking, debranching, cross cutting and other times)

The disadvantage of using .stm files only to calculate harvested tree cycle times from the subtraction of consecutive tree records is that it is impossible to know whether there was a delay between two records. However, .drf files can be used to identify which cycles have delays included in them (Olivera *et al.*, 2015).

.Stm files can be coupled with global navigation satellite systems (GNSS). This GNSS system provides a latitude and longitude coordinate for each tree harvested tree during the operation. This information provides researchers the opportunity to do research on harvesting operators in order to improve the operation (Olivera *et al.*, 2015). For example, Olivera *et al.* (2015) used these geographical coordinated to create a shapefile of all the stem records so that it can be overlaid on a slope surface to evaluate the effect of slope on productivity.

.Drf files

.Drf files, used specifically for operational machine monitoring, contain information regarding the use of time (utilisation, availability and downtime) and mechanical events (repair, maintenance, service, etc.) during an operation (Skogforsk, 2010; Olivera *et al.*, 2015). The user can set the minimum duration of an undefined downtime. Effective work time (E0) is defined as the productive work time excluding downtime and other times (terrain travel, other work and road travel). When working with learning curves, delayed free data is required to produce accurate performance data (Purfürst, 2010). The .drf file produces E5 times (effective work time, including delays shorter than five minutes), which is defined as hours of effective machine time including downtime and other times not exceeding five minutes per occasion (Skogforsk, 2010).

From .drf files, the beginning of each period of downtime and worktime can be identified (Skogforsk, 2010). With this information, it is necessary to cross-check the .stm files' time stamps and exclude all records that contain a delay or a worktime that did not relate to processing (Olivera *et al.*, 2015).

2.8 Conclusion

Extensive international and South African research have investigated the effect of environmental and mechanical factors on productivity. Mostly, the effect of tree size, shift work, species and terrain conditions on productivity are studied without taking into consideration the effect operators have on productivity (Purfürst & Erler, 2011). Cognitive abilities such as memory functions, non-verbal deduction, spatial perception, coordination, concentration, motivation, decision-making, pattern recognition, planning capacity and logic reasoning affect the success of a harvester operator (Parise, 2004; Ovaskainen, 2009; Tervo, Palmroth *et al.*, 2010; Häggström, 2015).

Selecting operators who exhibit above average cognitive abilities could lead to high initial productivity levels, and reduced downtimes and downtime-related costs. As a modern learning alternative, simulator-based machine training is more efficient than in-field training (Häggström, 2015). Research has shown that simulator-trained students produce up to 15% more timber when compared to non-simulator-trained operators, while machine repair costs decreased by up to 30% (Lapointe & Robert, 2000; Ovaskainen, 2009).

In terms of in-field machine learning, the learning phase for an average beginner harvester operator will take eight months to reach full potential but can range from 155 days to 488 days (Purfürst, 2010). Skilled operators can work at a PL of 140% relative to the population, while others (less skilled operators) will work at 50% relative to the population. Many beginner operators begin their PL at 50% to 60% compared to the relative mean of experienced operators (Purfürst, 2010; Purfürst & Erler, 2011).

The limitation of these studies is that none of the findings are based on South African conditions. Therefore, the importance of understanding the effect of operator selection, simulator training and machine training on beginner harvester operators' learning curves in South African conditions is emphasised.

3 Materials and methods

3.1 Background

Data for this study was obtained from a large South African based forestry company who employed newly installed CTL harvesting equipment in their forest operations. Thirty-six potential trainee candidates were exposed to psychometric testing as an initial selection process (Figure 4). Eight of the original thirty-six candidates were finally selected based on results of their psychometrics (Figure 4).

Figure 4: Flow chart for this study's procedure and data collection

Subsequent to psychometric testing, the eight candidates' were exposure to a simulator and subsequent simulator tests. After completing the simulator training and testing and an initial exposure to machines, these eight operators were exposed to 12 months of in-field harvester machine work (Figure 4). This sequence enabled the quantification of the impact of operator selection on simulator training results. Furthermore, the impact of both operator selection and simulator training on harvester productivity development can potentially be quantified and explained.

Finally, the learning curves for simulator training tests and harvester productivity development of the operators are constructed, explained and compared. The time (number of days) an operator needs to reach an acceptable level of performance in the simulator phase and the duration of the learning phase of an in-field beginner harvester operator are measured.

3.2 Current usage of fully mechanised harvesting (FMH) operations in South Africa

To emphasise the importance of this mechanised CTL study, the current status and trend of moving to FMH operations in South Africa was investigated. To do so, a forest harvesting operations survey was conducted in 2017. The overall goal of this survey was to underline the trend in harvesting operations to transition from motor-manual to mechanised harvesting operations, as well as to identify the status of outsourced harvesting operations in South Africa. In the survey, mechanised harvesting operations and outsourcing trends were emphasised.

The survey questionnaires included the following four questions for each respective company:

- In terms of the total planted area: How does the frequency of FMH operations compare to the frequency of motor-manual harvesting operations?
- In terms of the total planted sawtimber (ST) area where only FMH operations are used for harvesting: how does the use of purpose-built machines compare to that of excavator-based machines?
- In terms of the total planted pulpwood (P) area where only FMH operations are used for harvesting: how does the use of purpose-built machines compare to that of excavator-based machines?
- What are the differences in frequencies between harvesting contractors (outsourcing) and in-house harvesting (own operations)?

Therefore, the survey only focused on comparing the use of fully mechanised CTL operations with the use of motor-manual harvesting operations, without considering manual and semi-mechanised harvesting operations.

3.3 Psychometric tests

Psychometric testing, as part of the formal operator selection process, was implemented to select the final eight harvester trainee operators from the initial thirty-six potential candidates. The psychometric testing was completed by a contracted and trained industrial psychologist independently of this study. The data used in this study was made available to the author with all relevant permissions and consents.

Trainee operator selection and evaluation

The following determination tests were administered via psychometric testing:

- Two-hand coordination
- Time movement anticipation (zba)

- Cognitrone
- Signal detection

1. Determination test

   In this test, eye-hand-foot coordination and auditory discrimination of the candidate were assessed under the following three conditions:

   - Subtest 1 (daily functioning levels)
   - Subtest 2 (maximal stress/crisis phase)
   - Subtest 3 (recovery from crisis phase)

2. Distance/speed and direction estimation

   This test includes the evaluation of the operators' ability to estimate distance and the direction of moving objects.

3. Two hand coordination

   Both the speed and accuracy of the operators' coordination skills were evaluated.

4. Cognitrone

   This test evaluates the ability of an operator to make non-verbal decisions. This will eventually tell if the operator will be able to distinguish between, interpret and react to various signals.

5. Signal detection

   This test evaluated the concentration, attention and ability to detect small (but important) changes in the operator's environment and also evaluated visual recognition and visual acuities.

6. Results and interpretation

   The overall profile of an operator's A, B, C refers to the average of all his/her obtained scores, where: **A –** scores identify **good** candidates

   B – Scores identify **average** candidates

   C – Scores identify **poor** candidates

3.4 Simulator training

Once the selection process was completed, successful operators were exposed to a full simulator training course. This simulator replicated the controls, computer system and seat as found in the harvesters in question (Figure 5). Data from these simulator tests enables the analysis of the training progression of operators from inception to ‘ready for machine’ status. With a simulator, the operator become more comfortable with the controls and set-up of the machine and has the opportunity to improve his or her skills without the risks and costs involved with a real machine operating in dangerous conditions.

The results from the simulator training aimed to answer the follow questions:

- Does formal operator selection, with operators of different psychometric abilities, significantly differ in terms of PLs and test results on a simulator?
- Do the differences in individual operator psychometric results determine the start and finish PL’s of simulator training?
- Do the learning periods of operators who have different psychometric results vary?

Figure 5: In-house Ponsse simulator (Ponsse, 2017)

3.4.1 Simulator test and training design

All eight selected harvester operators (four thinning and four clear-felling operators) completed the following two repetitive tests before moving on to in-field machine training:

Test 1: This test comprises a 3D (three-dimensional) simulator test where seven touch points are located around the harvester at different heights above ground level and different distances away from the harvester frame (Figure 6). The purpose of the first test was to familiarise the operators with the controls and boom movement of the machine before they move on to a more complex test in Test 2.

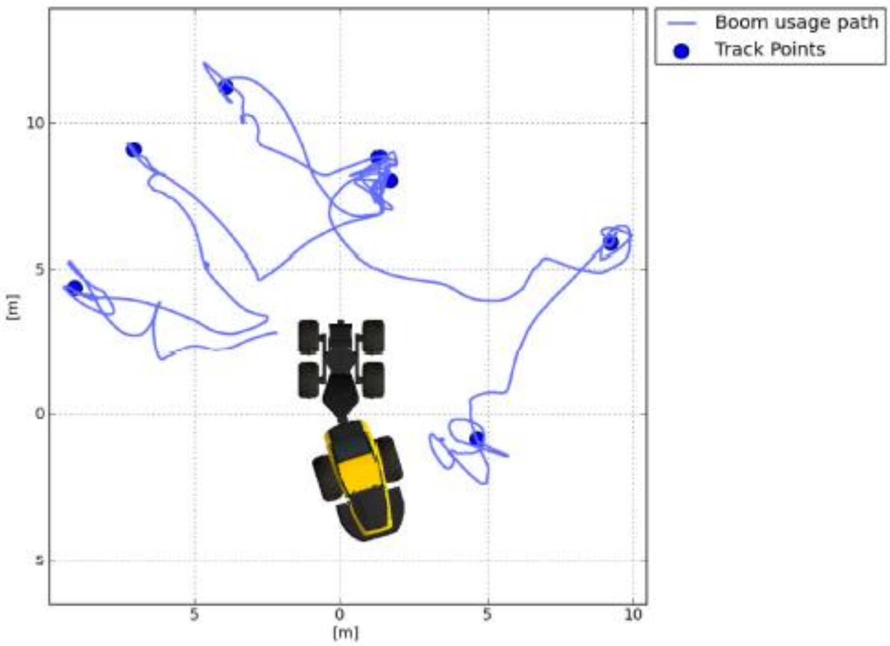

Figure 6: Top view of a 3D test example (Test 1)

Test 2: Operators fell three trees (for thinning operators) or four trees (for clear-fell operators) to the front and away from the machine frame towards an aiming point (Figure 7). The purpose of Test 2 was to teach operators how to use and position the harvester head, boom, grab and chainsaw bar when felling trees and how to control the tree while it is felled.

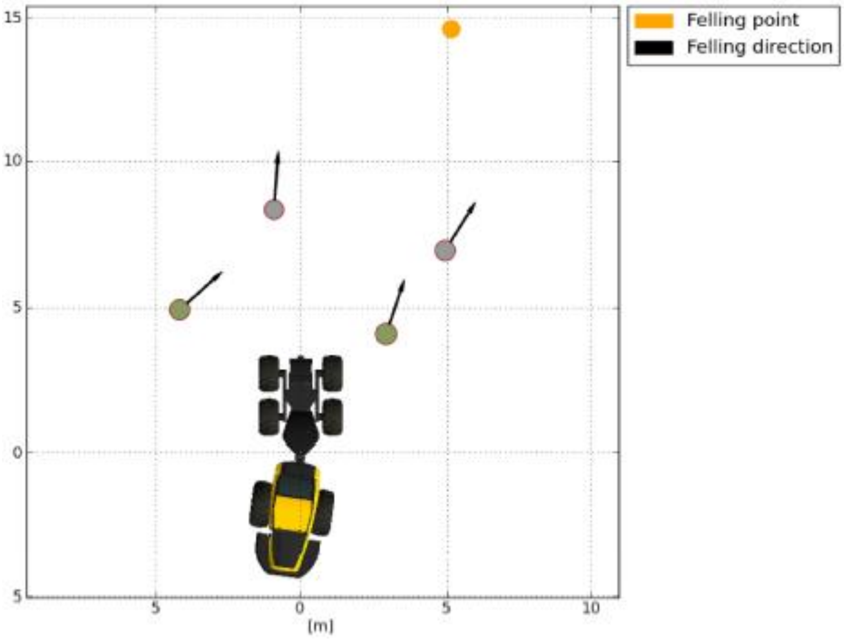

Figure 7: Top view: Felling four trees forwards example (Test 2)

3.4.2 Simulator data collection

The time was recorded for the completion of each test. Each operator repeats each test (repetitive measure design) three times per day until the end of the test period. Depending on the required end-level performance (defined by simulator trainer), each of the tests are repeated for a different number of days (Table 2).

Table 2: Repetitive measure design for Test 1 and Test 2 in each operation

Test	Tests per day	Days for training	Number of operators
Test 1 Thinning	3	19	4
Test 2 Thinning	3	14	4
Test 1 Clear-fell	3	9	4
Test 2 Clear-fell	3	7	4

3.4.3 Data analysis

For comparative purposes, each operator's relative performance is calculated by dividing each observed test result with the arithmetic mean of the population's test results (Equation 3). An operator's performance level (PL) of 1 would be the same performance level as the population mean performance level (PPL). To be able to show if an operator's "time per test" PL actually increases and not decreases relative to the PPL, an inverse calculation for each performance point is made over the line were performance = 1. If the inverse calculation is not made, the performance results will show that, as an operator reduces his "time per test" relative to the population, his PL for each test will also decrease relative to the PPL, which is the wrong interpretation.

$$Performance\ level = -\left(\frac{Po}{Pmean}\right) + 2 \qquad (3)$$

Where:

Performance level (PL) = operators' individual time per test relative to the population's mean performance level (PPL)

Po = Observed time per test in minutes

Pmean = Population's arithmetic mean time per test

The evaluation of "time per test attempt" for Test 1 and Test 2 was used to describe the simulator learning curve for thinning and clear-felling operators respectively. The following is derived from the simulator learning curve for Test 1 and Test 2, and used to describe the learning curve for each operator respectively and to compare the differences that exist between the operators:

- Start PL and end PL relative to the PPL
- The number of days it took an operator to reach the PPL of 1
- The total increase in performance (%) each operator gained from the start to the end of the learning curve
- The daily increase in performance (%) an operator gained
- The maximum PL an operator would reach over the learning period

After all eight operators (four thinning and four clear-felling) completed their simulator training, reaching a certain level of performance (defined by the external simulator teacher), they moved over to 'on-machine-training' in-field. Training staff from Ponsse Finland undertook a four week training program to ensure all operators were comfortable with both the machine and environment before the start of the learning phase.

3.5 In-field harvesting

3.5.1 Study site

The experimental study sites are located 70 km east of Ermelo near the village of Warburton in the Mpumalanga Highveld region of South Africa (Figure 8). All field operations, both thinning and clear-fell harvesting, took place on four different plantations, namely Jessivale, Dorsbult, Lochiel and New Scotland. These specific study sites have suitable terrain conditions for ground based systems. These plantations are planted to *Pinus patula, Pinus elliottii* and *Pinus taeda* for the purpose of sawtimber, plywood and pulp production.

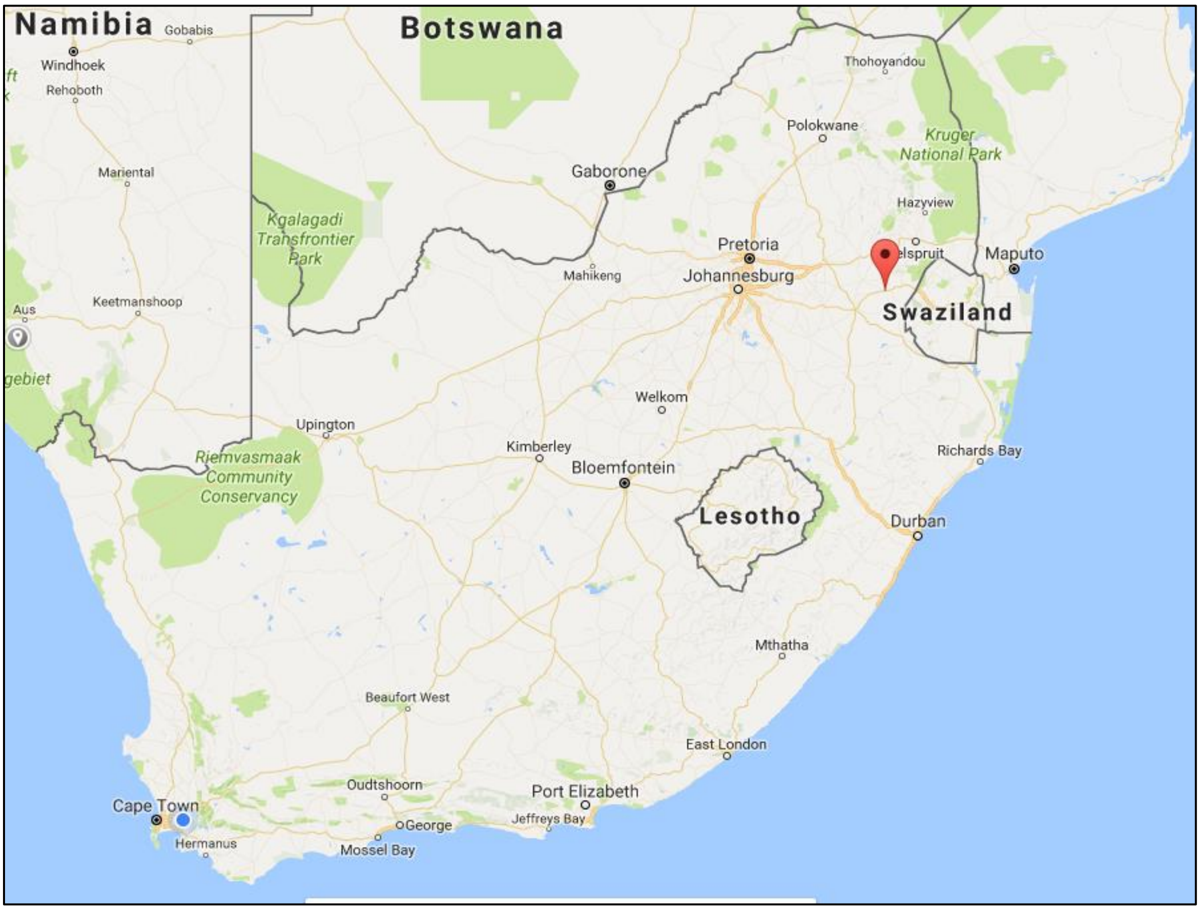

Figure 8: Warburton geo-location

Clear-felling took place on compartments where trees were on average 22 years old and first thinning compartments were on average 10 years old.

Table 3 provides descriptive statistics on the average tree dimensions harvested during the study period for each respective harvesting operation. According to the machine logging files, the total volumes harvested from June 2016 to July 2017 in clear-felling and thinning are 185 517 m^3 and 59 423 m^3 respectively.

Table 3: Descriptive statistics for each respective harvesting operation's tree dimensions derived from machine files

	Thinning			Clear-felling		
	DBH (cm)	Height (m)	Tree volume (m^3)	DBH (cm)	Height (m)	Tree volume (m^3)
Mean	21.98	11.59	0.18	29.78	19.59	0.54
Median	20.7	11.63	0.14	29.8	19.68	0.51
Range (min–max)	11–49.8	7.2–24.8	0.02–1.69	14–48.4	10.1–30.0	0.05–1.99
Std dev	5.35	3.1	0.16	4.28	2.56	0.21

3.5.2 Site characteristics

Warburton is situated in the summer rainfall area of South Africa, has a mean annual precipitation (MAP) of 614 mm (Figure 9) and is approximately 1741 m above sea level. The midday mean annual temperature (MAT) ranges from 15.4°C in June to 23.4°C in January. The coldest month of the year is June, with temperatures of 1°C.

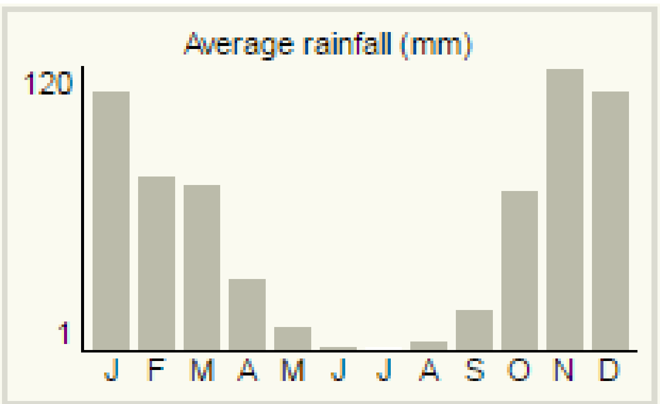

Figure 9: Annual rainfall distribution for Warburton [source: http://www.saexplorer.co.za]

MAT, MAP, altitude, dominant slopes with regards to total area and species for all four plantations, which are included in the study area, are shown in Table 4. The four plantations do not differ significantly from one another in terms of their climatic and environmental characteristics.

Table 4: Plantation's site attributes

	Jessivale	Dorsbult	New scotland	Lochiel
MAP (mm)	844	852	864	868
MAT (˚C)	15 (16.5–14.3)	15 (14.4–16)	15 (14.5–15.2)	15 (14.2–16.5)
Slope class with regards to area	0–35% = 90% 35–50% = 8 % >50% = 2%	0–35% = 82% 35–50% = 13% >50% = 5%	0–35% = 94% 35–50% = 5% >50% = 1%	0–35% = 81% 35–50% = 13% >50% = 6%
Altitude (m)	1670 (1394–1799)	1681 (1488–1803)	1615 (1447–1696)	1649 (1402–1814)
Species	*P patula, P elliottii, P taeda*	*P patula, P elliottii, P taeda*	*P patula, P elliottii, P taeda*	*P patula, P elliottii, P taeda*

3.6 Harvester operator learning curve and productivity development

To properly analyse the productivity development of eight CTL harvester operators (four thinning and four clear-felling operators), 269 logging files, including 154 compartments, were used on two Ponsse Bear harvesters and two Ponsse Beaver harvesters in the Mpumalanga Highveld region of South Africa.

3.6.1 In-field operations

All harvesting operations were carried out in compliance with the company's environmental laws and standards and legal requirements. In the clear-felling operation, two Ponsse Bear harvesters with Ponsse H8 harvester heads worked together with two Ponsse Elephant King forwarders. In the thinning operation, two Ponsse Beaver harvesters with Ponsse H6 harvester heads worked together with two Ponsse Buffalo forwarders. All harvesters felled trees to the left of the machine and processed stems (debranched and cross-cut) to the right of the machine. In clear-felling operations, corridors of four trees wide were applied, whereas in thinnings (first thinning), 5th row thinning were performed, resulting in four rows of trees remaining on each side of the thinned row. These four rows were then selectively thinned as the harvester moves through the compartment. The forwarders subsequently loaded the logs and hauled them from the strip road to the forest road where the logs were then stacked to be transported to the mill (Table 5).

Table 5: CTL operations framework matrix

Area / activity	Stand	Strip Road	Forest Road	Mill
Fell				
Debranching				
Crosscut				
Extract and stack				
Load and Transport				

Each harvester had two operators working in nine-hour shifts for the duration of the study (12 months). However, the study was focused on the productivity development (learning curve) of eight inexperienced harvester operators (four thinning and four clear-felling harvester operators) only and no use of forwarder data was made.

3.6.2 Machine description

Figure 10: Machines used for fully mechanised CTL operations

Individual machine (Figure 10) and specifications are listed in Table 6.

Table 6: Machines specifications

	Thinning machines		Clear-felling machines	
	Harvester	Forwarder	Harvester	Forwarder
Model	Ponsse Beaver	Ponsse Buffalo	Ponsse Bear 8W	Ponsse Elephant King
Output (kW)	129	205	240	205
Torque (Nm)	800	1 100	1 300	1 100
Wheels	6 wheels	6 wheels	8 wheels	8 wheels
Mass (kg)	17 100	18 400	24 500	23 700
Harvester head	H6	-	H8	-
Harvester crane	C44+	-	C6	-
Maximum load	-	14 tonnes	-	20 tonnes
Max boom reach (m)	11	7.8	11	7.8
Ground clearance	670 mm	680mm	700mm	800 mm
Fuel tank volume (l)	300	200	400	260

3.6.3 Data collection

The data collection period was approximately 12 months as it is assumed that an operator can be classified as experienced after 12 months (Purfürst & Erler, 2011).

3.6.3.1 On-board machine logging documents and attribute data

Following the completion of their simulator tests, all operators were exposed to four weeks of 'on-machine-training' in-field. After the four weeks of operator orientation on the machines, the on-board computers were enabled for data collection. All logged data (productivity data per operator) was collected through the data logging systems of the harvester. The data logging system on all the harvesters, based on the StanForD-standard, produces all the data needed in different file formats (Skogforsk, 2010). In this study, .stm files from the StanForD-standard were used to analyse each harvester operator's productivity development from inception to potential maturity (Purfürst, 2007, 2010; Strandgard *et al.,* 2013; Olivera *et al.,* 2015).

Data was extracted from StanForD's stem (.stm) files and compiled into two separate datasets (one each for thinning and clear-felling). .Stm files included compressed tree level data for each individual processed stem (tree). The following is reported data (variables) provided by the original .stm files:

- Stem identification number
- Site (compartment name)
- Machine identification
- Operator identification
- Species
- DBH
- Height
- Stem utilisable volume
- Diameter sections measured at 10 cm intervals
- Produced log assortment volume
- Products (ply wood, different sawtimber assortments, pulp logs)
- Time stamps (year, month, day, hour, minute and second)
- Shifts (calculated using time stamps)
- GPS coordinates for each tree (latitude and longitude)
- Single tree cycle time by subtraction of consecutive tree records (includes felling, moving the stem, debarking, debranching, cross cutting and other times)

Some data in the database had to be derived from reported data. These derived data per machine per operator were:

- Mean daily productivity (derived from the average of the sum of individual tree volumes harvested per productive E5 hour per day, reported in $m^{3}\cdot PMH^{-1}$)
- Mean of height, DBH and stem volume per productive day

Species were used as categorical variables for the purpose of statistical analysis.
Species:

- 1= *P. elliottii*
- 2 = *P. patula*
- 3 = *P. taeda*

In this study, the minimum duration of an undefined delay (do not specify why the machine is not working) was five minutes (E5 work time). When working with learning curves, it is important to work with as much delay-free time as possible. Furthermore, delay-free data is required to enable an accurate analysis of an operator's performance data (Purfürst, 2010). E5 times were used for the analysis of productivity development and the learning curve, which is defined as hours of effective machine time, including downtime and other times not exceeding five minutes per occasion (Skogforsk, 2010).

After 12 months of work, all logging files were collected from the harvesters and all information from the .stm files were decoded and extracted to a Microsoft Excel data sheet that was suitable for the use of statistical analysis. Once the derived variables (species, productivity, mean tree volume, mean DBH and mean height) were included in the datasheet, a standard statistical programme (Statistica™ Ver. 13 (Dell Inc, 2016)) was used to analyse the development of all the harvester operator's actual learning curves. The methods used are explained in section 3.6.4.1.

3.6.3.2 Time study

To ensure that there were no DBH, height and cycle time outliers present in the data recorded by the on-board data logging system, two manual time studies were conducted (one each for thinning and clear-felling operations). First, a representative compartment was selected for each respective time study. Prior to harvesting of a compartment, 150 representative (no edge trees) trees were numbered 1–150 in rows of four trees wide. Each tree's DBH was then measured using a DBH tape and every 5th tree's height was measured using a Haglof laser vertex. Subsequently, harvest cycle times were recorded for each of the 150 trees. The cycle times started as soon as the cutting bar started to cut the tree and ended as soon as the next tree was grabbed and the cutting bar started to cut the tree. Therefore, the cycle time included felling, processing and travel to the next tree. These measurements were then used to remove some outliers based on DBH, height, calculated volume and cycle times.

3.6.3.3 Discarding of outlier data

From a total 442 188 harvested tree data, only 62 118 clear-fell trees and 90 522 thinning trees were used due to the removal of outliers in the data. The lower and upper limits for

DBH, height, volume and cycle times were gathered from tree enumerations done for time study purposes on these specific harvesters. All stem records that met at least one of the following criteria were removed:

- A delay of longer than five minutes (300 seconds) was included in the cycle time
- No harvested time stamp
- Operator's logging data not reaching 12 months of harvesting work
- Thinning cycle time < 7 seconds
- Thinning tree heights < 5 m; > 21 m
- Thinning tree volumes < 0.1 m^3 ; > 2.5 m^3
- Thinning tree DBHs < 14 cm ; > 32 cm
- Clear-fell cycle times < 25 seconds
- Clear-fell tree heights < 10 m ; > 30 m
- Clear-fell tree volumes < 0.07 m^3 ; > 2 m^3
- Clear-fell tree DBHs <14 cm ; > 50 cm

3.6.4 Data analysis

3.6.4.1 Harvester operators' learning curves

Two methods of learning curve calculations were used to explain how an operator increases his productivity as a function of volume over time and to be able to compare operators' performance.

The first method, *Operator productivity learning curve (I),* was used to demonstrate how an operator's productivity increases over time as a function of volume. This method gives an indication of how each operator's productivity increases per month with different tree sizes (measured in percentage). The second method, *Operator performance learning curve (II)*, was used to compare the PL of each operator with the PPL.

Learning curve (I)

A model of productivity (m3/PMH) as a function tree volume, characterised by months for the complete 12 month period for each operator was developed at first, however, there was a large amount of variation, in terms of tree size, within the data and the fit of the model was poor. Therefore, to ensure that an increase or decrease in productivity is not an effect of an increase or decrease in tree size, each operator's learning curve is graphically presented monthly as a function of productivity (vertical axes) over tree volume (horizontal axis).

Therefore an operators' learning curve is generated with the use of a statistical software "Statistica", where a logarithmic regression model of productivity ($m^3 \cdot PMH^{-1}$) as a logarithmic function of tree volume, characterized by months for the complete 12 month period, are developed. This enables an understanding of how an operator increases his productivity on different tree volumes per month.

These logarithmic regression models from the graph are used to describe the learning curve and provide an understanding of the increase in productivity one can expect from a beginner operator working under similar conditions. To compare the learning curves of the operators, productivity increase (%) between months one and twelve was calculated at different tree sizes in m^3. This allowed for the understanding of how the percentage increase in productivity differs between tree sizes for each individual operator. These percentage increases are developed for each operator working in either thinning or clear-felling operations, with the purpose of comparing operators.

Learning curve (II)

Using each operator's logarithmic transposed regression model for the 12 work months (from *learning curve I*), each of the thinning and clear-felling operators' monthly productivity was calculated at mean tree volumes. By doing so, each individual operator's experience of his learning on the machine at average tree volume was displayed. The average tree volume for thinning and clear-felling operators were 0.18 m^3 and 0.54 m^3 respectively. By using the monthly calculated productivity and the population's mean productivity over the 12 work months, the relative performance for each operator was calculated with the purpose of comparing operators and discussing the learning curve (Equation 3).

$$Performance\ level = \left(\frac{Po}{Pmean}\right) \quad (3)$$

Where:

Performance level (PL) = operators' individual performance relative to the population's mean performance level (PPL);

Po = Observed productivity (m^3 pmh^{-1}); and

Pmean = Population's arithmetic mean productivity (m^3 pmh^{-1}).

The assumption for this study is that operators have a rapid initial learning progression but that productivity development slows down after a period of efficient work (Björheden, 2000; Ranta, 2004a; Purfürst, 2010; Gellerstedt, 2013). Beginner operators are faced with a steep learning curve at the beginning of the learning phase (in terms of controls, movement, planning, technique, etc.) but a relatively constant slower learning period follows where it can take up to five years for an average harvester operator to reach full potential in terms of his productivity.

4 Results

4.1 Current usage of mechanised harvesting systems (MHS) in South Africa

The results of the survey are compiled in Table 7. The table provides a breakdown of the extent of the use of mechanised harvesting operations (in percentage) as compared to that of motor-manual harvesting operations.

Table 7: Motor-manual harvesting vs MHS for each commercial forestry company where ST represents sawlogs and P represents pulp logs

Company	MHS	MHS				Motor-manual harvesting (%)	Contractor harvesting (%)	In-house harvesting (%)
	%	Purpose-built		Excavator-based				
		ST (%)	P** (%)	ST (%)	P (%)			
Mondi	100	70	5	30	95	0	100	0
Sappi	49	40	20	60	80	51	99	1
Merensky	100	100	0	0	0	0	60	40
York Timbers	40	100	100	0	0	60	60	40
MTO Lowveld	16	0	0	100	0	84	100	0
MTO Cape	30	50	0	50	0	70	73	27
PG Bison	65	20	100	6	0	35	80	20

From Table 7 it is seen that four of the seven companies use motor-manual operations on more than 50% of their planted areas. However, in terms of the average use of MHS operations versus the average use of motor-manual harvesting operations among all seven companies, MHS operations are used 57% of the time on average and motor-manual harvesting is used 43% of the time on average. Mondi and Merensky are the two companies that are most (100%) mechanised in terms of their harvesting operations and

MTO uses MHS systems the least (22.5%). However, Mondi has no in-house harvesting machines and makes use of 100% contractor-based harvesting operations, whereas Merenksy uses contractors 60% of the time. With regards to the seven companies' MHS: on average, 64% of their sawtimber area is harvested by means of purpose-built machines and 36% by excavator-based machines. Furthermore, 68% of their pulpwood areas are harvested by means of purpose-built machines and 32% by excavator-based machines. The harvesting operations of all seven companies were on average split at 82% for contractor-based operations and 18% for in-house (in-sourced) operations.

4.2 Trainee operator selection and evaluation

Table 8 shows the psychometric test scores achieved by the final eight trainee operators. Overall performances of operators are indicated by A (good), B (average) or C (poor).

Table 8: Operator psychometric test result summary

Operator number	Age	Eye-hand-foot coordination and auditory discrimination in:			Time Anticipation/ MDT	Direction Anticipation/MDD	Speed/ overall mean duration	Accuracy/ overall % error duration	Cognitrone	Signal detection	Overall performance
		Normal situation. 1st interval	Crisis situation. 2nd interval	Recovery [from crisis]. 3rd interval.							
1	24	A	A	A	B	B	A	A	A	A	A
2	22	A	A	A	B	B	A	B	A	A	A
3	24	A	A	A	A	B	A	A	A	A	A
4	30	A	A	A	B	B	A	B	B	B	B
5	28	B	A	A	B	B	A	A	A	A	A
6	19	A	A	A	B	C	B	B	B	A	B
7	21	A	A	A	A	C	A	A	A	A	A
8	26	A	A	A	A	B	A	A	A	A	A

Apart from the performance scores of the psychometric test, individual evaluations were provided by the psychologist who executed the tests. This evaluation may have had a bearing on why operators have different simulator and machine performance results:

- Operator 1: His concentration, attention and ability to detect small but important changes in his environment are above average, as are his visual recognition and visual acuities.
- Operator 2: His coordination skills are assessed as fast at an average rate of accuracy.
- Operator 3: His coordination skills are assessed as fast at an above average rate of accuracy.
- Operator 4: His attention and ability to detect small but important changes in his environment are average, as are his visual recognition and visual acuities.
- Operator 5: His non-verbal decision-making process appears to be very slow.
- Operator 6: His coordination skills are assessed as fast at an average rate of accuracy.
- Operator 7: His ability to estimate direction of moving objects appears to be below average.
- Operator 8: He has no difficulty in freeing himself emotionally following exposure to stressful conditions; he is able to return to previous levels of daily functioning.

4.3 Simulator tests

In total, 639 harvester simulator test results (396 for Test 1 and 252 for Test 2) from the eight trainee operators (four thinning and four clear-felling trainee operators) were analysed in order to describe learning curves of each trainee for each of the two simulator tests (Table 9). As thinning and clear-felling operations require specific skills and operators were either exposed to thinning or clear-felling operations, these learning curves cannot be compared. As such, results from four clear-felling operators and four thinning operators will be dealt with separately.

Table 9 provides descriptive statistics with regards to the thinning and clear-felling population's "time per test" results for Test 1 and 2 that were used to calculate each operator's relative PL.

Table 9: Thinning and clear-fell operators' descriptive statistics for test times for Test 1 and Test 2.

Test	Mean	Median	Range (min–max)	Std dev
Test 1 Thinning	1.62	0.92	0.59–2.15	0.34
Test 2 Thinning	1.09	0.91	0.44–1.95	0.3
Test 1 Clear-fell	1.73	0.96	0.59–1.81	0.28
Test 2 Clear-fell	2.51	0.92	0.47–2.42	0.35

4.3.1 Simulator learning curves

As trainees gain experience, their performance levels improve compared to a population mean, which was set as PPL 1.0. The end of the simulator learning phase for a trainee is defined as the point where no significant increase in performance is made from that point on for at least two consecutive days.

4.3.1.1 Thinning Test 1

All four thinning trainees listed in Table 10 show a maximum performance level (PLmax) higher than the average performance level of the population (PPL = 1) (Table 10 and Figure 11).

Table 10: Individual thinning operators' learning phase data for Test 1

Test 1: Test Time							
Trainee	PL start	Days to reach PL = 1	PL end and days to reach the end		Increase PL		PL max
					Overall	Per day	
			PL End	Days	%	%	
1	0	6	1.3	16	130	8.12	1.3
2	0.19	9	1.25	16	557.89	34.86	1.3
3	0.79	4	1.3	7	64.56	9.22	1.3
4	0.19	12	1.1	16	478.95	29.93	1.25
Mean	0.29	7.75	1.24	13.75	307.85	20.54	1.29
Median	0.19	7.50	1.28	16.00	304.47	19.58	1.30
25% - quantile	0.05	4.50	1.14	9.25	80.92	8.40	1.26
75% - quantile	0.64	11.25	1.30	16.00	538.16	33.63	1.30

The number of days it took a trainee to reach the PPL ranged between 4–12 days (mean = 7.75 days). The number of days to reach the end of the learning phase varied between the four trainees and ranged from 7 and 16 days (mean = 13.75 days).

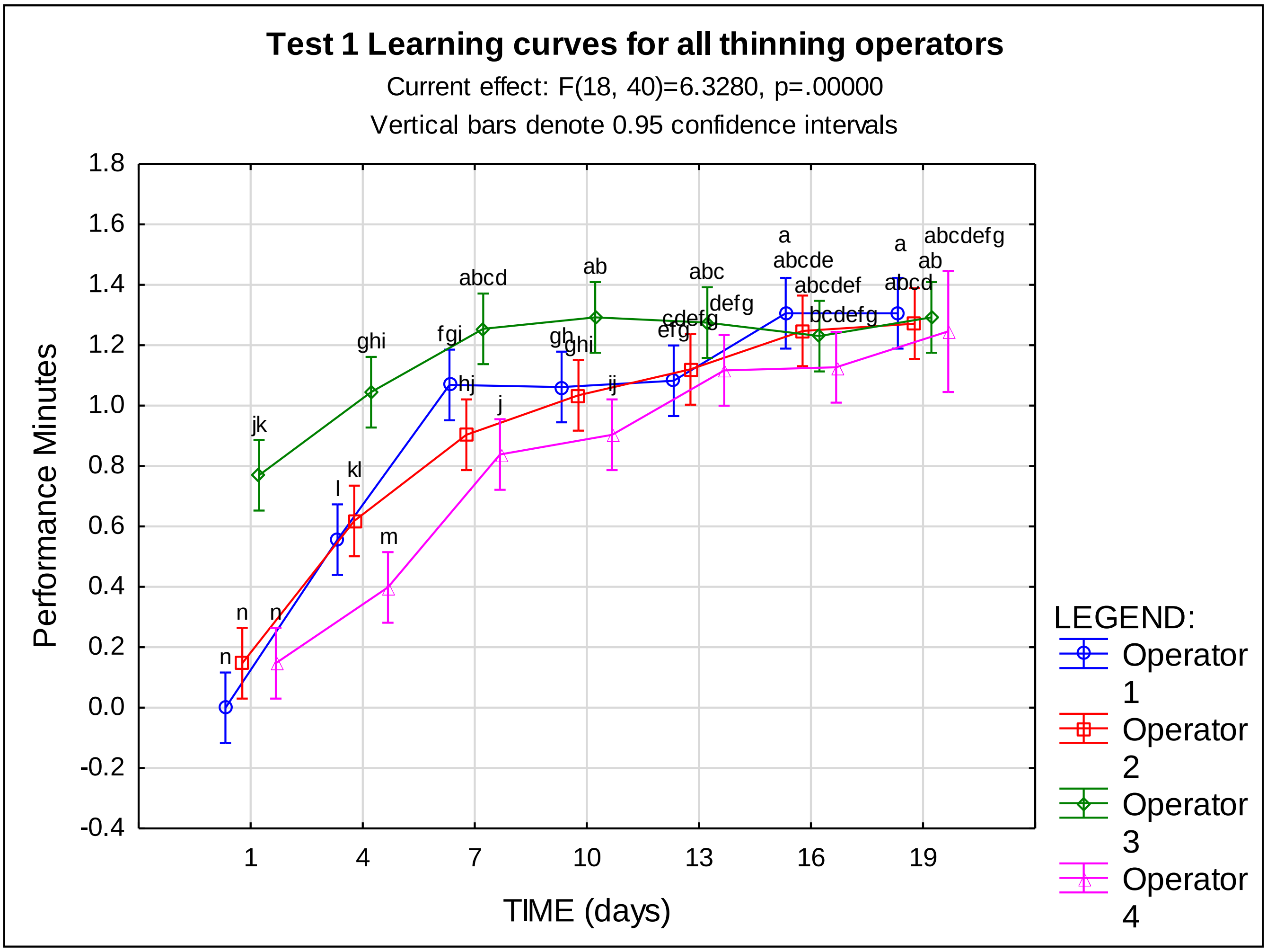

Figure 11: Test 1 Learning curve of all thinning operators (different letters indicate a significant difference in the means ($p < 0.05$))

At the beginning of the learning phase, trainees started at a PL between 21%–100% (mean = 71%) lower than the PPL but increased their performance by 307.9% on average at the end of the learning phase. There was no significant difference (see significance letters in Figures) between trainee performances at PLend (Figure 11), which varied between 10%–30% higher relative to the PPL (mean = 24%; median = 28%), with the inter-quartile ranges between 14% (25th percentile) and 30% (75th percentile). The daily increase in trainees' performance varied between 8.6%–37.19% from one another, with a mean = 22.32%. Trainee No. 3 performed the best of the four trainees as he reached the end of his learning phase nine days earlier than the other three trainees did. Furthermore, trainee No. 3 started at a significantly (see significance letters in Figures) higher PL than the other trainees. Even though trainee No. 1 started with the lowest PL of all four operators, he managed to end with the same PL than all the other operators (having had the same number of training days as operator No. 2 and 4).

4.3.1.2 Thinning Test 2

All four trainees listed in Table 11 show a PLmax that is higher than the average performance level of the population (PPL = 1) (Table 11 and Figure 12).

Table 11: Individual thinning operators' learning phase facts for Test 2

Test 2: Test time							
Trainee	PL start	Days to reach PL = 1	PL end and days to reach the end		Increase PL		PL max
					Overall	Per day	
			PL End	Days	%	%	
1	0.55	3.00	1.30	7.00	136.36	19.48	1.40
2	0.30	9.00	1.10	10.00	266.67	26.67	1.10
3	0.25	7.00	1.30	10.00	420.00	42.00	1.40
4	0.35	7.00	1.10	10.00	214.29	21.43	1.20
Mean	0.36	6.50	1.20	9.25	259.33	27.39	1.28
Median	0.33	7.00	1.20	10.00	240.48	24.05	1.30
25% - quantile	0.26	4.00	1.10	7.75	155.84	19.97	1.13
75% - quantile	0.50	8.50	1.30	10.00	381.67	38.17	1.40

Trainees reached the PPL within 3–9 days (mean = 6.5 days), while the end of the learning phase was reached between 7 and 10 days (mean = 9.25 days).

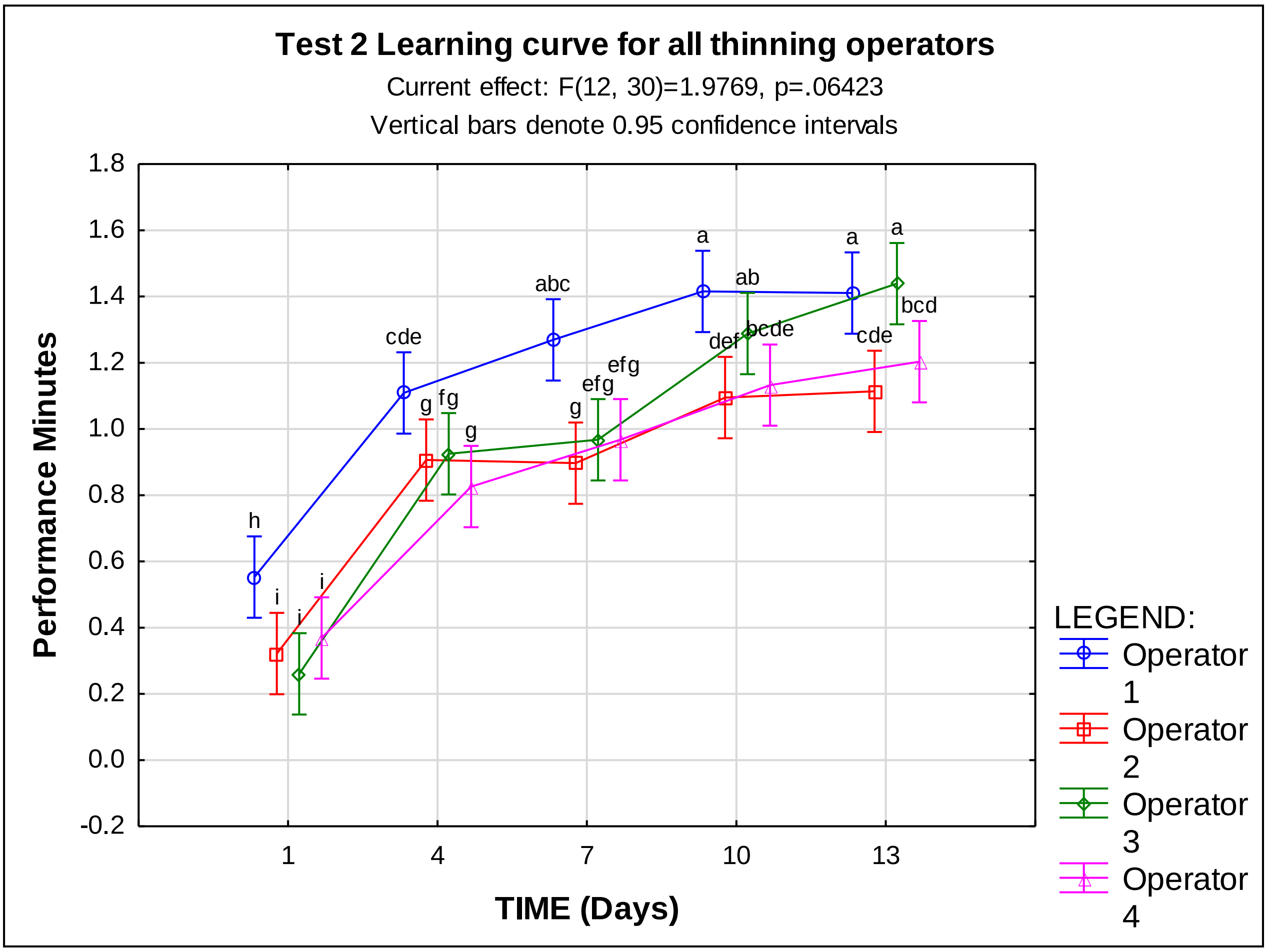

Figure 12: Test 2 Learning curve of all thinning operators (different letters indicate a significant difference in the means ($p < 0.05$))

At the beginning of the learning phase, the trainees started at a PL that was between 45%–75% (mean = 64%) lower than the PPL but managed to increase their performance by almost 259% on average. All trainees ended with a PL of between 10%–30% higher than the PPL (mean = 20% higher; median = 20% higher), with the inter-quartile ranging between 10% (25th percentile) and 30% (75th percentile) higher than the PPL. Figure 12 indicate that the end performances of trainee No. 1 and 3 did not differ significantly (see significance letters in Figures) from that of trainee No. 2 and 4. Thus, the end performances of trainee No. 1 and 3 (both above average skilled candidates according to psychometric tests) were significantly (see significance letters in Figures) higher than that of trainee No. 2 and 4 (trainee No. 4 being an average skilled candidate according to psychometric tests). Trainee No. 1 (above average skilled candidate according to the psychometric tests) performed the best of the four trainees (he started and ended with the highest PL and managed to reach the end of his learning phase three days earlier than the others three trainees). There were no significant differences (see significance letters in Figures) between the PLstart of trainees No. 2, 3 and 4, and all three trainees managed to reach the end of their learning phase after 10 days.

Summary

In both simulator tests, trainee No. 1 and 3 performed the best of the four operators as predicted by their psychometric test results (both above average skilled candidates). In both tests, they managed to end with the highest PL. Therefore, the psychometric tests gave some indication of which thinning trainee could eventually be successful on the simulator.

4.3.1.3 Clear-fell Test 1

All four trainees listed in Table 12 show a PLmax higher than the average performance level of the population (PPL = 1) (Table 12 and Figure 13).

Table 12: Individual clear-fell operators' learning phase facts for Test 1

Test 1: Test time							
Trainee	PL start	Days to reach PL = 1	PL end and days to reach the end		Increase PL		PL max
					Overall	Per day	
			PL End	Days	%	%	
5	0.5	5	1.35	6	170	28.33	1.35
6	0.65	4.5	1.2	6	84.61	14.10	1.25
7	0.4	4.5	1.2	7	200	28.57	1.3
8	0.6	6	1.35	6	125	20.83	1.35
Mean	0.53	5	1.28	6.25	144.90	22.96	1.31
Median	0.55	4.75	1.28	6	147.5	24.58	1.32
25% - quantile	0.43	4.5	1.2	6	94.71	15.79	1.26
75% - quantile	0.64	5.75	1.35	6.75	192.5	28.51	1.35

Trainees reached the population's mean performance test times between 4.5–6 days (mean = 5 days). The end of the learning phase was reached between 6 and 7 days (mean = 6.25 days).

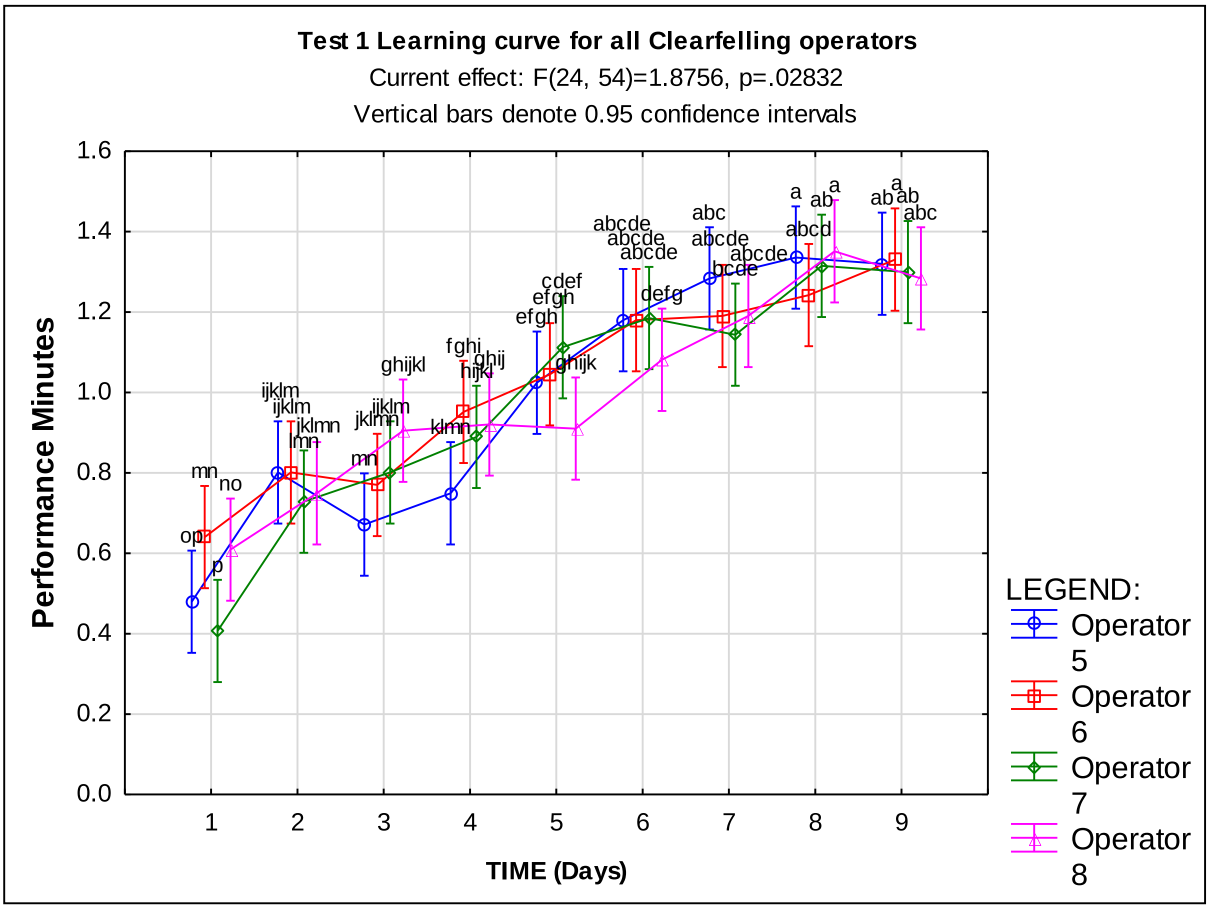

Figure 13: Test 1 Learning curve of all clear-fell operators (different letters indicate a significant difference in the means ($p < 0.05$))

At the beginning of the learning phase (day 1), the trainees started at a PL of between 35%–60% (mean = 46%) lower than the PPL but managed to increase their performance by almost 144% on average. From the significant letters in Figure 13, it is clear that the end performance of the trainees did not differ significantly from one another. All trainees ended with a PL that was 20%–35% higher than the PPL (mean = 28% higher; median = 28% higher), with the inter-quartiles being between 20% (25^{th} percentile) and 35% (75^{th} percentile) higher than the PPL. Trainee No. 6 (below average skilled candidate according to psychometric tests) started at a significantly (significant letters) higher PL than that of trainees No. 5 and 7; and trainee No. 7 started at a significantly lower PL than that of trainees

No. 6 and 8. However, from day one onwards, all operators' performance followed the same trend to the end.

4.3.1.4 Clear-fell Test 2

All four trainees listed in Table 13 show a PLmax that is higher than the average performance level of the population (PPL = 1) (Table 13 and Figure 14).

Table 13: Individual clear-fell operators' learning phase facts for Test 2

Test 2: Test time							
Trainee	PL start	Days to reach PL = 1	PL end and days to reach the end		Increase PL		PL max
					Overall	Per day	
			PL End	Days	%	%	
5	0.2	4	1	4	400.00	100.00	1.20
6	0.55	3	1	4	81.82	20.45	1.25
7	0.7	2	1.25	3	78.57	26.19	1.45
8	0.15	5.5	1.1	6	633.33	105.56	1.20
Mean	0.40	3.63	1.09	4.25	298.43	63.05	1.28
Median	0.38	3.50	1.05	4	240.91	63.10	1.23
25% - quantile	0.16	2.25	1.00	3.25	79.38	21.89	1.20
75% - quantile	0.66	5.13	1.21	5.5	575.00	104.17	1.40

Trainees reached the population's mean performance test times within 2–5.5 days (mean = 3.63 days). The number of days trainees required to reach the end of the learning phase did not differ significantly and varied between 3 and 6 days (mean = 4.25 days).

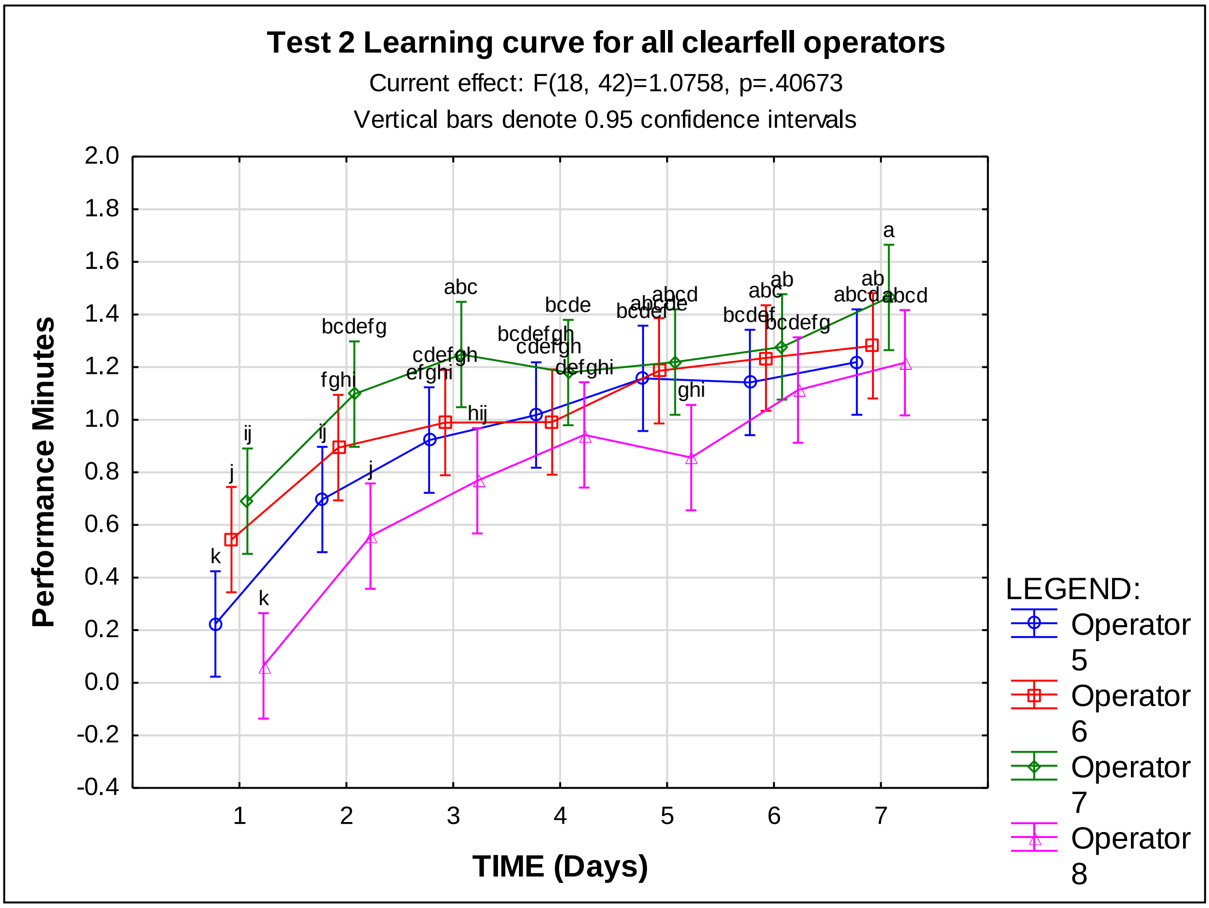

Figure 14: Test 2 Learning curve of all clear-fell operators (different letters indicate a significant difference in the means (p < 0.05))

At the beginning of the learning phase (day 1), the trainees started with a PL of between 30%– 85% (mean = 60%) lower than the PPL but managed to increase their performance by almost 298% on average. From the significant letters in Figure 14, it is evident that trainees' end performances did not differ significantly. All trainees ended with a PL of between 0%–25% higher than the PPL (mean 9% higher; median = 5% higher) with the inter-quartiles ranging between 0% (25th percentile) and 21% (75th percentile) higher than the PPL. Trainee No. 7 (above average skilled candidate according to psychometric test results) performed the best. He reached the end of his learning phase one day earlier than trainee No. 5 and 6, and three days earlier than trainee No. 8. Furthermore, trainee No. 7 started at a significantly (significant letters) higher PL than trainee No. 5 and 8 and ended with the highest PL (25% higher than trainee No. 5 and 6, and 15% higher than trainee No. 8). Even though trainee No. 8 started with the lowest PL, he managed to increase his PL to the second highest PL. This could be because trainee No. 8 is an above average skilled operator according to the psychometric test results and possesses the ability to improve his PL at a fast rate.

Summary

Trainee No. 7's results in Test 1 and Test 2 were contradictory. In Test 1, trainee No. 7 started and ended with the lowest PL and took the longest time to reach the end of his learning phase, ranking him as the worst trainee for Test 1. In Test 2, however, trainee No. 7 managed to start and end with the highest PL and took the shortest time to reach the end of his learning phase, ranking him as the best trainee for Test 2. The same conclusion is made for trainee No. 8, who did the best in Test 1 and the worst in Test 2 in terms of his start PL and end PL. Both trainees' No. 7 and 8 are above average candidates according to the psychometric test results. However, the psychometric tests did not give an indication of which clear-fell trainee could eventually be successful on the simulator due to contrasting results in Test 1 and 2 for two different trainees.

4.3.1.5 Overall result for all operators

Table 14 gives a summary of all the operators' average test results for Test 1 and Test 2 for thinning and clear-felling. Table 14 will eventually give an indication of the following for an average beginner operator in either thinning or clear-felling operations:

- the number of days an average harvesting operator will need to perform a simulator test up to the point where he is deemed fully experienced and skilled
- the expected starting performance, end performance and maximum performance with regards to the population's means performance (PPL) of 1.

Table 14: Summary of all operators' average test time performance results

Test time						
Operation	Test	PL start	PL = 1	PL end		PL max
			Days		Days	
Thinning	Test 1	0.29	7.75	1.24	12.75	1.29
Thinning	Test 2	0.36	6.50	1.28	11.50	1.28
Clear-fell	Test 1	0.54	5	1.28	7.5	0.94
Clear-fell	Test 2	0.40	3.63	1.19	5	1.28
Overall	Overall	0.39	5.72	1.24	9.2	1.19

Overall, an average beginner harvester operator will start at a PL of 60% lower than the PPL and end with a performance level of 24% higher than the PPL in 9.2 days (27.6 simulator test in total).

4.4 In-field operations

In this section, two methods of learning curve (I and II) calculation were conducted to explain how an operator increases his/her productivity as a function of tree volume over time and to be able to compare operators with one another. The first method, *Operator productivity learning curve (I)*, is used to demonstrate how an operator's productivity increases over time (months 1 – 12) as a logarithmic function of tree volume. This method gives an indication of how much (%) the productivity of each operator increases per month over different possible tree sizes. The second method, *Operator performance learning curve (II)*, is used to compare the operator's PL with one another and with the PPL. Furthermore, this method is used to test the effect of simulator training on the performance increase of an operator.

During the removal of outlier data points to ensure accurate learning curves, 65% of all stem records were removed from the dataset and 152 710 of the 442 188 stem records were used for further statistical analysis and productivity development calculations. The high percentage of outlier data removal is concerning. This can possibly be attributed to the unreliability of the on-board machine data logging system or even errors caused by the operators. Learning curves estimations were not possible for clear-felling operators No. 6

and 8 due to insufficient data. Therefore, all the thinning operators and clear-felling operators No. 5 and 7 is analysed and discussed.

4.4.1 Operator productivity learning curve (I)

4.4.1.1 Thinning operators (Operators No 1 – 4)

Operator 1:

Applying equations 4–15 that was derived from the logarithmic regression model of productivity as a logarithmic function of tree volume per month, the learning curve for Operator No. 1 is graphed for the purpose of productivity increase analysis over different tree volume classes (
Figure 15).

Work month: 1	Y = 58.9278+54.7264*log10(x)	(4)
Work month: 2	Y = 23.9626+14.4395*log10(x)	(5)
Work month: 3	Y = 28.8521+13.9781*log10(x)	(6)
Work month: 4	Y = 43.0225+23.4451*log10(x)	(7)
Work month: 5	Y = 39.0957+20.697*log10(x)	(8)
Work month: 6	Y = 66.2272+41.0255*log10(x)	(9)
Work month: 7	Y = 53.903+29.8782*log10(x)	(10)
Work month: 8	Y = 59.3984+34.7351*log10(x)	(11)
Work month: 9	Y = 64.6121+35.4348*log10(x)	(12)
Work month: 10	Y = 60.9985+33.1581*log10(x)	(13)
Work month: 11	Y = 75.2355+48.8977*log10(x)	(14)
Work month: 12	Y = 71.9169+39.5346*log10(x)	(15)

Where:

Y= Productivity ($m^3 \cdot PMH^{-1}$); and

X= Tree Volume (m^3).

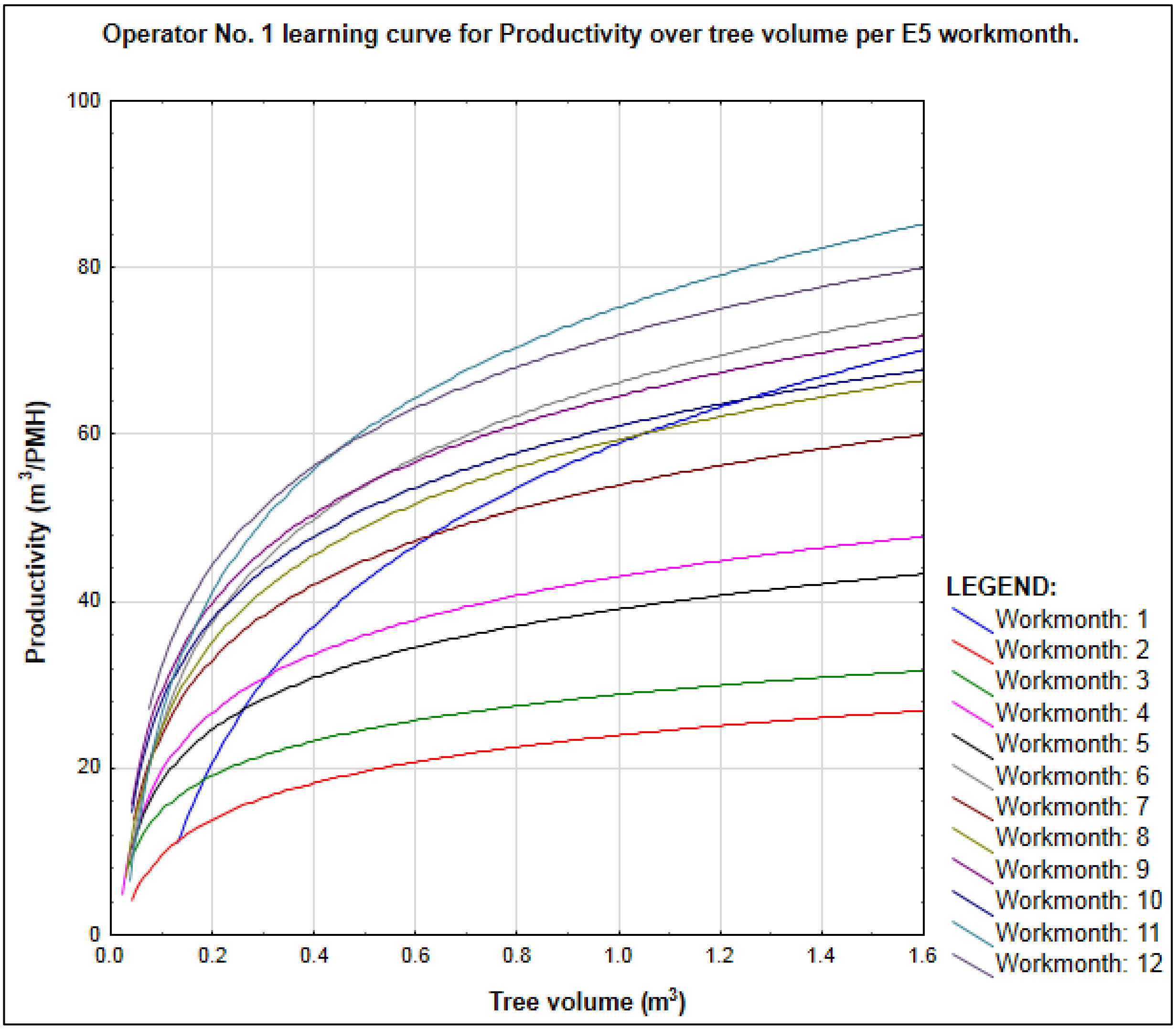

Figure 15: Learning curve I for Operator No. 1

Table 15 is constructed from Figure 15 to summarise the increase in productivity over different tree volumes for 12 work months. On average, Operator No.1 started with a productivity of 21.25 $m^3 \cdot PMH^{-1}$, ranging from 16 $m^3 \cdot PMH^{-1}$ with a tree size of 0.2 m^3, to a productivity of 25 $m^3 \cdot PMH^{-1}$ with a tree size of 1.4 m^3. Furthermore, Operator No.1 ended with an average productivity of 65.3 $m^3 \cdot PMH^{-1}$, ranging from 40 $m^3 \cdot PMH^{-1}$ with a tree size of 0.2 m^3 to 84 $m^3 \cdot PMH^{-1}$ with a tree size of 1.4 m^3. Operator No.1 increased his productivity with 207% on average over all tree sizes.

Table 15: Trainee 1's productivity progression for 12 months at varying tree volumes

Tree Volume (m^3) class measured at	Start Productivity ($m^3 \cdot PMH^{-1}$) (month 1)	End productivity ($m^3 \cdot PMH^{-1}$) (month 12)	Increase in productivity (%)
0.2	16	40	150
0.6	20	64	220
1	24	73	204
1.4	25	84	236
Overall	21.25	65.3	207

Operator 2:

With the use of Equations 39–50 that was derived from the logarithmic regression model of productivity as a logarithmic function of tree volume per month, the learning curve for Operator No.2 is visually graphed for the purpose of productivity increase analysis over different volume classes (Figure 16).

Work month: 1	Y = 29.0459+26.2893*log10(x)	(39)
Work month: 2	Y = 28.7097+19.053*log10(x)	(40)
Work month: 3	Y = 31.9778+17.5296*log10(x)	(41)
Work month: 4	Y = 43.6702+25.0394*log10(x)	(42)
Work month: 5	Y = 43.6615+25.5174*log10(x)	(43)
Work month: 6	Y = 60.463+37.5663*log10(x)	(44)
Work month: 7	Y = 52.7036+32.328*log10(x)	(45)
Work month: 8	Y = 47.6553+28.2842*log10(x)	(46)
Work month: 9	Y = 50.2486+29.731*log10(x)	(47)
Work month: 10	Y = 45.1178+25.124*log10(x)	(48)
Work month: 11	Y = 59.0114+38.6558*log10(x)	(49)
Work month: 12	Y = 60.87+40.4789*log10(x)	(50)

Where:

Y= Productivity ($m^3 \cdot PMH^{-1}$)

X= Tree Volume (m^3)

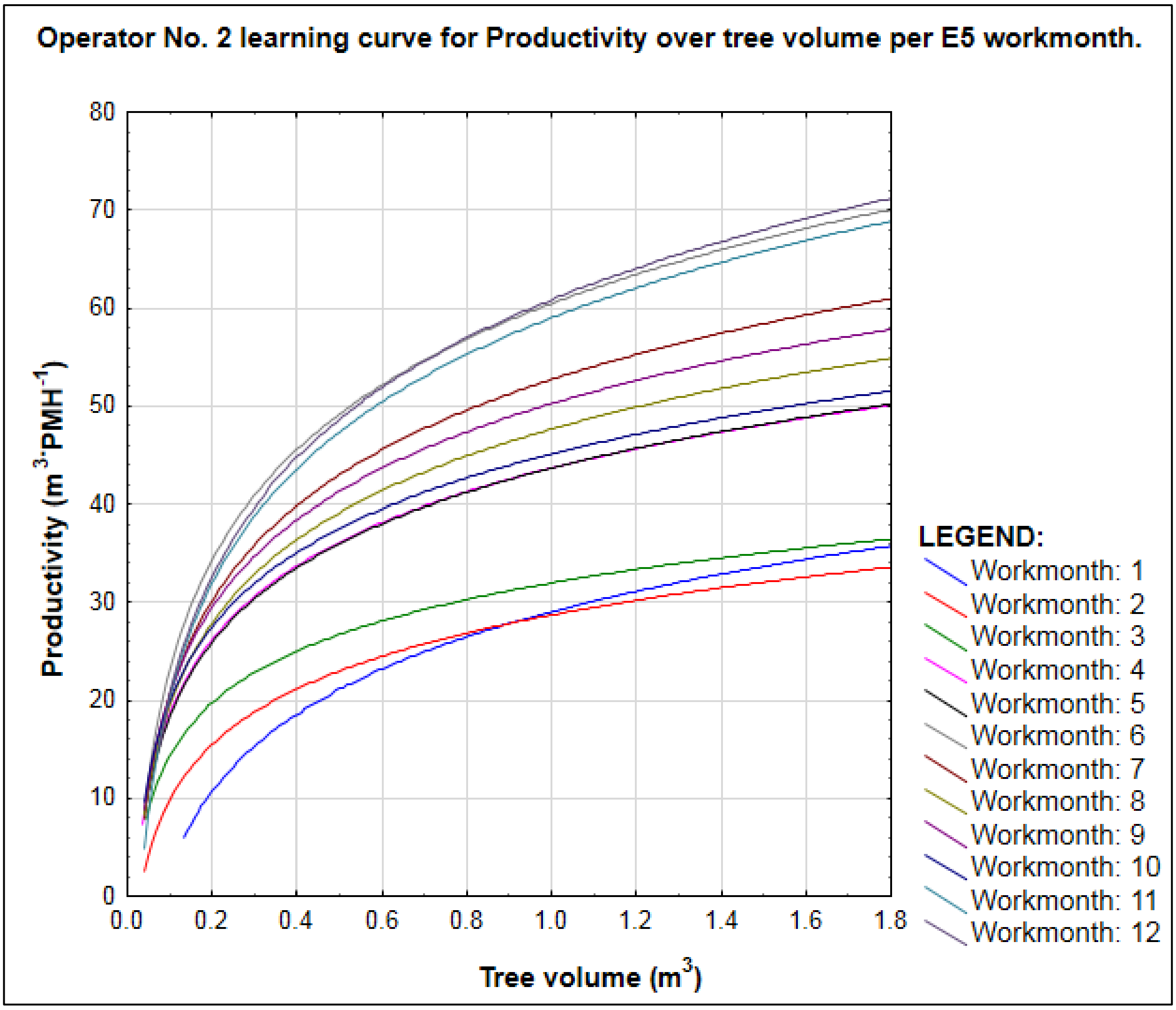

Figure 16: Learning curve I for Operator No. 2

Table 16 is constructed from Figure 16 to summarise the increase in productivity over different tree volumes for 12 work months. On average, Operator No. 2 started with a productivity of 25.8 $m^3 \cdot PMH^{-1}$, ranging from 10 $m^3 \cdot PMH^{-1}$ with a tree size of 0.2 m^3, to a productivity of 36 $m^3.PMH^{-1}$ with a tree size of 1.8 m^3. Furthermore, Operator No. 2 ended with an average productivity of 56.6 $m^3 \cdot PMH^{-1}$, ranging from 35 $m^3 \cdot PMH^{-1}$ with a tree size of 0.2 m^3, to 70 $m^3 \cdot PMH^{-1}$ with a tree size of 1.8 m^3. Operator No. 2 increased his productivity with 119% on average over all tree sizes (volumes).

Table 16: Summary of Operator No. 2's learning curve

Tree Volume (m^3) class measured at	Start Productivity ($m^3 \cdot PMH^{-1}$) (month 1)	End productivity ($m^3 \cdot PMH^{-1}$) (month 12)	Increase in productivity (%)
0.2	10	35	250
0.6	25	50	100
1	28	60	114
1.4	30	68	127
1.8	36	70	94
Overall	25.8	56.6	119

Operator 3:

With the use of Equations 51–62 that was derived from the logarithmic regression model of productivity as a logarithmic function of tree volume per month, the learning curve for Operator No. 3 is visually graphed for the purpose of productivity increase analysis over different volume classes (Figure 17).

Work month: 1 $Y = 51.6854 + 46.1097*\log10(x)$ (51)

Work month: 2 $Y = 50.2463 + 35.3741*\log10(x)$ (52)

Work month: 3 $Y = 47.1382 + 29.2584*\log10(x)$ (53)

Work month: 4 $Y = 47.684 + 28.1124*\log10(x)$ (54)

Work month: 5 $Y= 60.8087 + 37.5141*\log10(x)$ (55)

Work month: 6 $Y = 79.5766 + 50.1536*\log10(x)$ (56)

Work month: 7 $Y = 73.3875 + 46.2029*\log10(x)$ (57)

Work month: 8 $Y = 69.6289 + 42.2676*\log10(x)$ (58)

Work month: 9 $Y = 75.0749 + 45.8553*\log10(x)$ (59)

Work month: 10 $Y = 78.1693 + 48.7081*\log10(x)$ (60)

Work month: 11 $Y = 88.0656 + 58.6247*\log10(x)$ (61)

Work month: 12 $Y = 78.2039+40.0719*\log10(x)$ (62)

Where:

Y= Productivity ($m^3 \cdot PMH^{-1}$); and

X= Tree Volume (m^3).

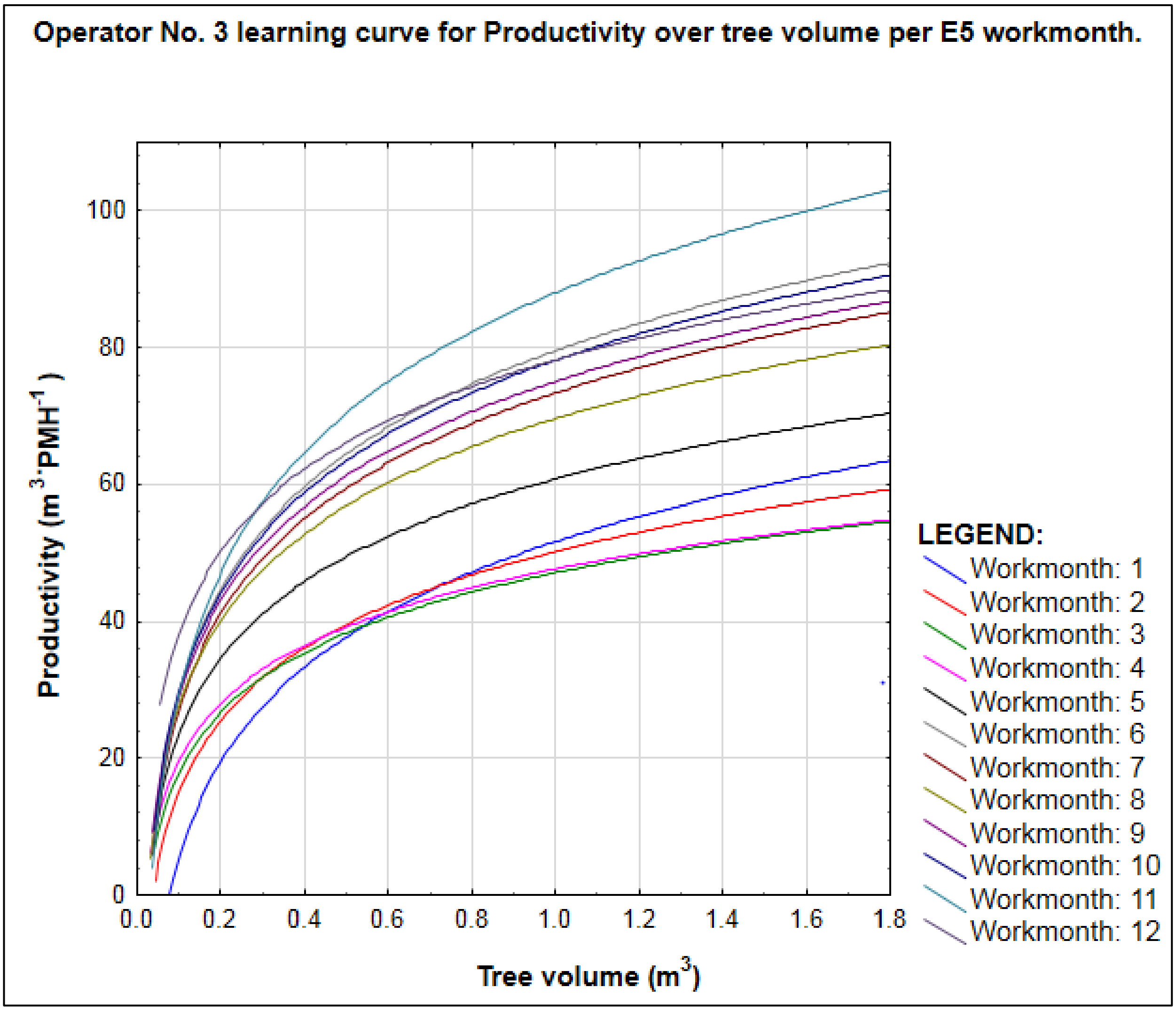

Figure 17: Learning curve I for Operator No.3

Table 17 is constructed from Figure 17 to summarise the increase in productivity over different tree volumes for 12 work months. On average, Operator No. 3 started with a productivity of 42.4 $m^3 \cdot PMH^{-1}$, ranging from 20 $m^3 \cdot PMH^{-1}$ with a tree size of 0.2 m^3, to a productivity of 52 $m^3 \cdot PMH^{-1}$ with a tree size of 1.8 m^3. Furthermore, Operator No. 3 ended with an average productivity of 82.6 $m^3 \cdot PMH^{-1}$, ranging from 50 $m^3 \cdot PMH^{-1}$ with a tree size of 0.2 m^3, to 104 $m^3 \cdot PMH^{-1}$ with a tree size of 1.8 m^3. Operator No. 3 increased his productivity with 94.8% on average over all tree sizes (volumes).

Table 17: Summary of Operator No. 3's learning curve

Tree Volume (m^3) class measured at	Start Productivity ($m^3 \cdot PMH^{-1}$) (month 1)	End productivity ($m^3 \cdot PMH^{-1}$) (month 12)	Increase in productivity (%)
0.2	20	50	150
0.6	40	75	87.5
1	50	88	76
1.4	50	96	92
1.8	52	104	100
Overall	42.4	82.6	94.8

Operator 4:

With the use of Equations 63–73 that was derived from the logarithmic regression model of productivity as a logarithmic function of tree volume per month, the learning curve for Operator No. 4 is visually graphed for the purpose of productivity increase analysis over different volume classes (Figure 18). Operator No. 3 did not do any work on the harvester during the 5th work month. There was no tree information available to draw a fit or derive an equation.

Work month: 1 Y = 29.1093+25.8554*log10(x) (63)

Work month: 2 Y = 32.5796+22.6058*log10(x) (64)

Work month: 3 Y = 27.8049+17.5706*log10(x) (65)

Work month: 4 Y = 28.5928+16.8845*log10(x) (66)

Work month: 5 Y = No fit not available because of invalid range of values

Work month: 6 Y = 44.3925+25.9341*log10(x) (67)

Work month: 7 Y = 44.3902+26.4768*log10(x) (68)

Work month: 8 Y = 42.9009+24.4646*log10(x) (69)

Work month: 9 Y = 41.3818+23.3033*log10(x) (70)

Work month: 10 Y = 50.3053+31.0116*log10(x) (71)

Work month: 11 Y = 67.167+47.3368*log10(x) (72)

Work month: 12 Y = 62.0175+37.2191*log10(x) (73)

Where:

Y= Productivity ($m^3 \cdot PMH^{-1}$); and

X= Tree Volume (m^3).

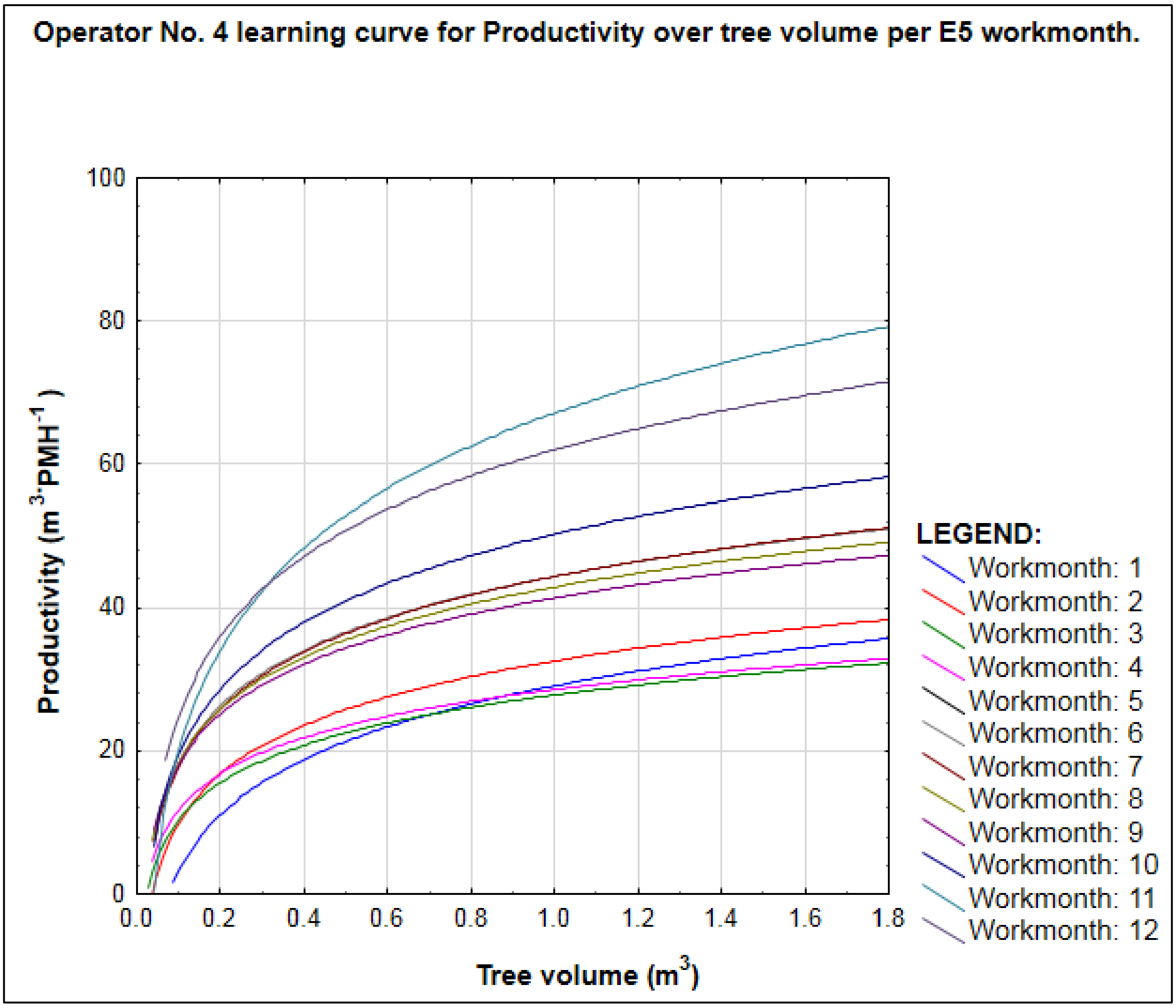

Figure 18: Learning curve I for Operator No. 4

Table 18 is constructed from Figure 18 to summarise the increase in productivity over different tree volumes for 12 work months. On average, Operator No. 4 started with a productivity of 27.6 $m^3 \cdot PMH^{-1}$, ranging from 10 $m^3 \cdot PMH^{-1}$ with a tree size of 0.2 m^3, to a productivity of 36 $m^3 \cdot PMH^{-1}$ with a tree size of 1.8 m^3. Furthermore, Operator No. 4 ended with an average productivity of 61.6 $m^3 \cdot PMH^{-1}$, ranging from 32 $m^3 \cdot PMH^{-1}$ with a tree size of 0.2 m^3, to 80 $m^3 \cdot PMH^{-1}$ with a tree size of 1.8 m^3. Operator No. 4 increased his productivity with 123% on average over all tree sizes (volumes).

Table 18: Summary of Operator No. 4's learning curve

Tree Volume (m^3) class measured at	Start Productivity ($m^3 \cdot PMH^{-1}$) (month 1)	End productivity ($m^3 \cdot PMH^{-1}$) (month 12)	Increase in productivity (%)
0.2	10	32	220
0.6	28	56	100
1	30	68	126.7
1.4	34	72	111.7
1.8	36	80	122
Overall	27.6	61.6	123

4.4.1.2 Clear-fell operators (Operators No. 6 and 8)

After all the clear-fell data was analysed, only two of the four operators' learning curves were revealed since insufficient data was available for clear-fell operators' No. 6 and 8.

Operator 5:

With the use of Equations 86–97 that was derived from the logarithmic regression model of productivity as a logarithmic function of tree volume per month, the learning curve for Operator No. 5 is visually graphed for the purpose of productivity increase analysis over different volume classes (Figure 19).

Work month: 1 $Y = 19.9465+18.3703*\log10(x)$ (86)

Work month: 2 $Y = 31.8843+32.9395*\log10(x)$ (87)

Work month: 3 $Y = 44.0709+51.1218*\log10(x)$ (88)

Work month: 4 $Y = 48.7052+53.7341*\log10(x)$ (89)

Work month: 5 $Y = 48.0732+47.8284*\log10(x)$ (90)

Work month: 6 $Y = 57.0747+65.3992*\log10(x)$ (91)

Work month: 7 $Y = 55.1391+58.8195*\log10(x)$ (92)

Work month: 8 $Y = 57.5502+59.6893*\log10(x)$ (93)

Work month: 9 $Y = 53.1953+51.749*\log10(x)$ (94)

Work month: 10 $Y = 56.2389+58.1319*\log10(x)$ (95)

Work month: 11 $Y = 53.4744+49.5718*\log10(x)$ (96)

Work month: 12 $Y = 53.0598+47.8012*\log10(x)$ (97)

Where:

Y= Productivity ($m^3 \cdot PMH^{-1}$); and

X= Tree Volume (m^3).

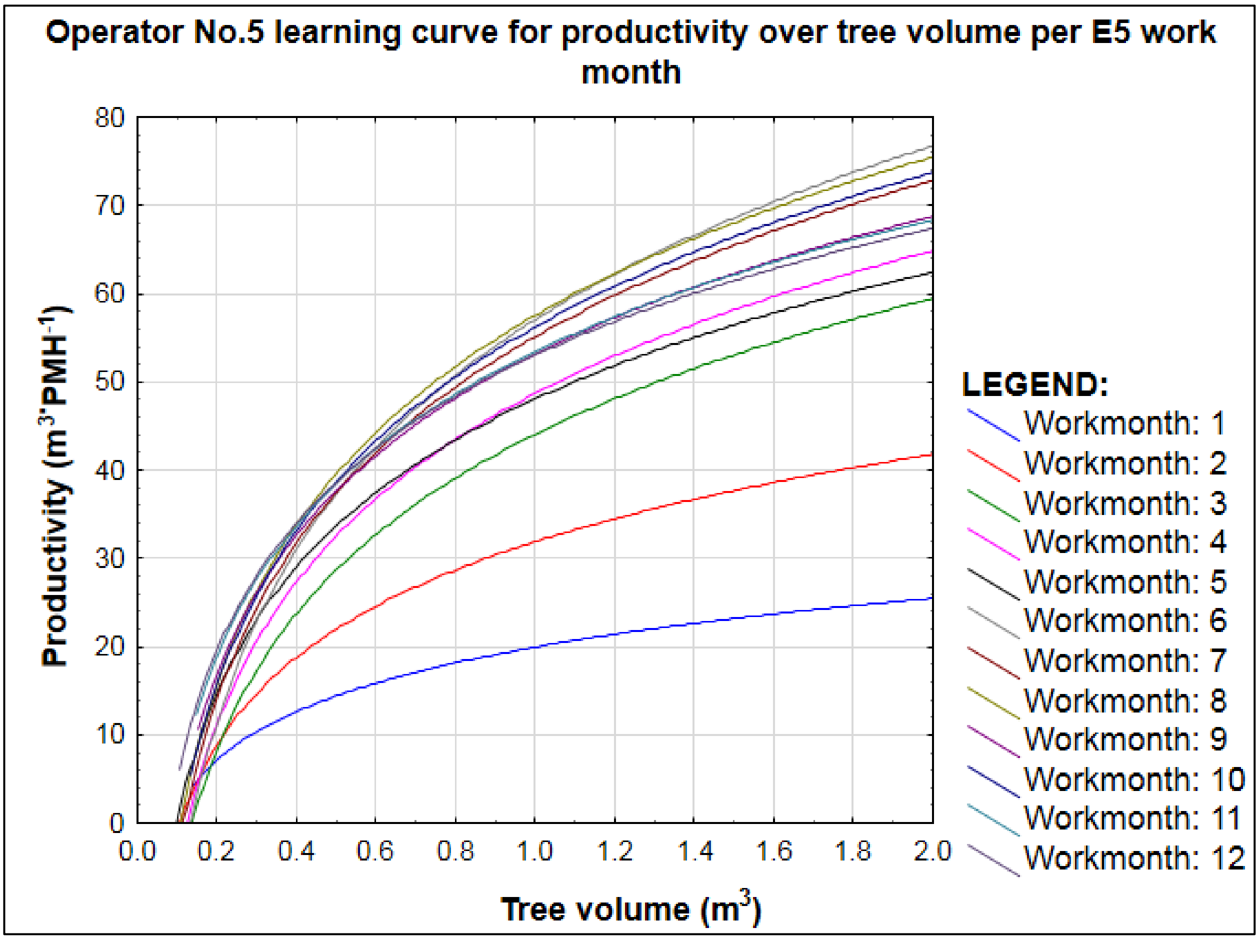

Figure 19: Learning curve I for Operator No. 5

Table 19 is constructed from Figure 19 to summarise the increase in productivity over different tree volumes for 12 work months. On average, Operator No. 5 started with a productivity of 18.25 $m^3 \cdot PMH^{-1}$, ranging from 8 $m^3 \cdot PMH^{-1}$ with a tree size of 0.2 m^3, to a productivity of 25 $m^3 \cdot PMH^{-1}$ with a tree size of 2 m^3. Furthermore, Operator No. 5 ended with an average productivity of 53.5 $m^3 \cdot PMH^{-1}$, ranging from 20 $m^3 \cdot PMH^{-1}$ with a tree size of 0.2 m^3, to 76 $m^3 \cdot PMH^{-1}$ with a tree size of 2 m^3. Operator No. 5's productivity increased with 193% on average over all tree sizes (volumes).

Table 19: Summary of Operator No. 5's learning curve

Tree Volume (m^3) class measured at	Start Productivity ($m^3 \cdot PMH^{-1}$) (month 1)	End productivity ($m^3 \cdot PMH^{-1}$) (month 12)	Increase in productivity (%)
0.2	8	20	150
0.8	16	50	212.5
1.4	24	68	183
2	25	76	204
Overall	18.25	53.5	193

Operator No. 7:

With the use of Equations 98–108 that was derived from the logarithmic regression model of productivity as a logarithmic function of tree volume per month, the learning curve for Operator No. 7 is visually graphed for the purpose of productivity increase analysis over different volume classes (Figure 20). However, Operator No. 7 only had 11 months of machine work data. Nonetheless, it was sufficient for the calculation and demonstration of the operator's learning curve.

Work month: 1 $$Y = 56.0497+59.629*\log10(x) \quad (98)$$

Work month: 2 $$Y = 61.5203+67.4716*\log10(x) \quad (99)$$

Work month: 3 $$Y = 60.1209+59.3465*\log10(x) \quad (100)$$

Work month: 4 $$Y = 55.3052+47.7333*\log10(x) \quad (101)$$

Work month: 5 $$Y = 73.71+75.2891*\log10(x) \quad (102)$$

Work month: 6 $$Y = 70.6234+70.2824*\log10(x) \quad (103)$$

Work month: 7 $$Y = 69.3578+68.2533*\log10(x) \quad (104)$$

Work month: 8 $$Y = 70.8588+69.6594*\log10(x) \quad (105)$$

Work month: 9 $$Y = 67.1431+63.3332*\log10(x) \quad (106)$$

Work month: 10 $$Y = 70.5223+68.6896*\log10(x) \quad (107)$$

Work month: 11 $$Y = 60.7754+50.6679*\log10(x) \quad (108)$$

Where:

Y= Productivity ($m^3 \cdot PMH^{-1}$); and

X= Tree Volume (m^3).

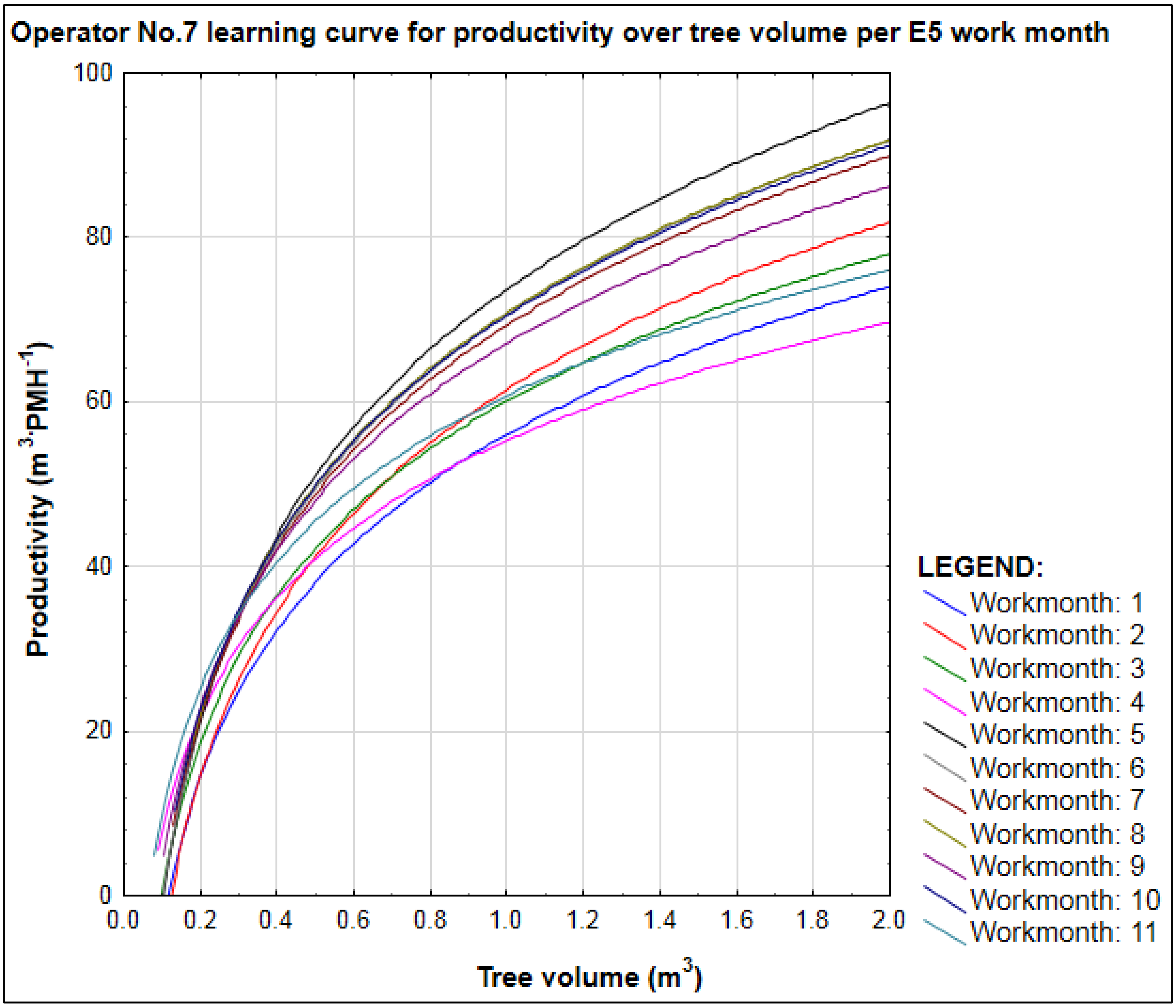

Figure 20: Learning curve I for Operator No. 7

Table 20 is constructed from Figure 20 to summarise the increase in productivity over different tree volumes for 12 work months. On average, Operator No. 7 started with a productivity of 49.3 $m^3 \cdot PMH^{-1}$, ranging from 15 $m^3 \cdot PMH^{-1}$ with a tree size of 0.2 m^3, to a productivity of 68 $m^3 \cdot PMH^{-1}$ with a tree size of 2 m^3. Furthermore, Operator No.7 ended with an average productivity of 68.3 $m^3 \cdot PMH^{-1}$, ranging from 24 $m^3 \cdot PMH^{-1}$ with a tree size of 0.2 m^3, to 96 $m^3 \cdot PMH^{-1}$ with a tree size of 2 m^3. Operator No. 7 increased his productivity with 38.6% on average over all tree sizes (volumes).

Table 20: Summary of Operator No. 7's learning curve

Tree Volume (m^3) class measured at	Start Productivity ($m^3 \cdot PMH^{-1}$) (month 1)	End productivity ($m^3 \cdot PMH^{-1}$) (month 12)	Increase in productivity (%)
0.2	15	24	60
0.8	50	68	36
1.4	64	85	32.8
2	68	96	41.1
Overall	49.3	68.3	38.6

4.4.1.3 Operators' productivity increase due to learning

Thinning operators

Table 21 shows that large differences occur between operators' increase in productivity. Operator No. 2 had the best productivity increase (212%), which is more than double that of the operator with the worst increase in productivity (Operator No. 3; 101.1%). Thus, it is necessary to calculate each operator's shape of the learning curve by using the monthly productivity models derived from Statistica in the previous section. This explains the differences each operator experiences during the learning phase on a harvester.

Table 21: Summary of productivity increases of thinning operators 1–4 over tree volume classes

Increase in productivity per volume class per operator						
Operator	0.2 m^3	0.6 m^3	1 m^3	1.4 m^3	1.8 m^3	Average
1	150%	87.5%	100%	100%	102%	107.9%
2	150%	220%	250%	204%	236%	212%
3	150%	87.5%	76%	92%	100%	101.1%
4	220%	100%	126.7%	111.7%	122%	156.1%
Average	167.5%	123.75%	138.2%	126.9%	140%	

Clear-fell Operators

Large differences occur between the two clear-fell operators' mean increase in productivity. Operator No. 5 had the best mean productivity increase (193%), which is more than four times that of operator No. 7 with an mean increase in productivity of 38.6%. Table 22 shows that there as small differences within each thinning operator's increase in productivity between tree sizes over the 12-month period, such as operator No. 7. Thus, it is necessary to calculate each operator's shape of the learning curve by using the productivity model derived from Statistica. This explains the differences each operator experiences during the learning phase on a harvester.

Table 22: Summary of productivity increases of clear-fell operators 5 and 7 over tree volume classes

Increase in productivity per volume class per operator					
Operator	0.2 m^3	0.8 m^3	1.4 m^3	2 m^3	Average
5	150	212.5	183	204	193
7	60	36	32.8	41.1	38.6

4.4.2 Operator performance learning curve (II)

4.4.2.1 Thinning operators:

Table 23 lists the monthly calculated productivity at mean tree volume and relative performance that each operator obtained for months 1 to 12. By using these data, the learning curves are explained and operator data is compared with regards to:

- Start PL
- End PL
- Increase in performance (%)
- Time (months) it took an operator to reach the PPL

Table 23: Monthly productivity and performance for each thinning operator

Month	Operator 1		Operator 2		Operator 3		Operator 4		Overall	
	Prod (m^3 pmh^{-1})	Perform	Prod (m^3 pmh^{-1})	Perform	Prod (m^3 pmh^{-1})	Perform	Prod (m^3 pmh^{-1})	Perform	Prod (m^3 pmh^{-1})	Perform
1	18.17	0.65	9.47	0.34	17.35	0.62	9.85	0.35	13.71	0.49
2	13.21	0.47	14.52	0.52	23.90	0.85	15.74	0.56	16.84	0.60
3	18.44	0.66	18.92	0.67	25.35	0.90	14.72	0.52	19.36	0.69
4	25.56	0.91	25.02	0.89	26.75	0.95	16.02	0.57	23.34	0.83
5	23.68	0.84	24.66	0.88	32.87	1.17	NO WORK	NO WORK	27.07	0.96
6	35.67	1.27	32.49	1.16	42.23	1.50	25.08	0.89	33.87	1.21
7	31.65	1.13	28.63	1.02	38.98	1.39	24.67	0.88	30.98	1.10
8	33.53	1.19	26.59	0.95	38.15	1.36	24.68	0.88	30.74	1.09
9	38.22	1.36	28.11	1.00	40.93	1.46	24.03	0.86	32.82	1.17
10	36.30	1.29	26.41	0.94	41.90	1.49	27.21	0.97	32.95	1.17
11	38.82	1.38	30.22	1.08	44.41	1.58	31.91	1.14	36.34	1.29
12	42.47	1.51	30.72	1.09	48.36	1.72	34.30	1.22	38.96	1.39

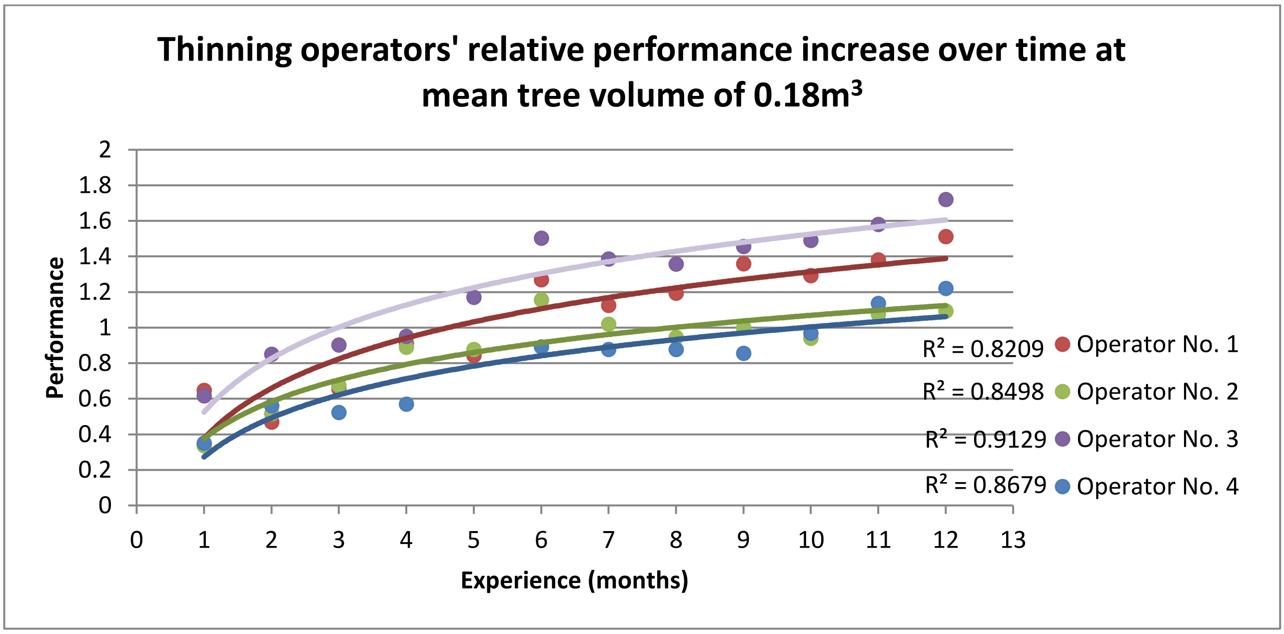

Figure 21: Thinning operators' learning curve II at mean tree volume (0.18 m^3)

From Figure 21 it is evident that all operators will have some degree of increase in performance after 12 months of effective harvester work. However, this study is interested in the *learning phase* of the operators, which is defined as the first rapid learning at the beginning of the learning curve. Table 24 is constructed from Figure 21 to summarise and explain the learning curve of each operator and to compare their results.

Table 24: Facts derived from Figure 21 for each thinning operator's learning curve II

Thinning operators							
Operator	PL start	PL = 1	PL end		Increase PL Overall	Increase PL Per month	PL max
		Month		Months	%	%	
1	0.5	5	1.5	12	200	16.67	1.5
2	0.3	6	1.15	6	283.33	47.22	1.15
3	0.62	5	1.5	6	141.93	23.66	1.72
4	0.35	10	1.22	12	248.57	20.71	1.22
Arithmetic mean	0.44	6.50	1.34	9.00	218.46	27.06	1.40
Median	0.43	5.50	1.36	9.00	224.29	22.19	1.36
25% - quantile	0.31	5.00	1.17	6.00	156.45	17.68	1.17
75% - quantile	0.59	9.00	1.50	12.00	274.64	41.33	1.67

All thinning operators reached a PL of 1 within the 12 months of harvesting work. On average, these thinning operators increased their performance by 218% (median = 224, Q1 = 156, Q3 = 274) ranging from 142% to 283%. Operator No. 3 had the lowest performance increase since he started at the highest PL (0.6), making him the best beginner operator. He did not have as much to learn compared to the other thee operators. Operator No. 2 had the highest performance increase over the 12 months as he started with the lowest PLstart (0.3) and had much to gain over 12 months. The average duration of a thinning operator's learning curve is nine months (ranging between six and 12 months). The PLs of Operator No. 2 and 3 both started to stagnate after six months of work, whereas the PLs of Operator No. 1 and 4 could still increase after 12 months of work. However, this cannot be tested as the data collection period for this study is only 12 months of harvested work.

4.4.2.2 Clear-fell operators

Table 25 lists the monthly calculated productivity at mean tree volume and relative performance that each operator obtained for months one to 12. By using this data, the learning curves were explained and operators were compared in terms of:

- Start PL
- End PL
- Increase in performance (%)
- Time (months) it took an operator to reach the PPL

Table 25: Monthly productivity and relative performance for each clear-fell operator

Month	Op 5		Op 7		Overall	
	Prod (m^3 pmh^{-1})	Performance	Prod ($m^3 \cdot PMH^{-1}$)	Performance	Prod ($m^3 \cdot PMH^{-1}$)	Performance
1	15.03	0.36	40.09	0.97	27.56	0.67
2	23.07	0.56	43.46	1.05	33.27	0.81
3	30.39	0.74	44.24	1.07	37.31	0.91
4	34.33	0.83	42.53	1.03	38.43	0.93
5	35.27	0.86	53.56	1.30	44.42	1.08
6	39.57	0.96	51.82	1.26	45.69	1.11
7	39.40	0.96	51.09	1.24	45.25	1.10
8	41.58	1.01	52.22	1.27	46.90	1.14
9	39.35	0.95	50.19	1.22	44.77	1.09
10	40.68	0.99	52.14	1.27	46.41	1.13
11	40.21	0.98	47.22	1.15	43.71	1.06
12	40.27	0.98	NO WORK	NO WORK	40.27	0.98

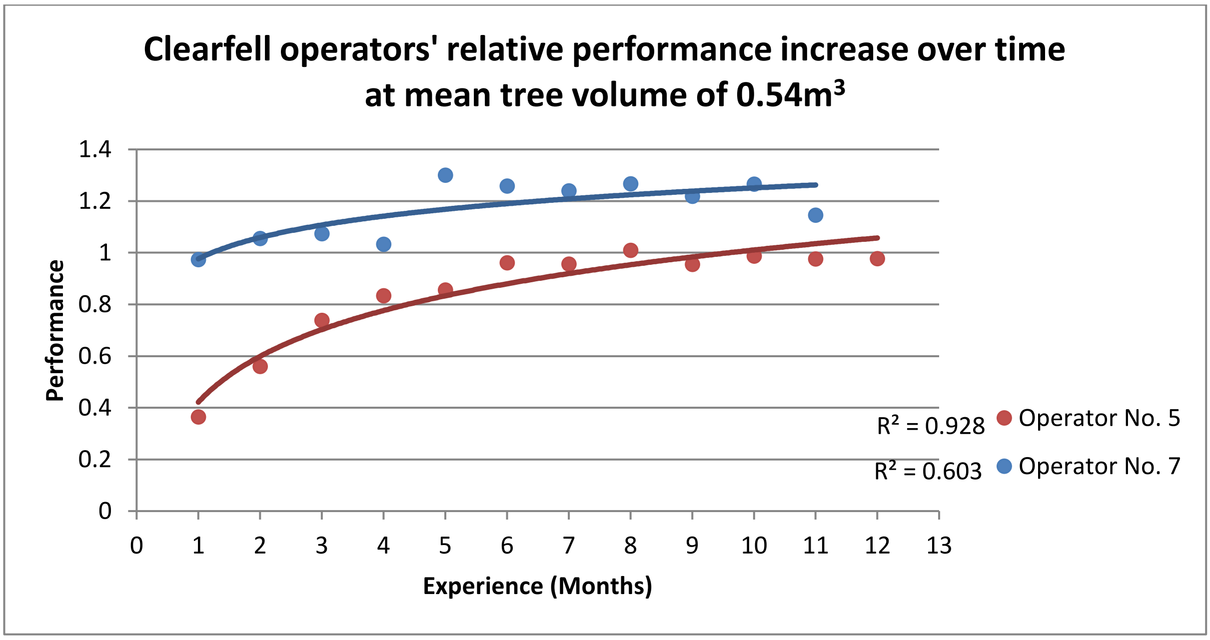

Figure 22: Clear-fell operators' learning curve II at mean tree volume (0.54 m^3)

Only Operator No. 5 and 7's learning curves were available due to insufficient data for the other operators. Thus, for Table 26, it is not possible to calculate a quantile value from a range of only two values. Therefore, only the range and means for each operator's results will be discussed. From Figure 22 it is evident that all clear-fell operators will have some degree of increase in performance after 12 months of effective harvester work. However, this study is interested in the *learning phase* of the clear-fell operators, which is defined as the first rapid learning at the beginning of the learning curve. Table 26 was constructed from Figure 22 to provide an explanation for the learning curve of each respective clear-fell operator, and to compare operator's results.

Table 26: Facts derived from Figure 22 for each operator's learning curve II

Thinning operators							
Operator	PL start	PL = 1	PL end		Increase PL		PL max
					Overall	Per month	
		Month		Months	%	%	
5	0.36	8	1.01	8	176.88	22.11	1.01
7	0.97	1	1.29	5	32.58	6.516	1.29
Arithmetic mean	0.67	4.50	1.15	6.50	104.73	14.31	1.15
Median	0.67	4.50	1.15	6.50	104.73	14.31	1.15

Both clear-fell operators reached a PL of 1 within the 12 months of harvesting work. On average, these clear-fell operators increased their performance by 104.73%, ranging from 32.58% to 176.88%. Operator No. 5 reached his maximum PL after eight months, after which the PL started to stagnate and create a plateau. The PL of Operator No. 5 showed the greatest increase as he started at the lowest PL and had much to gain over time. Operator No. 5's performance increased very little as he started with a very high PL of 0.97 and ended with a PL of 1.29, making him the better operator of the two. It can be assumed that he is a very skilled operator who started with a very high PL and did not have much to gain. The average duration of a clear-fell operator's learning curve is 6.5 months (ranging between five and eight months). The PLs of Operators No. 5 and 8 both started to stagnated after six months of work.

5 Discussion

5.1 Current trend of mechanised harvesting (MH) systems in South Africa

When comparing the results of this survey to the 2007 survey (Längin & Ackerman, 2007), there is a trend of moving away from motor-manual and semi-mechanised harvesting operations to mechanised systems. This was confirmed by Strandgard *et al.* (2013). In 2007, motor-manual harvesting operations were predominant (used 65% of the time) with manual operations contributing to only 9.5%, semi-mechanised operations to 19.5% and fully mechanised CTL operations to 6.4% (Längin & Ackerman, 2007). When compared to the current situation (Table 7), fully mechanised CTL operations are dominant and used in 57% of cases on average, while motor-manual harvesting operations are used 43% of the time on average. The survey did not investigate the usage of manual and semi-mechanised harvesting operations. As mentioned by Längin and Ackerman (2007) and Strandgard *et al.* (2013), mechanised operations are being used more regularly in South Africa, and, as such, is following a trend in forest industries across the globe. Concerning the seven companies' FMH operations, 64% of their sawtimber area is harvested by means of purpose-built machines and 36% by excavator-based machines. Furthermore, 68% of their pulpwood areas are harvested by means of purpose-built machines and 32% by excavator-based machines.

On average, the seven company's surveyed used contractor-based (outsourced) operations 82% of the time, while in-house (in-sourced) operations were used 18% of the time. This is very similar to the results of the 2007 survey where Längin and Ackerman (2007) reported that 88% of all harvesting operations are outsourced. According to Khosa (2000), the reasons why companies outsource their forest operations include:

- Reducing responsibilities and costs
- Downsizing of the number of direct employees
- Creating jobs
- Improving efficiency and response time to product demand
- Allowing companies to focus on core business

5.2 Effect of operator selection on simulator test results

From Table 27, some operators, either in thinnings or clear-felling, have similar overall psychometric test results. In this study, it is assumed that trainees with good psychometric test results could eventually have good simulator performance test results.

Table 27: Operator selection and simulator test result summary

Trainee	Overall Psychometric result	Simulator test results					
		Test1			Test2		
		Start PL	End PL	Days to end PL	Start PL	End PL	Days to end PL
1	A	0	1.3	16	0.55	1.4	6
2	A	0.19	1.25	16	0.3	1.1	6
3	A	0.79	1.3	7	0.25	1.4	7
4	B	0.19	1.1	16	0.35	1.2	6
5	A	0.5	1.35	7	0.2	1.15	4
6	B	0.65	1.2	10	0.55	1.2	4
7	A	0.4	1.2	10	0.7	1.2	3
8	A	0.6	1.35	10	0.15	1.2	6

This assumption was proven to be true with regards to the thinning operations. From Table 27, trainees' No. 1, 2 and 3 obtained an "A" overall psychometric test result. The start PL, end PL and days to reach the end PL of these three trainees varied dramatically due to unknown reasons. However, in both simulator tests, trainees No. 1 and 3 ("A" candidates) preformed the best of the four operators, as predicted from their psychometric tests results. In both tests, they managed to end with the highest PL. Furthermore, trainee No. 4 ("B" candidate) had the lowest end PL for Test 1 and second lowest PL for Test 2. This could be explained by his overall "B" psychometric test result. Therefore, trainees with above average ("A") psychometric test results performed better when compared to trainees with below average ("B") psychometric test results.

When clear-fell operations are considered, the assumption that trainees with good psychometric test results could eventually have good simulator performance test results was shown to be false as trainees' No. 7 and 8 obtained contrasting results in Test 1 and 2. In Test 1, trainee No. 7 started and ended with the lowest PL and took the longest time to reach the end of his learning phase, ranking him as the worst trainee for Test 1. In Test 2, however, trainee No. 7 managed to start and end with the highest PL and took the shortest time to reach the end of his learning phase, ranking him as the best trainee for Test 2. The same conclusion is made for trainee No. 8 who did the best in Test 1 and the worst in Test 2 in terms of his start PL and end PL. Both trainees' No. 7 and 8 are above average candidates according to the psychometric test results. Therefore, trainees with above average ("A") psychometric test results perform better and worse when compared to the below average trainee No. 6 ("B"). This could possibly ascribed to the small sample size and an absence of competition between the two operators (competition was more prevalent between four operators).

Ovaskainen (2009) found that a productive operator is not solely explained by one cognitive ability; instead, the mastering of different kinds of abilities seemed more important. With regards to the thinning and clear-felling operations, trainees' No. 3 and 6 performed the best in terms of their PLstart, PLend and increase in PL for the simulator results. The industrial psychologist who performed the psychometric tests indicated that trainees' No. 3 and 6 both exhibit above average concentration, attention and ability to detect small but important changes in their environment and their visual recognition and visual acuities are also above average. Therefore, these psychometric abilities appears to be important in selecting above average, successful simulator trainees. This corresponds with the findings of Parise (2004), Ovaskainen (2009), Tervo *et al.* (2010) and Häggström (2015) who listed the following as important psychometric abilities for an successful operator:

- Memory function
- Non-verbal deduction
- Spatial perception
- Coordination
- Concentration
- Motivation
- Decision-making
- Pattern recognition
- Planning capacity

- Logic reasoning

According to the findings of this study, psychometric tests are good measures for selecting trainees that will be able to either start at a high PL or more than double their PL over a short period. However, large inter-individual differences (due to unknown reasons) between trainees with significantly similar psychometric results are shown in Table 10, Table 11, Table 12 and Table 13.

5.2.1 Simulator learning curve

Thinning trainees

On average, a thinning trainee would start at a PL of 0.33 relative to the PPL of 1 and exceed the PPL in seven days. Furthermore, the learning curve of an average thinning trainee would proceed for 12 days as they increase their performance by 23% per day to add up to a total increase in performance of 294%. It can be assumed that a thinning trainee should only have to complete 36 test attempts (three tests per day) for a single test assessment before moving on to the next test assessment.

Clear-fell trainees

On average, a clear-fell trainee would start at a PL of 0.49 relative to the PPL of 1 and exceed the PPL in four days. Furthermore, the learning curve of an average clear-fell trainee operator would proceed for six days as they increase their performance by 40% per day to add up to a total increase in performance of 245%. Therefore, it can be assumed that a clear-fell trainee should only complete 18 test attempts (three tests per day) for a single test assessment before moving on to the next test assessment.

Overall

The results of this study show that, on average, a harvester trainee operator will start at a PL of 60% lower than the PPL and end with a performance level of 24% higher than the PPL. Furthermore, an average trainee would increase his performance by 269% with regards to his PLstart over a period of 9.2 days of efficient simulator training (Table 14). Due to this high percentage increase in performance, it can be assumed that all trainees are highly skilled and whose natural abilities suit the work of productive harvester operators. This is similar to the finding of Purfürst (2010) who found that beginner operators working in-field on a harvester machine to start at a PL of 44% below the PPL and increase their performance by 200% on average.

5.3 Operators' productivity increase over tree size classes due to learning

Thinning operators

Large differences occur between the thinning operators' mean increase in productivity. Operator No. 2 had the best mean productivity increase (212%), which is more than double that of the operator with the worst mean increase in productivity (Operator No. 3; 101.1%). Table 21 shows that there are small differences within each thinning operator's increase in productivity between tree sizes over the 12 month period, such as operator No. 1. Therefore it may be assumed that a thinning operator would gain the same amount of productivity increase over different tree sizes.

Clearfell Operators

Large differences occur between the two clear-fell operators' mean increase in productivity. Operator No. 5 had the best mean productivity increase (193%), which is more than four times that of operator No. 7 with an mean increase in productivity of 38.6%. Table 22 shows that there as small differences within each thinning operator's increase in productivity between tree sizes over the 12-month period, such as operator No. 7. Therefore, it may be assumed that a clear-fell operator would gain the same amount of productivity increase over different tree sizes.

5.4 Productivity increase at mean tree sizes

The results of this study indicate that thinning operators worked with an average tree size of 0.18m^3 during the 12 month period, where they started at an productivity of 13.71 $m^3 \cdot PMH^{-1}$ (month 1) and managed to increase their productivity at month 12 to 38.96 $m^3 \cdot PMH^{-1}$ (mean = of 28.8 $m^3 \cdot PMH^{-1}$ overall). Clear-fell operators worked with an average tree size of 0.54 m^3 during the 12 month period, where they started at a productivity of 27.5 $m^3 \cdot PMH^{-1}$ (month 1) and managed to increase their productivity at month 12 to 43.75 $m^3 \cdot PMH^{-1}$ (mean = of 41.9 $m^3 \cdot PMH^{-1}$ overall). These findings fall within the array of values reported by several other researchers ranging from 13.5 $m^3 \cdot PMH^{-1}$ to 60.5 $m^3 \cdot PMH^{-1}$ under various harvesting conditions (Kellog & Bettinger, 1994; McNeel & Rutherford, 1994; Tufts, 1997; Jiroušek *et al.*, 2007; Alam *et al.*, 2014; Eriksson & Lindroos, 2014; Martin, 2016; Williams & Ackerman, 2016). Furthermore, these beginner harvester operators managed to work at a greater mean productivity with smaller mean tree sizes compared to the operators in the studies mentioned above. This could be as a result of structured operator selection, simulator training, in-field machine training and support these beginner operators had during the course of this study.

5.5 Machine learning curve

The results of this study indicate that thinning operators would need 6–12 months to reach the end of their learning phase, with nine months being the average (Table 24). Furthermore, from the only two clear-fell operators that revealed a learning curve in this study, Operator No. 5 reached the end of his learning phase at month five, while Operator No. 7 reached his at month eight (Table 26). These findings fall slightly outside the array of values reported by Purfürst (2010) (6–11 months; mean = 9 months) and Calabrese (2000) (mean = 8 months). All operators in their respective operations have equal experience and exactly the same training background. Therefore, as stated by Olivera *et al.* (2016), variation between operator performances and learning curves are not necessarily explained by the differences in training nor the extent of experience obtained. However, these differences could rather be a result of different operator work techniques (Alam *et al.*, 2014) or levels of motivation and human abilities (Purfürst & Erler, 2011).

Of the six harvester operator that revealed a learning curve, three operators more than doubled their performance. Operator No. 7's performance increased the least (37%) as he started at a very high PL compared to the PPL and did not have much to gain over the course of a 12 month training period. On average, a thinning operator would increase his performance by 218% (Table 24), while a clear-fell operator would increase his by 104% (Table 26). The findings for thinning and clear-fell operations are similar to the findings of Purfürst (2010) and Purfürst and Erler (2011) (200% increase) and higher for both operations when compared to the findings of Heinimann (2001b) (50% increase).

5.6 Effect of simulator training on harvester learning curve

Ovaskainen (2009) proved that simulator-based training has a direct positive effect on the learning curve of operators working in-field on harvesters, in other words, their learning curves are shortened.

Thinning operators

The machine learning curve analysis revealed that thinning Operator No. 3 performed the best of the four operators because he started at a significantly higher PL than the others and his learning curve ended significantly earlier than that of the others. Furthermore, Operator No. 3 performed the best on the simulator for Test 1 as he started at a significantly higher PL than the rest and his simulator learning ended nine days earlier than that of the rest. Therefore, simulator training results provide an indication of how well an operator would operate on a machine since outcomes between simulator training and machine training are the similar. With regards to psychometric test results, Operator No. 3 exhibit above average concentration, attention and ability to detect small but important changes in his environment, and his visual recognition and visual acuities are also above average. These psychometric abilities can be the reason why he did significantly better that the rest of the operators.

Clear-fell operators

Operator No. 7’s machine learning performance increased very slightly as he started with a very high PL of 0.97 and ended with a PL of 1.29 relative to the PPL of 1.0. These outcomes of machine learning are similar to those he achieved on the simulator Test 2. With regards to simulator Test 2, Operator No. 7 managed to start at a significantly higher PL than the others and his learning curve ended significantly earlier than those of the others. It can be assumed that he is a very skilled operator who started with a very high PL and did not have much to gain. Operator No. 7 obtained average psychometric test results and his ability to estimate the direction of moving objects appeared to be below average.

This study proved that psychometric tests could be used as an operator selection tool to identify if an operator could be successful on a simulator. Furthermore, the study proved that simulator training results provide an indication of how well an operator would operate on a machine (outcomes of simulator training and machine training are the same).

Future studies should:

- Compare operators with poor psychometric test results to those with good psychometric test results
- Analyse more than two simulator test types to get more in-depth results of simulator learning and the effects of the results of psychometrics testing on operators.

- Make the in-field study period longer than 12 months to ensure that sufficient data is available for all operators
- Test the effect of slope, ground roughness, species and shift (day and night) on beginner operators' productivity
- Analyse different make of harvesters, not only a single brand such as Ponsse

Study limitations:

The following constitute the main limitations of this study:

1. The small sample sizes of only four thinning and four clear-felling operators is possibly not sufficiently representative enough as a benchmark for an average South African operator learning on simulators and on machines.
2. The study site is limited to the Highveld region of South Africa.
3. Only two learning curves could be produced for clear-fell operators.
4. Only modern harvesters with high productivity levels should be compared to the findings of this study.
5. Similar to previous South African CTL studies, the effect that terrain, weather and shift work have on productivity was treated as a constant influencing factor.
6. The amount of stem data information removed from the logging data due to large outliers was not ideal for the study of productivity development.

6 Conclusion

The objective of this study – to describe and model productivity development learning curves of beginner harvester operators in softwood sawtimber in both clear-felling and thinning operations – was achieved.

This study has also shown that, within 10 years, the South African forestry industry rapidly increased the use of FMH operations from 9.5% to 57%, as opposed to motor-manual harvesting. In some cases, the use of mechanised systems stands at 100%. Therefore, studies such as “Operator selection”, “Simulator training” and “Harvester operator learning curve analysis” are of great value and are very important in terms of improving costs, safety, productivity and work efficiency for harvester contractors and the South African forestry industry as a whole.

The results of this study show that, on average, a harvester simulator trainee will start at a PL of 60% lower than the PPL and end with a performance level of 24% higher than the PPL. An average simulator trainee will increase his performance by 269% with regards to his PLstart over a period of 9.2 days of efficient simulator training. This answers the question of what is an acceptable simulator training duration before operators move to the machine. Furthermore, simulator trainees with above average ("A") psychometric test results will perform better on a simulator than trainees with average or below average psychometric test results.

In-field thinning operators worked with an average tree size of 0.18 m^3 during the 12 month period, where they started at a productivity of 13.71 $m^3 \cdot PMH^{-1}$ (month 1) and managed to increase their productivity at month 12 to 38.96 $m^3 \cdot PMH^{-1}$ (mean = of 28.8 $m^3 \cdot PMH^{-1}$ overall). Clear-fell operators working with an average tree size of 0.54 m^3 during the 12 month period started at an productivity of 27.5 $m^3 \cdot PMH^{-1}$ (month 1) and managed to increase their productivity at month 12 to 43.75 $m^3 \cdot PMH^{-1}$ (mean = of 41.9 $m^3 \cdot PMH^{-1}$ overall). These findings answer the question of what is acceptable productivity ranges within particular operational and structural parameters in South Africa.

Finally, on average, a thinning operator who is formally selected and undergoes sufficient simulator training to efficiently operate a harvester machine would reach the end of the learning phase within 6–12 months, with nine months being the average time. The two clear-fell operators who were formally selected and underwent sufficient simulator training to efficiently operate a harvester machine reached the end of their learning curve after five and eight months. On average, a thinning operator would increase his performance by 218%, while a clear-fell operator would increase his by 104%. These findings answer the question of what an acceptable learning period for beginner harvester operators is and what performance increase is acceptable for operators who were formally selected and underwent sufficient simulator training.

The findings of this study could be used by a harvester contractor or company to identify whether their operations are functioning at acceptable PLs, provided that the conditions are similar to those found in this study. This would then allow for more accurate project costing and overall improved efficiency.

In order to obtain more meaningful results, future studies should include a greater number of operators and machines across various harvesting conditions to get a better understanding of the true learning curve of numerous operators. Furthermore, future studies should compare beginner operators who obtained good psychometric test results with those who obtained bad psychometric test results to identify if the selection process is of any value.

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