USE OF AUTOMATICALLY OBTAINED DATA IN THE QUANTITATIVE AND QUALITATIVE EVALUATION OF HARVESTER OPERATOR TRAINING

***Aigars Strubergs, Linards Sisenis, Ziedonis Sarmulis**
Latvia University of Life Sciences and Technologies, Latvia
*Corresponding author's e-mail: aigars.strubergs@lbtu.lv

Abstract
The study aims to find out the efficiency of periodic training of the harvester (cut-to-length) operator, using the automatically saved data of the harvester's information system. It has been established that logging service providers and training institutions do not analyze the operator's work before starting the training; therefore, the training is carried out according to certain, standard programs, without going into the previous performance of each trainee operator. The research uses data automatically saved by Ponsse harvesters during the year, obtained from Ponsse Manager. The study found that by using automatically saved data of the harvester information and performing data grouping with subsequent analysis, it is possible to determine the progress in the execution of specific stem processing operations and to identify operations where the instructor should pay increased attention during training. The research analyzed the data of 3 operators, obtained while working with Ponsse harvesters in clear-cutting. In the study, it was found that operator A reduced stem processing time by 3%, labor productivity increased by 15%, and fuel consumption per l m-3 decreased by 14% over 3 months. Operator B, after training, saw a 20% reduction in stem processing time, a 13% increase in work productivity, and a 5% increase in fuel consumption l m^{-3} over 3 months. Operator C had a 10% increase in stem processing time, a 1% increase in labor productivity, and a 2% increase in fuel consumption l m^3 after training.
Key words: harvesting, productivity, training, operator.

Introduction

Today, with newer, more productive, and more modern machines increasingly entering logging, efficient work is unthinkable without highly qualified operators. To be able to provide the capabilities offered by machines, increase productivity, and reduce fuel consumption and downtime, there is a growing need for highly qualified operators (Malinen *et al*., 2018) to periodically upgrade the qualifications of operators.

The given study aims to use the automatically saved data of the harvester's information system in the analysis of harvester operators training.

Modern information systems of logging machines allow to save a large amount of data, which can later be used in the analysis of the operators' work (Arlinger & Möller, 2014). Considering that the machine's information system records the working positions very precisely and the reliability of the data is high (Eriksson & Lindroos, 2014), there is no need for the researcher to be near the machine to record the data. One of the first StanForD 2010 data was used in operator productivity analysis by Purfürst & Erler, (2011), later by (Strandgard, Walsh, & Acuna, 2013) and others. Operator productivity is modeled using automatically obtained data (Liski *et al*., 2020). However, there are not many publications where such a method is used in the analysis of operator training (Strubergs *et al*., 2022). Such an approach can be used in the analysis of operator training (Palander *et al*., 2012), by analyzing the time spent in the execution of certain operations before training and later by observing and analyzing the execution time of operations after training, thus evaluating the effectiveness of training. The factors affecting the productivity of the harvester operator are not only the volume of the stem and the species of trees, but the speed and quality of operations have a significant impact on the time and productivity of the stem processing (Zimelis *et al*., 2015).

Materials and Methods

The study uses automatically obtained data from Ponsse harvesters using Ponsse Manager. Opti 4G 4.780 version installed for harvesters. Harvesters work in the areas managed by the Latvian State Forests in Latvia. The data are obtained for clear-cutting. To get an idea of the effectiveness of the training, data was collected from the harvesters on the work of three operators during the period of two months before the training and three months after the training and grouped by days. Practical work experience as harvester operator, operator A has 5 years, operator B has 1 year and Operator C has 2 years. The data collection period is tied to the operator training day. Operator A has data for the period from November 2021 to June 2022, with a training day on 27 January. For operator B, they were collected for the period from March 2022 to October 2022, with training on May 22. Operator C has data from December 2020 to July 2022, with a training day on February 10.

During the research period, operator A processed 5289 stems before the training, and 21373 stems after the training. Operator B processed 11906 stems before training, and 23523 stems after training. Operator C processed 8857 stems before training and 17342 stems after training.

From Ponsse Manager, data was manually transferred to Microsoft Excel for further data processing.

For each operator, the dynamics of changes in work productivity and stem processing time were determined sequentially by month, by sequentially creating their boxplot graph for each month of work. This way, the changes in mean values and the dispersion of the data are determined. Changes in the execution time of individual operations are determined before and after training, as well as changes in fuel consumption before and after training, both by evaluating changes in fuel consumption l h^{-1} and changes in fuel consumption l m^{-3}.

In data processing, statistical indicators were determined, variance analysis was performed and the significance of changes in results was performed.

Results and Discussion

Changes in labor productivity as a result of training

Before other data analysis is carried out, the influence of the average volume of the stems is ascertained. For operator A, in the period after training, the average volume of the processed stem increased by 9% (increase in volume is not significant, $p=0.44>0.05$). For operator B, after the training, the average volume of the processed stem decreased by 9% (here, too, the decrease has no significant effect, $p=0.12>0.05$). For operator C, in the period after training, the average volume of the processed stem increased by 11%, (the increase is not significant here either, $p=0.27>0.05$).

Comparing the average labor productivity indicators of the operators calculated by the harvester information system before and after the training, it was obtained that the labor productivity of the operator A after the training increased from 30.56±1.59 m^3 h^{-1} to 35.15±1.51 m^3 h^{-1}, or by 15%, the increase is not significant ($p=0.42>0.05$). For operator B, the average work productivity increased from 18.74±0.64 m^3 h^{-1} to 21.13±0.67 m^3 h^{-1} or by 13%, also showing a significant increase ($p=0.02<0.05$). For operator C, the average work productivity increased from 31.23±2.09 m^3 h^{-1} to 31.39±1.51 m^3 h^{-1} or by 0.6%, the increase is not significant ($p=0.95>0.05$).

To evaluate the dynamics of changes in labor productivity during the research period, a schedule was drawn up for each operator with the dynamics of changes in productivity before and after training. For Operator A, the changes are shown in 'Figure 1'.

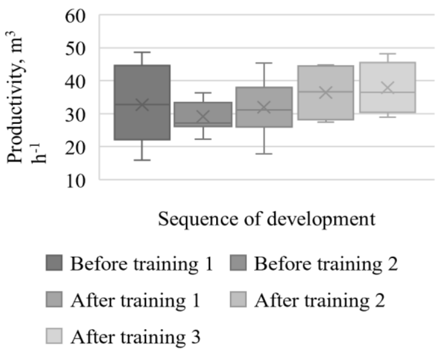

Figure 1. Change in productivity of operator Aduring months before and after training.

Looking at the data, it can be seen that before the training, the productivity of operator A decreased, but after the training, it tends to gradually increase. Likewise, after the training, the dispersion of the data decreased and the values became more concentrated around the average value.

For operator B, the dynamics of changes in work productivity before and after training are shown in 'Figure 2'.

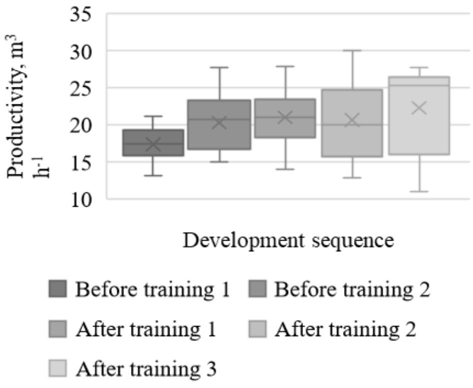

Figure 2. Change in productivity of operator B during months before and after training.

According to the information shown in 'Figure 2', it can be seen that operator B not only increased his productivity after training but also increased the dispersion of data around the average value. In the third month after the training, a sharp increase in the median values is observed, which in general indicates the positive effect of the training.

The change in operator C's work productivity in the development sequence is shown in 'Figure 3'.

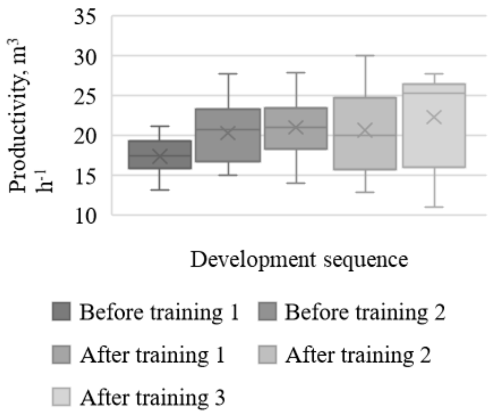

Figure 3. Change in productivity of operator C during months before and after training.

For operator C, in the first month after training, a decrease in work productivity can be observed, followed by an increase in work productivity, which, however, is not stable. Data dispersion decreased after training.

This information provides a general idea of the impact of the training.

Changes in stem processing before and after training. To understand the changes in labor productivity in the investigated time frame, the time spent on stem processing will be analyzed in the future. Similarly, when looking at labor productivity, first of all, the change in the total time spent processing the stem during the researched period will be examined for the operators. Similarly, the change in the total time spent processing the stem during the researched period will be examined for the operators. The change in the time spent by operator A for stem processing is shown in 'Figure 4'.

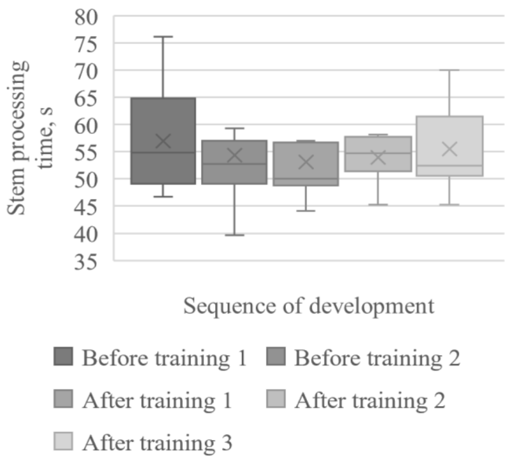

Figure 4. Operator A stem processing time during months before and after training.

Despite the slight decrease in stem processing time in the first month after training, a gradual increase in stem processing time can be observed in the following period, which, however, did not affect the increase in work productivity after training 'Figure 1', because on average, after training, the average stem processing time of operator A decreased by 3%. However, the reduction in processing time is not significant ($p=0.477>0.05$). The reduction of the median and data dispersion after training is also positive, which shows that the processing of stems becomes smoother.

Operator B had the greatest effect in reducing stem processing time from training 'Figure 5'.

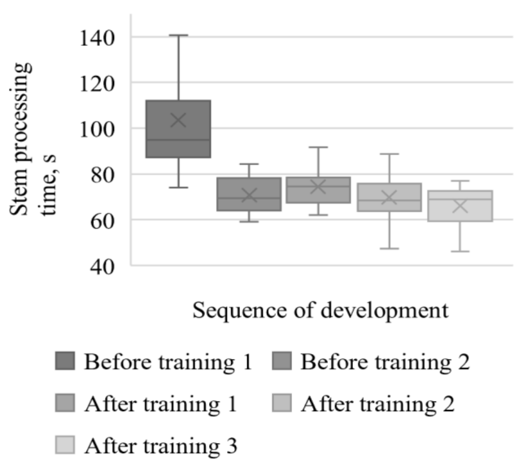

Figure 5. Operator B stem processing time during months before and after training

Operator B's stem processing time after training was reduced by 20% compared to the period before training. Significant time reduction ($p=3.66e^{-06}$ <0.05). After the training, the processing time of the stems is concentrated around the average value. Therefore, it can be concluded that processing has become smoother and processing times are more concentrated, which indicates the positive impact of the training.

For operator C, the only one examined, the training has negatively affected the processing time of the stems and the processing of the stems has become more uncertain.

For operator C, the only one examined, the training has negatively affected the processing time of the stems and the processing of the stems has become more uncertain. First, the processing time of the stem increased by 10%, the increase in processing time is significant ($p=0.032>0.05$). Second, the scatter of the data has increased, which may indicate greater variability during stem processing 'Figure 6'.

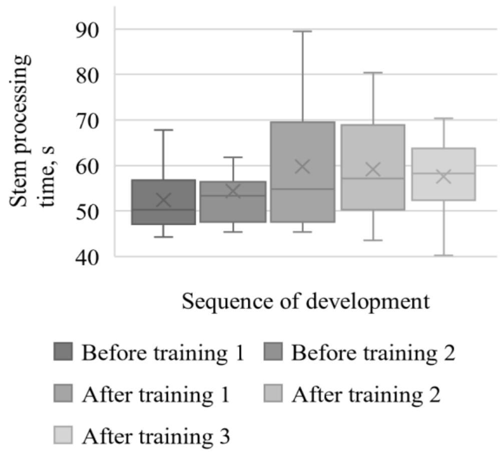

Figure 6. Operator C stem processing time during months before and after training.

In the following month, after the training, the numerical value of the maximum stem processing time for operator C increased by 32%, which may indicate difficulties in adapting to the new work methods and unexpected changes in the work process. Over time, the average stem processing time tends to decrease and the other indicators also stabilize.

Changes in execution time of individual operations

Since the harvester's information system records the time spent on each operation, the effect of training on the average time spent on each operation before and after training can be seen. Thus, it is possible to find out in which positions the training had a positive effect, but where more attention should be paid in the future.

The values of the time spent by operators to perform operations are reflected in Table 1.

According to the data presented in the table, it can be seen that for operator A, a decrease in time consumption can be observed in the operations ‘Grabbing the stem’ by 6%, ‘Pruning’ by 6%, and ‘Moving branches’ by 15%. The reduction of the time spent on all three operations is directly related to the selection of the optimal position of the harvester. A small 6% increase in time to ‘Sawing and stacking’ could be due to a small assortment of stack placement confusion. However, for operator A, the percentage change in operation completion time after training is not significant, as $p>0.05$ in all cases.

For operator B, larger and more significant changes in the execution time of operations can be observed. The biggest reduction in the execution time of operations can be observed in the operations ‘Moving branches’ by 40%, ‘Sawing and stacking’ by 29%, and ‘Felling sawing’ by 22%.

Table 1

Execution times of operator operations

Operation	Periods	Operator A			Operator B			Operator C		
		Time, s	Time change, %	p-value	Time, s	Time change, %	p-value	Time, s	Time change, %	p-value
Grabbing the stem	Before training	21.5±0.9	-6	0.33	29.1±1.8	-15	0.01	24.0±1.4	3	0.65
	After training	20.2±0.9			24.7±1.8			24.7±0.9		
Felling sawing	Before training	5.3±0.1	3	0.45	7.3±0.3	-22	$8.49e^{-08}$	3.7±0.1	10	0.01
	After training	5.4±0.1			5.7±0.1			4.1±0.1		
Sawing and stacking	Before training	10.6±0.3	6	0.21	26.7±1.3	-29	$2.63e^{-09}$	8.9±0.24	4	0.28
	After training	11.2±0.4			18.9±0.5			9.3±0.2		
Pruning	Before training	11.2±0.4	-6	0.18	16.7±0.6	-15	0.0001	8.3±0.2	19	0.0001
	After training	10.6±0.2			14.1±0.3			9.9±0.3		
Sawing	Before training	3.5±0.1	3	0.32	3.3±0.1	12	0.009	2.7±0.14	3	0.53
	After training	3.6±0.1			3.7±0.1			2.8±0.1		
Moving branches	Before training	3.6±0.3	-15	0.19	4.5±1.0	-40	0.022	6.0±1.1	34	0.18
	After training	3.1±0.3			2.7±0.1			8.1±0.9		

Unlike operators A and B, operator C, despite a slight increase in work productivity ‘Figure 2’ and a decrease in data dispersion after training, has an increase in the execution time of operations in all operations. When performing ‘Felling sawing’ and ‘Pruning operations’, the increase in execution time is significant. For operators A and C, the time of ‘Moving branches’ increased by 34%, which could indicate inadequate development technology and unsuccessful selection of the harvester position, as a result of which the stem is pruned in an unexpected place and, to comply with the requirements of logging technology, additional time is consumed for moving branches. Legally, the second operation which significantly, $p=0.0001<0.05$, increased the execution time of the operation by 19% is ‘Pruning’.

Fuel consumption analysis

Ponsse Manager captures the total fuel consumption in the period under review, without dividing the fuel consumption in the execution of individual positions. Therefore, we get the total fuel consumption for analysis. This is enough to observe the general trend of fuel consumption before and after training. To describe the effectiveness of training, two parameters are considered: fuel consumption for processing $1m^3$ stems and fuel consumption in liters per hour. On the left side of ‘Figure 6’, it can be seen that operator A, after the training, significantly, $p=0.026<0.05$, increased by 2% the average fuel consumption $l\ h^{-1}$ and the data dispersion decreased. On the other hand, on the right side of the picture, it can be seen that fuel consumption per m^3 of production has decreased significantly, $p=0.044<0.05$, after the training. The reduction in fuel consumption amounts to 14%, as well as reduced data dispersion around the average value. Looking at these two factors together, it can be concluded that after the training for operator A, the harvester was loaded more fully and by producing more production, fuel consumption and production units (m^3) decreased 14%, which indicates an increase in engine load. After the training, operator B's fuel consumption per unit of production also increased by 5%. However, this increase in fuel consumption is not significant, p=0.323>0.05.

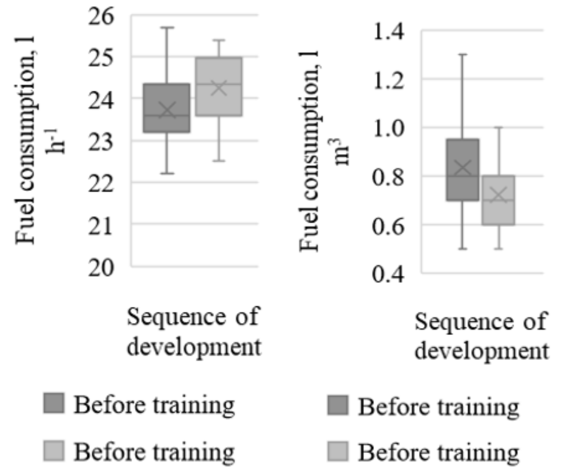

Figure 6. Chang Change in operator A's fuel consumption over time periods before and after training.

Looking at the fuel consumption changes that occurred as a result of operator B's training 'Figure 7', it can be seen that after the training, the fuel consumption per unit of time increased significantly, p=6.67e^{-12} <0.05. Fuel consumption increased by

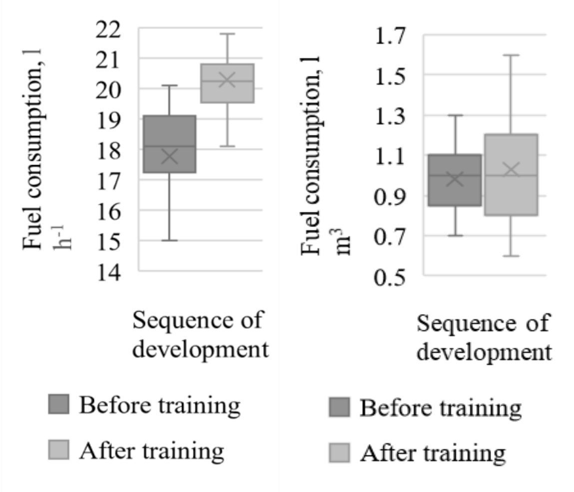

Figure 7. Change in operator B's fuel consumption over time periods before and after training.

The smallest effect on fuel consumption after training can be observed for operator C 'Figure 8'. Contrary to operators A and B, operator C's fuel consumption per time unit is insignificant, p=0.782, it decreased by 1%. On the other hand, the fuel consumption per volume unit increased significantly, p=0.838>0.05, by 2%.
By performing a regular analysis of the operator's work records, using automatically obtained data, it is possible to obtain information in which stem processing operations the operator needs to pay more attention to prevent errors in the execution of operations and increase work productivity.

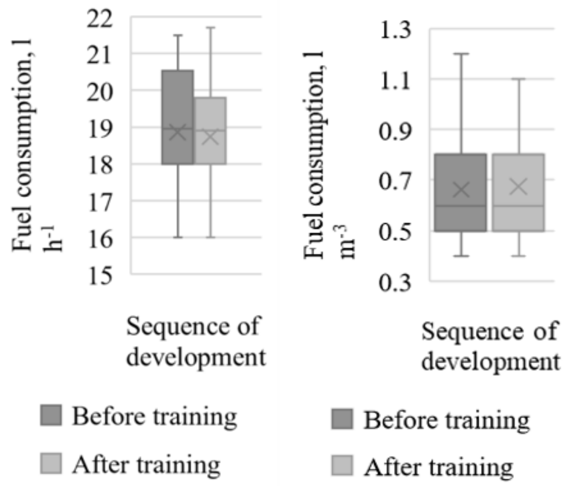

Figure 8. Change in operator C's fuel consumption over periods before and after training.

By using the manufacturer's program in the analysis of the operator's work, it is possible to evaluate each stem processing operation. In the program, it is possible to filter additional data by stem volume; however, it is not possible to separate individual tree species, which could provide more accurate information about the effect of the species on productivity. It is necessary to continue the research by creating opportunities in the analysis of labor productivity by including such variables as the species of trees and the nomenclature and quantity of the assortments to be prepared.

Conclusions

1. After the training for operator A, the processing time of the stem decreased by 3%, but the labour productivity increased by 15%, while the fuel consumption per unit volume decreased by 14%
2. A gradual increase in work productivity and a decrease in fuel consumption can be observed.
3. After the training, operator B saw a 20% decrease in stem processing time and a 13% increase in work productivity during the considered period, however, there was a 5% increase in fuel consumption per m^3.
4. Operator C has observed uncertainty after the training, because the stem processing time has increased by 10%, work productivity has increased by 1%, and fuel consumption has also increased by 2%.
5. The analysis of changes in the execution time of operations allows us to find solutions for reducing theexecution time of operations.

References

Arlinger, J. & Möller, J. J. (2014). Time studies based on automatic data collection. *Proceedings of the 5th Forest Engineering Conference, Gerardmer, France*, 23–26. Retrieved January 2, 2024, from https://www.formec.org/images/proceedings/2014/a158.pdf.

Eriksson, M. & Lindroos, O. (2014). Productivity of harvesters and forwarders in CTL operations in northern Sweden based on large follow-up datasets. *International Journal of Forest Engineering*, 25(3). 179–200. DOI: 10.1080/14942119.2014.974309.

Liski, E., Jounela, P., Korpunen, H., Sosa, A., Lindroos, O., & Jylhä, P. (2020). Modeling the productivity of mechanized CTL harvesting with statistical machine learning methods. *International Journal of Forest Engineering*. 31(3), 253–262. DOI: 10.1080/14942119.2020.1820750.

Malinen, J., Taskinen, J., & Tolppa, T. (2018). Productivity of Cut-to-Length Harvesting by Operators' Age and Experience. *Croatian Journal of Forest Engineering*. 39(1), 14–22. Retrieved January 2, 2024, from https://hrcak.srce.hr/193546.

Palander, T., Ovaskainen, H., & Tikkanen, L. (2012). An adaptive work study method for identifying the human factors that influence the performance of a human-machine system. *Forest Science*. 58(4), 377–389. DOI: 10.5849/forsci.11-013.

Purfürst, F. T. & Erler, J. (2011). The Human Influence on Productivity in Harvester Operations. *International Journal of Forest Engineering*. DOI: 10.1080/14942119.2011.10702606.

Strandgard, M., Walsh, D., & Acuna, M. (2013). Estimating harvester productivity in *Pinus radiata* plantations using StanForD stem files. *Scandinavian Journal of Forest Research*. 28(1), 73–80. DOI: 10.1080/02827581.2012.706633.

Strubergs, A., Lazdins, A., & Sisenis, L. (2022). Use of ctl harvester .hpr and .mom files to analyze impact of operator training on productivity. *ENGINEERING FOR RURAL DEVELOPMENT*, 432–437. DOI: 10.22616/ERDev.2022.21.TF148.

Zimelis A., Okmanis M., & Lazdiņš A. (2015). *Logset H5 harvestera darba ražīgums krājas kopšanas cirtēs. Harvester Logset H5 productivity in thinning*.2015/15.Silava. DOI: 10.13140/RG.2.2.28961.04961.