USE OF CTL HARVESTER .HPR AND .MOM FILES TO ANALYZE IMPACT OF OPERATOR TRAINING ON PRODUCTIVITY

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Abstract. The study aims to determine the applicability of the StanForD 2010 standard in the analysis of the impact of CTL harvester operator training on productivity. The productivity of harvester operators is affected by factors such as tree species, diameter, type of felling, terrain, operator experience, qualifications, and several other factors. However, there are not many studies that, in addition to the above-mentioned factors, have analyzed the impact of periodic training of operators on productivity. The study uses automatically obtained harvester production data from logging service providers. Data are from the John Deere harvester for the period July 2021 to December 2022. The harvester worked in cleaning cutting in the territory of the South Kurzeme forest district. The study used data acquired by two operators who received refresher training during the study period. Harvester Operator No. 1, has work experience of 6 years, and Operator No. 2 has work experience 12 years. Data on the development of four different species of trees in the two months before and two months after the training were used to determine the impact of operator training on productivity. Operator productivity was analyzed in three diameter groups for all species and separately for each tree species. The study found that using the automatically obtained data Operator No. 1 and Operator No. 2 average productivity after training increased by 7% and 29%, respectively. However, the effect of different stem diameters and tree species on productivity changes has been found. Operator No. 1 showed a decrease in productivity when processing deciduous trees in separate diameter groups, while Operator No. 2 showed a decrease in labour productivity in some conifer diameter groups. An in-depth data analysis is needed to find out the reasons for the decline in productivity by expanding the data set used.

Keywords: harvesting, productivity, training, harvester operator, automatically obtained data.

Introduction

In today's mechanized logging, harvester productivity is affected by several factors. Some of the influencing factors cannot be changed, such as tree species, DBH, type of felling, terrain, etc. There are several studies in this direction, where the influence of environmental factors is clarified [1; 2]. However, some factors are subject to change and are largely related to the behaviour of the operators, including psycho-emotional state, speed of reaction, speed of decision-making, and others [3]. One such variable is the training of the operator of the logging machine [4]. Periodic operator training plays a very important role in increasing productivity. Training can improve the skills of operators to perform certain activities. Training can take place in nature, in a logging machine, as well as the practical skills of operators can be developed with the help of a simulator [5]. However, simulators differ in environmental factors, which sometimes causes problems for the operator in making decisions. Training operators in nature is an expensive process because, firstly, the hourly cost of the logging machine itself is high and, secondly, a large part of the cost is fuel costs. Despite these costs, 8 - 16 hours of training is provided in Latvia, where the instructor follows the work of the operator in person and provides recommendations for more efficient work. Such a training model produces results, but to a large extent, the result depends on the professionalism of the instructor himself, from his ability to assess the situation and make recommendations. Better training results can be achieved by conducting a more detailed analysis of the operator's productivity using automatic harvester data before training. This method of data collection is relatively reliable and low cost [1; 6; 7]. This allows the instructor to focus on developing specific operator competencies during the training. In this study, harvester operator productivity is analyzed using data automatically stored in StanForD 2010 to determine the effect of training on productivity.

Materials and methods

The study used data obtained automatically from a John Deere harvester. Two operators are working in shifts with the 2016 John Deere 1070E harvester, equipped with an H413 harvester head and using the Timbermatic H 1.28.20 information system. The Harvester Information Systems support standard Stanford 2010. The data analysis used data from both operators two months before the training and two months after the training in the period from January 2021 to December 2021. The harvester worked in the forests managed by JSC "Latvia's State Forests" in the South Kurzeme forest district. Tree species used in the data analysis: Scots pine *(Pinus sylvestris)*, spruce *(Picea abies)*, birches *(Betula)*, and solid hardwood trees. The harvester operators have 6 and 12 years of experience. Both operators underwent 8-hour training in the felling area by an instructor at the Forest Machinery Operators Training Center.

The study used 38 743 stem records registered under the Stanford 2010 standard as .hpr and .mom files. Data on each treated trunk are recorded in compressed files. The following data is used from the .hpr file: trunk identification number, tree species, timestamp (year, month, day, hour, minute, and second), when the tree was cut, diameter at breast height (DBH), volume, operator identifier. Using time stamp entries, the time of the stem processing cycle is calculated for each stem by determining the difference between two consecutive stem timestamps [8]. The cycle time includes sawing the tree, moving the harvester's head in the cutting area, delimbing, cross-cutting, reaching for the next tree, and grabbing the tree. To prevent errors during the processing of the last stem, a .mom file was used, from which timestamps are used for maintenance, repair, travel, etc., which closes the trunk processing. The structure of .hpr and .mom files is created in .xml format, therefore Microsoft Excel is used to open files and select data for sorting. Power Query Editor is used for data processing convenience. Because four operators work with the harvester in shifts, the data on the operators who were trained in the respective time interval is separated from the total amount of data. Productivity before and after training was compared to determine the effectiveness of the training. When grouping the data, productivity was obtained by processing different species of trees, and the stem was divided into DBH groups: 0-10.0 cm, 10.1-20.0 cm, 20.1-30.0 cm. Data selection took into account tree species and diameters found in fellings before and after training. Statistical data processing was performed with the publicly available data processing program R.

Results and discussion

During the data processing, tree species that were not found in all felling areas or appeared as individual trees with a DBH exceeding 30.0 cm were excluded from the total data. In the analysis for Operator No. 1 10315 stems with an average DBH of 142 cm and an average volume of 0.028 m3 were used before the training, but 9169 stems with an average DBH of 155 cm and a volume of 0.036 m3 were used after the training. Operator 2 used 8120 stems with an average DBH of 160 cm and an average volume of 0.036 m3 treated before the training, and 11139 stems with an average DBH of 142 cm and a volume of 0.027 m3 after the training. Productivity before and after training was compared for both operators by tree species and DBH groups.

Comparing productivity changes for all species in the DBH section increases productivity before and after training for both operators (Fig. 1). Analysis of variance shows a significant difference.

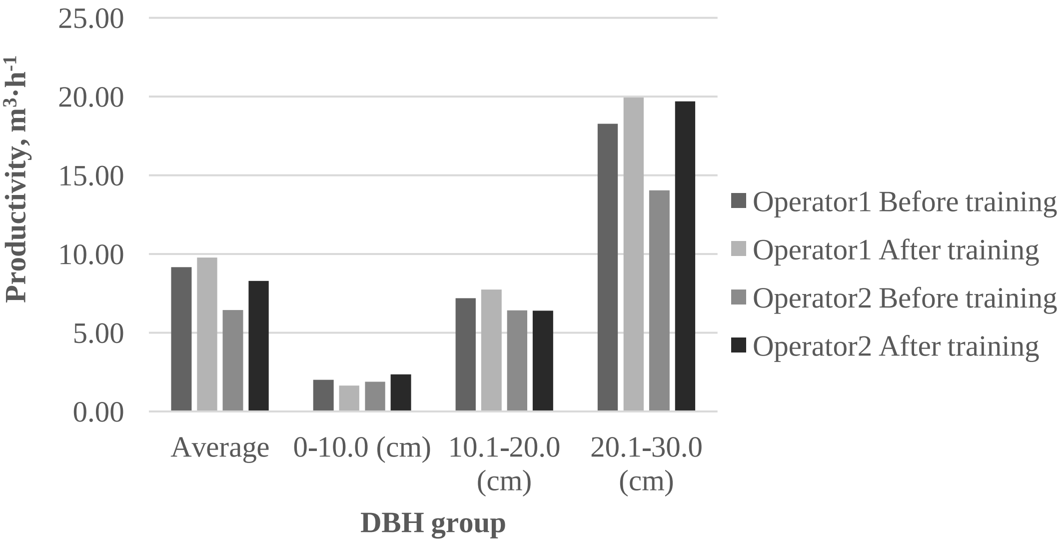

Fig. 1. **Changes in productivity of both operators on average and different DBH groups**

For the first operator, a significant difference by species was found when treating trees corresponding to the average DBH of sawn trees, p = 7.069e-07 < 0.05, and also showed a significant difference in productivity in the section by different DBH groups p = 8.135 e-12 < 0.05. Also, operator No. 2 showed a significant difference in the cut by species when treating trees corresponding to the average DBH of sawn trees, p = 8.135 e-12 < 0, and also shows a significant difference in productivity in the cut by different DBH groups p = 2.775e-14 < 0.05. According to the overall results, the training has yielded a positive result, respectively for Operator No. 1 and 2 productivity for all tree species, and the average DBH by sawn trees increased by 7% and 29%, respectively. Differences are observed in the DBH group 0-10.0 cm, where Operator No. 1 shows a decrease in productivity by 18%, but Operator No. 2 productivity increased by 24%. In the DBH group, 10.1-20.0 cm for Operator No. 1 productivity increased by 7%, but Operator No. 2 productivity did not change. In the DBH group, productivity increases of 20.1 -30.0 cm is 9% and 77%, respectively.

Figure 1 can only give a general idea of the changes in productivity due to changes in the stem DBH. To get a more complete picture of the factors influencing productivity, in further analysis each operator has been analyzed separately and the species of trees to be cut have been singled out.

Operator No. 1

Figure 2 shows Operator No. 1 data on productivity change before and after training by tree species. During the analysis of variance, it was found that operator No. 1 productivity is affected by tree species p = 2.2e-16 < 0.05 and also by training p = 2.2e-16 < 0.05. Determining the effect of training and tree species interaction, it was found that the operator's productivity changes are influenced by both mentioned factors, and between them, there is an interaction effect p = 6.946e-06 < 0.05.

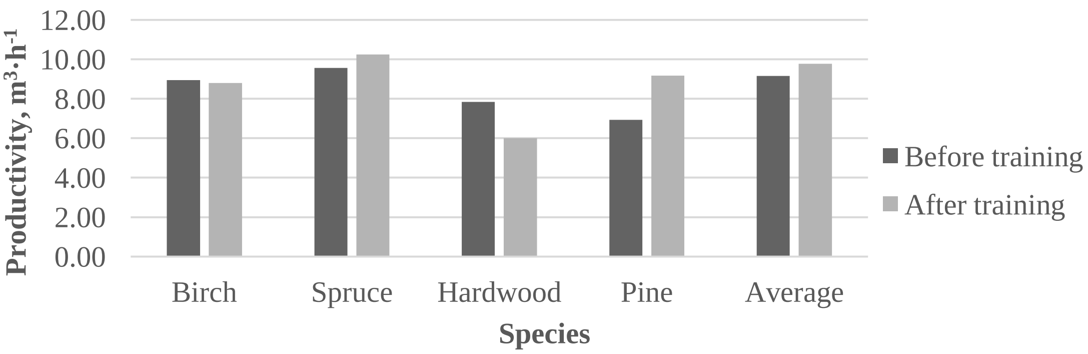

Fig. 2. **Changes in the average productivity of Operator No.1 by tree species**

After training Operator, No. 1 average productivity decreased by 2% with birch, increased by 7% with spruce, decreased by 23% with solid hardwood trees, and increased by 32% with pine. The average productivity after training, excluding tree species, increased by 7%, so it can be concluded that the training had a positive result, however, it can be seen that operator No. 1 problem is caused by leaf tree processing. The following analysis distinguishes tree species and DBH groups to determine which DBH group's productivity has changed (Fig. 3.). Changes in productivity are observed in all DBH groups.

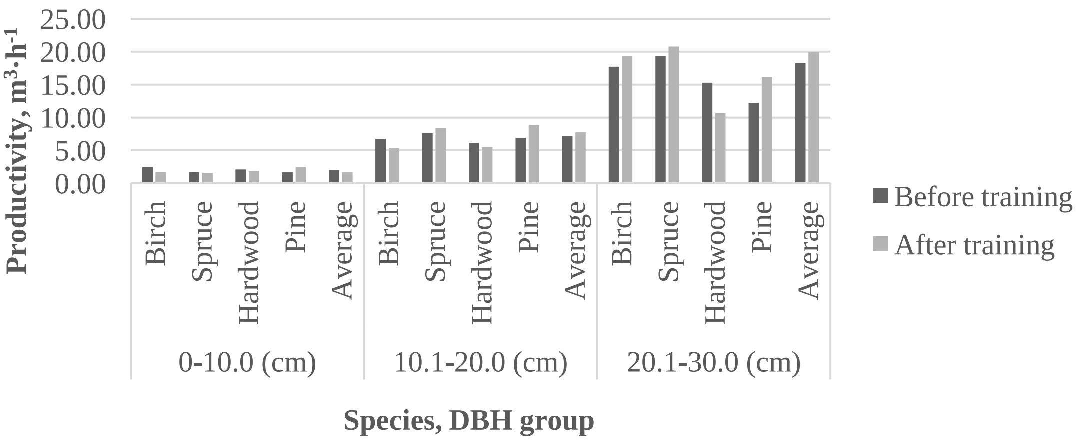

Fig. 3. **Operator No. 1 changes in productivity before and after training, distinguishing between DBH and tree species**

Operator No. 1 percent change in productivity is shown in Table 1.

Table 1

Operator No. 1 changes in productivity as a result of training

Species	DBH group		
	0-10.0 cm	10.1-20.0 cm	20.1-30.0 cm
Birch	-44%	-26%	9%
Spruce	-10%	10%	7%
Hardwood	-14%	-11%	-43%
Pine	33%	22%	24%
Average	-5%	3%	4%

When working with solid hardwood trees, productivity decreased in all DBH groups after training. For birch, it decreased in DBH groups 0-10.0 cm and 10.1-20.0 cm. Taking into account that the average productivity after training increased by 2%, for Operator No. 1 it is necessary to perform an in-depth analysis of each felling developed to conclude whether the decrease in productivity when processing deciduous trees is a coincidence or a trend related to the applied working methods.

Operator No. 2

Figure 4 shows Operator No. 2 data on changes in productivity before and after training, distinguishing between different tree species. Examining the differences in productivity in terms of tree species, significant differences were found p = 2.56e-05 < 0.05, as well as a significant effect of training, was observed, p = 8.734e-06. There is no interaction effect between tree species and training p = 0.3748 > 0.05.

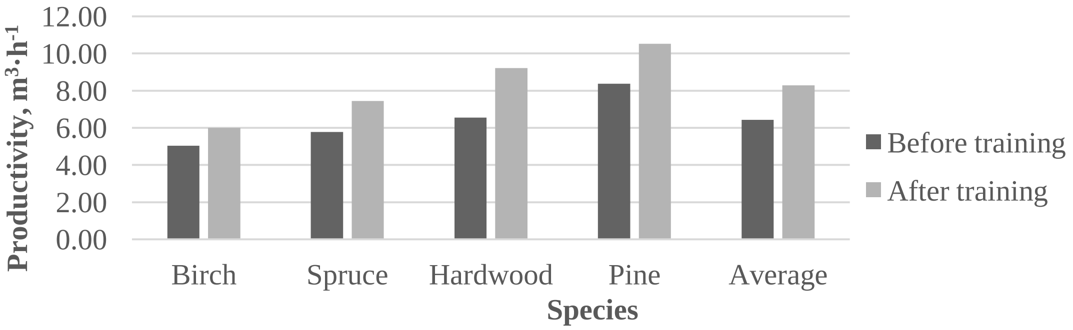

Fig.4. **Operator No. 2 changes in average productivity by tree species**

After training average productivity of Operator No. 2 increased by 19% for birch, 29% for spruce, 41% for solid hardwood trees, and 26% for pine. Average productivity, summarizing all tree species, increased by 29%. The following analysis distinguishes tree species for individual DBH groups to determine which DBH group's productivity has changed (Fig. 5).

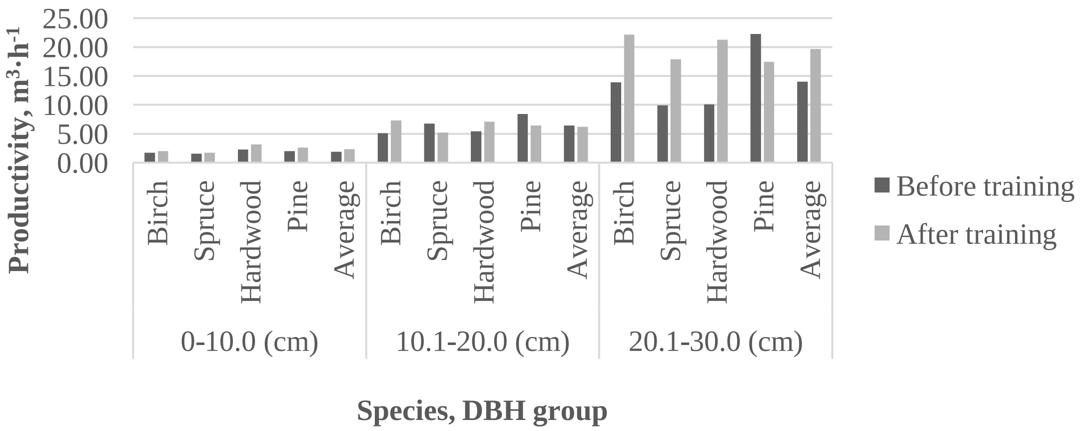

Fig. 5. **Operator No. 2 changes in productivity before and after training, distinguishing between DBH and tree species**

Changes in productivity are observed in all DBH groups. The percentage change in productivity for Operator No. 2 is shown in Table 2.

Table 2

Percentage change in productivity for Operator No. 2

Species	DBH group		
	0-10.0 cm	10,1-20,0 cm	0-10.0 cm
Birch	13%	44%	60%
Spruce	10%	-23%	81%
Hardwood	39%	31%	111%
Pine	28%	-24%	-22%
Average	23%	7%	57%

Taking into account both, tree species and DBH groups, for Operator No. 2 after training in the DBH group 0-10.0 cm, when processing all tree species, an increase in labour productivity is observed. In the DBH group 10.1-20.0 cm, productivity was reduced by 23% with spruce and 24% with pine. Consequently, this DBH group shows an overall increase in productivity of 7%. In the DBH group 20.1-30 cm, when processing pine, there was a decrease in productivity by 22%, but the average productivity increased by 29%.

Using automatic data from the harvester information system, the study found that operators No. 1 and 2 increased productivity by 2% and 40%, accordingly, after one day of training. Such results are confirmed by other researchers [9]. However, a slightly broader analysis revealed a reduction in productivity in both graduation classes after training for both operators. As Dvořák et al found in their study, there is a close link between the operator's human factor and the machine [10]. The effects of the human factor were also described by Malinen [11] in his study that different cognitive abilities may be observed depending on the age and experience of the operator [12]. The reduction in productivity is probably due to the instructions given by the instructor during the training process. First of all, to find out, additional in-depth analysis should be performed, not taking the training day as a reference point, but dividing the two-month interval used in the study into smaller time sections after the training. Secondly, the amount of data needs to be increased to include the nomenclature of the assortments prepared to clarify the impact of the assortments prepared on productivity. In this way, it will be possible to find out the trend of changes in productivity of both operators and the reasons why productivity has decreased in certain categories.

Conclusions

1. Automatically generated harvester data provide a sufficient amount of qualitative information to perform an in-depth analysis of the impact of training harvester operators on productivity.
2. The use of a timestamp in .hpr and .mom files allows very precise data grouping and aggregation, as well as a selection of unused data.
3. The use of automated data in the analysis of operators' productivity allows for more accurate identification of issues where the operator needs to pay close attention to the work process.
4. As a result of one day of training, the average productivity of Operator No. 1 increased by 2%, but Operator No. 2 – by 29%.
5. An in-depth analysis showed that, despite the overall increase in productivity, Operator No. 1 decreased productivity in the development of leaf trees, while Operator No. 2 productivity decreased when processing conifers.

Author contributions:

Original idea, A.S., A.L. and L.S.; methodology, A.S. and A.L.; software, A.S.; data collection, A.S.; data analysis A.S., L.S.; writing – original draft preparation, A.S.; writing – review and editing, A.L. and A.S. All authors have read and agreed to the published version of the manuscript.

References

[1] Olivera A., Visser R., Acuna M., Morgenroth J. Automatic GNSS-enabled harvester data collection as a tool to evaluate factors affecting harvester productivity in a Eucalyptus spp. harvesting operation in Uruguay. International Journal of Forest Engineering, vol *27*(1), 2016, pp. 15-28.

[2] Nurminen T., Korpunen H., Uusitalo J. Time Consumption Analysis of the Mechanized Cut-to-length Harvesting System. Silva Fennica, vol. 40(2), 2006, pp. 335-363.

[3] Purfürst F. T. Learning curves of harvester operators. Croatian Journal of Forest Engineering, vol. 32(2), 2010, pp. 89-97.

[4] Alam M., Walsh D., Strandgard M., Brown M. A log-by-log productivity analysis of two Valmet 475EX harvesters. International Journal of Forest Engineering, vol. 25(1), 2014, pp.14-22.

[5] Eriksson M., & Lindroos O. Productivity of harvesters and forwarders in CTL operations innorthern Sweden based on large follow-up datasets. International Journal of Forest Engineering, vol. 25(3), 2014, pp.179-200.

[6] Palander T., Nuutinen Y., Kariniemi A., Väätäinen K. Automatic time study method for recording work phase times of timber harvesting. Forest Science, vol. 59(4), 2013, pp. 472-483.

[7] Rossit D. A., Olivera A. A Big Data approach to forestry harvesting productivity. Computers and Electronics in Agriculture, vol. 161, 2019, pp. 29-52.

[8] Arlinger J., Möller J., Sorsa J.A., Räsänen T. Introduction to StanForD2010. [online] [31.03.2021]. Available at: https://www.skogforsk.se/english/projects/stanford/

[9] Strandgard M., Walsh D., Acuna M. Estimating harvester productivity in Pinus radiata plantations using StanForD stem files. Scandinavian Journal of Forest Research, vol. *28*(1), 2013, pp. 73-80.

[10] Dvořák J., Malkovský Z., & Macků J. Influence of human factor on the time of work stages. Journal of Forest Science, vol. *54*, (1), 2008, pp. 24-30.

[11] Malinen J. Productivity of Cut-to-Length Harvesting by Operators' Age and Experience. Croatian Journal of Forest Engineering, vol. 39, 2018, pp. 15-22.

[12] Kirk P.M., Byers J.S., Parker R.J., Sullman M.J. Mechanisation Developments within the New Zealand Forest Industry: The Human Factors. Journal of Forest Engineering. Vol. 8(1), 1997, pp.75-80.