1. LEARNING CURVE ASSESMENT OF HARVESTER OPERATOR ON MECHANIZED FOREST LOGGING

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1.1. ABSTRACT

Among many factors affecting harvester productivity, operators´ skills and abilities are crucial for overall success of forest logging companies. Moreover, general knowledge about the time frame needed for a harvester operator to reach stable productivity is the main issue when planning production for a learning period. In this study twenty-five operators were assessed during their learning process, which resulted in different skill level development between them. Therefore, correlations were performed to establish whether it is possible to identify more productive operators during earlier stages of the learning process. Data used in this study was obtained from forest machines equipped with on board computers, created by StanForD guidelines. All observed productivities have been relativized by local models using species and volume per tree as dependent variables. According to the results, an average of 974,5 productive working hours are needed for an operator to reach a stable performance. Moreover, for the studied population, a correlation coefficient (R) of 0,87 was established between performance at already 100 accumulated PWH with corresponding final performance. Hence, it can conclude, that operators with higher abilities to operate harvester machines can be spotted already in the initial phases of the learning process. This fact can potentially save time to forest machinery owners when selecting operators, which would furthermore result in an enhanced overall production.

Keywords: Uruguay; learning curve; productivity; human influence; harvester operation; forest operator.

1.2. INTRODUCTION

In the recent history, forest operations in Uruguay had a significant increase due to large industrial investments mostly for cellulose propose, which have a constant need of wood supply. The annual wood flow for the mentioned industry, reaches around 9 million cubic meters of round wood, which equals to around 64% of the total wood removal (MGAP DGF, 2018; Uruguay XXI, 2017).

In order to fulfil this wood demand in Uruguay, the adopted technology in forest operations is mostly developed by Scandinavian countries under the logging cut-to-length system. Olivera et al. (2016), stated that 60 % of the forest harvesting operations are as described, and harvester – forwarder scheme is widely used.

Lorenzo (2010), quoted that by the year 2008 (before the first large pulp mill started its operations in Uruguay), the total number of forest machines in the forestry sector was roughly one hundred. Currently, with information gathered for this study, the total number of forest machines working in the forest logging sector is around 350. Meaning that, following the forest industry development, the mechanization of forest operations in Uruguay has also grown dramatically during the last 10 years. Consequentially, there is a continuous demand for qualified operators to drive this growing number of machines.

1.2.1. <u>Harvester Productivity</u>

When assessing harvester productivity models, the traditional methodology has mostly been carried out using time and motion techniques, which is largely defined as time and work consuming (Purfürst, 2010; Strandgard et al., 2013). Moreover, this type of studies have a narrow scope since they are made for a small sample size and short time lapses. On the other hand, automatic data collection by on board computer (OBC), which is a standard equipment on almost every single grip harvester and forwarder, is a potentially efficient and cheaper way of collecting harvester performance data from larger number of harvesters and/or over longer time periods. Despite the fact that logging machines have been equipped with computers on board for already many years, the automated harvest data collection, received little attention to date.

In order to handle same information between different type/brand of machines, OBC collects and stores data of operations regarding international guidelines known as Standard for Forest Machine Data and Communication (Arlinger et al., 2012; Räsänen & Sorsa, 2010; Skogforsk, 2015), abbreviated as StanForD. Strandgard et al. (2013), assessed productivity of harvester machines, comparing traditional techniques and OBC collected data. Among the outcomes, no significant difference has been found between different data collecting methodologies.

Forest harvester machine productivity, is a very relevant aspect that must be addressed by every forest company, due to the fact that this type of technology requires large investments and operational costs (Bramucci & Seixas 2002, Akay et al. 2004). The same authors stated that many factors can influence the productivity of the harvester, among others: slopes, topography, volume per tree, species, volume per hectare are widely mentioned. Kirk et al. (1997), described that operational productivity of a harvester machine has a strong correlation with the tree size: as volume per tree decreases, productivity (m^3 per hour) also decreases.

Productivity has been studied in *Eucalyptus spp*. plantations in the South America. The factors mostly addressed in those studies were effect of species and volume per tree. Among the results, regression models were obtained for different species and volume per tree was used as a dependent variable (Bramucci & Seixas 2002; Olivera et al. 2016; da Silva 2012). It has also been concluded, that higher volume per tree results in a higher productivity (m^3 per hour) of the harvester machine. Regarding different eucalyptus species, when they represent straighter, non-crooked stems and softer branches, higher productivity (m^3 per hour) of harvesters can be expected. Furthermore, Olivera et. al. in 2016, also measured other aspects in the productivity such as slopes and shift (day-night) effects, however no significant differences have been observed in the studied scenario. On the other hand, there was significant differences in performances between operators, even though they had the same training programs.

1.2.2. <u>Human influence in productivity</u>

Due to the high capital investment required for mechanized logging systems, a skilled operator is an essential part of profitable and sustainable business plan. Since the unit cost (U$ m^{-3}) is heavily influenced by the production rate, ability to learn new tasks quickly and efficiently, is crucial (Kirk et al., 1997).

Experience and skills of an operator have been an interest of many scientists and authors (Gellerstedt, 2002; Häggström, 2015; Purfürst & Erler, 2011; Purfürst, 2007; Westerberg & Shiriaev, 2013). Purfürst and Erler (2011), reported that at stand level, operators differ by a factor of 2.2 working at thinning operations in Germany. Furthermore, large productivity differences up to 40% has also been observed for different operators using the same harvester (Kärhä et al., 2004).

The human influence is a hard and complex aspect to asses (Nurminen et al., 2006) , but one of the outcomes that various authors mention is despite the variability between operators, experience is positively correlated with higher performance (Häggström, 2015; Purfürst, 2010).

1.2.3. Learning Curve

The learning curve can be defined as a relation between performance level and the experience of an operator (Purfürst, 2010). It can be expected that the productivity will increase with the higher level of experience of the operator. The replacement of an experienced operator by a new harvester operator can be estimated by a production loss of about 49,650 Euros (S. Gellerstedt et al., 2005); the reason for that is the time needed to reach potential productivity.

Purfurst (2010), studied the learning curve of operators working with conifers in Germany among a variety of scenarios but mainly at thinning operations. From the mentioned study, it has been concluded that it takes around eight months for an operator to achieve a stable performance, although the variability among operators is high. In another study in Canada, it was described that the time span to reach an experienced level goes between 8 and 12 months (Calabrese, 2000).

Learning curve length can also be addressed using number of productive or effective working hours. It has been found, that in order to achieve an experienced level operator, the amount of hours needed is between 1000 and 1500 working hours (Wagner, 2004).

In Uruguay, there is a lack of information regarding learning process that an operator must go through when working with forest machines. Furthermore, similar sites of forest production can be found in Brazil and Chile, however there are no published studies of the harvester operators' learning curves.

1.2.4. Selecting harvester operators

Selecting an operator is another important area requiring attention, however there are no established selection programs formalized in Uruguay. Potential losses as a result by selecting operators with low or inappropriate performance, could be extensive (Kirk et al., 1997). Therefore, formal selection and knowledge from the learning programs would improve the chances to employ only suitable candidates. In a competitive market, where efficiency in every process must be accomplished to assure the competitiveness on the long term, skilled operators are essential

Pagnussat et. al. (2017), stated that skills and abilities of the operator are important, however behavioural profile has to be also considered to accomplish stable operators. The behavioural profile is defined as an individual's natural predisposition for a particular kind of work. Furthermore, it was argued that to improve the efficiency of forest operations and increase productivity, it is crucial to hire workers with tacit knowledge or natural abilities as well as the right personality, combined with sources of motivation (Parise, 2005; Volodina et al., 2015).

In regard to abovementioned, some questions arise: How long would it take for a new operator to reach an acceptable and stable production when driving a harvester machine? Is it possible to select potentially higher performance operator already in early learning phases? Hence, the objectives of this study are: a) Describe the learning curve of harvester operator in the Uruguayan scenario of pulp production and b) Measure correlations between initial performances of new operator and final performance after learning period.

With this knowledge, forest companies would improve the ability to identify for how long production, and in turn the operation´s cash flow, are likely to be affected by new operators. Furthermore, it would enable them more accurate wood flow plan estimations from newly mechanized logging operations. In addition, the opportunity to identify skilled operators in the early stages of selection, could be an overall production enhancement for logging companies.

1.3. MATERIALS AND METHODS

For a period of three years, a database of 35 operators with no previous experience has been assessed, collecting every individual productivity over the time throughout their learning process. From those, 25 resulted with accurate information that was incorporated in this study. All operators have gone through the same agenda to operate directly a harvester machine, which included 50 hours of simulator led by harvester professional trainers and then 50 hours of operation *in situ* also escorted by trainers. During the simulation phase, future operators were subjectively evaluated by trainers regarding different aspects of the operation: tree approaching, felling technique, fork stems handliness, crane coordination, stump height, bucking position, prolixity of processed logs, among others. Furthermore, they were also given theoretical knowledge about forest operations.

After the simulation phase operators were working directly on the machinery (harvesters). A fleet of 20 harvester provided the data for the whole study. All of them, were brand/model: PONSSE Ergo, crane type: PONSSE C44, and PONSSE H7 harvester head was the most used one. Because all harvesters had the same technology, the effects added by different technologies were avoided. In addition, during the study, clear cut logging methodology was applied and fully debarked of 6,5 meters length logs were produced.

All machines used, were equipped with OBC and control systems software OPTI 4G Ponsse version 4.728. Data has been processed since operator started working directly in a harvester until their performance showed to be stable. It has been recorded and stored according StanForD standards in defined drf, prd, stm files (Skogforsk, 2015). Among them, drf files were mostly used, which are specific for operational time monitoring and contain complete shift information of events during working hours, detailed in sub shifts. To reduce the influence of time when the machine was not productive, all production related times were included: processing, terrain travel and road travel; as shows in the figure 1. According to IUFRO (1995) partition of working time corresponds with "productive working time" (PWH). The computer was settled to record the sub shift classification within an interval of 3 minutes, as it is the common setting for uruguayan loggers.

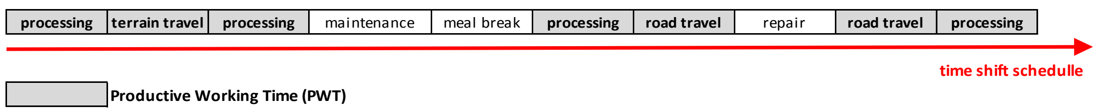

Figure 1. Scheme of time decomposition during working shift, sub shift in drf files, highlighted the time considered for this study. Adapted from StanForD.

During logging, operators were working in different forest stands, in the east and west of Uruguay, all of them *Eucalyptus ssp*. owned by the company Montes del Plata. Before attaining into any stands, the mentioned forest company, provided inventory data with information showed in table 1.

Table 1. Detail of inventory information counted for every stand where the study was carried out.

Variable	Description
Stand ID	Identification number
Year	year of plantation
Species	*Eucalyptus globulus ssp. globulus,* *Eucalyptus globulus ssp. maidennii,* *Eucalyptus grandis,* *Eucalyptus dunnii,* *Eulcalyptus viminalis*
Regime	Regime of the forest:
Dt.In.	date when the inventory has been done
Sup	area of the stand in hectares
age	years of the stand
N	trees per hectare
N>8	trees per hectare with commercial value (higher than 8 cm at DBH)
DBH	diameter at breath height (cm)
HM	Medium height of the trees (m)
HD	Dominant height (m)
Va	medium volume per tree (m3/tree)
IMA	Medium annual increment (m3/year/hectare)
V mcs	commercial volume per hectare
VT	total commercial volume of the stand
E Inv	Error of the inventory
Group specie	Aggrupation regarding specie and location: Glob_1, Glob_2, Maid_1, Gran_1. (Defined for this study)

For the purpose of this study, every stand has been grouped in four categories according to *Eucalyptus spp.* species and location. Then, each group, was assigned by a corresponding productivity model (known by historic data of companies involved) with volume per tree as independent variable. Finally, those regression models were used to relativize each instant productivity of operators (observations) while they were accumulating working hours. Therefore,

$$P_R = P_I / P_E \qquad (1)$$

Where, $\mathbf{P_R}$ is the relativized productivity or Performance, $\mathbf{P_I}$ is the observed productivity in m^3 PWH^{-1} or trees PWH^{-1} (observations), and $\mathbf{P_E}$ is the expected productivity (m^3 PWH^{-1} or trees PWH^{-1}) according to known models and the matching inventory data.

Then, considering P_R as a dependent variable and Accumulated PWH (APWH) as independent variable, nonlinear models were carried out using InfoStat (2016) software to establish which model fit best. Therefore, general model as bellow:

$$P_R\ (f) = APWH \qquad (2)$$

Assuming, that models for expected productivity (P_E) are accurate and the sample of operators have a normal distribution, it is expected that the average coefficient of P_R, when operators reach stable productivity, will be close to 1.

1.3.1. <u>Criteria for discarding data</u>

Some observations were discarded from the database. The criteria to limit the dismissed data is detailed as bellow:

(1) Shifts that the report by operator showed issues with the operative system of the machine, in order to avoid data loaded when the machine could be recording wrong measurements, e.g. sensors issues.

(2) Shifts that a non-conventional assignment was required, e.g. road edge cuttings.

(3) Observations with working time laps shorter than 15 minutes or less than 20 processed trees, in order to avoid sub or over valuated data.

1.3.2. <u>General analysis</u>

To select which model fitted best, Akaike's information criterion (AIC) at 0.01 level of significance has been used to compare models. Therefore, the model with lowest AIC value is the most suitable to describe the learning curve. A stepwise process, of selecting the fit model for learning curve, has been done for each operator separately, and then, for all the operators together in order to obtain the general model.

Afterwards, tests with the selected models were carried out, to confirm the accuracy. Hence, the fit model was checked for homoscedasticity and normality of errors, predicted values of the model and observations were used for linear regression to visualize distribution and to obtain parameters such as correlation with the selected model, among others.

1.3.3. <u>Individual analysis</u>

Other analyses were carried out for each operator. First, it was defined the amount of productive working hours needed to reach a stable performance individually. The learning curve, in general, shows significant increases in productivity over accumulated working hours, which due to the fluctuation of the data and the variability of all factors that influence productivity, does not fall again. For the strong variation of data and the fact that the curve becomes asymptotic, it is not possible to define the end of the learning phase in a purely mathematical way. Therefore, the same approach described by Purfurst (2010), was used to determine the end of the learning: when the curve shows to reach a stable level and has been recorded the first large maximum, combining visual and mathematical properties.

Then, for each individual operator, the average performance value at every 50-accumulated productive working hours and corresponding final performance has been estimated. Finally, in order to propose other ways of measuring duration of the learning process, it was defined for each operator the required amount of days, processed stems and volume to reach stable productivity.

1.3.4. <u>Correlations</u>

All information has been summarized by initial performance (Pi), every 50-accumulated productive working hours (P50, P100, P150, P200, etc.) and final performance (Pf). This information was settled to assess correlations between performances at initial stages of the learning process with final performance. Since it is not possible to make repetitions for each operator at different moments of APWH, Spearman coefficient was carried out to estimate correlations. Furthermore, Principal Component Analysis was used to evaluate association among different groups of variables.

To accomplish the proposed objectives, during this three-year period of collecting information, it has been gattered a database of 1.634.217 trees, or 337.440 cubic meters of wood, that has been processed.

1.4. RESULTS

1.4.1. <u>General model</u>

A general model of the learning curve was established with the observations of 25 operators during their learning process. The best fitted model corresponds to a

Monomolecular model, meaning that productivity starts at the lowest level, then rises at decreasing rate over time; and finally, at the end, the curve asymptotes. Despite, the Monomolecular model showed to have the lowest AIC coefficient, the Logistic presented a very close value. Regarding this result, Parker et al., (1996) and Purfürst (2010), explained the learning curve as a logistic model with an initial phase of increasing increments that switches to decreasing increments becoming asymptotic at the final phase.

Figure 2 shows the resulted curve, including the dispersion of all observations from this study. Each parameter of the model was obtained with p>values lower than 0,001. Equation (3) presents the general learning model and parameters are shown in table 2.

$$P_R = \left[alfa * \left(1 - beta * e^{(-gamma * APWH)}\right)\right] \quad (3)$$

Table 2. Parameters alfa, beta and gamma from the learning general model of harvester operators.

Parameter	**Cota INF**	**Conta SUP**	**Initial Value**	**Estimation**	**E.E.**	**T**	**p-value**
ALFA	-1e030	-1e030	1,734	**1,030**	0,009	111,278	<0,0001
BETA	-1e030	-1e030	0,001	**0,734**	0,012	60,239	<0,0001
GAMMA	-1e030	-1e030	0,001	**0,003**	1,3E-04	22,260	<0,0001

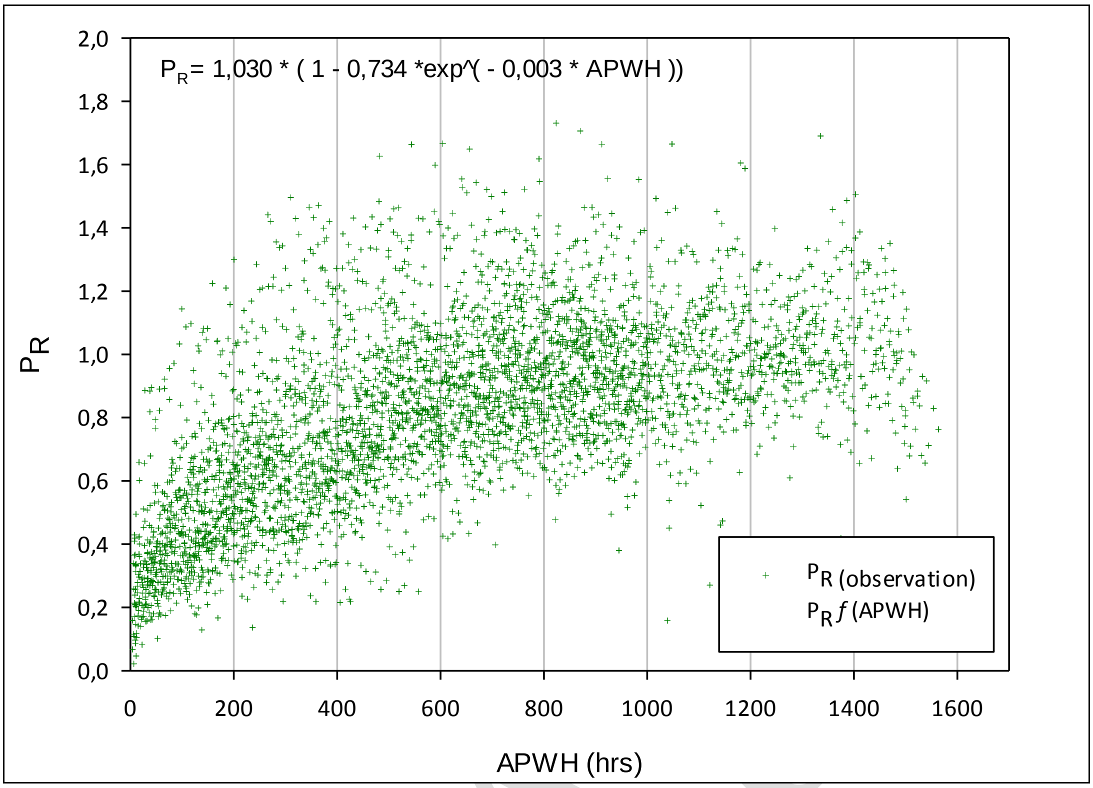

Figure 2. Performance distribution regarding Accumulated Productive Working Hours and regression learning model.

With the resulted learning model, is observed that performance of an average operator at initial time, when operating harvester machine, is placed in 27,4% of the potential. The average increment, in relative terms of productivity, is 0,08% per PWH; and higher rates are at the beginning, reaching 47,0% of the potential productivity within 100 PWH (performance increased at this phase by 0,21% per PWH).

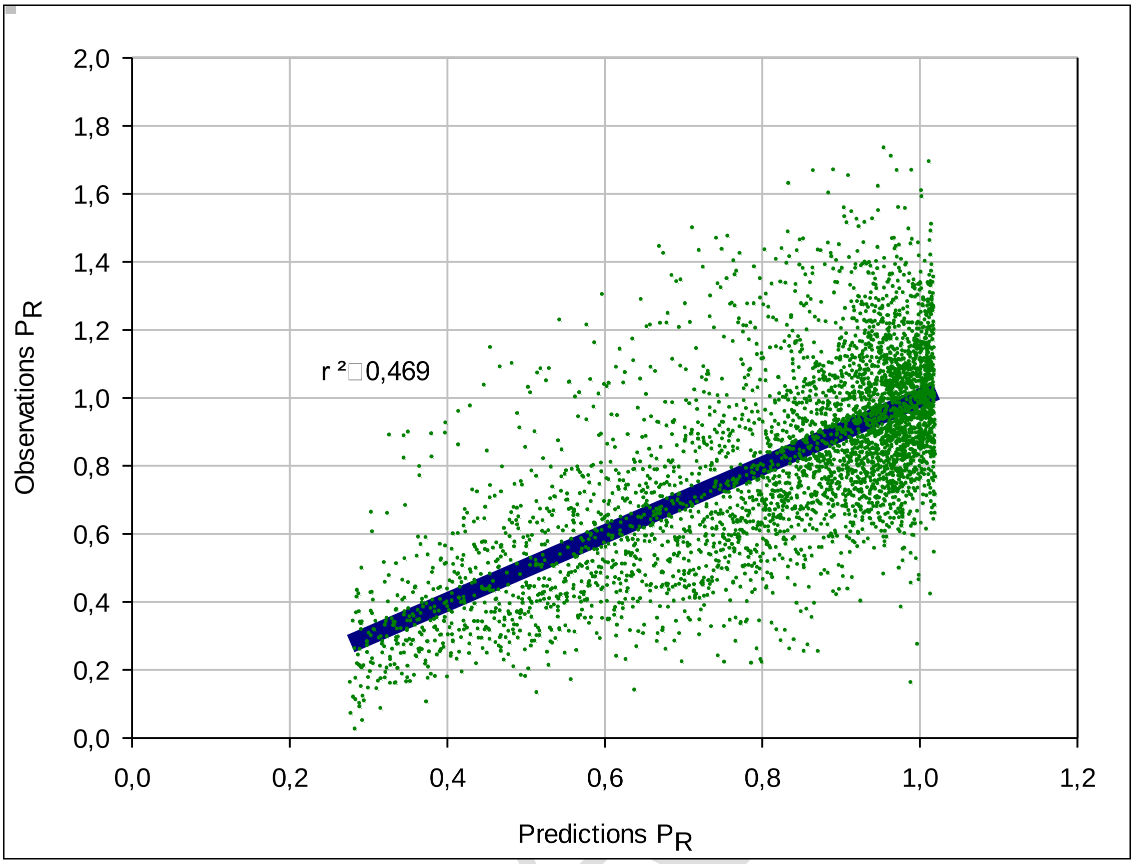

Figure 3. Linear regression with predicted values from the general model and observations.

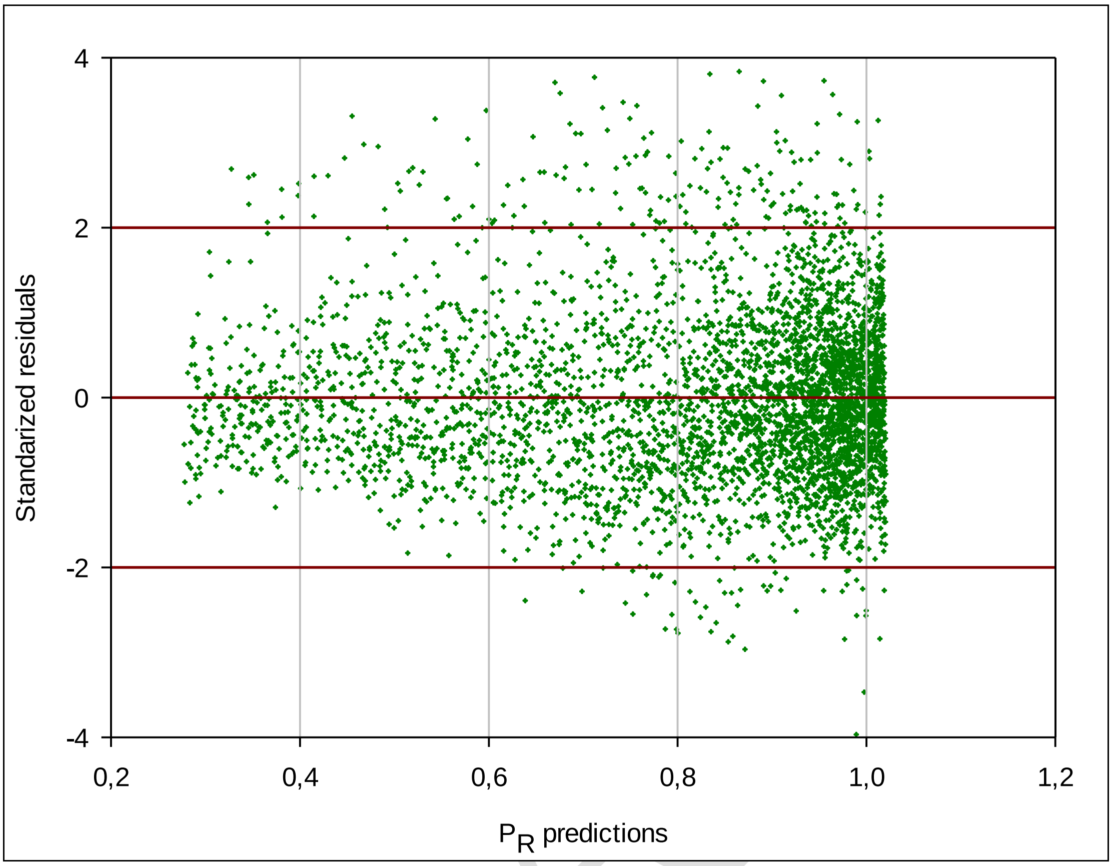

Figure 4. Standardized residuals distribution for general model.

Figure 3 shows a coefficient of determination (R^2) of 0,469 between prediction of the model and observations, therefore, 46,9% of variability in all observations is explained by the model. Regarding distribution of the standardized residuals, showed in the figure 4, a normal distribution is observed. In both figures, gathering of observations towards value 1 is noted, meaning that the performance of operators was stabilized at this level, hence, previous local productivity regression models were suitable for type of production and the studied forest scenarios.

1.4.2. <u>Individual Analysis</u>

Some of the individual models (which fitted best for each individual operator) are represented in figures 5, then, summary of the analysed data on table 3.

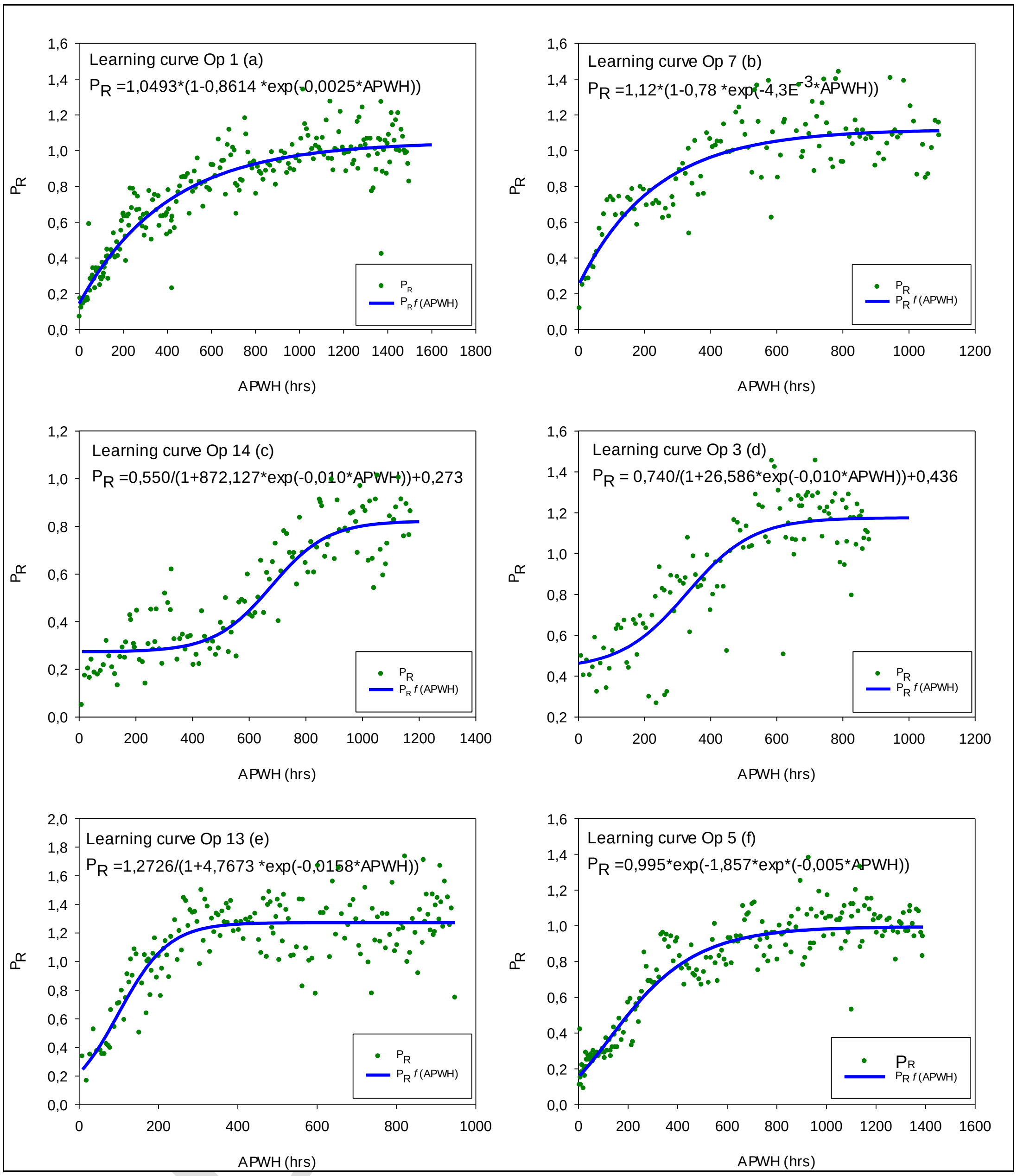

Figure 5. Individual learning models for a sample of studied operators, where: **a** and **b** corresponds to Monomolecular model; **c**, **d** and **e** corresponds to Logistic model; and **f** correspond to Gompertz model.

Table 3. List of operators with corresponding data of: coefficient of determination (R^2) for the fitted individual model, performances level at different accumulated working hours (Pi, P50, P100, P200, P500, P750, P1000), final performances (Pf) and amount of PWH to reach final performance. In the bottom of the table are the average values (**Average**) for each variable and the predicted values from de General Model (**G Model**).

Op.	**R^2**	**Pi**	**P50**	**P100**	**P200**	**P500**	**P750**	**P1000**	**Pf**	**hrs_**
1	0,84	0,138	0,264	0,332	0,547	0,813	0,950	1,027	1,029	1016,8
2	0,52	0,500	0,834	0,688	0,803	1,155	1,181	1,432	1,320	1046,1
3	0,74	0,450	0,449	0,518	0,579	1,090	1,205	1,175	1,157	717,9
5	0,81	0,188	0,255	0,308	0,453	0,736	0,906	1,054	1,000	929,0
7	0,70	0,216	0,417	0,701	0,726	1,143	1,112	1,223	1,098	788,2
8	0,45	0,377	0,892	1,050	1,092	1,292	1,292	1,359	1,376	587,3
9	0,83	0,205	0,323	0,460	0,560	0,870	0,977	1,047	1,040	890,8
11	0,89	0,227	0,265	0,346	0,506	0,945	1,041	1,104	0,998	742,9
13	0,67	0,250	0,395	0,672	0,986	1,319	1,144	1,270	1,258	602,2
14	0,82	0,111	0,194	0,238	0,334	0,362	0,673	0,812	0,803	1052,9
15	0,76	0,270	0,323	0,320	0,489	0,575	0,798	0,877	0,849	1014,5
16	0,60	0,258	0,386	0,550	0,577	0,899	0,960	1,043	1,107	1168,0
17	0,65	0,266	0,362	0,522	0,614	0,708	0,801	0,938	1,043	1187,5
19	0,62	0,259	0,277	0,559	0,577	1,083	0,923	1,024	1,129	1153,7
20	0,62	0,322	0,365	0,473	0,523	0,743	0,807	0,923	0,897	972,4
21	0,74	0,329	0,360	0,352	0,472	0,671	0,803	0,865	0,885	1163,6
23	0,72	0,255	0,376	0,433	0,474	0,751	0,843	0,965	1,011	1235,5
24	0,70	0,203	0,312	0,432	0,519	0,760	0,903	0,940	0,952	1214,5
25	0,71	0,232	0,309	0,391	0,398	0,656	0,888	0,839	0,956	1288,9
26	0,74	0,108	0,378	0,343	0,428	0,652	0,825	0,780	0,945	1282,4
28	0,68	0,439	0,511	0,570	0,711	0,980	1,141	1,115	1,104	932,6
29	0,74	0,258	0,356	0,528	0,659	0,938	1,126	1,160	1,154	920,3
30	0,69	0,333	0,436	0,456	0,673	0,849	1,007	1,042	1,038	878,8
31	0,69	0,378	0,460	0,498	0,785	0,874	1,029	0,986	1,005	773,8
34	0,81	0,417	0,453	0,449	0,540	0,866	0,945	1,021	0,994	824,0
Av.	**0,71**	**0,280**	**0,398**	**0,488**	**0,601**	**0,869**	**0,971**	**1,041**	**1,046**	**975,4**
G. M.	**0,47**	**0,274**	**0,370**	**0,470**	**0,615**	**0,861**	**0,950**	**0,992**	**1,009**	

Op.: operator number, **R^2**: coefficient of determination, **Pi**: initial performance, **P50**: average performance at 50 PWH, **P100**: average performance at 100 PWH, **P200**: average performance at 200 PWH, **P500**: average performance at 500 PWH, **P750**: average performance at 750 PWH, **P1000**: average performance at 1000 PWH, **Pf**: stabilized performance (final), **hrs**: number of PWH to reach stable performance.

Table 3 shows summarized performances at different moments of the learning progress for each studied operator, R^2 of each individual model and number of hours needed to reach stable performance. R^2 values for the general model, showed a coefficient of 0,47 which is high considering that all the operator effects are included for this model. When assessing at individual models, R^2 values are higher (average of 0,71) as it would be expected. The average number of hours needed to achieve the stable performance is 975,4 PWH; or expressed otherwise, regarding this study, the end of the learning curve corresponds to an average of 142 days (around 6,5 months) or 10.007,5 m^3 processed wood. The average Initial performance is 28% of the expected potential, showing at 100 APWH an average of 49% of its potential; similar results were also observed by applying the general model.

1.4.3. <u>Correlations</u>

Correlation of measured productivity, between all learning process phases and final performance of each individual operator, are presented in table 4. It shows, when assessing first stages from 100 APWH and further, performances are already highly correlated (coefficients above 0,83) with final performance, those values presented high values of significance (p value < 0,01).

Table 4. Correlation coefficients between performances at different initial stages and at the end of the learning period on the left side of the table, p-values for each coefficient on the right side of the table.

	Pi	**P50**	**P100**	**P150**	**P200**	**Pf**
Pi	**1,00**	2,8 E^{-4}	0,01	2,3 E^{-3}	0,01	0,02
P50	0,74	**1,00**	7,4 E^{-4}	1,7 E^{-4}	6,1 E^{-4}	0,01
P100	0,52	0,69	**1,00**	6,8 E^{-6}	1,8 E^{-5}	1,9 E^{-5}
P150	0,62	0,77	0,92	**1,00**	3,8 E^{-6}	3,7 E^{-5}
P200	0,55	0,70	0,87	0,94	**1,00**	4,6 E^{-5}
Pf	0,46	0,54	0,87	0,84	0,83	**1,00**

Pi (initial performance level), **P50** (50 APWH performance level), **P100** (100 APWH performance level), **P150** (150 APWH performance level), **P200** (200 APWH performance level) and **Pf** (final performance level).

In figure 6, Principal Component Analysis is designed to visualize the association between initial learning phases performances with final performance and in turn how operators are ordered. It shows the operators distribution by their performance: on the right side are located those with higher performance values and on the left side are those with lower performances values during learning process. In addition, concerning performances during initial times, is possible to state that individual performances at 100

APWH and further are positively and strongly associated with its final performance; while initial performance and at 50 APWH are positively associated but not as strongly. Hence, outstanding operators at initial phases are highly probable to have higher potential, in terms of productivity (m^3/PWH), when its learning is fulfilled.

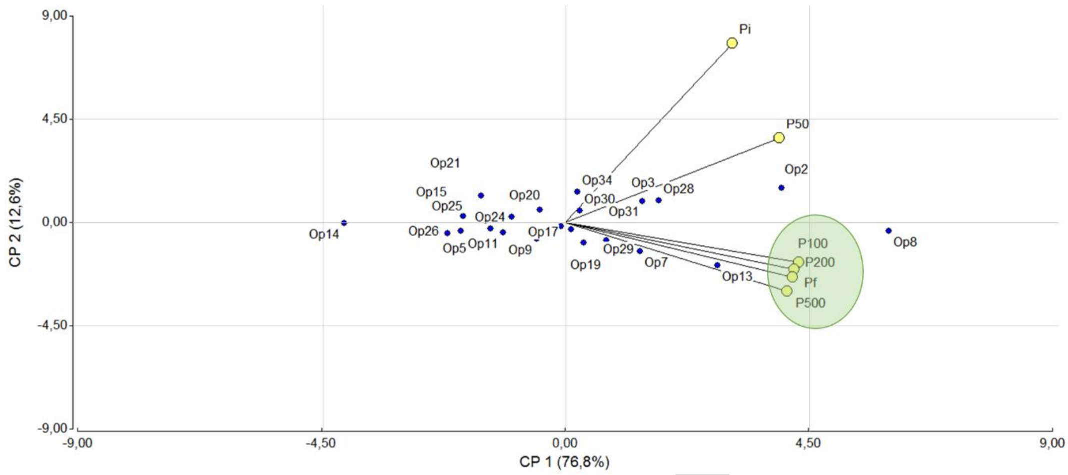

Figure 6. Biplot of performances among different initial time periods and when stabilized (final performance). **Op** (operator's distribution regarding matching performances during learning), **Pi** (initial performance level), **P50** (50 APWH performance level), **P100** (100 APWH performance level), **P150** (150 APWH performance level), **P200** (200 APWH performance level) and **Pf** (final performance level).

1.5. DISCUSSION

The described general model explains the learning development until an operator reaches stable productivity; operator being without previous experience and learning process including 50 hours in simulator and theorical instructions as described in materials and methods. Since this curve was done in relative terms of productivity, any company with the knowledge of potential productivity regarding their own scenarios, will be able to plan and estimate the wood flows when they are facing training process of new operators.

The learning process can be described as the following:

(1) An operator recognizes and memorizes the movements of the commands and keyboard controls while operating. At this phase productivity should have increasing increments (Parker et al. 1996).
(2) After being familiarized with controls, by repetitions, the operator starts automatizing the movements, increasing coordination skills, e.g doing several movements at one time. Automatic mode and multitasking starts (Purfurst, 2010).
(3) Operator makes fewer mistakes, understands how a tree reacts and anticipates future movements looking for efficiency along every stage of the process.

When carrying out individual models, the first phase of the learning process defined above, is just visualized for scattered operators. Nevertheless, the majority of them did not show this phase. Probably because all the observations have been taken when operators had already started working in the machine and not when they were at the simulator, hence they mostly have already learned and were familiarized with the crane and harvester head controls. This could be a reason why this model happen to be monomolecular and not logistic as explained by other authors (Parker et al., 1996; Purfürst, 2010).

The time frame needed for an operator to finish its learning, showed to be shorter than the figures presented by Purfürst (2010). It can be stated, that in pulp wood production studied scenario, when harvesting single assortment, using clear-cut as harvesting method and homogeneous forests (monoculture and even aged), operators might have faster learning. Therefore, the more homogeneous and standardized is the production, the shorter learning time is needed to reach potential performance.

On the other hand, this study was done with relatively newer harvesters in comparison with other studies. Machines were continuously updated, enhanced and technology was improved, resulting in more intuitive commands, which makes it easier for new operators to develop control of the machine. Furthermore, as new development and researches are still being carried out by manufacture companies towards automatization in control systems, it can be expected faster learning periods for future operators at the phases 1 and 2 described above.

In this study, the learning curve was assessed for just one type of cut to length system machine, therefore forwarder machines should be also addressed for the same purpose in order to count overall information of the logging system (harvester-forwarder). Using StanForD files from OBC, showed to be accurate and suitable when addressing productivity models of logging operations, especially at very standardized productions such us for pulp purposes. Hence, the methodology employed within this study can be also emulated for further productivity assessments.

Another important finding is the possibility of recognizing higher productive operators already at early stages of the learning process. But due to the fact, that already at 100 PWH operators present a significant cost for any company, it is important to select skilled operators even sooner when possible. As subjective evaluations at the simulator phase did not corresponded with the same criteria for all studied operators, it was not possible to measure associations with final performance. Therefore, additional studies to identify skilled operators are needed; requiring the design of evaluation tools and/or methodologies at simulator phase of the learning process.

Nevertheless, according to Häggström (2015), productivity is a system composed by three main parts: human (skills and abilities), technology (tools and prostheses) and the organization (culture and structure of the company). Therefore, to select operators just by their abilities to drive a machine must not be taken as an isolated criterion. Each company has its own structure, resources, ways to motivate teams, among other factors, that must be put in consideration. Hence, in order to accomplish an appropriate selection, behavioural profiles studies, customized by organization types, must be also included (Pagnussat & Lopes 2017).

1.6. CONCLUSIONS

A period of approximately six and a half months (975,4 PWH), depending on the shifts schedules of each company, is needed for an operator to reach a stable productivity. However, the productivity of an operator during their learning period is represented by a monomolecular model which becomes asymptotic when the learning is finished; hence, the operator can still slightly increase its productivity during some time. This study, gives forest logging companies information to make suitable plans of the wood flows during periods of training new operators in the organization.

It is possible to encounter skillful and productive operators in early stages of the learning process; although behavioral profiles, regarding company's culture and work organization, must be consider in order to be complemented with previous statement. The outcome could enhance overall harvesting production, either while building new harvesting teams or when replacing new operators for already existing ones.

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