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Learning Curves of Harvester Operators

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Abstract – Nacrtak

Single grip harvesters may reach very high productivity levels but are very expensive forestry machines. Therefore, they have to work very efficiently. This paper will analyse the learning curves of harvester operators and the influence of human factors described in a qualitative and quantitative manner. Based on long term production logging files (StanForD), the performance of 32 operators was collected over a period of three years (3,351 stands, 0.65 mil. m³). 16 of the operators were beginners and their learning curve was analysed and drawn as a sigmoid function. Most operators begin their career between 50% and 60% of the mean performance and double their performance (200%) by the end of the learning phase. The differences and variation in the learning curve between individual operators are large and generalisations are to be made with care. A learning curve phase productivity loss of 24% was calculated for the average 8 month duration, which equates to approximately 45000 Euro.

Keywords: harvester operator, learning curves, harvester productivity, harvester operations, human influence.

1. Introduction – *Uvod*

The modern forest industry uses thousands of single grip harvesters. They may reach very high productivity levels but are very expensive forestry machines. Therefore, they have to work very efficient. Numerous different factors have an influence on this productivity, many of which have already been determined and described in literature (Purfürst 2009). One factor is often disregarded when considering mechanical work performance; the human factor. As Kirk et al. (1997) mentioned: »A skilled operator is essential if the investment in the machinery is to be maximized by the contractor«. Purfürst (2009) analysed 53 harvester productivity models in regards to the operator effect. Most of these models do not use the operator as an influencing factor, only mentioning the experience of the operator. However, the intra-individual (Purfürst 2010) and temporally observed variability in the operator performance level can be very high and will increase with the experience of the operator. The replacement of an experienced operator by a new harvester operator alone can be estimated by a production loss of about 49,650 € (Gellerstedt et al. 2005). The training costs are still not taken into account, however, and can account for up to 15,000 € (Gellerstedt et al. 2005). Therefore it is necessary to briefly present a rough outline of the learning curve concept.

Driving a single-grip harvester is a complex and an exacting type of work. Performance varies over time. Within a day there are variations of the whole mental system based on tiredness and daily rhythms. Throughout the seasons there are also variations based on light, weight of roundwood and driving conditions. But there still are variations without an external influence factor. When a harvester operator starts his career he usually has a very low performance. Over time he makes less mistakes, learns to ignore unimportant information and his coordination skills increase. Through repeating work cycles very often he will develop an »automatic« mode of working where functions are coordinated by the cerebellum instead of by the cerebrum. With work experience he gets well trained and his and the system – performance increases over time. This effect is based on the aptitude of the operator.

The relation between productivity and experience is called a learning curve. A learning curve describes the level of performance through learning over time. It can be calculated by the quotient of learning results and the time needed. To measure the experience of a harvester operator directly still remains a problem. Currently, only productivity, time and some influencing factors can be measured. The assumption is that the more time the operator spends the more familiar he/she will become with the machinery, hence his/her skill level increases. However, this does not presume that the productivity of the whole harvesting system increases proportionally. At the same time, other influencing factors such as age and health of the operator or age and condition of the machinery can change the productivity level. The »real« learning curve is often not quantifiable. For this reason the learning curve is often interpreted as the relation between productivity and time or cycles of work.

The learning curve describes the performance level reached by an individual operator. However, the operator and the harvester with its configurations form a unit. Only this unit has reached the measured performance. Therefore the only possibility is to set the focus on the whole harvester system, as separating the influence of the operator and the harvester is not possible.

The difference between less trained and well–experienced operators can be very high. Some analyses of learning curves in the forestry sector have already been described for forest workers (Garland 1990), forwarders (Harstella 2004), wood transportation (Björheden 2000), harwarders (von Bodelschwingh 2003), cable-yarder teams (Dodd and McNeel 1996) and cable yarder operators (Stampfer 1999). Stampfer et al. 2002 found in the case of helicopter yarding (K-Max) that the difference in performance between an experienced and an inexperienced operator was nearly 2:1. Nonetheless, analyses of learning curves of harvester operators are rare. Parker et al. (1996) studied a forwarder operator and a harvester operator. The greatest increases of performance are within the first 30 days but the level of performance fluctuates greatly. Heinimann (2001) analysed a harvester driver and found that with small diameter trees the performance increases by 50% within one year.

The learning curve effect can be divided into different segments. Stampfer (1999) suggested two phases: the first phase is called the learning phase where the operator continuously increases his performance. The second one is the working phase where the operator is working at a relatively constant performance level. Therefore, Jacke 2000 suggested a division into three phases. The first model is equivalent to the description of the so called »inexperienced« and »experienced« operator that is used by most authors (Purfürst 2009, Purfürst and Erler 2006). Current learning curve analyses are often restricted to the first phase e.g. the training in the simulator. The second phase is often disregarded and consistent performance level of the operator is assumed.

The length of the learning curve is discussed differently. The reaching of the »experienced« level is often described as a number of productive machine hours and it differs between 1000 and 1500 Productive Machine Hours (PMH) (Gabriel 2005, Jacke and Wagner 2002, Wagner 2004). Other authors describe it as a time span between 8 and 12 months (Calabrese 2000), or in hundreds of PMH (Loschek et al. 1998) or as a number of harvested trees (Heinimann 1998).

The duration of the learning curve can be reduced through a structured training program (Kirk et al. 1997). Even the sleeping time of the harvester operator has an influence on the learning time and therefore on the learning curve (Dinges and Kribbs 1991).

The learning curve effect is not restricted to new operators. Von Bodelschwingh and Pausch (2003) describe the training effect of an »experienced« driver on a machine other than his own and discover that he reaches a working plateau after 20 days. Hoellerl (2005) found that for a harvester driver with the change of control (control stick) about four weeks acclimatization is needed to reach his previous level.

Concerning the shapes of the learning curve, there is general consensus in the literature that it first raises and then flattens. Jacke (2000) describes that a learning curve can be represented through a number of exponential – functions, but also suggested that it is hard to describe complex movement patterns. Björheden (2000) instead uses a simple e-function for the analysis of mechanized skidding. Dodd and MCNeel (1996) divide the compensation function into two linearly rising lines, with the transition between the two at 100 working days. Calabrese (2000) describes the learning effect as a multistage process.

Currently there is a lack of knowledge to explain the learning curve and the impact of the learning process. This study examines duration, shape, differences and costs of learning curves of harvester operators and the influence of human factors described in a qualitative and quantitative manner.

2. Material and methods – *Materijal i metode*

2.1 Environmental conditions and operators – *Okolišni uvjeti i vozači*

The experimental study sites were located in Germany with the focus on East Germany and Bavaria, south Germany. For comparability, only pine–dominated stands were selected for the analysis. The harvesting system included thinning of marked trees in young stands with a CTL single-grip harvester. For most stands this was the first thinning and extraction corridors were built. Distances between working corridors were 20 to 24 meters. Only sites with a slope less than 10% were considered. Over 90% of the harvested trees were pines (*Pinus sylvestris* L.). Other tree species included Spruce (*Picea abies* (L.) H.Karst. – 6.1%), Larch (*Larix decidua* Mill. – 0.6%), Birch (*Betula pendula* Roth – 1.7%) and hardwood (0.7%).

Most data were collected through the data logging systems of the harvester and evaluated by additional information from time studies on sites. In total the information of 52 operators was recorded but only 32 were considered for the analysis due to the following rules:

⇒ Machinery (only three types of harvesters for small diameter thinning were selected: John Deere 1070, Valmet 901 and Ponsse Beaver),

⇒ Tree stands (spruce, larch and hardwood dominated stands were not considered),

⇒ Harvesting system (only thinning was considered rather than clear-cut or wind throw-areas),

⇒ Operating sites (number of the working areas had to be more than 15 per operator),

⇒ Other factors such as: e. g. incomplete information about the operator.

There are differences in the operators' educational and practical background. Some of the operators had taken a harvester education program or course at a forestry academy. These courses varied from one day to seven weeks. More than half of the operators (56%) had three years of training as a forest worker. Some (28%) had completed a different trade such as mechanics, carpentry or butchery and learnt harvesting on the job-site. The hours spent operating the harvester varied as well from relative beginners to well experienced operators that had been working in this field for seven years and longer.

2.2 Logging documents – *Proizvodni dokumenti*

The study was based on logging documents from the harvester computer. With automatic harvester data logging the StanForD-Standard was used and the production information was stored in defined files (»prd«, »pri«, »drf«, »stm«) depending on the system (Skogforsk 2007). Additional information on times, dates, harvesting data, operators and software was also included. For example, the types of time are Effective time, G15-time, Move-time, Runtime, Work time and Repair time. The G15-time, which is defined as hours of effective machine time including downtime not exceeding 15 minutes per occasion, was used for all of the analyses.

2.3 Data analysis – *Analiza podataka*

A program written by the author analyses the huge number of StanForD files, by parsing different variables. A big problem is the partly inconsequent realization of the StanForD-Standard. The variances in collecting software types and versions installed in harvesters made it very difficult to analyse the data automatically. Nonetheless, the parsed StanForD data was written into a database. As the size and duration of the operation per stand differs, the information had to be harmonized and weighted, based on the time variable. These data were analyzed with standard statistical programs independent from the real stand-size. The analysis of the production data is based on the stand, weighted by time (days).

The information about stems, times and harvested volume were used to create performance information for every stand and operator for a specific date. To compare the operator it is necessary to find a reference performance. The choice of the type reference is difficult and based on the data and the use (Purfürst 2009). In this study a relative mean was used as a representative for the whole population and was calculated with one logarithm regression. Only the influence factor of the tree volume was considered. Afterwards every value was divided by this regression value to calculate the relative performance. The value of 1 is equivalent to the mean performance.

$$P_r = \frac{P_0}{P_m} = \frac{P_0}{e^{0.684 * in(tvol) + 3.543}} \qquad (1)$$

Where:

P_r Relative productivity, m³/h
P_o Actually observed productivity, m³/PMH
P_m Model productivity, m³/PMH,
tvol Volume/tree, solid cubic meter

The level of performance in this study is defined as the arithmetic mean of the relative performance of 60 days. After several attempts it was established that the period of 60 days is a sensible compromise. It is long enough to reproduce several harvest stands and short enough to include other performance–influencing factors such as the learning curve.

The learning curve indicates a significant increase in performance as a function of time, which under a certain level of tolerance does not fall again. The challenge is to determine if it is solely due to fluctuations in performance by non-temporal (external) factors or to an actual increase associated with the ability of the harvester operator. The process of learning ends, but usually not with the achievement of the average power (Performance Level = 1), but stops beyond. It is therefore important to determine the end

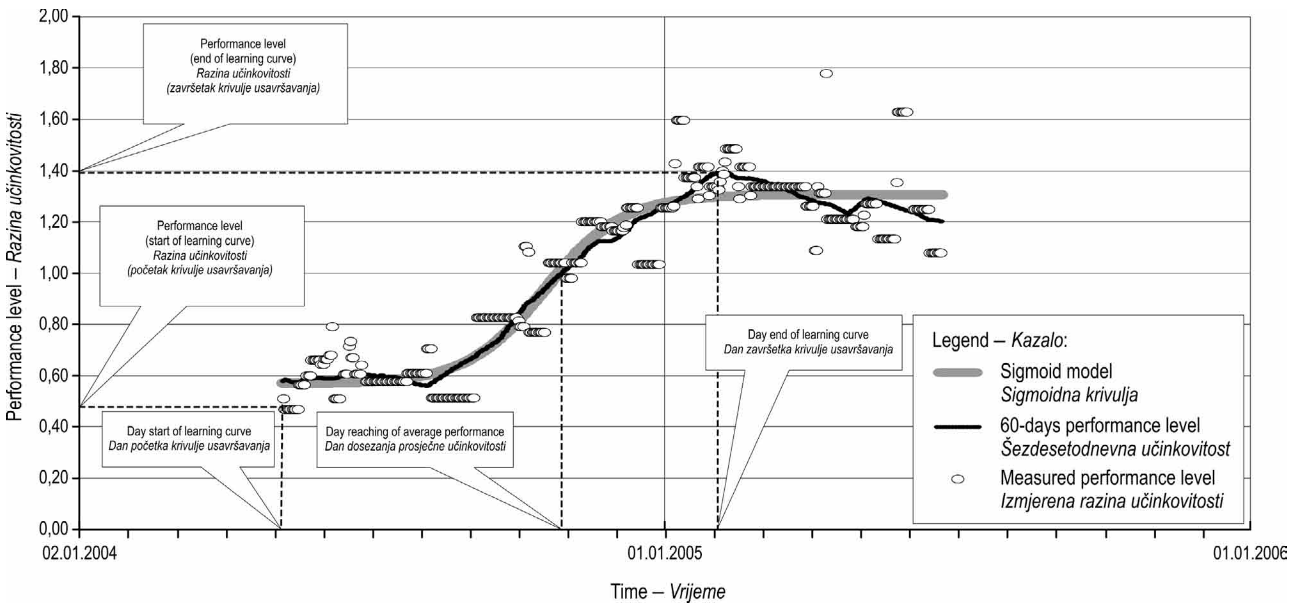

Figure 1 Example of a learning curve, 60-days performance level and sigmoid model (Operator No. 22)
Slika 1. *Primjer krivulje usavršavanja, šezdesetodnevna razina učinkovitosti i sigmoidni model (vozač br. 22)*

of the learning phase. Because of the strong differentiation of the data it is not possible in a purely mathematical way. Therefore, the end of the learning phase will be determined from a combination of visual and mathematical properties as the first (large) maximum is determined by the end of the increase in benefit levels over time. Fig. 1 shows an example of driver No. 22. It is clear that by the end of summer 2004, the subject has already reached a local maximum, but after that the learning increases again. Thus, this is only a scattering and not the real end of the learning phase. The next maximum, which was reached at the beginning of February 2005, was characterized by a subsequent decrease in benefit levels.

To describe the learning curve, a sigmoid model was used and solved with a nonlinear regression:

$$PL(t) = \frac{PL_{\max} - a}{1 + b * e^{-c*t}} + a \qquad (2)$$

And

$$PL_{\min} = \frac{PL_{\max} + b*a}{1+b} \qquad (3)$$

Where:

$PL(t)$ Performance level over time

PL_{max} Maximum performance level

a, b, c Variable

t Working days

Start-parameter for regression solution: $PL_{max} = 1.4$, $a = 1.0$, $b = 1.0$, $c = 0.001$

3. Results – *Rezultati*

4.5 million stems from 3351 stands and 32 operators were analyzed, which represents approximately 0.65 million cubic meter (m^3) of harvested wood. The mean volume is 0.147 m^3/tree. The arithmetic mean production is 9.8 m^3/PMH (geometric mean: 8.93 m^3/PMH). Nearly 70% of the variation in productivity can be explained with the tree-volume ratio. Data from the logging documents were recorded during December 2003 and September 2006.

The logging documents of 16 of 32 operators reveal a learning curve. There is a large variation in statistical values. Table 1 shows the facts of the learning curves of these harvester operators.

13 of the 16 drivers listed in Table 1 show at their maximum a performance level ($PL_{\max}$) above the average ($PL = 1$). The number of days before overtaking the average levels of performance is highly differentiated with a range between 68 and 286 days (mean: 193 days). The duration of time before reaching the end of the learning phase differs too. The range is between 155 and 488 days (arithm. mean: 255 days, median 227 days). It can be generally assumed that the duration of the learning period is approximately 8 months, but the standard deviation is high.

At the beginning of the study these operators started at a performance level between 0.33 and 0.76, wherein the average is 0.56. Half of operators' interquartile range begin their career between 51% and

Table 1 Facts of the learning-phase for individual operators
Tablica 1. *Podaci o usavršavanju pojedinih vozača*

Operator – *Vozač*	PL_{Start}	$PL(1)$	PL_{End}		Increase *PL* – *Povećanje PL*		PL_{Max}
					Overall – *Sve*	per day – *po danu*	
		Days – *Dana*		Days – *Dana*	%	%	
2	0.39	281	1.14	281	292	0.23	1.14
5	0.33	–	0.68	237	206	0.15	0.85
8	0.51	75	1.43	192	280	0.48	1.43
10	0.76	232	1.29	355	170	0.15	1.29
11	0.61	68	1.11	140	182	0.36	1.13
12	0.59	385	1.05	488	178	0.09	1.05
13	0.50	286	0.86	232	172	0.16	1.03
14	0.52	–	0.86	127	165	0.27	0.99
15	0.62	88	1.22	130	197	0.46	1.47
16	0.60	155	1.11	212	185	0.24	1.40
17	0.69	105	1.28	221	186	0.27	1.38
18	0.63	274	0.98	460	156	0.08	1.10
20	0.51	263	1.34	350	263	0.24	1.34
22	0.51	168	1.40	279	275	0.32	1.40
24	0.67	135	1.05	155	157	0.25	1.05
28	0.58	–	0.76	183	131	0.10	0.76
Arithmetic mean	0.56	193	1.10	255	200	0.24	1.17
Median	0.59	168	1.11	227	183	0.24	1.12
25%-quantile	0.51	105	0.95	176	169	0.15	1.05
75%-quantile	0.62	274	1.28	331	220	0.28	1.39

PL_{Start} – Performance Level at the beginning of the learning phase – *Razina učinkovitosti na početku usavršavanja*
$PL(1)$ – Reaching the Performance Level of 1 (mean overall) – *Dosezanje razine učinkovitosti 1 (prosjek)*
PL_{End} – Performance Level at the end of the learning phase – *Razina učinkovitosti na kraju usavršavanja*
Increase *PL* – Increasing of the Performance Level – *Povećanje razine učinkovitosti*
PL_{Max} – maximum reached Performance Level – *Najveća razina učinkovitosti*

61% of the mean performance and most operators double their performance (200%) by the end of the learning phase.

The performance level achieved by the end of the learning phase varies between 0.68 and 1.43. With large differences, the mean value is 110% (median: 111%) and the inter-quartile ranges between 0.95 (25% percentile) and 1.28 (75% percentile).

There are no significant correlations between the duration of the learning phase, final level of performance (p=0.571) and maximum level of performance (p=0.940). It is therefore not possible to prove statistical significant correlations between the types of learning curves based on the data used in this investigation. The increase in performance throughout the learning phase of the regression line is on average with 0.24 percentage points per day, and the values turn out very differently. The increase per day correlated significantly with the achieved levels of performance at the end of the learning phase (p=0.002) and with the maximum level of performance achieved (p=0.002) which is on average 117%.

To describe the shape of the learning curves a sigmoid model was used. After tests, it is assumed that this model describes the learning curves with sufficient accuracy. This is confirmed by the residuals, which have approximately normal distribution and homoscedasticity. However, learning curves can be very individual. Fig. 2 shows four typical types of adjustment of the sigmoid model. For example: the function of operator No. 20 has a clear sigmoid shape

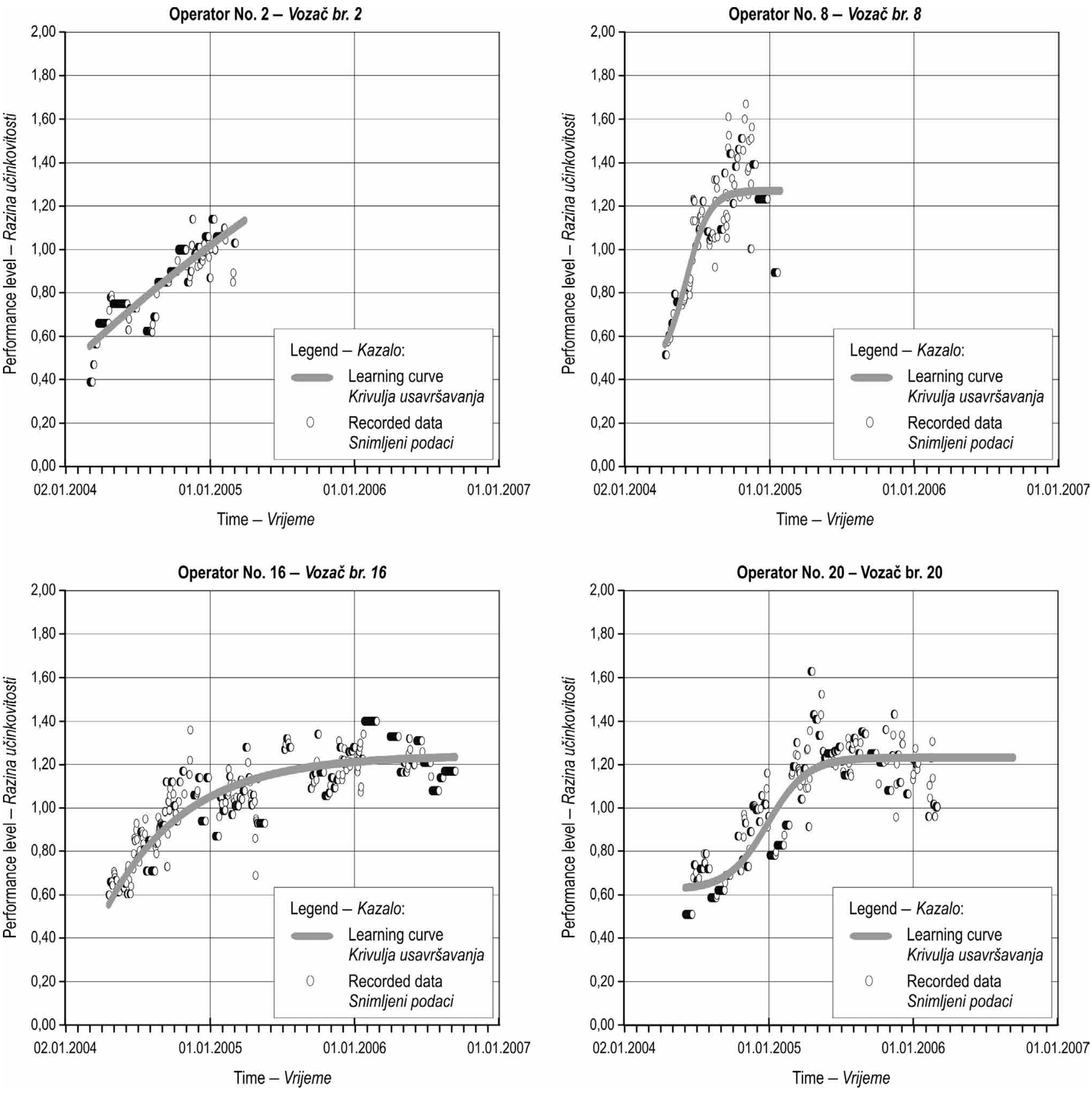

Figure 2 Different types of learning curves of four operators (sigmoid model)
Slika 2. *Različite vrste krivulja usavršavanja za četiri vozača (sigmoidni model)*

with a convex (from down) followed by a concave gradient. Other only have a convex gradient, for example operator No. 16.

The average cost, time and effort for the learning phase of a new operator can be calculated. On the basis of the logging documents, a mean production loss of about 330 PMH can be expected in the use of a new harvester operator. This corresponds to a reduced productivity of approximately 24% in the first 8 months. This means nearly two month of productivity and costs per harvester of ca. 45,000 €. Possibly increased wear or repair costs and training course fees are not included. Significant correlation between the performance level of the operator and the non-productive times such as repair time could not be recognized.

4. Discussion – *Rasprava*

After analyzing the logging data and documents, it has been calculated that on average an operator reaches the end of the learning phase in the plateau phase of work after nine months. The inter-quartile range is about 6–11 months. This is slightly lower than the previously described figure of 8–12 months (Calabrese 2000) and confirms the previously assumed, but rarely empirically investigated figure of 1000–1500 PMH (Gabriel 2005, Jacke and Wagner 2002, Wagner 2004). For 16 operators a learning curve effect could be demonstrated, in which their performance roughly doubled. These results are higher than the 50% performance increase over a year described by Heinimann (2001). He does not, however, make any statements about the existing experience of the operator at the start of data acquisition. Moreover, it seems appropriate to describe the end of the learning curve with the time required.

In this study learning curves were represented with the model of the sigmoid function, which proved suitable for describing the increase in productivity of a harvester operator. Therefore, the four parameters to be determined correspond well to the actual course of the performance level. The suggestion that a sigmoid function cannot adequately portray a multi-stage learning process (Calabrese 2000) could not be confirmed. The results also showed that a simple e-function (Björheden 2000) or a composite linear function (Dodd and McNeel 1996) could not reflect the actual course in an adequate way.

A significant correlation between the performance level and the repair time could not be detected in this study. This is in conflict with the results of Kirk et al. (1997). The explanation could come from the way the data were analysed. This study is focused on the operator rather than on different stages of learning curves as described by Kirk et al. (1997).

This study was focused on dense, first thinning stands where differences in the operators' skill levels are especially emphasized (Kärhä et al. 2004). However, an effective driver can operate efficiently in all phases of the work cycle (Ranta 2004). In this analysis intra-daily fluctuations and the impact of shift work were not considered. These two factors may result in fatigue and can have an important influence on individual performance (Nicholls et al. 2004). By using stem-based logging data these intra-daily fluctuations can be considered. Other factors such as motivation and physical condition can affect changes in performance over time. These factors, however, are not detailed in this study. The influence of the weather and seasons could be observed in this study but are not yet verified.

Using long term logging documents (historical data) will always result in a lack of information about the stand and the actual conditions and events that happen onsite. Additionally, the difficulties with the inconsequent realization of the StanForD-standard and deficits in calibration of harvester measurements can affect the variation of the data. However, an advantage of using historical logging documents is that there is no influence of the observer as in time studies. Therefore, data may misrepresent the overall performance to some degree but the tendency can be generalized.

In the future more tasks performed by the harvester operator will be automated, (Note: either delete or explain both). The performance of the whole harvester system will increase (Löfgren 2004). This automation involves a risk of creating a boring job and reducing the operator's alertness (Gellerstedt 2002). The boredom may decrease the performance over a long period more than the automation increases the performance. In contrast, it is also possible that additional tasks are requested of the operator and the workload does not really decrease. All of this can have an influence on the operator's learning curve. A lot of further research is suggested for this field.

5. Conclusions – *Zaključci*

This study indicates that the operator has a decisive influence on the harvester performance. For a large number of operators the learning effect could be demonstrated – performance was roughly doubled within the mean period of 8 months. The differences and variation between the individual operators are large and the training phase can be quite expensive. However, once you have good experienced operators – keep them. They are your most valuable assets.

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Sažetak

Krivulje usavršavanja vozača harvestera

Jednozahvatni harvesteri mogu doseći visoku razinu proizvodnosti, ali su istodobno skupi šumski strojevi. Brojni različiti čimbenici utječu na njihovu proizvodnost te su oni dosad već prepoznati i opisani u literaturi. Jedan je čimbenik često zapostavljen kada je riječ o strojnom radu u šumarstvu, a to je čovjek. Razlika između slabije obučenih i iskusnijih radnika može biti značajna.

Poveznica između proizvodnosti i iskustva naziva se krivulja učenja. Ona opisuje razinu radnoga učinka u usavršavanju (učenju) tijekom vremena. Može se izračunati kao kvocijent rezultata usavršavanja i vremena potrebnoga za obavljanje radnih zadataka. Neposredno mjerenje i praćenje razine iskustva za vozače harvestera još je uvijek problem. U današnje vrijeme samo se proizvodnost, vrijeme trajanja rada te neki utjecajni čimbenici mogu neposredno izmjeriti, što je problem pri spoznaji krivulje učenja i utjecaja postupka usavršavanja. Ovo istraživanje proučava trajanje, oblike, različitosti i troškove krivulja učenja kod vozača harvestera, te utjecaj ljudskih čimbenika opisanih kakvoćnim ili količinskim varijablama.

Lokacije za provedbu ovoga istraživanja bile su u Njemačkoj, a odabrane su proredne borove sastojine. Sustav pridobivanja drva uključivao je sječu doznačenih stabala i sortimentnu metodu izradbe drva jednozahvatnim harvesterom (CTL). Na osnovi dugoročnih proizvodnih datoteka iz informacijskoga sustava vozila (StanForD) prikupljeni su podaci o učinku za 32 vozača u vremenskom razmaku od 3 godine (obuhvaćena je 3351 sastojina i 0,65 mil. m³ izrađenoga drvnoga obujma). Šesnaestero vozača bili su početnici i njihove krivulje učenja bile su raščlanjene i oblikovane kao sigmoidne funkcije. Prisutne su bile i različitosti u predznanju između pojedinih vozača. Nekolicina vozača završila je programe ili tečajeve osposobljavanja za rad harvesterom na šumarskim učilištima.

Većina vozača na početku svoje karijere ostvaruje između 50 i 60 % prosječnoga radnoga učinka koji se udvostručuje (200 %) na završetku procesa usavršavanja. Za opisivanje krivulje usavršavanja primijenjena je sigmoidna krivulja. Na osnovi testova ustanovljeno je da spomenuti model opisuje krivulje učenja zadovoljavajućom preciznošću. Razlike i varijabilnosti krivulja učenja između pojedinih vozača velike su i poopćavanje mora biti pažljivo provedeno. Ipak, može se pretpostaviti da vrijeme usavršavanja (učenja) iznosi 8 mjeseci, ali uz veliku standardnu devijaciju. Na osnovi dokumentiranih izvještaja o radu strojeva može se očekivati manja proizvodnost kod vozača početnika u iznosu od prosječno 330 proizvodnih sati rada stroja (PMH). To se poklapa sa smanjenjem proizvodnosti od 24 % u prvih 8 mjeseci rada i razumijeva gotovo dvomjesečnu prosječnu proizvodnost i troškove u visini od 45 000 €.

U vremenu trajanja procesa učenja završna razina radne učinkovitosti (p = 0,571) i najveća razina radne učinkovitosti (p = 0,940) ne pokazuju značajnu povezanost. Zbog toga je nemoguće dokazati statistički značajnu povezanost između tipova krivulja učenja u ovom istraživanju. Prema regresijskoj krivulji faze usavršavanja povećanje je učinkovitosti u prosjeku 0,24 % po radnom danu, no i te su vrijednosti podložne promjenama

Ovo istraživanje pokazuje da vozač ima presudan utjecaj na razinu učinkovitosti rada harvestera. Za većinu je vozača dokazan utjecaj usavršavanja (učenja). Različitosti i varijacije između pojedinih vozača velike su i usavršavanje može biti iznimno skupo. Kakogod, u slučaju da postoji kvalitetan iskusan vozač – valja ga zadržati, jer su takvi vozači najvredniji čimbenik radnoga procesa.

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