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Measuring Learning Curves for Chainsaw Tree Cutting in Tanzania

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***Abstract* - Learning curve theory can be useful for estimating the long-term development of production rates and costs for forest operations. Making decisions as to the investments in forest operations machines in the initial phases of new forest ventures requires good estimates of production rates and costs. Since policy considerations may include adoption of new technologies, the learning curve analysis should be used in the planning and scheduling of new forest operations. The paper illustrated an application of learning curve theory in the estimation of tree cutting production rates and costs which are essential in planning of forest operations. The analysis suggests a new approach to planning and control of tree cutting forest operations. The models can assist forest managers in planning and scheduling chainsaw tree cutting operations in similar stands. However, the form of the learning curve can be applied in the analysis of learning curves in logging operations.**

***Keywords* – Chainsaw Tree Cutting, Learning Curves, Logging.**

I. Introduction

Most forest plantations in Tanzania have reached maturity and tree cutting operations are intensified. The plantations provide an important share of the country's industrial timber [7]. As there is an increasing share of industrial wood being harvested from plantations, ways to improve the planning and control of such operations are inevitable. In initial investments to be made, decisions on the appropriate tree cutting equipment or machines has to be made. Effective planning and control of forest operations requires detailed information on every aspect of logging operations. Such decisions can be based on researches on ways to improve the estimation of production rates and costs. Researchers have shown that for a wide variety of production processes, as an individual worker or crew continually repeats the production process, productivity shows a gradual and predictable improvement as the worker learns [25].

Learning curve theory postulates that the repetition of a process leads to time reduction or to the reduction of then required effort for the particular process [23]. For example, in tree cutting operations, a worker, who begins tree cutting operations for the first time, begins with a lot of mistakes and takes longer time to cut a single tree. However, as he repeats the production, his performance improves and productivity can be estimated in a predictable manner using learning curves. Thus the curves are a useful tool that can be used in planning of future forest operations. Learning curve theory and models can be useful for estimating the long-run development of production rates for forest operations such as tree cutting. Based on the theory by [24], the rate of improvement for any particular production process can be measured and used reliably to predict future production rates and costs.

The learning curve theory has been applied to study a number of forest operations based on the assumption that the learning rate was essentially constant during the learning phase and provides a reliable method for predicting and forecasting production output rates during the learning phase. The few studies did have incorporated the learning phenomenon into the planning and scheduling of forest operations [8, 10, 22, and 25]. The learning curves (LCs) are intended for the current production improvement and describe the plans of long-term improvement. Learning curve theory is based on the following assumptions [23]:

- The time (the cost) that is required, for a given target or one unit of product to be completed will be less each time when the target is achieved or the accumulated production is increased.
- The time (the cost) will be decreased in a declining distribution.
- The reduction of time will follow a foreseeable distribution.

Empirical studies of this phenomenon [6, 7, and 24] revealed that the time required to perform a task decreases as the task is repeatedly done. The amount of improvement however, increases as more units are produced. "In many cases the rate of improvement has sufficient consistency to allow its use as a prediction tool" [7].

Tree cutting operations involve a production process that can utilize the theory to develop curves for use in planning and scheduling future operations. An application of learning curve theory in predicting production rates and costs in such operations was done in a plantation tree cutting operation at Sokoine University of Agriculture in Tanzania [10, and 22]. Little effort has been spent on studying and developing Tree cutting operation skills, although on the job training for forest workers has been identified as an activity of great importance for the overall efficiency of forestry operations [11]. Studies of learning curves for machine operators performing complex forest work [18] indicate that the learning phase may be several months. This study describes the learning curves observed in tree cutting work when cutting trees using chainsaws in plantation, while controlling and quantifying influencing factors other than human skills (i.e., factors technology, human skills (e.g. experience, aptitude, motivation) and Conditions of work (e.g. weather, legislation) [5].

According to [7] the learning curve theory in forestry tells us that we can expect the productivity of new workers to improve as they gain experience in a particular forest operation. However, there have been very few applications of the learning curve theory in forestry [7, 11, and 22]. Nevertheless, few applications do not mean that foresters have not recognized the existence of the learning phenomenon and tried to incorporate it into planning and scheduling forest activities [7].

In Tanzania, for example, despite the increasing logging operations which require proper operations planning, foresters have not been able to make use of the learning curves in operations planning and control. This is based on the fact that research in forestry especially on harvesting operations had not progressed to a point where specific learning curves are suggested for the highly variable, complex, repetitive tasks [11]. But also according to [10] managing data for development learning curves which is intrinsically non-linear, was a problem in forestry due to incapacity of data management tools like computers and software's which is no longer a problem with the advancement of computer technology today. This fact must have delayed the adoption of learning curves in planning forest operations. Therefore, the learning behaviour and the learning rate of tree cutting crews with different experiences and skills were not known. Some harvesting operations are strongly influenced by climatic conditions, e.g. heavy rains, making such operations so costly or difficult to be carried out. Therefore, it is reasonable to close them down during such periods [22].
Therefore, it was difficult to forecast production in cutting operations in the current logging industry in Tanzania which includes among other things internal labour forecasts, production scheduling, establishing costs, budgets and the overall performance evaluations of the industry.

Various models have been proposed, in order to describe the learning curves (learning phenomenon). However, according to [14] different operations can develop trends that are characteristics of themselves that yield different results in the attribution of learning in the various companies. But also none of the various models for the learning curves, that have been proposed and used by the technologies or companies, is generally acceptable as superior [23]. Therefore, this study aimed at developing learning curves as tools for decision making during timber harvesting operations in plantation forests to fill this knowledge gaps. The developed learning curves will be used in planning and control of tree cutting operations for optimum productivity, reduced costs and improved safety of labour and machines.

This study was aimed to incorporate learning curves concept in forestry to assist forest managers in planning and control timber harvest operations. The paper suggests new learning curve models suitable for forest operations and illustrates its application with data on crosscut saw and chainsaw tree cutting in Tanzania. The study specifically derived and applied learning curve models for predicting the productivity and costs of tree cutting operations by chainsaws in plantation forest in Tanzania.

II. Materials and Methods

A. Study Site

This study was carried out at the Sokoine University of Agriculture Training Forest (SUATF), Olmotonyi, in Arusha region, Tanzania (Figure 1). It lies between latitudes 3' 15º – 3' 18º south and longitudes 36' 41º – 36' 42º East. It is bordered by Meru forest plantations to the East and West while Arusha catchment forests borders to the North with Timbolo and Shiboro villages to the South.

The forest covers about 840 hectares of natural and plantations. Currently about 80% of the forest area is covered by plantation forest of softwood and hardwood species while the rest is a natural forest. The main tree species grown include *Cupressus lusitanica, Pinus patula, Eucalyptus sp., Grevillea robusta* and *Acacia sp*. SUATF is on the slopes of Mount Meru, at between 1 740 to 2 320 m above sea level [21]. The seasonal climate includes a consistently dry period between June and October. Rainfall patterns vary considerably, but average annual precipitation is about 1200 mm. The mean annual temperatures range between 18°C in the morning to 23°C in the afternoon.
This study was carried out in this forest on the understanding that being a training forest unlike other plantation forests, interference from management could be minimised in the course of implementing the experiments.

During this study, logging was carried out using common tools used in other forest plantations in Tanzania. Tree cutting was done by using chain saws. Skidding was done manually, by semi-mechanised methods using farm tractors as well as by using oxen while hauling was performed using farm tractors fitted with trailers.

B. Experimental design

Study groups

The study was conducted on tree cutting operations. The crews were divided into two groups. The first consisted of newly recruited crews (start-up crews) which were engaged during the study and the second group consisted of experienced tree cutters (crews with experience in tree cutting). Each group was first studied in situ for up to three months, after which they were trained and studied again.

Tree cutting was done using chainsaws, as they are used for timber harvesting in both natural and plantation forests in Tanzania. One crew (two individuals) used chain saws.

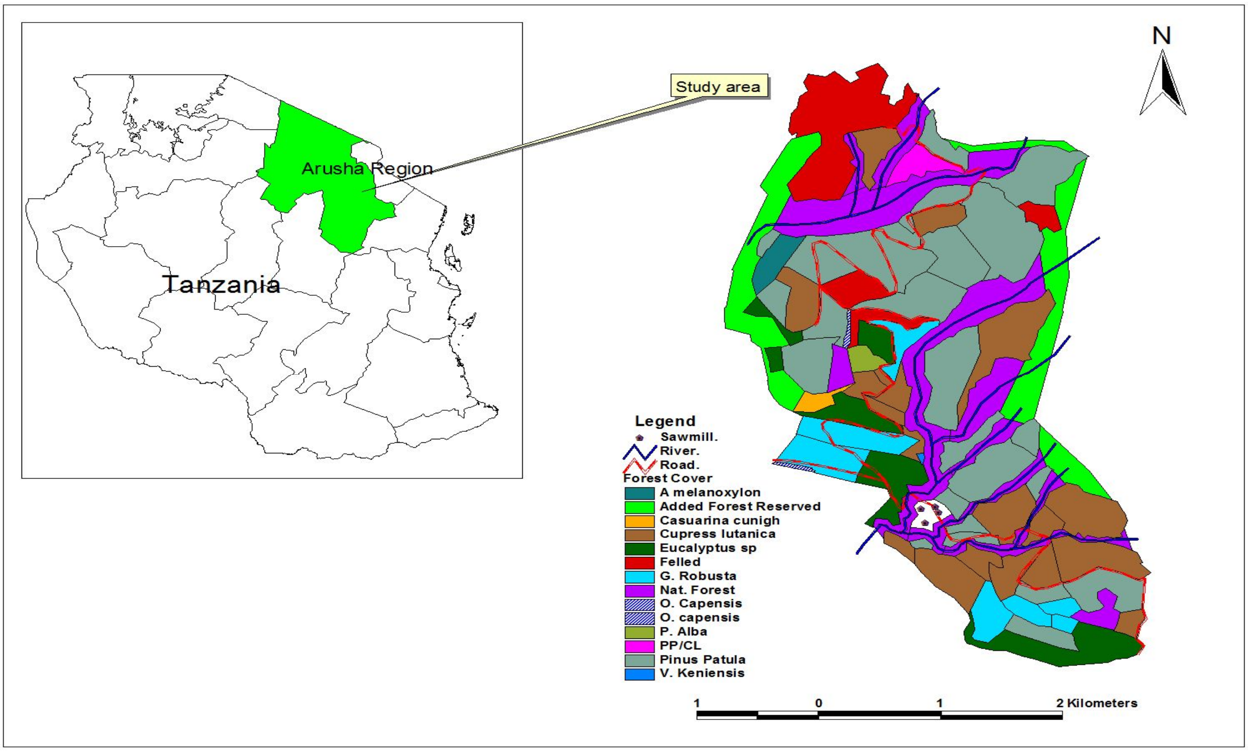

Fig.1. Location and map of study area showing different forest cover types

Start-up crews

Crews in this category were made up of individuals without prior experience in tree cutting operations. The chainsaw operator was a man aged 29 years old. He had occasionally been involved in different forest related activities including carrying out forest inventory, log skidding and log loading as a casual labourer for over four years.

Experienced crews

Crews in this category comprised individuals who had previously been involved in tree cutting operations using the chainsaw. This category involved a chainsaw operator who had worked for over 8 years in the same forest as an operator. Prior to his current assignment he had been involved in different activities including work at the tree nursery, log skidding and loading. The crew (31 years old) revealed that he did not receive any formal training on either logging operations or chainsaw tree cutting operations. He learned the operation of the chainsaw from a retired operator while assisting him in tree cutting for about two months in thinning operations which are considered less intensive.

C. Training plan

The training programme focused on hands-on skills based on the recommended tree cutting practices such as directional felling, proper limbing and bucking practices, appropriate ergonomic postures during tree cutting, proper use and maintenance of cutting tools and chainsaws. Accident prevention and safety precautions were also emphasized to reduce workplace accidents and risk hazards. The methods for safety and health training ranged from passive, information based techniques (e.g., lectures) to learner-centred performance-based techniques (e.g., hands on demonstrations), hypothesising that greater knowledge acquisition and more transfer of training to work setting will occur (thereby improving behaviours safety performance and reducing negative safety and health outcomes).

Training incorporated specific group requirements. Swahili language was used for training the crews. After the training sessions, field work and work studies were then performed concurrently. Tree cutting productivity and costs were then determined based on the chainsaw time study results.

D. Data collection

1) Productivity and costs data

Productivity studies of tree cutting operations were performed on clear felling operations. Snap-back (zero-reset) time study methods were used to collect data on productive and delay times. This method provided immediate insight into the operation being studied as observed by [1]. Selected independent variables that might affect tree cutting productivity, costs and workers' learning rates were measured and recorded concurrently during the time studies. The selected variables measured and recorded were; stump diameter and diameter at breast height (over bark), in centimetres, tree height, in meters, number of logs bucked, log lengths, in centimetres, number of trees cut per day, and terrain slope in percentages.

Labour, equipment and machine costs (fixed and variable costs) were obtained from both primary and secondary sources. Equipment and machinery costs included: purchase price, depreciation, interest, taxes, oil, fuel, lubricants and insurance costs. Labour costs included direct wages and other indirect costs like incentives and fringe benefits.

E. Data analysis

Data were analyzed to establish logging production rates, costs, and learning curves. Data analysis was carried out using MINITAB 15 Computer Software, Microsoft excel spreadsheet and Statistical Package for the Social Sciences (SPSS) programs after obtaining independent, dependent and control variables.

F. Development of learning curves

Number of trees harvested was used as a measure of unit of production as there was no great variability in tree sizes. To account for the many variables that influence productivity in forest operations and yet simultaneously consider the effect of cumulative production on productivity, the proposed non-linear formulation by [9] [10] as shown below were used.

$$Y = \alpha_0 + \alpha_1 X_1 N^{\beta_1} + \alpha_2 X_2 N^{\beta_2} + \dots\dots + \alpha_m X_m N^{\beta_m} + \alpha_{m+1} N^{\beta_{m+1}} + \varepsilon_m \quad (1)$$

Where

Y = the dependent variable to be estimated (e.g., the time required to fell the N^{th} tree),

α_j = a regression parameter (j = 0,1, …, m+1) measuring the contribution of variable X_j to variable Y,

X_j = an independent variable (e.g. Dbh of the N^{th} tree)

N = the cumulative number of units produced (e.g., the number of trees felled),

β_j = a regression parameter (j = 0.1, ..., m+1) measuring the rate at which the contribution of variable X_j to variable Y changes in proportion to the cumulative number of units produced.

ε = a random error term.

A major difficulty with the model of equation (1) is that it is intrinsically nonlinear and according to [9] there is no way to transform it into a linear approximation (as can be done with the log-linear model of equation (1). Therefore SPSS was used for curve analysis. Statistical Package for the Social Sciences (SPSS) is useful statistical software owing to its big databases. SPSS provides modules for analyzing tables of data. It has multiple functions but the ones used in this study are the functions related with models of regression.

a) Modelling learning behaviour

The learning behaviour for this system was considered to follow the general model as expressed in equation 1. But also the measure of 'learning' 'b' could be estimated by hand using selected data as the unit number doubled. Thus;

$$f(2x) = a(2x)^b \quad (2)$$

While $f(x) = ax^b$ (3)

Dividing equation (2) by (3)

$$\frac{f(2x)}{f(x)} = \frac{y_{2x}}{y_x} = \frac{a(2x)^b}{ax^b}; \quad \text{but} \quad \frac{y_{2x}}{y_x} = 2^b$$

Therefore $b = \dfrac{\log\left[{y_{2x}}/{y_x} \right]}{\log(2)}$ (4)

This equation was used as a spot check, real slope, and thus real learning rate, was computed by regression using all observations.

G. Predictive capability of the models and or predictors

In generating the models, each model and the predictors of the dependent variable were tested for significance. The first approach was to test all the possible predictor variables to the dependent variable for each sub operation per experiment for each crew. Multicollinearity was tested using Variance Inflationary Factor (VIF) to ensure that variable that are highly correlated not all of them get included in the models. For the matter of maintaining uniformity all predictors that were found to have statistically significant predictive capability in most models per activity were held constant for such specific sub activity per experiment to avoid predicting the dependent variable of the same activity and probably of the same crew in the same experiment using different predictors. With the fact that forest activities as for other activities that are performed outdoor in uncontrolled environment is affected by a number of uncontrolled factors a conservative decision was worth to avoid dropping many variables that would leave the dependent variable subject to more uncontrolled variabilities.

As a result some predictors were found to have no significant contribution when t-statistics were performed on coefficients. In this experience, a predictor variable can be significant in one experiment and non significant in another experiment although not always the case. However, the overall models were found to be significant. In cases where these kinds of findings were observed, a specific discussion is given to at least give a justification for such findings and its pertaining decisions. Experience shows that in more advanced regression analysis there might be several variables predicting the dependent variable and even if the overall model is significant, not all of these variables need to be significant [20]. In fact the overall model could be significant but none of the individual variables might be significant because significance test tests the significance of unique variability which is an important issue in multivariate statistics [19]. On the other hand [10] argues that a researcher can commit a common mistake on assuming that when many variables have non-significant p-value they are all unnecessary and can be removed from the regression equation. Although, when one variable is removed from the equation, the others may become statistically significant.

H. The learning curves

The learning curves have been developed to account for the many variables that influence productivity in forest operations at the same time considering the effect of cumulative production on productivity. The general equation by [10] (Equation 1) which is intrinsically non-linear was considered for that effect. For this case, independent variables (i.e. Dbh and the number of logs produced, NLogs) that were found to have a significant influence on the traditional operations-productivity models developed using ordinary least squares for different experiments (Equations 5 through 10) were also assumed to affect the learning curves. This is because the magnitudes of the independent variables will never be constant for all trees felled and thus, will have a strong influence in operations for which production rates are to be estimated by these types of equations [9].

The general hypothesis for this case was as follows;

$$T = \alpha_0 + \alpha_1 DbhN^{\beta} + \alpha_2 Dbh^2 N^{\beta 1} + \alpha_3 NLogs \quad (5)$$

Where,

T = the time required to fell the N^{th} tree,

α_i = a regression parameter (i = 0,1..) measuring the contribution of the independent variables to time 'T',

β= a regression parameter (i = 0.1…,) measuring the rate at which the contribution of independent variables (Dbh and Dbh^2) to time 'T' changes in proportion to the cumulative number of units produced, and N is the number of trees felled.

The results from learning curve analysis are presented for each crew category as well as per the specific experiments. The primary assumption was that learning would occur to all crews despite the status of their experience. The learning curve models have been developed by considering first, the effective time only and secondly by considering the effective and necessary delay times on the assumption that unnecessary delay times can be eliminated through different mechanisms such as training, supervision and or motivation. The learning curve models with effective time only are denoted by 'T_{Eff}' while the one with necessary delay times are denoted by 'T_{Necd}'. Although the emphasis will be given to the model with necessary delay times as they are inevitable, these two models are given to provide an opportunity to measure and compare the actual performance of the crews given all other factors are controlled. Generally, results showed that the learning rates between crews and or across the experiments were somewhat different. The results are given in the following sub-sections;

III. Results and Discussion

1) The learning curves for chainsaw cutting operations

a) The learning curves of the experienced chainsaw operator

Before training

Results show that the learning index of the experienced operator when studied for the first time (equation 6) was -0.002, corresponding to a learning rate of about 0.1%.

$$T_{Necd} = -2.3185 + 0.1794 DbhN^{-0.002} + 1.199 NLogs$$

$$T_{Necd} = -2.3185 + 0.1794 DbhN^{-0.002} + 1.199 NLogs, \quad R^2 = 0.42 \quad (6)$$

Learning rate corresponding to Equation (6) = 0.1%

$$T_{Eff} = -2.8634 + 0.1696 DbhN^{-0.03665} + 1.07188 NLogs, \quad R^2 = 0.6 \quad (7)$$

Learning rate corresponding to Equation (7) = 2%

After Training

Equation 7 shows a learning index of -0.044 corresponding to a learning rate of 3% after the training.

$$T_{Necd} = -2.61 + 0.236 DbhN^{-0.044} + 1.026 NLogs, \quad R^2 = 0.44 \quad (8)$$

Learning rate corresponding to Equation (8) = 3%

$$T_{Eff} = -2.7186 + 0.15175 DbhN^{-0.0086} + 0.971 NLogs, \quad R^2 = 0.68 \quad (9)$$

Learning rate corresponding to Equation (9) = 1%

After Break

Results showed that the learning index after the break was -0.047 which implies a learning rate of 3%.

$$T_{Necd} = -1.66 + 0.1034 DbhN^{-0.047} + 1.0814 NLogs, \quad R^2=0.44 \quad (10)$$

Learning rate corresponding to Equation (10) = 3%

$$T_{Eff} = -2.4854 + 0.06346 DbhN^{-0.1222} + 1.01112 NLogs, \quad R^2 = 0.64 \quad (11)$$

Learning rate corresponding to Equation (11) = 8%

b) The learning curves for the start up chainsaw operator

Before training

Equation 12 shows a learning index of -0.463 corresponding to a learning rate of 27% observed before training for the start up chainsaw operator's cutting operations.

$$T_{Necd} = -0.986 + 0.2648 DbhN^{-0.463} + 1.503 NLogs, \quad R^2=0.56 \quad (12)$$

Learning rate corresponding to Equation (12) = 27%

$$T_{Eff} = -1.8563 + 0.4461 DbhN^{-0.3248} + 1.2077 NLogs, \quad R^2 = 0.66 \quad (13)$$

Learning rate corresponding to Equation (13) = 20%

After training

The learning index from equation (14) is -0.03 which corresponds to a learning rate of 2%.

$$T_{Necd} = -3.24 + 0.21 DbhN^{-0.03} + 1.143 NLogs, \quad R^2 = 0.48 \quad (14)$$

Learning rate corresponding to Equation (14) = 2%

$$T_{Eff} = -3.2577 + 0.1547 DbhN^{-0.03179} + 1.106 NLogs, \quad R^2 = 0.69 \quad (15)$$

Learning rate corresponding to Equation (15) = 3%

After Break

The crew observed a learning index of -0.03 (Equation 16) and a learning rate of about 2%.

$$T_{Nedd} = -2.88 + 0.2284 DbhN^{-0.03} + 1.2175 NLogs, \quad R^2 = 0.45 \quad (16)$$

Learning rate corresponding to Equation (16) = 2%

$$T_{Eff} = -3.12 + 0.1881 DbhN^{-0.04917} + 1.064 NLogs, \quad R^2 = 0.68 \quad (17)$$

Learning rate corresponding to Equation (17) = 4%

The results from experienced chainsaw crew when studied for the first time show a lower learning rate (i.e.

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near to zero) which improved slightly in subsequent experiments. Consequently, the crew observed relatively flat learning curves although the curves were somehow steeper after the training and after the break as compared to the first experiment. The trend showed by this crew during the first study indicates that, being experienced, the crew might have reached 'a working plateau' beyond which no further improvement could be expected without additional investment. Some of the investments that may assist in improving crew's productivity at such a stage according to [9] may include training in improved methods or the purchase of new equipments but also change of technology [12]. After training (of which other factors above were held constant) the crew observed a relatively steeper curves at increased learning rate which implies that despite being experienced the crew had not reached a production 'working plateau' although, the curve levelled immediately after cutting the first 50 trees.

On the other hand, the start up crew showed a higher learning rate with a steeper curve at the beginning of the operations as expected. Their results are higher compared to one found by other scholars. For example, [10] who conducted a study on crews with no prior experience in using chainsaws for cutting trees found a learning rate of 14% which is about 56% lower compared to the findings of this study. The 32% learning rate observed may be a result of several factors. That, the crew being aware of been studied could have struggled too much to impress the observer as he does not know the fate of failing to perform to the expectations. This is probably one of the effects time and motion approaches that makes one-on-one observation [10] which was used in this study. [19] time-and-motion and work-sampling methods are vulnerable to error because the workers may change their behaviour upon being observed, the problem is more severe for continuous observation. Another reason could be a self motivation after securing a place to work where earning was now made possible.

After the training, the crew did not experience much learning as it was as low as 2%. However, this doesn't mean that the crew did not improve performance because the productivity analysis indicated that the crew improved productivity significantly. This implies that after training the crew was now able to lower the total cutting time per tree which does not differ significantly from tree to tree at this stage probably due to the accumulated knowledge and experience (learning occurred). Therefore, a crew observed a relatively levelled curve implying for a working plateau phase. Further, the crew did not observe any significant change in learning rate when compared to that from the training phase.

Experiences from learning curve analysis show that rates of learning are highly affected by the technology levels unlike in manual operations where human factors may lead. For example, [9] reported that felling-machine operators using an interactive simulation model as a training device "learned" at rates significantly below those reported by [11] (which was an average of 10% in choker setting operation study). The learning rate for the operator who improved the most during the study was 3.3%. Reduced learning rates (i.e. nearer to 0%) are to be expected in mechanized operations where machine-pacing largely determines the rate of production; hence the much more rapid rate of productivity improvement in [11] choker-setting studies.

The productivity trends observed in this study for different experiments and crews gives a reflection of the production costs as well. That, unit production costs decreases with cumulative output. If the learning is measured by cumulative outputs rather than by alternatives such as elapsed time or cumulative investment, that learning remains proprietary and that the effects of past experience are persistent [10], then the unit production costs may assume the same type of curves (but on decrease) of the production trends. During the 1960s, many dozens of studies documented strong cost-quantity relationships in a broad range of industries. Some of these built on what [24] had rather generically called the cost-quantity relationship to estimate changes in average costs over time. These studies include [13] [4] on machine manufacturing.

Traditionally, there is a number of variability in forest operations especially on timber harvesting. It is evident that most forest industries in the developed world have changed the logging technologies amongst other technologies so as to account for the challenges in the working environment. Therefore, although chainsaw studied provide insights on the current and probably long term production and costs trend in our environment, effort must be taken to introduce new technologies in the sector.

I. Production forecasting as a case study

1) Productivity and costs forecast

The developed productivity, costs and learning curve models are intended to assist forest managers to better plan logging operations in the areas of tree cutting with chainsaw in plantation forests. To create a clear understanding in the use of these models, case studies are demonstrated as follows;

Assume harvesting operation of a plantations forest (*Pine* and *Cypress* species) planted at 2.44 m by 2.44 m spacing with MAI of 25 m^3 over bark per hectare per year. The number of trees that remain after 25 years of maturity after three thinnings is 490. The estimated allowable cut is 284 m^3 of saw logs and 71m^3 of chip logs making a total of 355 m^3 of the standing volume per ha according to the Tanzania Forest Plantation Management Technical Order number one of 2003 [10]. The total time and costs required for the crew to harvest this forest can be computed from equations 18 and 19 respectively. Therefore;

$$T = \frac{A}{P} \tag{18}$$

Where;

T = is the amount of time required for a crew to finish the tree cutting operation, hrs

A = the estimated allowable cut of the saw logs, m^3/ha, and;

P = the crews production rate, m^3/hr

$$C = C_C * A \quad (19)$$

Where;
C = the total production cost required to finish the cutting operation, Tanzanian Shillings (TShs).
C_C = the production unit cost, Tshs/m^3, and;
A = the estimated allowable cut of the saw logs, m^3/ha.

If the same type of forest is to be harvested by using chainsaws by crews with different experiences the results would be as follows;

a) Experienced chainsaw operator

If the experienced operator is to harvest the forest without being trained on the job (hands on skills), based on the observations in Table 1 he would therefore require 67 hours of work if unnecessary delays are assumed to be eliminated. Otherwise he would require 74 hours with unnecessary delays inclusive. Taking in consideration that a crew works continuously for an average of 3 hours per day in the 8 hours scheduled by the management for a crew to qualify for a wage it means that this crew will require about 23 and 25 days to cut this forest with necessary and unnecessary delays inclusive respectively.
On the other hand the total costs that will be incurred with this type of crew with consideration of the unit production cost would be 84,000 and 93,000 Tanzanian Shillings (TShs) if productivity with necessary and unnecessary delays is respectively considered.

The estimated production time and costs of the same crew with a consideration that he receives training prior to his engagement in the tree cutting operations and the situation after suspending operations for about three months is shown in Table 1.

Table 1: The projected time and costs of harvesting a ha of forest plantation by an experienced chainsaw operator

Time category	After training		After the break	
	Time, hrs	Costs, TShs	Time, hrs	Costs, TShs
With necessary delays	64 (22)	81 000	53 (18)	66 000
With Unnecessary delays	72 (24)	90 500	60 (20)	74 600

Note: the numbers in bracket are the equivalent days in respect to the estimated time, hrs; 1580 Tanzanian Shillings (TShs) = 1 United States Dollar (Us$).

The projections here shows that the operator will require relatively less time and the operation will cost less as he resumes the operation.

b) Start up chainsaw operator

The experience from forest harvesting in Tanzania shows that most logging workers are engaged without prior experience in logging operations. Under such a circumstance a projected production time and costs of the start up chainsaw operator with consideration of different experience and trained skills is shown in Table 2.

Table 2: The projected time and costs of harvesting a hectare of forest plantation by a start up chainsaw operator

Time category	Before training		After training		After the break	
	Time, hrs	Costs, TShs	Time, hrs	Costs, TShs	Time, hrs	Costs, TShs
With necessary delays	89 (29)	111 800	53 (18)	65 500	66 (22)	83 800
With Unnecessary delays	96 (32)	121 800	52 (17)	66 930	73 (24)	92 400

Note; the numbers in bracket are the equivalent days in respect to the estimated time, hrs, 1,580 Tshs = 1 US$

2) Productivity projection with learning curves

Logging manager and planners may calculate the hours required to produce determinate product taking account of the learning curve. Therefore, the time required for a crew to cut a certain tree in the production series can be estimated by using the learning models developed for each experiment. For a clear understanding in this case study, fixed variables will be used to avoid uncontrolled variability in forecasting cutting production times for each crew. These variables will include the average number of logs and the Dbh. The learning index will vary depending on the experiment as revealed by the learning models. Therefore, the average Dbh as obtained from the descriptive statistics will be 32cm while the average number of logs will be 3. The projections are therefore done for each crew category as follows;

a) Time projections for the chainsaw operators

The time analysis for the experienced chainsaw operator will be determined by using equations (16, and 18) and for the first time, and after training experiments respectively. Assume that the manager wants to forecast the time required by an experienced crew to cut the 201 tree in the production series in the same plantation forest.

If the experienced crew is to harvest the forest prior to receiving any training then the time required to cut the 201st tree for example would be;

$$T_{201} = -2.3185 + 0.1794 * 32 * 201^{-0.002} + 1.199 * 3$$
$$= 6.96 \text{ minutes}$$

After receiving some training

$$T_{201} = -2.61 + 0.236 * 32 * 201^{-0.044} + 1.026 * 3$$
$$= 6.45 \text{ minutes}$$

If the same type of forest is to be harvested by new operator (a recruit) prior to receiving any formal on the job training and acquired substantial experience, then the time required would be obtained by substituting the relevant variables in equations 12. While equation 13 can be used to determine the time required if the same crew receives training.

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Before training;

$$T_{201} = -0.986 + 0.2.648 * 32 * 201^{-0.63} + 1.503 * 3$$
$$= 3.82 \text{ minutes}$$

After receiving some basic training;

$$T_{201} = -3.24 + 0.21 * 32 * 201^{-0.03} + 1.143 * 3$$
$$= 5.9 \text{ minutes}$$

The time required after the break would also be;

$$T_{201} = -2.88 + 0.2284 * 32 * 201^{-0.03} + 1.2175 * 3$$
$$= 7.0 \text{ minutes}$$

IV. Conclusion

Results show that experienced chainsaw operator had a very low learning rate (near to zero) which implies that being experienced he might have reached a 'working plateau' beyond which no further improvement could be expected without additional investments. These investments would include training, change of technology or motivations. Furthermore, it was found that pre-training learning rate for an inexperienced chainsaw operator was 27% for total cutting time including necessary delays but only 20% for total cutting time after all delays had been eliminated. This observation could implied by the operator was able to reduce substantially the necessary delay as he kept on learning and improved his actual cutting time. However, delay free models are meaningless in real world. Generally all crews showed higher learning rates after the training that signifies the importance on the job training.

On the other hand, all the start up crews showed steeper learning curves as they resume operation after the break implying that they had forgotten some basic conducts. The analysis of the forgetting factors showed that the knowledge of the experienced chainsaw operator appreciated by 17% while the start-up operator depreciated by 22%. This means that the experienced crew produced 17% more than before the break. Generally the improvements observed during this study on safety levels and production, especially after the training signifies the importance of training the crews on some basic skills and knowledge despite their experience.

Finally, this study has incorporated the learning curve theory in forestry industry where operations are performed outdoor unlike other industries where learning curves have been applied. The study has contributed to the understanding of labour learning behaviour and their response to training in forest operations under ideal conditions and has developed specific models to assist foresters in planning for forest operations.

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