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ERROR IMPACT OF REGRESSION MODELS ON FOREST ROAD SPACING

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Abstract

Statistical time prediction models are common in production estimation of different forest machineries. These models are usually developed using multiple regression method. Application of regression method causes considerable errors. In this paper, firstly the confidence interval curves of the parameters used in the yarding and installation time predicting models of tower yarder in Austria are presented.

The second part of this study deals with the effect of the error of regression models on optimal road spacing of tower yarder based on the minimization of total costs of roading, yarding and installation. Finally to choose the best optimal spacing under uncertainty, we used the multiple criteria decision making process considering the criteria like minimum total cost (Euro/m^3) as economical criteria, soil erosion, soil compaction in the skid trail, area of constructed roads (m^2/ha), reforestation costs and facilitate of silvicutural treatments to the stands.

Key words: error, confidence interval, yarding, optimal road spacing, multiple criteria decision making

INTRODUCTION

In science, the terms uncertainties or errors do not refer to mistakes or blunders. Rather, they refer to those uncertainties that are inherent in all measurements and can never be completely eliminated. In some fields, uncertainties may be measured in orders of magnitude while in other fields uncertainties may be less than parts per million, PPM. A large part of a scientist's effort is devoted to understanding these uncertainties (error analysis) so that appropriate conclusion can be drawn from variable observation. Experimental errors may be divided into two classes: systematic errors and random errors. If we make repeated measurements of the same quantity, we can apply statistical analysis to study the uncertainties in our measurements. This type of analysis yields internal errors, the uncertainties are determined from the data themselves without requiring further estimates. The important variables in such analyses are the mean, the standard deviation and the standard error.

In forestry, error has been studied mainly in forest inventory and different forestry models. Boyland (2002) indicated that effective use of models stems from an understanding of the simplifications and abstractions that take place during model

creation. Errors are mistakes in measurement that are out side of truth of measured variable, which is termed accuracy errors. The error resident in the choice of structure termed as translation errors. Translation error occurs in the creation of the system that structures data or a relationship. Models represent systems with two basic building blocks: data and algorithms. Both accuracy and translational errors are found in data and algorithms. Many algorithms have hypothesis and theory. Algorithms expressed statistically are continually evaluated, perhaps using r^2 and SE. When algorithms are not statistical expressions, but simulation equations or other rules for change, they lack convenient measures of error and error is more difficult to assess.

Vanclay, Skovsgaard (1997) presented evaluating forest growth models. They emphasized that evaluation should not be a mere afterthought to model construction, but should be considered at every stage of model design and construction, when component functions are formulated and fitted to data, and when these components are assembled to provide the completed model.

The Finnish multisource national forest inventory used standard error of tree stem volume and the volume by tree species to compare field data-based estimates and corresponding simulation results based on MS-NFI output thematic maps (Kattila, Tomppo, 2006). In China, Xu et al. (2004) used a cell-based spatially explicit forest landscape model designed to explore successional dynamics under natural and anthropogenic disturbance so called LANDIS. In this study, a stand-based assignation (SBA) approach was developed to stochastically assign species age cohorts to each cell based on forest inventory data. As a probability-based approach, SBA will introduce errors in LANDIS input. To assess the effect of recurrence frequency of the majority species age cohort from 20 Monte Carlo simulations were used to quantify the uncertainty in species age cohorts for individual cell.

To make correct inferences about long-term changes in biomass stocks, Chave et al. (2004) indicated it is essential to know the uncertainty associated with above-ground biomass (AGB) estimates while in the past it was rarely evaluated carefully. They quantified four types of uncertainty that could lead to statistical error in AGB estimates: error due to tree measurement; error due to the choice of an algometric model relating AGB to the other tree dimensions; sampling uncertainty, related to the size of the study plot and representativeness of a network of small plots across a vast forest landscape. In USA, McRoberts et al. (1999) reported that the precision of annual forest inventory estimates may be negatively affected by uncertainty from sampling error, procedures for updating plots not measured in the current year and measurement errors. Using Monte Carlo simulation techniques the impact of those sources of uncertainty on final inventory estimates was investigated. Smith, Health (2001) also used examined uncertainties in forest carbon budget projections with Monte Carlo analyses of the model FORCARB. Gertner (1987) used error propagation method to approximate the precision of simulation estimates and compared this method with a crude Monte Carlo method for obtaining simulation variances. At its worse, the error propagation approximation of standard deviation diverged from Monte Carlo approximation by 16% for a 50-year projection.

In forest engineering, statistical time predicting models are common in production study of different machineries. Usually these models are developed using multiple regression method based on statistical data collected by different time study methods. To develop such a model, the most important variables affect the time of working cycle are measured. Concerning to multiple regression, there are two assumptions: (1) the depended variables are non-stochastic, that is, the values of x's are fixed or selected in advance, and (2) the x's are measured without error. The assumptions can not be validated, so they do not play a major in the analysis. However, they do influence interpretation of the regression results. The first assumption is satisfied only when the experimenter can set the values of x variables at predetermined levels. It is clear that under no experimental or observational situations this assumption will not be satisfied. The second assumption is hardly very satisfied. The errors in measurement will affect the residual variance, the multiple correlation, and the individual estimates of the regression coefficients. The exact magnitude of the effects will depend on several factors, the most important of which are the standard deviation of the error of measurement and the correlation structure between the errors. The effect of the measurement errors will be to increase the residual variance and reduce the magnitude of the observed multiple correlation coefficient (Chatterjee, Price, 1991).

The productivity models for cable logging systems in the previous studies have been developed by multiple regression. It has been assumed that yarding time or productivity per cycle is a function of the variables like tree volume, yarding distance, lateral yarding distance, slope, yarder type, working system, silvicultural treatment, felling method and learning curve effect of the crew (De Labor, 1993; Howard, Coultish, 1993; Kellog et al. 1996; Huyler, LeDoux, 1997; McNeel, Dodd, 1997; Visser, Stampfer, 1998; Heinimann et al. 2001; Torgensen, 2002 ; Hartley, 2003; Stampfer, Steinmueller, 2004). Installation of cable systems, unlike ground based logging systems, requires considerable time and effort. Stampfer et al. (2006) developed a cable corridor installation time model. Some researchers have studied productivity of cable systems in Austria (Stampfer, Steinmueller, 2004; Viertler, 2003; Svaton, 2000; Limbeck-Lilienau, 2002; Stampfer et al. 2003; Proell, 2000; Visser, Stampfer, 1998; Toplitsch, 1999). But the error of time models and its impact on road spacing have not been investigated. Thus this paper studies the statistical confidence interval of yarding and installation time predicting models of a tower yarder in Austria and its affect on optimal road spacing. The Promethee method is used to decide the best optimal road spacing under uncertainty.

METHOD OF STUDY

Site of study

The study site located in Privatstiftung Hempel in Etmissl of Styria in Southern Austria. The stands were harvested using Wanderfalke tower yarder (Table 1). It was used to yard the whole trees to the road side in this study. This yarder was combined

with a Woody 50 processor. The working team included yarder operator, one chainsaw operator, and one choker setter.

Table 1
Site study description

98 to 198	Yarding distance (m)
16 to 27	DBH (cm)
0.20 to 0.64	Tree volume (m^3)
37 to 77	Slope of cable way (%)
Fir	Stand composition
872-2536	Stand density (n/ha)

Installation and yarding and time predicting models

To evaluate the installation cost per cubic meter, the equations developed by Stampfer et al. (2006) were used. They developed the time predicting models for set up and take down the cable yarding systems where 155 cable corridors originated in mountainous regions of Austria.

Installation time (h) = Set-up (h) + Take-down (h)

Set-up time (h) = EXP (1.42 + 0.00229 × corridor length (m) + 0.03 × int. support height (m) + 0.256 × corridor type – 0.65 × extraction direction + 0.11 × yarder size + 0.491 × extraction direction × yarder size)

$R^2 = 0.78$

Take-down (h) = EXP (0.96 + 0.00233 × corridor length (m) – 0.31 × extraction direction – 0.31 × int support + 0.33 × yarder size)

$R^2 = 0.64$

Table 2 presents the factors used in the set-up and take-down models.

Table 2
Cable corridor factor recorded for installation study

Factor	Units	Description
Extraction direction	1/0	Uphill (1) or downhill (0) extraction
Yarder size	1/0	Large yarder, mainline pull>35 kN (1) or small yarder (0)
Corridor type	1/0	Differentiates between first corridor (1) installation or subsequent installation from the same landing location
Intermediate support	1/0	Presence (0) or absence (1)

For yarding time model, it was assumed that the yarding cycle time is a function of variables such as slope, yarding distance, harvest intensity, tree volume, stand density and lateral yarding distance.

Confidence interval and error

Mean difference square of one variable is used to compute confidence interval. The variance of the coefficient of simple regression is s_b^2 = DMS/SSX and confidence interval would be: $b \pm t_\alpha (s_b)$. Estimated Y has two kinds of error: Variance of mean and variance of regression coefficient. Variance of estimated Y can be computed as following formula:

$$S_Y^2 = DMS\ (1/n + x^2/SSX)$$

This variance is a function of x (deviation of x from the mean). The confidence interval for estimated Y by regression is $Y \pm t_\alpha(S_Y)$.

Confidence intervals for individual regression coefficients can be obtained from the least squares fit using the t distribution. If a confidence region is desired for the entire (p+1)× a vector β of regression coefficients, it would not be appropriate to use the (p+1) individual confidence intervals. Instead a 100(1-α) % confidence ellipsoid for β is given by

$$(b-\beta)'\ X'X\ (b-\beta) <= (p+1)\ s^2\ F_{\alpha;p,\ (n-p-1)}$$

This confidence region takes into account the correlation among the elements of b.

Similarly 100(1-α)% confidence ellipsoid for the (k×1) vector of linear combinations of the regression coefficients, Tβ, is given by

$$(Tb-T\beta)'\ [T(X'X)^{-1}T']^{-1}(Tb-\ \beta) <= \ (p\ +\ 1)\ s^2\ F_{\alpha;k,\ (n-p-1)},$$

where T is a (k× (p+1)) matrix of known constants.

An estimator of β can be obtained subject to the condition Tβ= a,

where T (k ×(p+1)) and a (k×1). The estimator is given by $\hat{\beta}_\alpha = \hat{\beta} + (X'X)^{-1}$

$$T'[T((X'X)^{-1}\ T']^{-1}\ (a-\ T\hat{\beta}).$$

Given T (k×(p+1)), β (p+1) and a(k×1), a test of H_0: Tβ =a can be carried out by employing the test statistics

$$(T\hat{\beta} - a)'\ [T((X'X)^{-1}\ T']^{-1}(T\hat{\beta} - a)/ks^2,$$

which has an F distribution with k and (n-p-1) degree of freedom if H_0 is true (Jobson, 1991).

For multiple regressions, the confidence intervals of the coefficients can be easily evaluated using statistical software. Using the data base of this study, the confidence interval of the coefficients of the variables was computed at the probability level of 5% using SPSS 12 to draw the upper and lower bounds of the model.

Road spacing using minimization of roading and yarding cost

The roading cost in study area varies from 16 to 22 Euro/m with an average value of 20 Euro/m. The logging volume ranges from 50 to 150 m^3/ha. The hourly cost of the tower yarder is about 185 Euro/h. The roading, installation and yarding cost per cubic

meter were computed for different yarding distances in the range of the observations of this study.

Road density was evaluated from this formula:

$$\text{Road density (m/ha)} = \frac{K}{\text{Yarding distance (Km)}}$$

The actual road density and average yarding distance are 33.3 m/ha and 200 m respectively in Mayr-Melnhof Company. If we put these values in above formula, it gives K value of 6.7. Road spacing and road density are related by the following formula:

$$\text{Equivalent Road spacing (m)} = \frac{10000}{\text{Road density (m/ha)}}$$

For different forwarding distances in the range of observation, road density and road spacing were calculated. The yarding cost per cubic meter was derived through the model and average load volume. Roading costs per cubic meter was computed using road density, harvesting volume of 100 m^3/ha, and average roading cost of 20 Euro/m. Table 3 presents the specification of Austrian forest roads (Stampfer, 2007).

Table 3
Standards of Austrian forest roads

Specification	Main road	Secondary road
Use	Truck and trailer	Truck
Passage time	Permanent	Seasonal
Roadbed width (m)	5-5.5	4.5-5
Road way width (m)	3.5-4	3-3.5
Max. Longitudinal gradient (%)	10(12)	12 (15)

Installation costs were estimated using installation time models, fixed and labor costs and average harvesting volume per corridor. The harvesting volume per corridor ranged from 82 to 170 cubic meters, with an average of 121.2 cubic meters.

Promethtee method

The error of regression equations caused an uncertain condition for deciding the best road spacing. Thus To choose the best optimal spacing among three alternatives, the multiple criteria decision making process was applied. The criteria such as minimum total cost (Euro/m^3) as economical criteria, soil erosion, soil compaction in the skid trail, area of constructed roads (m^2/ha), reforestation costs and facilitate of silvicutural treatments to the stands were taken into consideration. The usual preference method was applied to run Promethee method to evaluate the alternative using Decision Lab software. The Promethee-GAIA methodology is known as one of the most efficient but also one of the easiest decision aid methods in the field. Particularly user-friendly software, called Decision Lab. The Decision Lab 2000 software is an up-to-date implementation of

the Promethee-GAIA methods. It includes many practical developments, such as the treatment of missing values, the definition of categories of actions or criteria, as well as powerful group decision extensions through the definition of multiple scenarios. Decision Lab is developed by the Canadian company Visual Decision (www.visualdecision.com).

This software treats based on the matrix including potential alternatives and evaluation criteria. Promethee requests additional information. For each criterion a specific preference function must be defined. This function is used to compute the degree of preference associated to the best action in case of pair wise comparisons. These shapes are usual, linear, V-shape, U-shape, level and Guassian (Brans et al., 1986). Promethee-GAIA calculates positive and negative preference flows for each alternative. The positive flow is expressing how much an alternative is dominating (power) the other ones, and the negative flow how much it is dominated (weakness) by the other ones. Based on these flows the partial ranking is obtained. The ordinal ranking is based on the balance of the two preference flows (Brans and Mareschal, 2000).

RESULTS

Productivity model

Based on the model developed by Stampfer et al. (2003), the variables such as tree volume, yarding distance, lateral yarding distance and slope of cable way were significantly used in the productivity model. The net productivity averaged 7.03 m^3/h.

Productivity (m^3/h) = -10.19 + 29.879 × tree volume$^{0.2}$ (m^3) – 0.0000412 × Yarding distance^2 (m) – 0.08 × Lateral yarding distance (m) – 0.07 × Slope (%))

(1) Rsq= 0.38, n=590

The significance level of ANOVA table shows that the model is significant at α=0.05.

Table 4

ANOVA of yarding productivity model

	Sum of Squares	df	Mean Square	F	Sig.
Regression	4421.735	4	1105.434	90.172	0.000
Residual	7171.628	585	12.259		
Total	11 593.363	589			

Table 5 presents the summary statistics of residuals of this model.

Yarding distance, lateral yarding distance and tree volume have higher coefficient of variation among the variables used in the model. Therefore these variables cause more error in the modelling than the other variables.

Diminishing uncertainty in yarding model

In order to reduce the uncertainty of the yarding model, lateral yarding distance with high coefficient of variation is dropped from model. It should be noted that yarding

Table 5
Statistics of residual for yarding model (1)

	Minimum	Maximum	Mean	Std. Deviation
Predicted Value	2.327	19.031	7.029	2.739
Standard Error of Predicted Value	0.155	0.687	0.311	0.085
Residual	-7.347	53.578	0.000	3.489
Std. Residual	-2.098	15.302	0.000	0.997

In Table 6 the summary statistics of the parameters used in the modeling are presented.

Table 6
Summary statistics of the parameters

	Minimum	Maximum	Mean	Std. Deviation	CV%
Net productivity	1.10	64.61	7.029	4.437	63.12
PSH_0 (min.)	1.32	13.480	5.379	1.8	33.5
Yarding distance (m)	5	192	84.848	48.95	57.7
LYD (m)	0	38	10.401	8.10	77.9
Tree volume (m^3)	0.07	1.65	0.285	0.21	73.7
Harvest intensity (%)	1.01	63.18	38.238	14.01	36.6
Stand density (n/ha)	369.68	2862.45	1585.48	778.49	49.1
Slope (%)	37	77	58.49	9.69	16.6

distance and tree volume have high coefficient of variation but these parameters are necessary for modelling so that the model can be applied for real prediction of yarding cost.

Productivity (m^3/h) = 21.99 × tree volume$^{0.2}$ (m^3) – 0.000103 × Yarding distance^2 (m) –0.145 × Slope (%))

(2) Rsq= 0.80, n=590

Based on significance level of Table 7, the model makes sense at α=0.05.

Table 7
Analysis of variance of yarding productivity model (2)

	Sum of Squares	df	Mean Square	F	Sig.
Regression	32 779.547	3	10 926.516	805.593	0.000
Residual	7961.673	587	13.563		
Total	40 741.220	590			

Table 8 presents the descriptive statistics for residuals of this model.

Table 8
Summary statistics of predicted values and confidence interval for all observation for model 2

	Minimum	Maximum	Mean	Std. Deviation
Predicted value	2.001	17.009	7.11	2.239
Standard error of predicted value	0.136	0.668	0.250	0.081
Residual	-7.408	55.292	-0.081	3.676
Std. residual	-2.012	15.014	-0.022	0.998

The standard error for second model is relatively less than first model (Table 5 and Table 8).

Error of regression model for yarding time

Table 9 presents the standard error of coefficient and confidence intervals.

Table 9
Error and confidence intervals for yarding model

Variable	Unstandardized Coefficients		t	Sig. level	95% Confidence Interval for B	
	B	Std. Error			Lower bound	Upper bound
Tree volume$^{0.2}$	21.991	1.214	18.119	0.000	19.607	24.375
Yarding distance^{2}	-0.000103	0.0000176	-5.882	0.000	-0.000138	-0.000069
Slope	-0.145	0.014	-10.217	0.000	-0.173	-0.118

The yarding distance was differed and the other variables held constant at their average value to use the lower and upper bound of the model for studying ORS.

Installation time predicting model and its confidence intervals

The models to predict the time of set-up and take-down were presented in the section 1.2. Using the confidence intervals of the coefficients of the variables, the upper and lower bounds of model can be derived at the probability level of 5%.

Set- up time prediction model

Table 10 presents that the VIF values of the variables used in set-up time prediction model are not high, this means that co-linearity is not a problem in this model.

Take- down time predicting model

The confidence interval, tolerance and VIF values of the variables used in take-down model are presented in Table 11. The low value of VIF can be interpreted as lack of co-linearity among the dependent variables of take-down model.

Table 10

Confidence intervals, tolerance and VIF value of the variables in set-up model

Dependent variables	95% Confidence Interval for B		Tolerance	VIF
	Lower bound	Upper bound		
Constant	0.63	1.397	-	-
Corridor length	0.00173	0.00285	0.86	1.163
Int. support height	0.019	0.041	0.802	1.247
Corridor type	0.111	0.401	0.808	1.237
Extraction direction	-0.831	-0.469	0.912	1.097
Yarder size	-0.098	0.321	0.639	1.566
Extraction direction× yarder size	0.227	0.755	0.32	3.128

Table 11

Tolerance and VIF value of the variables in take-down model

Dependent variables	95% Confidence Interval for B		Tolerance	VIF
	Lower bound	Upper bound		
Constant	-0.093	2.007	-	-
Corridor length	0.00164	0.00301	0.871	1.147
Int. support	-0.475	-0.127	0.795	1.257
Extraction direction	0.502	0.121	0.934	1.07
Yarder size	0.121	0.534	0.667	1.499

Table 12 presents the summary statistics of the parameters for installation time equations (Stampfer et al., 2006).

The variables such as extraction direction, intermediate support height and its existence caused more error in the installation time prediction models due to their higher coefficient of variation. However all the variables included in the installation models are important. Eliminating each of them will give a weak model that can not be useful for time predicting in cable logging planning. Therefore the original models of Stampfer et al. (2006) are used.

Road spacing

To derive optimal road spacing installation, yarding and roading cost per cubic meter were graphed for different road spacing were graphed. The total cost graph was drawn to find the lowest cost where the road spacing is optimized (Fig. 1).

Based on Fig. 1, the minimum total cost occurs at 35.93 Euro/m^3. The corresponding road spacing is 284 m which is optimal spacing. The optimal road density and yarding distance are 35.3 m/ha and 95 m respectively.

Table 12
Descriptive statistics of the parameters in installation models

	Minimum	Maximum	Mean	Std. Deviation	CV%
Extraction direction	0 (downhill)	1 (uphill)	0.48	0.50	104
Corridor type	0 (subsequent installation)	1 (first installation from the landing)	0.63	0.48	76
Diagonal corridor length (m)	88	735	309	127.14	41
Intermediate support height (m)	0	20	5.65	6.44	114
Intermediate support	0 (not exists)	1 (exists)	0.54	0.62	115
Yarder size	0 (Mainline pulling power<35 kN)	1 (Mainline pulling power<35 kN)	0.54	0.50	93
Set-up time (worker-h)	1.5	56.6	6.374	7.27	114
Take-down time (worker-h)	1	17.5	2.746	2.86	104

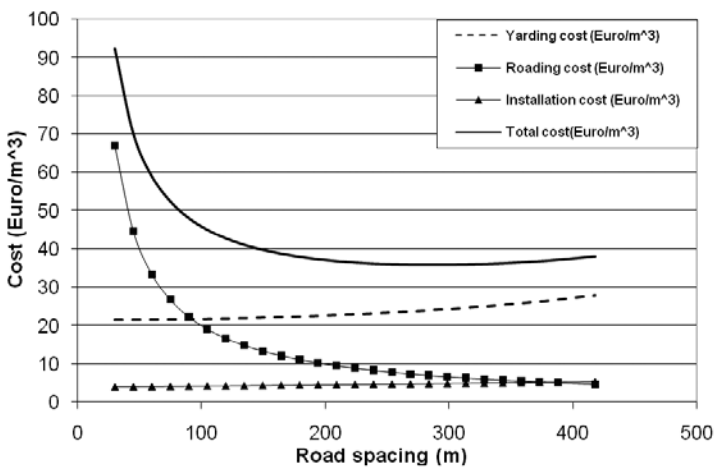

Fig. 1. The total cost summary and road spacing for tower yarder for two-way yarding

The confidence intervals of installation and yarding models were used to graph the upper and lower bound of total cost curve (Fig. 2).

Table 13 presents the optimal spacing, density and yarding distance based on Fig. 2.

The minimum total cost is listed in Table 13 for three road optimal road spacing alternatives. The area of road constructed per ha was calculated based on the road density

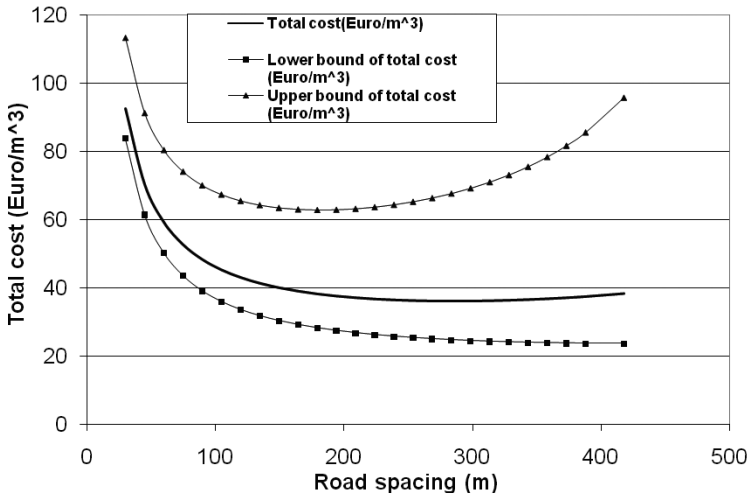

Fig. 2. Total cost and its upper bound and lower bounds costs for different road spacing

Table 13
Optimal road spacing, road density and yarding distance for different total costs

Costs	Minimum total cost (Euro/m^3)	Optimal road spacing (m)	Optimal road density (m/ha)	Optimal yarding distance (m)
Upper bound of total costs	62.62	179	55.8	60
Lower bound of total costs	23.63	418	23.93	140
Mean total costs	35.93	284	35.3	95

of three alternatives and considering the right of way of 10 m. To evaluate the soil erosion, soil compaction and reforestation costs depending on road spacing, there is no research data available. Therefore it was assumed that the higher road spacing will result the higher soil erosion, the higher soil compaction, the higher reforestation cost and the poor facility for silvicutural treatments to the stands. The same weight for all criteria was assumed (Table 14).

The results of partial and complete ranking are presented in Table 15. The best alternative was optimal road spacing of 179 m (resulting from the upper bound of regression model).

A special feature of the Decision Lab software, called the walking weights allows to modify the weights and to observe the resulting modifications of Promethee II ranking. If

Table 14
Preferences and weight for criteria

	Alternatives			
Criterion	ORS(179m)	ORS(418m)	ORS(284m)	Weight
Harvesting total cost	1	9	6.444	1
Soil erosion	9	2	5.719	1
Road area	1	9	6.38	1
Soil compaction	9	3	6.1838	1
Reforestation cost	4.7	2	3.3	1
Facilitate silvicultural treatment	10	1	5.8	1

Table 15
Ordinal and cardinal ranking according to the Φ^+, Φ^-, and Φ values
(same weight for all criteria)

Ranking	**1**	**2**	**3**
Alternatives	ORS (179 m)	ORS (284 m)	ORS (418 m)
Φ^+	0.67	0.50	0.33
Φ^-	0.33	0.50	0.67
Φ	0.33	0	-0.33

the weight of first criteria (total cost per cubic meter) is increased up to 38% or more than this value, then ORS 418 m would be the best solution. Also if we increase the weight for the roading area per ha up to 38% or more, the best solution will be found at ORS of 418 m. Using walking weight method indicated that increasing or decreasing the other criteria would not change the best decision (ORS of 179 m) when holding the rest constant.

CONCLUSION

The working time equations have considerable statistical error which should be taken in consideration when applying for logging planning.

To decrease the standard error of yarding time model, the lateral yarding distance was dropped from the model. Based on Fig. 2, the error of the regression models has high influence on installation and extraction costs by cable yarders. This caused an uncertain situation where optimal road spacing ranged from 179 m to 418 m in the study area. Under uncertainty the multiple criteria decision was implemented to choose the best road spacing considering different criteria (Table 15). However the next studies should evaluate the relation between road spacing with the parameters such soil erosion, soil compaction and reforestation costs to get an exact preference for running multiple criteria decision methods.

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