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A Three-Step Neural Network Artificial Intelligence Modeling Approach for Time, Productivity and Costs Prediction: A Case Study in Italian Forestry

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Abstract

The improvement of harvesting methodologies plays an important role in the optimization of wood production in a context of sustainable forest management. Different harvesting methods can be applied according to forest site-specific condition and the appropriate mechanization level depends on a number of factors. Therefore, efficiency and functionality of wood harvesting operations depend on several factors. The aim of this study is to analyze how the different harvesting processes affect operational costs and labor productivity in typical small-scale Italian harvesting companies. A multiple linear regression model (MLR) and artificial neural network (ANN) have been carried out to predict gross time, productivity and costs estimation in a series of qualitative and quantitative variables. The results have created a correct statistical model able to accurately estimate the technical parameters (work time and productivity) and economic parameters (costs per unit of product and per hectare) useful to the forestry entrepreneur to predict the results of the work in advance, considering only the values detectable of some characteristic elements of the worksite.

Keywords: ANN, AI, mechanization, accuracy, multivariate statistics, harvesting

1. Introduction

Forests and timber represent a vital contributor to rural areas from the economic, environmental and social viewpoint and wood harvesting is one of the most important management activities both to meet production objectives and shape the composition of the future forest (FAO 1997). This active management can be done through several techniques to guarantee the correct implementation of forestry operations, to increase operators' productivity and efficiency and to improve workers qualifications and occupational safety. Worldwide, the improvement of harvesting methodologies plays an important role in the optimization of wood production in a context of sustainable forest management (Maesano et al. 2013). Different harvesting methods are applied according to forest site-specific condition and degree of mechanization. The appropriate mechanization level depends on several factors. In Italy, wherever terrain characteristics are suitable, the forest managers have replaced the chainsaw to alternative highly mechanized systems, especially for the harvesting of specialized forest plantation such as poplar (Spinelli and Magagnotti 2011) and eucalyptus (Picchio et al. 2012), but in mountainous areas, where numerous restrictions related to environmental protection are imposed, the conventional and traditional mechanization is applied (Baraldi and Cavalli 2008, Zimbalatti and Proto 2009). The three main wood harvesting methods are: full-tree (FT), tree-length (TL), and cut-to-length (CTL). Anyway, the choice of a harvesting method depends on the final product required and can be divided into the following groups, sorted to relevance and level of diffusion:

⇒ motor-manual FT/TL harvesting: felling and processing with a chainsaw, and skidding with a farm tractor and winch or grapple

⇒ motor-manual CTL harvesting: felling and processing with a chainsaw, and skidding with a farm tractor and bin or trailer

⇒ partially mechanized FT/TL harvesting: felling and processing with a chainsaw, and skidding with a skidder or cable crane

⇒ partially mechanized CTL harvesting: felling and processing with a chainsaw, and skidding with a forwarder

⇒ fully mechanized CTL harvesting: felling and processing with a harvester and skidding with a forwarder

⇒ fully mechanized FT harvesting: felling with a feller-buncher, extraction with a skidder, and processing with a processor.

In general, motor-manual operations are frequently applied in steep terrain and the farm tractor equipped with forestry winches, grapples, trailers or bins is the most widely used means of timber extraction. Skidders, cable cranes and forwarders are used where farm tractors are limited by terrain steepness and roughness and to guarantee more productivity and safety with respect to traditional extraction methods.

Consequently, each harvesting system has its specific features that depend on natural and production conditions, the technology used, and the role of manual operations in the overall process (Gerasimov and Sokolov 2014, Apăfăian et al. 2017). Therefore, efficiency and functionality of wood harvesting operations depend on several factors (Proto et al. 2017). For this reason, the forest scientific community aimed to produce empirical models or to comparatively assess the performance of two or more operational alternatives to predict the performance of operational behavior (Musat et al. 2016). One of the common ways to evaluate the harvesting systems productivity is to measure working time for every single phase and to evaluate cost-production (Picchio et al. 2009, Bîrda and Borz 2012). The determination of these factors for each phase (felling, bunching, skidding, loading, etc.) can define corresponding time models and help forest managers to choose the best method of extracting wood, and efficiently manage the process of harvesting activity (Ghaffariyan et al. 2012). The forest operations productivity studies are considerable and have a long tradition. Anson (1953) associated the effect of independent variables on time consumption and Steinlin (1955) recommended to measure the time consumed and the quantity produced for carrying out a statistical evaluation to relate the two quantities. Harstela (1988) showed that time studies offer different resolution depending on the level of detail in which they describe the studied process, while Bergstrand (1991) suggested to separate functional elements that react to different work characteristics for developing accurate sub-models. Kanawaty (1992) identified the basic techniques of work study including optimization of planning processes and implementation of standards for machine utilization. Mundel and Danner (1994) defined time study as a set of procedures for determining the amount of time required, under certain standard conditions of measurement, for tasks involving some human, machine, or combined activity. Björheden et al. (1995) normalized the time study procedures adapting to the specificity of forest work processes to allow the direct measurement of time expenditure on work elements. In the last decade, several studies (Costa et al. 2012, Spinelli et al. 2013, Costa et al. 2014, Naghdi et al. 2016) have addressed the application and/or extrapolation of time studies results for determining appropriate harvesting rates, the accuracy of measurements, the time study techniques to develop new mathematical models. Therefore, these studies have expanded to determining the influence of the operating environment, the operational efficiency and the integration of harvesting with operator skills, and the dynamics of human-machine systems.

Artificial intelligence (AI) multivariate methods based on artificial neural networks (ANNs) are well-known computational systems to predict the output of complex systems and solve multifaceted nonlinear problems (even without prior information with high accuracy (Nabavi-Pelesaraei et al. 2018). Generally, ANN is an alternative to traditional methods of modeling (e.g., the statistical regression models) and has greater generalizability, less susceptibility to noise and outliers, and the ability to model nonlinear relations compared to regression models (Haykin 2009). These characteristics are important in modeling the growth and yield of forest stands. In addition, when variables are many and include both quantitative and qualitative ones, the most effective approaches resulted to be non-linear (Assirelli et al. 2018). There are still few examples of AI approaches in forestry (Bui et al. 2017, Reis et al. 2018). For example, in the study of Sanquetta et al. (2018) different AI models (i.e., *k*-nearest neighbors (KNN) and ANN) were tested to estimate merchantable volumes of Japanese cedar (*Cryptomeria japonica*) trees in a homogenous plantation in southern Brazil. These models with respect to traditional ones tended to give lower bias, better precision and accuracy in the middle portion of the stems. Moreover, Vieira et al. (2018) used two AImodels (i.e., ANN and adaptive neuro-fuzzy inference system) to estimate the growth in diameter and total height of eucalyptus trees.

The purpose of this study is to analyze how the different harvesting processes affect operational costs and labor productivity in typical small-scale Italian harvesting companies. A comparative study of conventional and innovative logging operations, under as uniform conditions as possible, has been conducted for supporting decision-making when selecting relevant technology and machinery in harvesting activities. A traditional linear (Multiple Linear Regression; MLR) and an artificial intelligence neural network (ANN) non-linear approach have been adopted on a database composed by a series of qualitative and quantitative variables to predict gross time, productivity and costs.

2. Materials and Methods

2.1 Study Sites and Harvesting Methods

The research was carried out in three experimental sites in Southern Italy (Calabria Region), in Fabrizia (Site A), Cardinale (Site B) and Brognaturo (Site C) municipalities (Fig. 1). The study area covered a total area of 47 hectares (10, 12 and 25 ha in site A, B and C, respectively) with an altitude ranging from 980 to 1150 m. The main characteristics of the study sites are shown in Table 1.

Fig. 1 Three study sites in Southern Italy (Calabria Region)

Table 1 Main characteristics of five test worksites

Characteristics	Site 1A	Site 1B	Site 2A	Site 3A	Site 3B
Municipality	Fabrizia (VV)		Cardinale (CZ)	Brognaturo (VV)	
Prevalent Specie	Chestnut	Chestnut	Calabrian pine	Beech	Silver fir
Government	Coppice	Coppice	High forest	High forest	High forest
Altitude, m a.s.l.	1050	980	1110	1090	1150
Stand density, plants/ha	600	600	750	500	550
Total volume, m^3/ha	470	500	700	575	700
Average DBH, cm	16	15	24.5	29	30
Average height, m	14.5	14	25	23.5	27.4
Average tree volume, m^3	0.10	0.13	0.42	0.6	0.57
Slope min, %	48	61	40	25	17
Slope max, %	68	73	80	71	64
Slope medium, %	58	67	27	55	42
Roughness	Medium	High	Medium	High	Medium
Total volume extracted, m^3	2350	2250	1680	1437	1375
Volume per ha, m^3/ha	470	500	140	115	110

Three different processes of wood harvesting were adopted using the TL systems and the FT systems. In total, five test worksites were monitored (1A, 1B, 2A, 3A and 3B) and different harvesting methods were applied (Table 2).

In the first study area, located in the municipality of Fabrizia (Province of Vibo Valentia), the TL system was adopted and two different coppice chestnut forest stands (*Castanea sativa* Mill.) were monitored and marked with letters 1A and 1B. In site 1A (38°28'24" N – 16°16'30" E), a Stihl MS 261C-M (2.9 kW) chainsaw was used for felling and delimbing. The felling team consisted of two chainsaw operators and a farm tractor, (Landini Landpower 165 TDI, 121.6 kW), equipped with forest winch used for skidding, worked in moderately rough terrain (UK Forestry Commission 1995). In site 1B (38°27'29"N – 16°16'01"E), classified as roughness class III and with slopes greater than

60 percent, the same team worked in felling while the bunching phase was realized using a Greifenberg TG700 (84 kW) cable crane. The same farm tractor equipped with a grapple was used for extracting trees.

In the second study area (2A: 38°36′59″ N – 16°23′34″ E), located in the municipality of Cardinale (Province of Catanzaro), the FT system was adopted and selective felling was applied in a Calabrian Pine (*Pinus nigra* Arn. ssp. *laricio Poiret* var. *Calabrica Delamare*) forest. Tree felling team was composed of two operators and the working phase was performed by chainsaw (Husqvarna 560 XP, 3.5 kW), whereas a John Deere grapple skidder was used for skidding operations involving a single operator. The forest was classified as roughness class II, while the slope varied between class IV and V.

In the third study area, located in the municipality of Brognaturo (Province of Vibo Valentia), two high forests of different age were studied, beech (*Fagus sylvatica* L.) and silver fir forest (*Abies alba* Mill.); the sites were monitored and marked with letters 3A and 3B. In this site (38°34′51″ N – 16°22′17″ E), after the felling, the trees were delimbed by a team of two workers equipped with two chainsaws (Husqvarna 560 XP, 3.5 kW) and extracted by a farm tractor with forest winch. In the second site (3B: 38°32′47″ N – 16°21′22″ E), the felling phase was the same as that in 3A, while a John Deere grapple skidder was used for skidding operations. In the beech stand, the terrain conditions were difficult with respect to the silver fir forest with higher inclination and roughness. With respect to other two sites (1A and 1B), in the sites 2A, 3A and 3B, the delimbing phase was assisted by a mini-excavator (32 kW) for moving the logs and the work time of this machine was assessed with a flat rate of 30% of the gross time required for tree bunching.

Table 2 Description of the experimental design of the five test work sites

Site	Harvesting method	Felling	Delimbing	Bunching	Extraction
1A	TL	Chainsaw 1		Farm tractor + winch	
1B	TL	Chainsaw 1		Cable crane	Farm tractor + grapple
2A	FT	Chainsaw 2	(Mini-excavator)	Forest loader	Skidder + grapple
3A	TL	Chainsaw 2	(Mini-excavator)	Farm tractor + winch	
3B	FT	Chainsaw 2	(Mini-excavator)	Forest loader	Skidder + grapple

2.2 Time Study

The time study data were collected during the spring of 2016 and the autumn of 2017. The times of the different work phases were measured separately using the repetition-timing method to determine the total yarding cycle time. Each work cycle was divided into work elements and classified as productive time or delay time, following the terminology »Forest Work Study Nomenclature« suggested by a subcommittee of IUFRO Working Party $3.04.02 (Work study; Payment, Labour productivity) (Björheden et al. 1995) and approved by the IUFRO Division 3 and timed using a digital chronometer (i.e., 1 min = 100 unit), Tag-HeuerMicrosplit™. Particularly, regarding the extraction cycle using a farm tractor and skidder, the productive time was subdivided into six elements:

⇒ travel unloaded (similar for winch and grapple): begins when the skidder/farm tractor leaves the landing area and ends when the skidder stops in the stump area

⇒ release and hooking (farm tractor+winch): begins when the worker has just grabbed the cable and sets the choker on the tree about 0.5–1.0 m away from the tree end, and ends when the operator starts winching

⇒ winching (farm tractor+winch): begins when the driver starts to winch and ends when the tree has arrived at the rear part of the farm tractor

⇒ grabbing (skidder/farm tractor+grapple): begins when the grapple opens and takes the trees and ends when the grapple is closed

⇒ travel loaded (similar for winch and grapple): begins when the machine moves to the landing and ends when it reaches the landing

⇒ unhooking (similar for winch and grapple): begins when the machine reaches the landing and ends when the load is unhooked.

Concerning the cable crane, seven yarding phases were monitored (Proto et al. 2016):

⇒ outhaul empty: begins when the operator is ready to move carriage from landing out to choke setter and ends when the choke setter touches the choke

⇒ hook descent: begins when the operator locks the carriage and begins to release the hook, and it ends when the operator starts to connect with the load

⇒ lateral out: begins at the end of outhaul empty and ends when the choke setter is ready to hook a turn (choke setter's forward motion has stopped and is ready to begin setting the chokers)

⇒ hookup: begins at the end of lateral out and ends when the choke setter has completed hooking the chokers and signals to begin yarding

⇒ lateral in: begins at the end of hookup and ends when the turn is pulled up to the carriage and the carriage begins to move up the corridor

⇒ in haul: begins at the end of lateral in and ends when the turn has reached the position on the deck where it can be directly unhooked at the landing

⇒ unhook: begins at the end of in haul when the carriage passes over the tripblock and ends when the chokers have returned to the carriage.

2.3 Economic Evaluations

To calculate the hourly cost of wood harvesting in the different study sites, many parameters were considered (Olsen and Kellogg 1983) and the Miyata (1980) method was applied. To calculate the production cost for 1 m^3 of wood, the cost analysis employed the following parameters: the number of operators, the hourly cost of an operator, the hourly cost of machines, the volume of wood extracted and productive machine hours excluding all delay times. The purchase prices and operator wages required by the cost calculations were obtained from catalogues and accounting records. Cost calculations were based on the assumptions adopted in recent economic studies (Magagnotti and Spinelli 2011, Spinelli and Magagnotti 2011, Proto and Zimbalatti 2016, Proto et al. 2018). In the machine cost calculation, the relocation costs have not been considered. The principal technical and economical parameters and the machine cost are shown in Table 3.

2.4 Modeling Approaches

The statistical analyses were performed on the matrix composed of 6 quantitative and 4 qualitative (i.e., categorical) variables per 252 cycles (i.e., observations). Six quantitative variables are: average slope, average DBH, wood biomass per hectare (m^3 ha^{-1}), bunching

Table 3 Assumed cost parameters and calculated hourly machine costs

Description	Felling/Delimbing			Bunching/Extraction			
	Chainsaw 1	Chainsaw 2	Mini–excavator	Farm Tractor with winch/grapple	Cable crane	Skidder with grapple	Forest loader
Purchase price, €	1100	940	50,000	79,000	150,000	200,000	80,000
Initial investment (no tires cost)	1100	940	48,500	76,200	149,400	197,000	78,200
Salvage value, €	220	188	10	15,240	29,880	39,400	15,640
Economic life, years	3	3	10	10	10	10	10
Productive machine hours, h/year	700	700	800	1000	800	740	800
Engine power, kW	3.5	2.9	32	121	84	110	88
Interest rate, %	4	4	4	4	4	4	4
Fuel consumption, L/h	1.32	1.09	2.79	17.58	12.50	15.00	10.23
Lubricant consumption, L/h	0.59	0.49	0.30	0.54	0.40	0.38	0.45
Fuel price, €/L	1.55	1.55	1.05	1.05	1.05	1.05	1.05
Lubricant price, €/L	4.5	4.5	9	9	9	9	9
Tires cost, €	–	–	1500	2800	600	3000	1800
Qualified labor cost (ancillary wage included), €/h	15	15	15	15	15	–	15
Specialized labor cost (ancillary wage included), €/h	–	–	–	–	21	21	–
Hourly machine cost, €/h	5.50	4.58	24.45	37.95	51.35	68.95	33.25

distance (m), extraction distance (m) and load per cycle (m^3 $cycle^{-1}$). The four qualitive variables, expressed as dummy variables are: governance (management of coppice or high forest), machine used for log extraction (tractor with winch, cable crane, skidder with grapple), working system (TL or FT) and roughness (medium or high), classified in relation to the presence of obstacles on the ground (outcropping rocks, stone, etc.) in accordance with UK Forestry Commission (1995).

A three-step approach was applied (Guerrieri et al. 2016). In the first step, the gross time (minutes per transported load) was estimated based on the above ten variable matrix. In the second step, the gross productivity (m^3 h^{-1} per operator) was estimated based on ten variable matrix together with the gross time estimated (11 variables). In the third step, the cost per m^3 (€ m^3) and cost per hectare (€ ha^{-1}) was estimated based on ten variable matrix together with the estimated gross time and productivity (12 variables).

The model for gross time, productivity and costs estimation was developed using a non-linear regressive ANN approach compared with a MLR model. As the database is composed of a series of qualitative and quantitative variables, the best way to find a regressive solution is a non-linear approach. ANN was developed based on the input layer (x-block) to estimate the output layer (y-block). Between the input and output layers, one or more hidden layers were built by the ANN procedure based on its architecture. The number of hidden layers used was equal to 3 nodes. The type and the complexity of the process or experimentation usually iteratively determine the optimal number of the neurons in the hidden layers (Gupta 2013).

The ANN model was developed using a Multi-Layer Feed Forward Networks (MLFN) structure, the method often used for function approximation (Mossalam and Arafa 2017). The ANNs models are massively parallel systems with large numbers of interconnected simple processors. These networks are fine-grained parallel implementations of non-linear static or dynamic systems (Hassoun 1995). The general regression neural network (GRNN) was trained with a back-propagation learning algorithm. Out of 252 observations, only 227 samples (90%) were used to construct the models to avoid overfitting. The remaining 25 samples (10%) were then used to test the performance of the models (internal test). The partitioning was conducted using the sample set partitioning based on joint *x-y* distances (SPXY) algorithm (Harrop Galvao et al. 2005) that considers the variability in both *X*- and *Y*-spaces. The training of the ANN was carried out using a learning equal to 0.5 and a momentum equal to 0.1. The training procedure was repeated 1,000,000 times and the best performing MLFN was selected based on the independent test set. The final architecture of the ANN includes a different number of nodes in the hidden layer depending of the kind of variable to be estimated. Performance parameters, such as the *r* correlation coefficient between the observed and predicted and the Root Mean Squared Error (RMSE), were reported for both training and test sets. A variable impact neural network analysis was performed to assess the relative importance of each variable (Abdou et al. 2012). Operatively, this index is similar to the linear regression Variable Importance in the Projection (VIP) scores (Chong and Jun 2005, Febbi et al. 2015). The ANN analysis has been performed using Palisade Neural Tools 7.6.

The ANN model performance (*r* correlation coefficient and RMSE) on the same datasets has been compared with a MLR model applied on the same partitioned datasets. Ordinary linear regression approaches, such as MLR, are widely used in the agricultural and forestry frameworks for the estimation of quantitative parameters (Costa et al. 2012). MLR is the most common form of linear regression analysis, generally used to explain the relationship between one dependent variable (*y*-block) and two or more independent variables (*x*-block).

3. Results and Discussion

In the three study sites, 252 cycles and more than 250 h of operations were analyzed and evaluated. The total productivity (m^3/PMH) in worksite 1 (1A+1B) was 0.85 and 0.74, in worksite 2A it was 1.6 and in worksite 3 (3A+3B) it was 1.5 and 1.70, respectively. Data regarding the total travel distance for the cycles, number of logs and total volume are shown in Table 4.

Mean and standard positive deviation values of the gross time, gross productivity and costs (per m^3 and hectare) for each worksite were visually reported by

Table 4 Elements related to bunching and extraction operations

Worksite	Bunching distance m	Extraction distance m	Logs N/load	Load m^3/cycle
1A	21.15	350.84	3.63	0.57
1B	26.54	200.25	4.06	0.58
2A	–	366.10	4.54	1.74
3A	41.64	391.00	1.80	1.16
3B	–	236.00	4.61	2.39

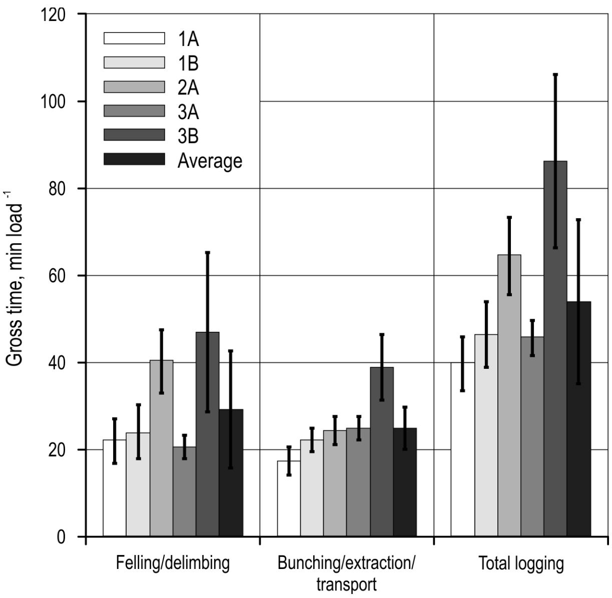

Fig. 2 Mean (±SD; whiskers) gross time of logging in five sites, divided into different operations

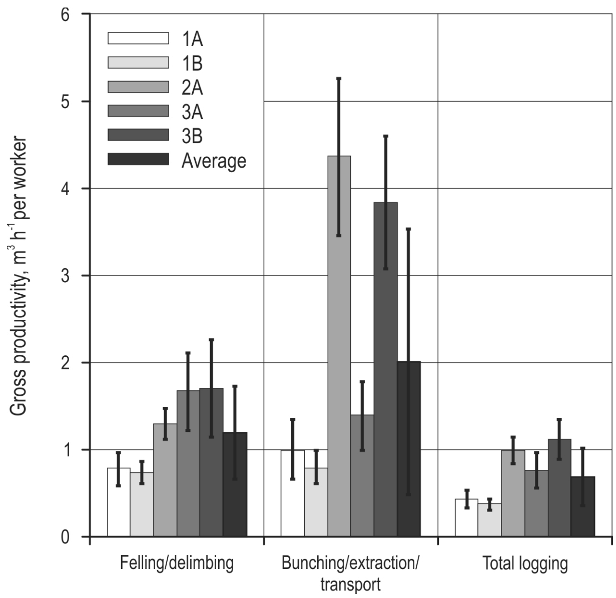

Fig. 3 Mean (±SD; whiskers) gross productivity of logging in five sites, divided into different operations

histograms. Figs. 2 and 3 show the operating results referred to the total gross times and productivity, for all operations concerning the forest work performed. Figs. 4 and 5 show the economic results of the five sites relative to the evaluation of the costs per unit of product and per unit of surface, in relation to the extraction systems adopted.

Regarding the felling phase, although the same team and systems were used, a different productivity (m^3 h^{-1} per worker) was observed (1.55, 1.47, 2.58, 3.34 and 3.38 in site 1A, Site 1B, Site 2A, Site 3A, and Site 3B respectively). This was due to the different tree sizes with higher unit volumes for the sites 2A (0.38 m^3), 2B (0.64 m^3) and 3B (0.54 m^3), compared to sites 1A (0.16 m^3) and 1B (0.14 m^3). The average bunching distances were 21, 27 and 42 m in site 1A, Site 1B, Site 3A, respectively, while this phase was not adopted in site 2A and Site 3B. The bunching productivity varied significantly at different sites monitored. The extraction distances varied form the minimum of 200 m in site 1B and the maximum of 391 m in site 3A. The unit complete productivity (m^3 h^{-1} per worker) was 0.42, 0.37, 0.99, 0.75 and 1.12 in site 1A, Site 1B, Site 2A, Site 3A, and Site 3B, respectively. Costs per unit of product (€ m^{-3}) were lower in sites 3B (38.56) and 3A (41.45), due the lowest cost for wood extraction of the skidder use, while the costs were much higher in sites 1A (65.19) and 1B (86.27), where the cost of extraction was very high. The worst result was obtained in site 1B with the use of the cable crane, in a terrain with high slope. The costs per hectare reach the maximum value in site 1B with € 43,137 and the lowest cost in site 3B with € 4241. The lower logging costs per hectare, obtained in sites 3B, 2A and 3A, as well as higher work productivity, are to be correlated to the different volume of extracted wood, which at these sites was considerably lower (110, 140 and 115 m^3 ha^{-1}, respectively), compared to sites 1A and 1B (470 and 500, respectively).

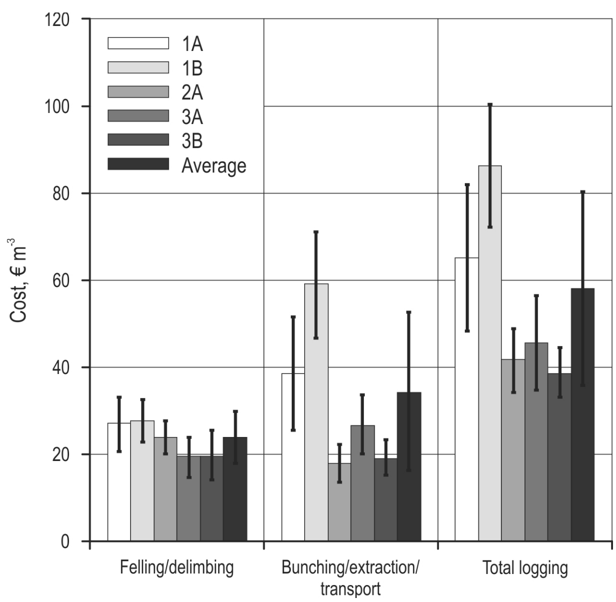

Fig. 4 Mean (±SD; whiskers) cost per m^3 of logging in five sites, divided into different operations

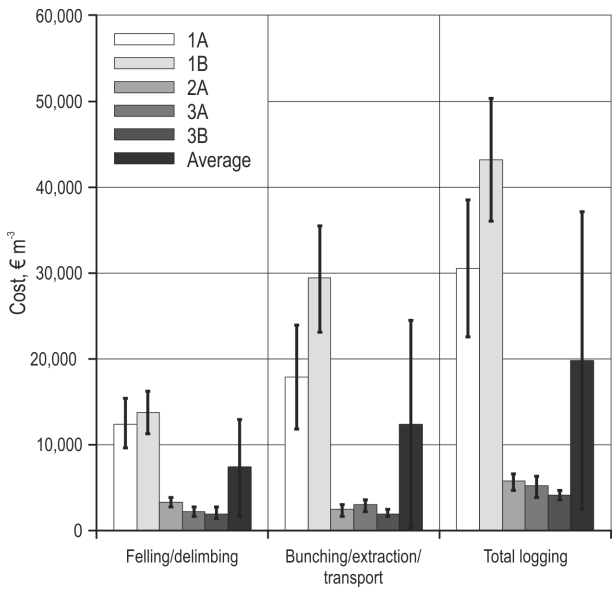

Fig. 5 Mean (±SD; whiskers) cost per hectare of logging in five sites, divided into different operations

Table 5 shows the results of the MLR and ANN models for both training and internal test, for the estimation of gross time, gross productivity and cost. Comparing the two methods, it is possible to observe definitely higher performances (up to 10% higher) of the ANN approach for both modeling and test sets to estimate gross time, cost per m^3 and cost per hectare, while results are comparable for gross productivity estimation. MLR test set correlation coefficient (*r*) results ranged from 0.86 (gross time) to 0.98 (gross productivity) estimation. ANN test set correlation coefficient (*r*) results ranged from 0.96 (gross time) to 0.99 (cost per hectare) estimation.

Fig. 6 shows the scatter plots of the observed versus predicted estimation of gross time, gross productivity, cost per m^3 and cost per hectare in both MLR and ANN. In both MLR and ANN modeling approaches, the prediction of gross productivity resulted visually linear. ANN models predicted vs observed scores resulted closer to the bisectrix (i.e. perfect attribution).

Fig. 6 clearly shows the superiority of estimation with ANN method with respect to MLR method. This difference is even more accentuated in the estimation of the cost per hectare, where the deviation of the predicted value from the observed value calculated with MLR is higher. The difference between the worksites is also more evident with significantly lower costs per hectare for the worksites 2A, 3A and 3B, managed to high forest, with respect to the worksite 1A and 1B, managed to coppice.

Table 6 reports the percentage of VIP scores of the ANN models for the estimation of gross time, gross productivity, cost per m^3 and cost per hectare. In the prediction of the gross time, the variable »load per cycle« has the most important impact (20.22%). For the estimation of the gross productivity, it is the »wood

Table 5 Characteristics and principal results of MLR and ANN models (training and internal test) in estimating gross time, gross productivity, cost per m^3 and cost per hectare: number of cases, training time, number of trials, *r* correlation coefficient, Root Mean Square Error (RMSE)

	MLR				ANN			
	Gross time	Gross productivity	Cost per m^3	Cost per ha	Gross time	Gross productivity	Cost per m^3	Cost per ha
	Training (90% sample size)				Training (90% sample size)			
Number of cases	227				227			
Training time	Not available				00:06:01	00:05:12	00:05:02	00:05:52
Number of trials	Not available				1,000,000	1,000,000	1,000,000	1,000,000
Number of nodes	Not available				4	3	3	3
r correlation coefficient	0.945	0.983	0.942	0.973	0.979	0.983	0.986	0.996
Root Mean Square Error (RMSE)	7.495	0.059	7.436	3999.245	4.713	0.046	3.672	1576.23
	Testing (10% sample size)				Testing (10% sample size)			
Number of cases	25				25			
r correlation coefficient	0.863	0.983	0.875	0.922	0.962	0.984	0.966	0.992
Root Mean Square Error (RMSE)	12.847	0.071	11.141	6614.403	7.495	0.077	5.995	2237.59

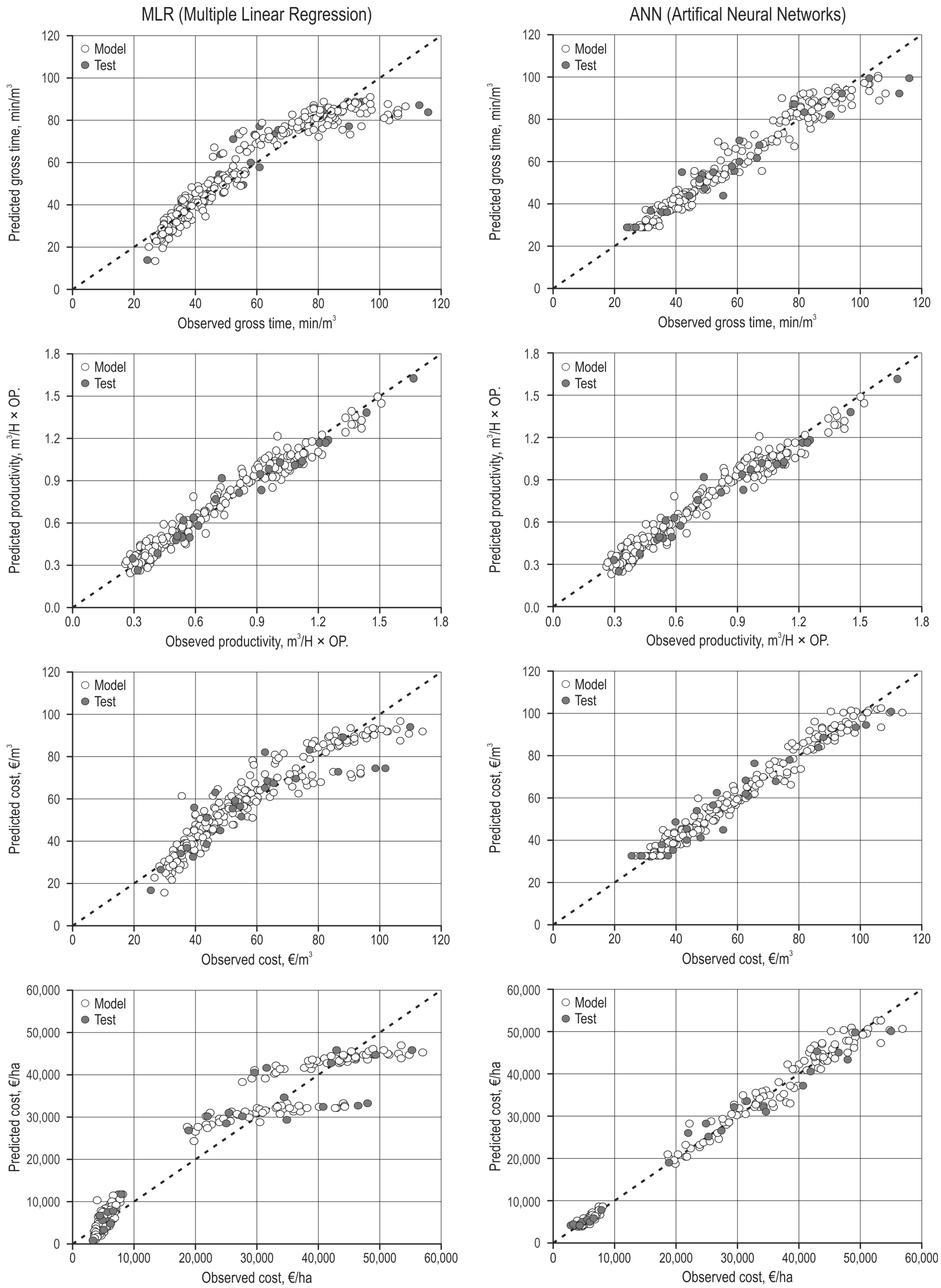

Fig. 6 Scatter plot of the observed versus predicted gross time, gross productivity, cost per m^3 and cost per hectare obtained from the MLR (left side) and ANN models (right side). Lines represent the bisectrices (i.e. perfect attribution)

Table 6 Percentage of Variable Importance in the Projection (VIP) scores of ANN models in estimating gross time, gross productivity, cost per m^3 and cost per hectare

		Gross time %	Gross productivity %	Cost per m^3 %	Cost per ha %
Quantitative variables	Average slope	17.07	12.88	10.90	10.56
	Average DBH	15.62	12.54	9.22	21.60
	Wood biomass per hectare	8.96	18.49	7.14	3.44
	Bunching distance	6.24	1.13	1.41	7.63
	Extraction distance	6.93	0.39	2.00	6.22
	Load per cycle	20.22	4.26	12.35	6.40
	Gross time pred.	–	10.08	13.78	6.36
	Gross productivity pred.	–	–	11.79	18.80
Qualitative variables	Government	5.75	10.63	10.36	2.47
	Machine used for log extraction	12.29	15.01	4.92	9.37
	Working system	3.56	7.11	9.24	5.04
	Roughness	3.35	7.48	6.89	2.12

biomass per hectare« with a percentage of 18.49% and finally for the Cost per m^3 and per ha, these are »gross time prediction« (13.78%) and »average DBH« (21.60%).

The obtained MLR and ANN models were based on heterogeneous input dataset, constituted by quantitative (DBH in cm, biomass in m^3, distance in m, time in min, productivity in m^3 h^{-1}, costs in €) and qualitative variables (governance, working system and roughness). These models proved to be extremely efficient as well as generalizable and robust, but the ANN model has a higher predictive capacity and accuracy than the MLR. The ANN model adopted is highly able to accurately estimate the technical parameters and economic parameters useful to the forestry entrepreneur to predict the results of the work in advance, taking into account only the detectable values of some characteristic elements of the worksite.

4. Conclusions

The wood harvesting is composed of several consecutive operations over time, such as the felling of trees, delimbing, wood extraction, loading and transport. This process can be represented by empirical models to meet different objectives, such as the planning of forest wood chain, the calculation of the cost of harvesting and the convenience to adopt different working systems and degrees of mechanization. For this reason, the interest in exploring alternatives to ordinary linear regression, such as ANN predictive modeling is constantly growing. In this study, the authors compared the MLR and ANN analysis allowing to produce models that, in addition to better adapting to the original data, can also manage collinear variables, facilitating the extraction of models from large amounts of field data and different forest operations.

The system was successfully used in the field tests and provided accurate and satisfactory data observing higher performances of the ANN approach than the MLR. Although ANN models are somewhat less practical than standard regression equations, they are certainly more robust in terms of variable oscillations and higher repeatability and are particularly suitable, unlike linear models, for modeling systems with greater complexity and more difficult to manage.

The comparison of the various modeling approaches indicated that the generated models could predict work time, productivity and costs per unit of product and per hectare. The statistical models developed through numerous and different harvesting systems tested in this study could be used for harvesting planning and productivity optimization. Considering the recent dynamic growth in mechanized forest operations (Spinelli et al. 2017, Mederski et al. 2018), it is fundamental to select the correct wood harvesting method, and this study enables taking into consideration all qualitative and quantitative variables to obtain a valid and accurate prediction.

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