Taylor & Francis
Taylor & Francis Group

Forest Science and Technology

ISSN: 2158-0103 (Print) 2158-0715 (Online) Journal homepage: www.tandfonline.com/journals/tfst20

Activity recognition in motor-manual cross-cutting operations by machine learning on multimodal data

Stelian Alexandru Borz, Tomi Kaakkurivaara, Gabriel Osei Forkuo & Nopparat Kaakkurivaara

To cite this article: Stelian Alexandru Borz, Tomi Kaakkurivaara, Gabriel Osei Forkuo & Nopparat Kaakkurivaara (06 Aug 2025): Activity recognition in motor-manual cross-cutting operations by machine learning on multimodal data, Forest Science and Technology, DOI: 10.1080/21580103.2025.2543281

To link to this article: https://doi.org/10.1080/21580103.2025.2543281

FOREST SCIENCE AND TECHNOLOGY
https://doi.org/10.1080/21580103.2025.2543281

RESEARCH ARTICLE

OPEN ACCESS Check for updates

Activity recognition in motor-manual cross-cutting operations by machine learning on multimodal data

Stelian Alexandru Borz[a], Tomi Kaakkurivaara[a,b], Gabriel Osei Forkuo[a] and Nopparat Kaakkurivaara[b]

[a]Department of Forest Engineering, Forest Management Planning and Terrestrial Measurements, Faculty of Silviculture and Forest Engineering, Transilvania University of Brasov, Brasov, Romania; [b]Department of Forest Engineering, Faculty of Forestry, Kasetsart University, Bangkok, Thailand

ABSTRACT
In forest operations, established time-study methods, such as the use of a stopwatch and video recording, have dominated for several years. Advancements in machine learning and innovative data loggers present opportunities to reconsider and enhance these methods. This study utilized a neural network algorithm to learn from and generalize multimodal data collected by noise dosimeters and accelerometers placed at two different locations. It involved the implementation of seven distinct neural network models aimed at recognizing operator activities during chainsaw work. The classification accuracy (CA) of distinguishing between "work" and "other" work events reached impressive levels with various combinations of datasets. Notably, the poorest performance was associated with data from the operator's back-mounted accelerometer alone (CA = 63%), whereas the best results emerged from combining data from the accelerometer on the chainsaw with a noise dosimeter (CA = 99.8%). This research highlights the viability of using accelerometers and noise data to analyze chainsaw operations, suggesting that defined network architectures and parameters can efficiently handle large datasets. This capability will facilitate the documentation of efficiency and delays in cross-cutting and delimbing activities without requiring specialized knowledge of forest operations or time studies. Data collection can span several working days and cover multiple locations, thereby minimizing the time spent on data management and analysis. Future developments in this model could enable a more granular analysis of the chainsaw work duration, further improving our understanding of operational efficiency in forestry.

ARTICLE HISTORY
Received 30 May 2025
Revised 8 July 2025
Accepted 30 July 2025

KEYWORDS
automation; big data; teak harvesting; time consumption

Introduction

Timber harvesting operations play a pivotal role in wood procurement supply chains. The decision on the level of mechanization used in these operations is influenced by the availability of machinery and personnel, local forest management practices, terrain and stand conditions, tree species and size, and concerns about environmental impacts (Labelle and Lemmer 2019; Engler et al. 2024). Therefore, motor-manual operations can applied in several workplaces. For example, tree felling and processing are performed motor-manually in several parts of the world. Motor-manual operations account for a significant share globally in regions characterized by the availability of cheap labor, difficult terrain, broad-leaved forests dominated by large trees, or when there is a generally low level of technical skill in forest operations (Lundbäck et al. 2021; Di Fulvio et al. 2024). Hence, productivity research on motor-manual forest work remains a relevant topic for supporting forest operations.

Teak (*Tectona grandis* L.f.) is highly valued in Thailand and neighboring countries because of its suitability for high-end products, such as boat decks, countertops, indoor flooring, and outdoor furniture (KU, ITTO, TEAKNET, 2022). In Thailand alone, the area of teak monoculture plantations is approximately 100,000 ha. These planted forests typically require forestry operations, including two thinning steps before clear-cutting during the rotation period, which are executed using the tree-length harvesting method (FIO 2021; KU, ITTO, TEAKNET, 2022). These operations are mainly conducted with a high input of motor-manual labor, particularly during the felling and delimbing of trees, as well as when crosscutting them into logs at a log yard (Kaakkurivaara et al. 2022). Specifically, operations at log yards involve measurement and grading, followed by log crosscutting. Usually, this task is performed by teams of two workers; one operated a chainsaw, whereas the second assisted with an iron rod to lift the cross-cutting point of the stem off the ground. After bucking, the logs are individually accounted for and the log ends are stamped with a log ID number and a forest plantation logo (Kaakkurivaara 2019). In the above-described harvesting operation,

CONTACT Nopparat Kaakkurivaara fforn rm@ku.ac.th Department of Forest Engineering, Faculty of Forestry, Kasetsart University, 50 Ngamwongwan Rd., Lat Yao, Chatuchak, Bangkok 10900, Thailand

planning decisions and resource allocation are important tasks due to labor-intensive and time-consuming operations. In addition, these tasks are challenging because of the lack of data describing the operational performance. For instance motor-manual operations in forestry are commonly used in Thailand, accurate data to support proper planning, such as time and productivity rates, are not available (Rianthakool et al. 2018). A similar situation can be found in other regions across the world where motor-manual tree-length harvesting methods are integrated to achieve high-value recoveries (Vusić et al. 2013; Ghaffariyan 2022). Motor-manual operations are a central subject of productivity analysis due to their high degree of human involvement and operational variability (Kanawaty 1992; Uusitalo 2010; Poje et al. 2024).

Conventional time data collection methods have typically relied on time recording using stopwatches, hand-held computers, and video recordings for further analysis in time studies aimed at investigating productivity in forestry operations (Anson 1953; Steinlin 1955; Olsen and Kellogg 1983; Harstela 1988; Bergstrand 1991; Kanawaty 1992; Björheden et al. 1995; Nurminen et al. 2006; Uusitalo 2010; Mousavi et al. 2011; Ghaffariyan et al. 2012; Spinelli et al. 2013; Câmpu and Ciubotaru 2017; Proto et al. 2020; Poje et al. 2024). Recently, automation and digitalization of research process have become integral to data collection and analysis in forest operation studies. For instance, multimodal data collected from sources, such as video recordings, sound dosimeters, and accelerometers, can be processed using machine learning algorithms, such as neural networks and random forests for activity recognition (Keefe et al. 2019; Becker and Keefe 2022; Borz and Proto 2024). This new data processing technology has the potential to mitigate the main disadvantages of conventional methods, including the availability of trained and experienced forest work researchers, the accuracy and reliability of data, and the limitation of collecting data only in a short term (Uusitalo 2010). Furthermore, motor-manual operations have their own special features when studying human work behavior with chainsaw and their combined effect, instead of the observation of forest machine work, when studies are aiming at producing reliable estimates of work productivity (Câmpu and Ciubotaru 2017; Poje et al. 2024).

Depending on the harvesting method used, motor-manual operations may be required at landing or in a log yard to delimb or fully process trees into logs (Verani et al. 2008; Grebner et al. 2022; Kaakkurivaara et al. 2022). In general, these workspaces are characterized by a high variability in local features (stem size and quality, timber assortments, work experience, etc.) and the work methods may differ significantly. This variability is further enhanced by work behaviors and the characteristics of the tools used (chainsaw type and other aids). Altogether, these factors can complicate the design of time studies, which require well-trained experts and considerable resources for implementation. Therefore, alternative solutions have been investigated to overcome these limitations and to enable the collection and analysis of large datasets with reduced effort. These solutions rely primarily on collecting data through sensors and processing them to determine the duration of relevant operational events using techniques, such as thresholding and machine learning. For instance, Borz et al. (2019) used various modalities, including wearable devices equipped with GNSS functionalities, noise dosimeters, and accelerometers, to document events in time and space to assess the ergonomic conditions of motor-manual willow felling using brush cutters. In their approach, thresholding was employed to differentiate the data based on the known features of the signals used. Keefe et al. (2019) developed a smartphone application that can detect relevant operational events through sensors integrated into devices using machine learning. They reported outstanding event-recognition accuracy when extracting relevant features from larger datasets. High recognition accuracy, reaching 100%, has been reported when using neural networks to predict events in motor-manual willow felling using brush cutters (Borz 2021). However, these developed methods only work for specific problems for which they were designed. Furthermore, the economic context of different regions largely dictates the level of worker welfare; consequently, their ability to purchase and own the technology necessary for collecting data in time studies. This often leaves the responsibility of conducting time studies to trained researchers, who must find suitable methods to manage large datasets with minimal effort. Therefore, the use of dedicated devices, such as precise noise dosimeters and accelerometers, can be advantageous; they document data which can be used for time studies as well as provide meaningful information for the productivity assessment of various operations. Their use can be particularly effective when costs do not exceed those associated with the use of a specialized productivity related recording device.

The goal of this study is to investigate the suitability of multimodal data collected from motor-manual stem crosscutting for activity recognition and further utilize these data in time-study research, specifically through analysis using machine learning algorithms. The objectives of this study are as follows: i) to identify the model class that performs best in classifying working versus non-working events based on acceleration and noise pressure signals, and ii) to determine the neural network architecture and hyperparameter settings that yield the highest event classification accuracy. These objectives were supported by three distinct datasets (acceleration data collected from both the chainsaw and the worker's back, along with sound pressure level data recorded at the worker's helmet level), which were used to develop seven model classes based on the number and type of input signals.

Materials and methods

Study location and organization of work

This study was conducted on a teak plantation in the province of Kanchanaburi, Thailand (Figure 1). The log

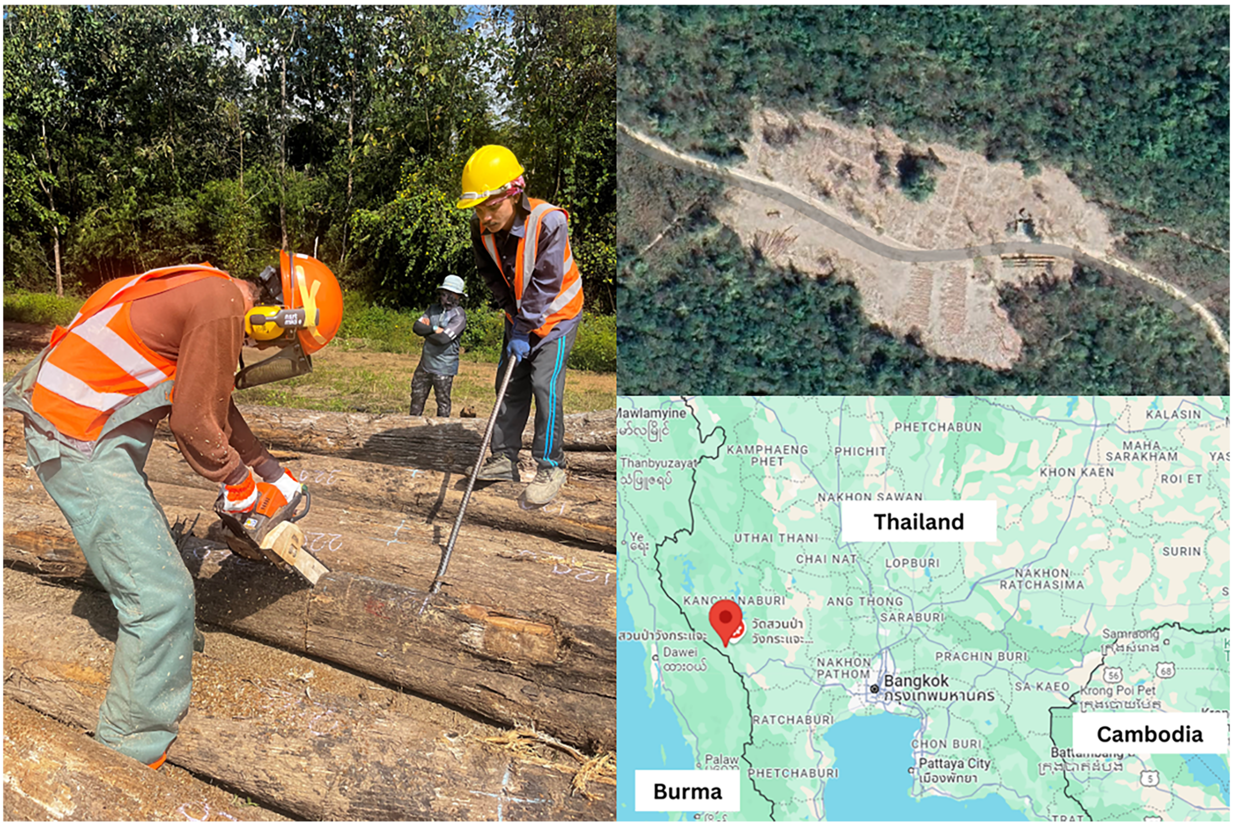

Figure 1. Motor-manual operation of Teak stem crosscutting (left) on log yard (upper right) in western Thailand (lower right).

yard was located at approximately 14°10'58.8"N–98°55'34.3"E, at an elevation of approximately 200 m above sea level (a.s.l.), where teak harvesting was done by the Forest Industry Organization, a state-owned enterprise (FIO 2015). The company manages approximately 78,250 ha of teak plantations in Northern and Western Thailand, and performs harvesting operations from March to October, depending on the weather conditions, or until the annual local cutting plans are fulfilled. Data were collected from harvested tree stems in a clear-cut compartment, where the trees were 30 years old, and the average tree size was 0.45 m^3. The stems were extracted to the log yard and placed parallel to each other using a farm tractor. The age and size of the trees and the extraction method were carefully selected to represent the typical conditions of teak harvesting. The chainsaw used was a Stihl MS 180 without technical modifications, and the operators used common personal protective equipment (PPE) as required.

Data collection

Field data were collected over two days of observation (17th and 18th November 2022) using the three devices. Two Extech VB300 triaxial accelerometers (Extech Instruments 2014) were positioned on the front handle of the chainsaw and back of the worker between the scapulae (Figure 2). A sound dosimeter (Paillard 2021) was attached to the worker's helmet using adhesive tape, maintaining a distance of approximately 10 cm between the microphone and ear. All devices were set to sample data at a rate of one second.

The noise dosimeter can record data on the A, C, and Z weighting scales. It features an adjustable log interval, is calibrated by the manufacturer, exhibits low sensitivity to temperature and vibrations, and it is well balanced in terms of accuracy and weight (Paillard 2019). The instrument was set up using a dedicated software to sample the dB(A) weighting scale. Other important settings included the bandwidth, which was set to 16 kHz (with a sampling frequency of 32 kHz), and the time constant for sound level measurement, which was set to 125 ms. The collected variables included L-max, L-min, and LAeq, where LAeq is the equivalent exposure to noise based on the log interval that defines the time between two successive recorded samples. This interval defined the integration period for LAeq and the observation periods for L-max and L-min. The recorded data are stored in nonvolatile memory, and dedicated software is used to download them as either string- or time-labeled data.

The triaxial accelerometers used are miniaturized devices that are lightweight and can collect acceleration (g) data along three axes (x, y, and z). Using dedicated software, the data can be exported in Microsoft Excel format, which includes an identification string, identification numbers for the records, measured responses for the three axes for each record, and the automatically computed vector magnitude and time label.

Data processing

Both types of data logger produced time-referenced datasets. The time labels of the records were used as features to pair the data, which were exported to

Figure 2. Instrumentation of data collection: triaxial accelerometers placed on operator's back (1) and chainsaw (2), and sound pressure meter on helmet (3).

Table 1. Description of the datasets.

Dataset	Abbreviation	Description
Acceleration, front handle of the chainsaw	ENC	Collected by a triaxial accelerometer mounted on the front handle of the chainsaw by adhesive tape, time-labelled records at a rate of one second
Acceleration, back of the worker	ENB	Collected by a triaxial accelerometer mounted on the back of the worker between scapulae by a pericardic strap, time-labelled records at a rate of one second
Equivalent exposure to noise	LAeq	Collected by a noise dosimeter mounted on the worker's helmet by adhesive tape, time-labelled records at a rate of one second

Microsoft Excel. For the acceleration data, vector sums (Euclidean norms) were retained for analysis, whereas for the noise data, the equivalent sound pressure level was included (Table 1). The dataset used for analysis contained 25,031 valid records. Based on these data, two manual annotation rules were applied, informed by the known properties of acceleration and sound behavior when working with chainsaws.

Accelerometer data from the ENC dataset were manually classified based on the magnitude of the records. Records with magnitudes > 2 g were preliminarily classified as working events. Based on the magnitude of the LAeq dataset, records with magnitudes > 80 dB(A) were classified as working events. These levels were dictated after visual interpretation of results (see example in Figure 3). In both cases, records that did not meet the criteria for inclusion in the "Working" category were categorized as "Other" events. Subsequently, a paired visual analysis was conducted to determine the classification of records that received different annotations during the preliminary classification. Based on the magnitudes of the ENC and LAeq, a final judgment was made regarding the classification of each record. For example, high magnitudes in the ENC records, when associated with low LAeq magnitudes—which are not typical for a running chainsaw—were classified as "Other" events. Conversely, lower magnitude records from ENC paired with high magnitudes in LAeq were classified as "Working" events. Such situations are commonly observed, as events, such as chain sharpening, may exhibit high magnitudes in ENC and low magnitudes in LAeq. Similarly, the action of moving along the stems typically resulted in low acceleration magnitudes because the chainsaw was not used for cutting, whereas the sound magnitudes remained high because the chainsaw engine was on.

Activity recognition by machine learning

Activity recognition using machine learning was conducted by considering all possible combinations of input signals to be used as features, where the target variable was the class of events: "Other" and "Working." A neural network was designed using the Orange Visual Programming Software (Demsar et al. 2013) by varying its architecture in terms of the number of hidden layers and neurons. For training and validation, the ReLU activation function and ADAM optimizer were utilized because of their high performance in solving complex nonlinear tasks (Nair and Hinton 2010; Maas et al. 2013; Kingma and Ba 2015), particularly for similar input signals (Borz 2021). The number of iterations was maintained at the maximum enabled by the software (1,000,000), and training and testing were performed using a stratified cross-validation with 5 folds. All models were tested by one to five hidden layers of 10, 50 and 100 neurons each for network architecture and parameters with ReLU as activation function, ADAM as solver and regularization parameters α = 0.0001, 0.001, 0.01, and 0.1.

A total of 420 models were trained and tested to identify the best model for sensor-based activity recognition, with 60 models developed for each model class (Table 2) based on the number of layers, number of neurons in each layer, and the regularization parameters used. The evaluation of the models was based on

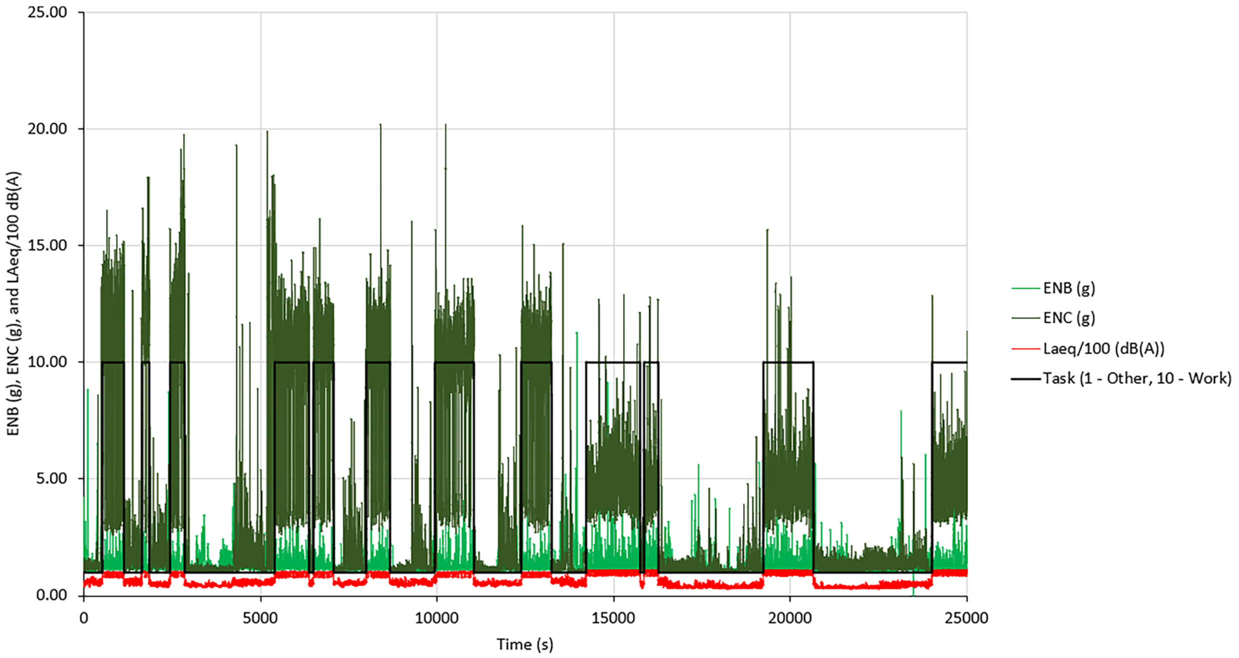

Figure 3. Magnitude of the used signals in the time domain. Legend: ENB – Euclidean norm of the acceleration data as collected by the datalogger placed on the worker's back, ENC – Euclidean norm of the acceleration data as collected by the datalogger placed on the front handle of the chainsaw, LAeq – the equivalent exposure to noise collected by the datalogger placed on the worker's helmet. Note: the two classes of events are codded by 1 for "Other" and by 10 for "Working".

Table 2. Description of the model classes (MC) and selected input datasets by features.

	ENC	ENB	LAeq
MC1	Π	Π	Π
MC2	Π	Π	
MC3	Π		Π
MC4		Π	Π
MC5	Π		
MC6		Π	
MC7			Π

classification accuracy (CA), a metric that characterizes the proportion of correct predictions (Kamilaris and Prenafeta-Boldú 2018). Additionally, other metrics that characterize the classification performance were computed and reported for comparison with other studies (see Supplementary Material). These included the area under the receiver operating characteristic curve (AUC), F1 score (F1), precision (PREC), recall (REC), specificity (SPEC), and binary cross-entropy (LOSS) as examples of metrics used to assess classification performance (Fawcett 2006; Kamilaris and Prenafeta-Boldú 2018). Training and testing were conducted using cross-validation because of the limited data available for task recognition. Cross-validation improves the robustness of classification models and mitigates overfitting. It partitions the dataset into a number of folds, retaining one-fold for validation and using the remaining folds for training. This process was repeated several times and the targeted classification performance metrics were reported as average values.

Data analysis

The initial dataset was characterized in terms of primary descriptive statistics by considering each input signal (ENB, ENC, and LAeq) and event class. A check for normality was conducted for each signal corresponding to a particular event using the D'Agostino–Pearson test. Subsequently, the data from the three signals are plotted in the time domain to illustrate their magnitude variations based on the event class. This analysis helped to better understand the structure of the data, particularly the features relevant for machine learning, such as class imbalance and intra- and interclass similarities (Bulling et al. 2014; Chen et al. 2018). Part of the analysis was supported by Microsoft Excel, which includes a copy of the Real Statistics add-in (Real Statistics using Excel, 2025). Activity recognition using machine learning was performed using the Orange Visual Programming software version 3.37, and the performance metrics were compared using Microsoft Excel. The metrics characterizing the classification performance were recorded in a Microsoft Excel spreadsheet, and used to create bar charts to compare the classification accuracy of the models.

Results

Description of data

The main descriptive statistics for the data are presented in Table 3. For convenience in reporting the signals in the time domain (Figure 3), the magnitude of the LAeq signal was divided by 100 and this adjusted value is shown in Table 3. The signals analyzed had the same distribution across classes of events, with "Working" accounting for approximately 39% of the total. The primary differentiation in the mean magnitude of the acceleration data was observed in the ENC signal, which registered 7.18 g for "Working" events and 1.5 g for "Other" events. Similarly, the LAeq signal

Table 3. Descriptive statistics of the datasets.

Signal	Event	Minimum value	Maximum value	Mean ± Standard deviation value	Median value	Number of observations
		Descriptive statistics				
ENB (g)	Other	0.00	11.29	1.27 ± 0.37	1.16	15272
	Working	1.04	9.15	1.32 ± 0.34	1.22	9759
ENC (g)	Other	1.00	19.69	1.50 ± 1.19	1.23	15272
	Working	1.06	20.21	7.18 ± 3.45	5.73	9759
LAeq/100 (dB(A))	Other	0.30	1.02	0.49 ± 0.11	0.49	15272
	Working	0.52	1.12	0.98 ± 0.09	1.00	9759

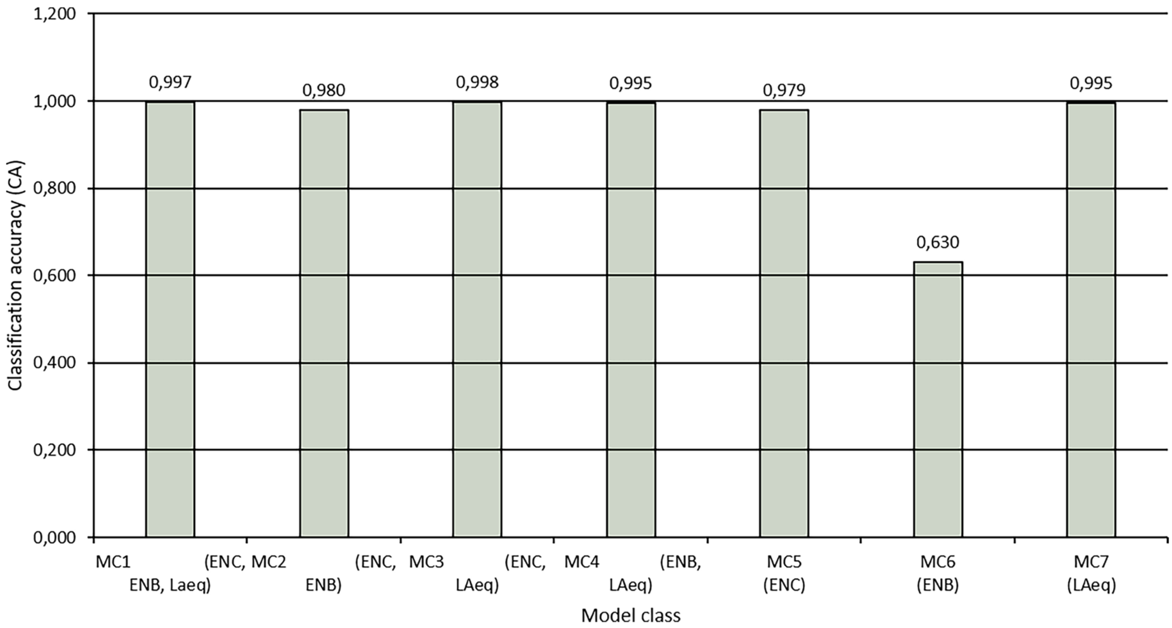

Figure 4. Classification accuracy of the best performing models in each model class.

showed means of 0.49 for "Other" and 0.98 for "Working" events. Although the range of values in the ENB signal was wide, the mean values for the "Other" and "Working" events were relatively close in magnitude.

None of the datasets passed the normality assumption; therefore, median values were reported to characterize the central tendency. There was a slight class imbalance in the data, as indicated by the dominance of the "Other" events. These events included tasks, such as maintenance, movement of the worker between the bunches of stems and to the rest and maintenance areas, and setting up and removing the data loggers.

However, Figure 3 shows the distribution of signal magnitudes in the time domain, along with a description of the event classes observed in the data. "Working" events were distinguishable in the ENC and LAeq signals, which was not typical for the ENB signal. These signals serve as good examples of multimodal data sourced by the same modality but from different locations. There was a wide variation in the magnitude of the ENC signal, which was largely characteristic of the "Working" events. This variability primarily stemmed from the different vibration spectra recorded when the chainsaw was actively used for cross-cutting compared to when it was idle, while the worker moved between locations where cross-cutting was required. Other events, such as moving to the rest area, performing maintenance tasks, and taking breaks, exhibited different patterns in the magnitude of the ENC signal, which, in many cases, was similar to that captured in the ENB signal.

From the data presented in Figure 3, it appears that the ENB and LAeq signals were the most effective at differentiating events in their patterns. For example, the magnitude of LAeq/100 approaching 1 (100 dB(A)) indicates that the chainsaw was operating at near-full capacity. The variation in LAeq/100 for "Working" events was narrower, although it was related to that of ENC in identifying sub-events, such as actual cutting and the movement of the chainsaw in idle mode between the locations of crosscutting (detailed data not shown here). However, owing to the way the data were annotated, it was not possible to accurately subdivide the "Working" event into individual sub-events like moving and crosscutting.

Activity recognition

The primary metric used to determine which model performed best on a particular set of input datasets was the classification accuracy. Figure 4 shows the classification accuracy (CA) of the models that worked optimally with the datasets listed in Table 4. Figure 5 illustrates the pairwise differences in classification accuracy at the class level among the models, and the

Table 4. Class-level classification performance of the best performing models in each model class.

Model class and signals	Event class	Hidden layers	Neurons	Learning rate	CA	Correctly classified	Incorrectly classified
MC1	Other	3	50	0.01	0.997	15242	30
ENC, ENB, LAeq	Working					9723	36
MC2	Other	1	100	0.0001	0.980	14867	405
ENC, ENB,	Working					9658	101
MC3	Other	4	50	0.0001	0.998	15250	22
ENC, LAeq	Working					9719	40
MC4	Other	5	10	0.0001	0.995	15192	80
ENB, LAeq	Working					9722	37
MC5	Other	3	10	0.1	0.979	14835	437
ENC	Working					9664	95
MC6	Other	3	10	0.01	0.630	10471	4801
ENB	Working					5235	4524
MC7	Other	2	50	0.01	0.995	15189	83
LAeq	Working					9726	33

supplementary material includes the full range of the developed models along with their classification performance metrics.

As shown in Figure 4, using both ENC and LAeq signals resulted in the best classification accuracy of 99.8%. Except for model class MC6, which yielded the lowest classification accuracy, all models demonstrated effective event classification (CA = 97.9% – 99.8%), with only minor performance differences ranging from −1.77 to 1.88% (Figure 5). The lower classification performance of the MC6 model was expected because of the attenuation of the vibration signal emitted by the chainsaw as it propagated through the worker's body. This finding is consistent with the data presented in Figure 3, which reveal a rather non-discriminative pattern for the ENB signal.

Table 4 provides full details of the class-level classification performance of the best-performing models, including data on correctly and incorrectly classified instances. The optimal architecture and hyperparameters varied significantly across the models in terms of the number of hidden layers, neurons, and learning rate. The computational time required to train and validate the models depended largely on the architecture (number of hidden layers and neurons) and learning rate in most cases (data not shown). If two or more models within a class returned similar classification accuracies, the model requiring fewer computational resources was retained for analysis. This was the case for the models from classes MC4 and MC5.

Discussion

This study represents the first attempt to determine whether accelerometers and noise dosimeters have the potential to produce suitable data for machine learning analysis aimed at reliably investigating activities in motor-manual work. The activity recognition method described herein serves as a cornerstone for the automation of motor-manual operational studies, where researcher expertise and time spent on data collection do not limit the ability to conduct studies. Although the event classes in this study were simplified to "Working" and "Other," this was a justified decision within the scope of this research. The primary objective was to first establish the feasibility and potential of the ML approach for a robust binary classification of chainsaw operational states, laying the groundwork for more granular analyses in the future.

A critical consideration in studies of this nature is the validation of the proposed methodology. While a direct, concurrent validation against conventional time-study methods (e.g., stopwatch and video analysis) or the use of a fully independent, 'neutral' dataset for the exact same operational period was not undertaken in this initial investigation, this was a deliberate choice reflecting the study's foundational aims. The immediate goal was to demonstrate that the chosen sensor modalities (chainsaw-mounted accelerometer and helmet-mounted dosimeter) could, with appropriate ML algorithms, reliably distinguish between active chainsaw use ("Working") and other states ("Other") based on inherent signal characteristics. Establishing this fundamental capability was deemed a crucial prerequisite before embarking on more resource-intensive studies involving detailed comparative validation, which would be essential for finer-grained activity breakdowns (e.g., differentiating felling, bucking, delimbing, walking). The high classification accuracies achieved in distinguishing these two broad states, particularly when combining ENC and LAeq signals, provide strong evidence for this initial feasibility. The distinct patterns observed—high acceleration and noise during active work versus lower or different patterns during other activities—supported this binary classification approach, with thresholds for "Working" events (e.g., >2g for ENC, >80 dB(A) for LAeq) initially informed by visual interpretation of the signal data from active chainsaw operations.

Encouraging results were obtained regarding the method used, which can be further used to develop time studies that analyze the time distribution of motor-manual work into two main components: effective time and delays. These positive results suggest that further advancements may allow for the detection of different work elements. Moreover, the scalability of the recording method is significant because data collection can be easily expanded to multiple locations within the harvesting compartment where the study participants are working. Our study demonstrates that the recording time can be extended without adding significant extra time to collect, analyze, and interpret data. Consequently, data can be gathered from several locations over the course of a week before collection and analysis using

 E-ISSN 2158-0715

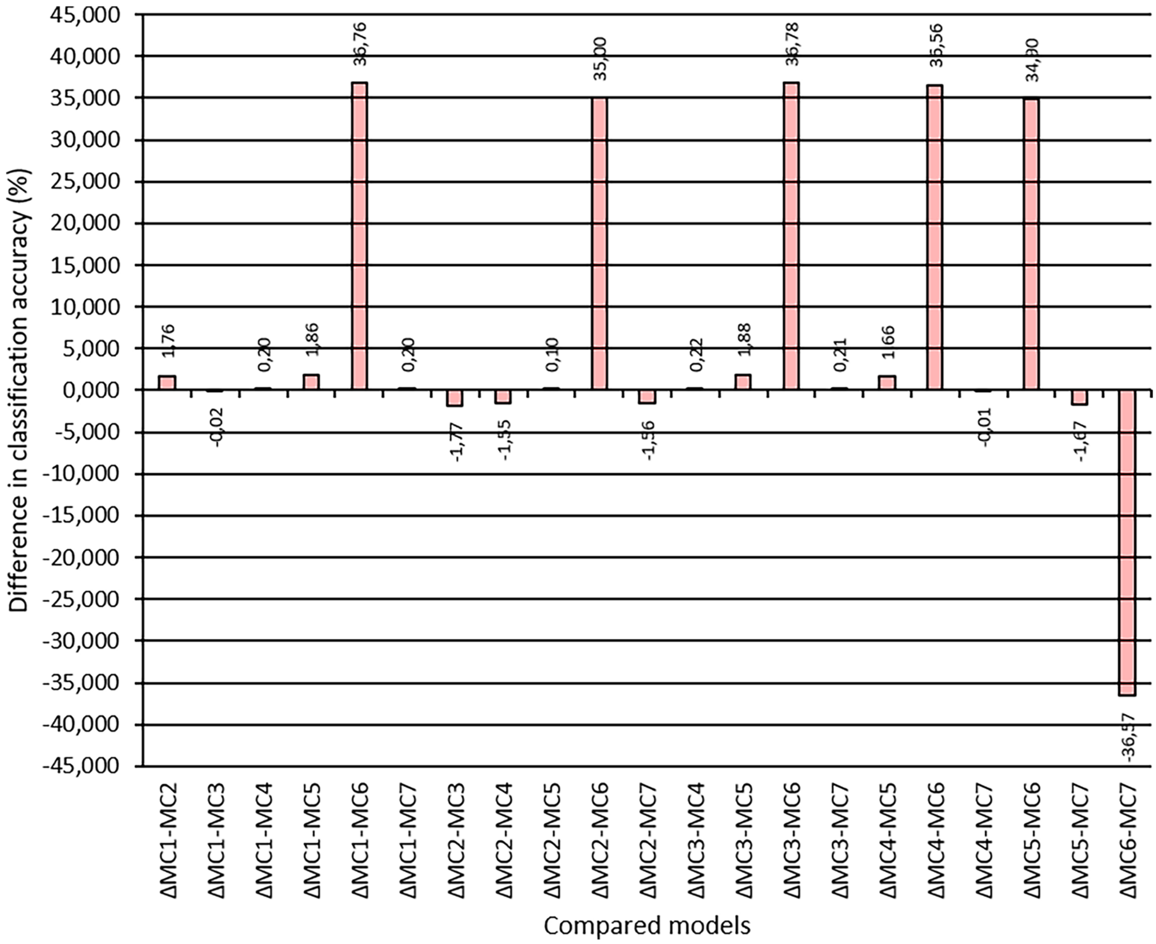

Figure 5. Differences in classification accuracy between each two best performing models of each model class.

machine-learning algorithms. Generally, the placement location's invariance in magnitude is negligible owing to the neural network's ability to standardize input signals.

High classification accuracy was observed across several models that incorporated ENC, LAeq, or both for activity recognition. In contrast, the ENB-based model performed poorly on its own and did not yield accurate results when combined with either the ENC or LAeq signals. Comparisons between the ENB-based model and other model groups revealed important differences, as illustrated in Figure 5, and adding the ENB signal as a third feature did not enhance classification accuracy.

From a feasibility standpoint, placing the accelerometer at the back of the operator poses challenges if the data recording period exceeds one day. However, the placement of the accelerometer on the chainsaw (as shown in Figure 2) can be achieved in a manner that does not interfere with the operator's work. It appears that for optimal performance, the combination of ENC and LAeq signals is suitable for the accurate classification of events, except in situations where multiple chainsaws operate close to one another, which can complicate the interpretation of the noise source data (LAeq). In such scenarios, using the ENC signal alone is the best option because adding an ENB signal does not improve the classification accuracy.

Although the utilization of machine learning for productivity studies is a relatively new research area, few related studies have been published regarding its accuracy in forestry. A similar binary classification study using a brush cutter based on three data modalities (speed, accelerometer, and their combination) achieved an accuracy of 99.9% (Borz 2021). In a study by Borz and Proto (2024), weed control by farm tractors equipped with rotary tillers showed accuracy levels for three event classes ranging from 90.1% to 92.2%. When compared to these previous studies, the recognition accuracy was high, with neural networks effectively predicting events in the motor-manual crosscutting of stems. Based on the similarities between these studies, it can be assumed that the delimbing process achieved approximately the same classification accuracy.

This study used a relatively small dataset for training and validation and, as noted, lacked tests with unseen data from a completely separate trial or direct comparison to conventional methods for the same tasks. However, an increase in the amount of data may not significantly improve classification accuracy for this binary task, as it is approaching 100%. While this study focused on a commonly used type of chainsaw, future research should include several types of petrol- and battery-powered chainsaws. This is important for a more thorough investigation of sound pressure level detection and interpretation, as these measurements are sensitive to the distance between the source and dosimeter and may be sensitive to variations in the magnitude of the LAeq signal level. Implementing these methods for larger sample sizes, and critically, validating them against established methodologies and unseen datasets, would increase the computational power requirements but also significantly bolster confidence in the approach, particularly for more granular activity classifications. Such steps are essential to fully understand the expected level of accuracy in advance, particularly when comparing it with conventional methods because datasets are scaled up to cover a broader scope of study.

Conclusions

The results of our study are promising, indicating highly significant event classification in the time domain for both productive and nonproductive tasks involved in the motor-manual crosscutting of teak stems. In addition, the findings highlight the ideal combinations of data loggers for achieving optimal classification performance and the best placement locations for these devices. This approach has significant implications for both practice and science, as it can enhance the effectiveness of data collection, processing, and analysis in motor-manual time studies. Effectiveness can be improved by addressing key challenges, such as the need for highly qualified experts, logistical restrictions that limit one expert to observing events in a single location, the duration of studies, and the overall effort required to collect, process, and analyze data for time consumption classification. Moreover, there is potential for further improvements to extend our approach, allowing for a deeper exploration of elemental time studies through machine learning, thereby providing an effective means for process improvement.

Declaration of interest statement

Authors declares no conflict of interest.

Funding

National Research Council of Thailand (NRCT) and Kasetsart University: contract number N42A670571; Ministry of Research, Innovation and Digitization, CNCS/CCCDI–UEFISCDI, project number PN-IV-P8-8.1-PRE-HE-ORG-2023-0141, within PNCDI IV.

ORCID

Stelian Alexandru Borz http://orcid.org/0000-0003-4571-7235
Tomi Kaakkurivaara http://orcid.org/0000-0002-5876-1318
Gabriel Osei Forkuo http://orcid.org/0000-0001-8478-8066
Nopparat Kaakkurivaara http://orcid.org/0000-0001-5470-188X

References

Anson CJ. 1953. The development of time study. Work Study. 2(12):19–25. doi: 10.1108/eb060120.

Becker RM, Keefe RF. 2022. A novel smartphone-based activity recognition modeling method for tracked equipment in forest operations. PLOS One. 17(4):e0266568. doi: 10.1371/journal.pone.0266568.

Bergstrand KG. 1991. Planning and analysis of forestry operation studies. Skogsarbeten Bulletin 17, Uppsala, Sweden, 17 p.

Björheden R, Apel K, Shiba M, Thompson MA. 1995. IUFRO Forest Work Study Nomenclature. Test Edition, SLU, Swedish University of Agricultural Sciences, Department of Operational Efficiency, Garpenberg, Sweden, 16 p.

Borz SA. 2021. Development of a modality-invariant multi-layer perceptron to predict operational events in motor-manual willow felling operations. Forests. 12(4):406. doi: 10.3390/f12040406.

Borz SA, Proto AR. 2024. Predicting operational events in mechanized weed control operations by offline multi-modal data and machine learning provides highly accurate classification in time domain. Forests. 15(11):2019. doi: 10.3390/f15112019.

Borz SA, Talagai N, Cheţa M, Chiriloiu D., Gavilanes Montoya, A.V.; Castillo Vizuete, D.D.; Marcu, M.V. 2019. Physical strain, exposure to noise and postural assessment in motor-manual felling of willow short rotation coppice: Results of a preliminary study. Croat J For Eng. 40(2):377–388. doi: 10.5552/crojfe.2019.550.

Bulling A, Blanke U, Schiele B. 2014. A tutorial on human activity recognition using body-worn inertial sensors. ACM Comput Surv. 46(3):1–33. doi: 10.1145/2499621.

Câmpu VR, Ciubotaru A. 2017. Time consumption and productivity in manual tree felling with a chainsaw – A case study of resinous stands from mountainous areas. Silva Fenn. 51(2):1657. doi: 10.14214/sf.1657.

Chen K, Zhang D, Yao L, Guo B, Yu Z, Liu Y. 2021. Deep learning for sensor-based human activity recognition: Overview, challenges and opportunities. ACM Comput Surv. 54(4):1–40.

Demsar J, Curk T, Erjavec A, Gorup C, Hocevar T, Milutinovic M, Mozina M, Polajnar M, Toplak M, Staric A, et al. 2013. Orange: Data mining toolbox in python. J Mach Learn Res. 14:2349–2353.

Di Fulvio F, Acuna M, Ackerman P, Ackerman S, Spinelli R, Abbas D, Kaakkurivaara N, Sánchez-García S, Guerra SPS. 2024. Benchmarking operational conditions, productivity, and costs of harvesting from industrial plantations in different global regions. Int J For Eng. 35(2):225–250. doi: 10.1080/14942119.2023.2296789.

Engler B, Hartmann G, Mederski PS, Bont LG, Picchi G, Alcoverro G, Purfürst T, Schweier J. 2024. Impact of forest operations in four biogeographical regions in Europe: Finding the key drivers for future development. Curr For Rep. 10(5):337–359. doi: 10.1007/s40725-024-00226-4.

Extech Instruments. 2014. 3-axis G-Force datalogger. Prod Datasheet. 723/12 – R1.

Fawcett T. 2006. An introduction to ROC analysis. Pattern Recognit Lett. 27(8):861–874. doi: 10.1016/j.patrec.2005.10.010.

FIO. 2015. Sai Yok 2 plantation management summary. Forest Industry Organization, 15 p. [in Thai].

FIO. 2021. Forest plantation database. Forest Industry Organization [in Thai].

Ghaffariyan MR. 2022. An overview of work productivity evaluation of farm tractors in timber skidding operations. Silva Balcan. 22(3), 21–36. doi: 10.3897/silvabalcanica.23.e82383.

Ghaffariyan MR, Naghdi R, Ghajar I, Nikooy M. 2012. Time prediction models and cost evaluation of cut-to-length (CTL) harvesting method in a mountainous forest. Small-scale Forestry 12(2): 181–192. doi: 10.1007/s11842-012-9204-4.

Grebner DL, Bettinger P, Siry JP, Boston K. 2022. Chapter 12. Forest harvesting systems. In: Grebner DL, Bettinger P, Siry JP, Boston K, editors. Introduction to forestry and natural resources. 2nd ed. Academic Press; p. 295–311.

Harstela P. 1988. Principle of comparative time studies in mechanized forest work. Scandinavian J. For. Res. 3(1-4): 253–257. doi: 10.1080/02827588809382513.

Kaakkurivaara N. 2019. Possibilities of using barcode and RFID technology in Thai timber industry. Maejo Int J Sci Technol. 13(1):29–41.

Kaakkurivaara N, Kaakkurivaara T, Ketkaew C, Sakulya T, Borz SA. 2022. Modelling productivity in extraction operations by simulations based on GNSS documented data: An example from skidding teak wood in Thailand. Trans Univ Brasov Series II: For Wood Ind Agr Food Eng. 15:13–32. doi: 10.31926/but.fwiafe.2022.15.64.2.2.

Kamilaris A, Prenafeta-Boldú FX. 2018. Deep learning in agriculture: A survey. Comput Electron Agric. 147:70–90.
Kanawaty G. 1992. Introduction to work study. International Labour Office, Geneva, 467 p.
Keefe RF, Zimbelman EG, Wempe AM. 2019. Use of smartphone sensors to quantify the productive cycle elements of hand fallers on industrial cable logging operations. Int J For Eng. 30:132–143. doi: 10.1080/14942119.2019.1572489.
Kingma DP, Ba JL. 2015. ADAM: A method for stochastic optimization. In: Proceedings of the 3rd international conference on learning representations. ICLR, 7–9 May 2015.
KU, ITTO, TEAKNET. 2022. Teak in Mekong for a sustainable future. Bangkok, Thailand: Kasetsart University; Yokohama, Japan: International Tropical Timber Organization; and TEAKNET, Kerala, India. 359 p.
Labelle ER, Lemmer KJ. 2019. Selected environmental impacts of forest harvesting operations with varying degree of mechanization. Croat J For Eng. 40(2):239–257. doi: 10.5552/crojfe.2019.537.
Lundbäck M, Häggström C, Nordfjell T. 2021. Worldwide trends in methods for harvesting and extracting industrial roundwood. Int J For Eng. 32(3):202–215. doi: 10.1080/14942119.2021.1906617.
Maas AL, Hannun AY, Ng AY. 2013. Rectifier nonlinearities improve neural network acoustic models. In: Proceedings of the 30th international conference on machine learning. ICML, 16–21 June 2013.
Mousavi R, Nikouy M, Uusitalo J. 2011. Time consumption, productivity, and cost analysis of the motor manual tree felling and processing in the Hyrcanian Forest in Iran. J For Res. 22(4):665–669. doi: 10.1007/s11676-011-0208-2.
Nair V, Hinton GE. 2010. Rectified linear units improve restricted Boltzmann machines. In: Proceedings of the 27th international conference on machine learning. ICML.
Nurminen T, Korpunen H, Uusitalo J. 2006. Time consumption analysis of the mechanized cut-to-length harvesting system. Silva Fenn. 40, 335–363. doi: 10.14214/sf.346.
Olsen ED, Kellogg LL. 1983. Comparison of time study techniques for evaluating logging production. Trans. ASAE 26: 1665–1668.
Paillard B. 2019. NSRT_mk3 and NSRTW_mk3 User's manual. Convergence instruments.
Paillard B. 2021. NSRT_mk3_Dev Data sheet. Convergence instruments.
Poje A, Lipužič B, Bilobrk I, Pandur Z. 2024. Time composition, efficiency, workload, and noise exposure during tree felling and processing with petrol and battery-powered chainsaws in mixed high forest stands. Forests. 15(5):798. doi: 10.3390/f15050798.
Proto AR, Sperandio G, Costa C, Maesano M, Antonucci F, Macrì G, Scarascia MG, Zimbalatti G. A Three-Step Neural Network Artificial Intelligence Modeling Approach for Time, Productivity and Costs Prediction: A Case Study in Italian Forestry. Croat J For Eng. 41(1): 35–47.
Real Statistics Using Excel. [accessed 17 of February 2025] https://real-statistics.com/.
Rianthakool L, Kaakkurivaara N, Diloksumpun P, Arunpraparut W. 2018. Supply chain operations in teak plantation. In: Proceedings of the 6th international forest engineering conference, 16–19 April. Rotorua, New Zealand; (FEC2018).
Spinelli R, Laina-Relańo R, Magagnotti N, Tolosana E. 2013. Determining observer and method effects on the accuracy of elemental time studies in forest operations. Baltic Forestry 19(2): 301–306.
Steinlin H. 1955. Zur Methodik von Feldversuchen im Hauungsbetrieb. Mitt Schweiz Anst Forstl VerWes 31: 249–320.
Uusitalo J. 2010. Introduction to forest operations and technology. JVP forest systems Oy.
Verani S, Sperandio G, Picchio R, Spinelli R, Picchi G. 2008. Field handbook – Poplar harvesting, International Poplar Commission Thematic Papers. Working paper IPC/8, Forest management division. Rome: Food and Agriculture Organization.
Vusić D, Šušnjar M, Marchi E, Spina R, Zečić Ž, Picchio R. 2013. Skidding operations in thinning and shelterwood cut of mixed stands-Work productivity, energy inputs and emissions. Ecol. Eng. 61, 216–223. doi: 10.1016/j.ecoleng.2013.09.052.