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EFFECT OF TRAINING PARAMETERS ON THE ABILITY OF ARTIFICIAL NEURAL NETWORKS TO LEARN: A SIMULATION ON ACCELEROMETER DATA FOR TASK RECOGNITION IN MOTOR-MANUAL FELLING AND PROCESSING

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Abstract: *Producing dynamic, real-time reliable data on the performance of timber harvesting operations has gained lately a lot of momentum due to the necessity to proactively manage the fleets of machines and machine allocation and to better monitor them in different operational environments to be able to understand their capability and performance. Techniques of Artificial Intelligence (AI) have been used recently to get accurate data at a low cost in many fields of science. In particular, the use of Artificial Neural Networks (ANN) has been proved to enhance classification accuracy in many applications. This work deals with the effect of factors that are typically used to set up an ANN on the performance of classification, by a case time-and-motion study implemented for motor-manual tasks under an experimental approach. A protocol was designed to vary the number of neurons in a hidden layer, number of iterations to train the ANN and the number of folds for cross-validation of data during training. The protocol was applied to a set of median-filtered vector-magnitude data collected at a 1Hz sampling rate by a triaxial accelerometer which was documented by a video approach to encompass five types of events. The results were promising, showing that it is possible to accurately classify the data by various performance metrics. The overall recall, for instance, may be as high as 98%. However, the number of iterations and neurons used to train the ANN are factors that significantly affect the classification performance. We conclude that implementing the ANN architectures to learn from filtered acceleration data has a lot of potential in long-term monitoring of motor-manual work and that future studies should be implemented to resemble the variation of operational conditions.*

Key words: *motor-manual work, time and motion, monitoring, automation, Artificial Intelligence, Artificial Neural Network, event, factors, classification performance.*

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1. Introduction

Timber harvesting can be carried out by the operational implementation of a wide set of technical systems [28], which can be operationalized in various conditions [33]. The choice of a harvesting system, however, needs to meet sustainability criteria in several performance areas [17], [26] that aim at increasing the system's overall performance. Moreover, to ensure their sustainable use, such systems need to be adaptable and flexible enough for the operations carried out by their owners [11] and from an optimization point of view they need mathematical approaches to balance their resource allocation and outputs in different key performance areas [40]. Such approaches are often relying on the data provided by time and motion studies [5] which nowadays are seen to group all the ways in which time consumption is measured and analyzed in different work situations, whether the work is performed by people, machines or is automated [15].

Mechanical chainsaws are among the tools often used in timber harvesting operations [4], [28] being widely recognized for their flexibility and adaptation to various operational conditions [6]. As such, they enable cutting functions for a wide set of tree dimensions, starting with small trees [9] and ending with very large trees [18, 19]. Such a variability of conditions in tree felling and processing operations is known to affect the shape of performance functions that could be obtained by modelling approaches [2], [18], [38], while the derived functions themselves need substantial sets of data which is challenging in terms of collection, processing and analysis [8], [29]. In addition, there is often a trade-off between the resolution of data collection and the accuracy of the collected data [37], and taken together, these challenges may prevent data availability for system's analysis and design [39] which is the backbone of timber harvesting optimization.

Progress has been made to automate data collection, processing and analysis for motor-manual operations, which are known to be carried out by tools not equipped with internal production monitoring or management systems. For instance, [10] and [12] have used external acceleration dataloggers to collect event data and artificial arbitrary thresholds to classify it, an approach that was enabled by a clear data separability in the time domain. [27] used the same type of dataloggers to classify the work intensity in manual cultivation work based on readily known thresholds, while [22] have used sensors incorporated into smartphones to monitor and classify the work in motor-manual felling. Still, the performance of different data classification alternatives is under-investigated in forest operations while a promising approach in event separation and classification is that of using the techniques of Artificial Intelligence (AI). Methods of artificial intelligence (AI) based on artificial neural networks (ANN) are already well-known in multivariate computing applications where they are used to predict the output of complex systems and to solve nonlinear multilateral problems [30]. In general, ANN is seen as an alternative to traditional modelling methods and holds a higher generalization, lower susceptibility and the ability to model nonlinear relationships [16]. As such, when there is a mix of many quantitative and qualitative variables, the most effective approaches have been nonlinear [3]. In particular, Artificial Neural Networks (ANN) stand for a group of AI techniques that are used for supervised learning from a data sample followed by testing the learned algorithms on the rest of the data set [16]. The technique itself is a promising tool, including in forest operations where it was found to be able to deal with quite complex datasets [36].

The aim of this study was to test the performance of an ANN in classifying the time consumption on events specific to motor-manual work under a controlled experiment. The focus was on the parameters set to train the ANN to see which combination of neurons set, iterations performed and number of cross-validation folds used does affect the learning and discrimination ability of an ANN setup to learn from data collected by accelerometers.

2. Materials and Methods

2.1. Description of the Study Area and Protocol Used in the Field Experiment

The field phase of the study was carried out at the practical learning station of the Faculty of Silviculture and forest engineering of Brasov (Brasov, Romania, 45˚37 '00.89'' N - 25˚37'20.08'' E, 660 m a.s.l.), in the early spring of 2017. This study location was chosen due to the possibility of controlling to some extent the experimental conditions. Simulations of typical motor-manual events were carried out by the use of a 2.8 kW mechanical chainsaw (Figure 1) manufactured by Husqvarna (Husqvarna 550 XP model). The model is characterized by a displacement of 50.1 cm^3, idling speed of 2800 rpm, maximum power speed of 10,800 rpm, and a weight of 4.9 kg. The experiment was carried out with the help of an experienced operator, who simulated different tasks specific to tree felling and processing (Figure 1). These consisted in events of making the felling cuts, movements along the logs and crosscutting to buck the logs, which were intercalated with the observation of the chainsaw on the soil and in the hand of the operator, both, turned off and in the idle state.

Fig. 1. *Description of the experimental study. Legend: from left to right: operator and the chainsaw used, placement of the datalogger on the chainsaw, making felling cuts and bucking*

The used logs were purchased from a harvesting contractor working near the study area and they could be classified into two groups. The first group that has been used to simulate the felling cuts had an average diameter of 30 cm and consisted of logs of Norway spruce, while the second group had an average diameter of 44 cm and beech logs. The logs of both categories had a mean length of about 4.5 m.

The main data used in this study was collected by a VB 300 datalogger equipped with a triaxial accelerometer sensor produced by Extech® (FLIR Systems, Waltham, Massachusetts, United States). The device was chosen mainly due to its small size (95×28×21 mm, 20 g), technical capabilities (sampling range ±18 g, resolution 0.00625 g, accuracy ±0.5 g, sampling rates between 50 ms and 24 h, internal memory of 4 Mb) and due to the possibility to attach it to the chainsaw in such a way that would not obstruct the tool's handling (Figure 1). As a trade-off between data accuracy and battery life, and given the results reported by other studies using the same datalogger [10], [12] it was set using the dedicated software to collect data at a sampling rate of 1Hz. In parallel, a high-resolution video camera (16 MP) integrated into a smartphone (S5, Samsung) was used to collect the comparative field data by a continuous monitoring of all the tasks simulated by the operator.

2.2. Data Preprocessing

Data recorded by the video camera and the acceleration datalogger were downloaded into a personal computer. Video files were transferred from the internal memory of the phone, using the usual download procedures and were stored in a folder, while the data stored in the internal memory of the datalogger was downloaded through the dedicated software and saved in a Microsoft Excel worksheet (Microsoft Corporation, Redmond, USA, 2010) along with its time labels. Then, the video data was analysed in slow motion and the observed events were separated on their specific time intervals. Each event was coded by a string (Table 1) and the respective codes were used to document the accelerometer's outputs, resulting in a data set (hereafter *E*, containing a number of e = 5 events).

Table 1

Codes used to document the data and their description

Event	Numerical code	Description
Off	0	Time spent with the engine off
IdleH	1	Time spent with the engine in idle state, chainsaw held in hand
IdleS	2	Time spent with the engine in idle state, chainsaw on the ground
Throt	3	Time spent with the engine throttled, chainsaw on the ground
Cut	4	Time spent in cutting, chainsaw held in hand

The data measured by the accelerometer and used to build the initial database was pre-processed in two more steps. First, the vector magnitudes (Equation 1) were taken as primary inputs from the acceleration dataset because they normalize the data collected on the three axes and, therefore, they provide a magnitude measurement which is independent of the datalogger orientation in the three-dimensional space. Accordingly, the magnitude of data, measured in terms of amplitude in the time domain was expected to provide a sufficient variation to enable the separability of events. This would have been true based on the results shown by other studies [10]. However, given the succession of events at short time intervals as well as the transitions in the data amplitude (Figure 2), it was necessary to filter the initial data to provide a better separability.

$$Vm_j = \sqrt{x_j^2 + y_j^2 + z_j^2} \qquad (1)$$

where:

Vm_j is the magnitude of the acceleration vector j;

x_j – response on the x axis for observation j;

y_j – response on the y axis for observation j;

z_j – response on the z axis for observation j.

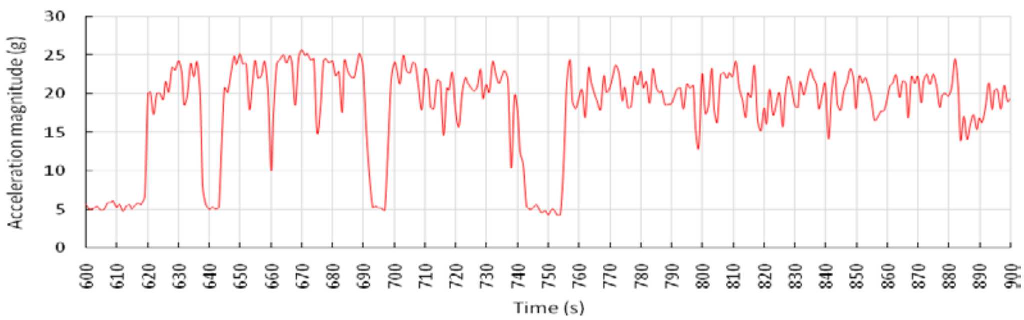

Fig. 2. *Variation of acceleration's magnitude data in the time domain showing intra- and inter-event amplitude*

Filtering of initial data has been done by the use of a median filter (*MF*) and a window size (kernel) of 3 seconds ($MF_{k=3}$). The choice of a median filter was related to its ability to preserve the edges at transitions in the amplitude's range [24], therefore to preserve the correct timing of the observed events. The choice of the kernel size set at k = 3 was also a trade-off between preserving the acceleration signal's shape in the time domain and enhancing the signal-to-noise ratio, with the first one trying to preserve short spikes that characterized real event changes (see, for instance, the acceleration magnitude at time frame 660, Figure 2).

2.3. Configuration of the Artificial Neural Network

Setup of the ANN was carried out using the Orange Visual Programming Software [13] and it assumed the use of the rectified linear unit function (ReLu) as an activation function because it can solve nonlinear problems at high performances [25], [31]. The stochastic gradient-based optimizer (Adam solver) was chosen mainly due to its low training costs [23]; in addition, it was used a L2 penalty regularization term set at 0.0001. Then, all the dataset was used for training purposes by following a protocol (hereafter $P_{f\times i\times n}$) designed to vary the number of folds used for cross-validation (f = 5, 10 and 20, respectively), number of iterations (i = 10, 100 and 1000, respectively) and the number of neurons in the hidden layer (n = 5, 10, 15, 20, 25, 30, 50, 75 and 100, respectively). The approach resulted in the successive training of data using a set of 81 (3 × 3 × 9) combinations which was done for the aggregated average data contained in E (*Overall*) as well asfor each event (class) contained in E (e= *Off*, *IdleH*, *IdleS*, *Throt* and *Cut*, respectively). For each $P_{f \times i \times n}$ and E, a set ($R_{AUC \times PREC \times REC}$) of 10 repetitions were undertaken to train the ANN to be able to stabilize its tests outputs. Each repetition in R considered the computation of the area under curve (*AUC*), precision (*PREC*) and recall (*REC*) as the ANN training performance parameters used in this study. The choice of these performance metrics was based on approaches commonly used in similar studies [20]. Based on the initial data contained in each R both, the mean and standard deviation values were extracted to be able to produce the comparative results of this study. The setup of the ANN training, as described above, was based on the fact that there are many methods described to choose the number of neurons and hidden layers [21], [34], with no consensus so far on the best one to be applied to a given case. Also, the meaning and interpretation of the *AUC*, *PREC* and *REC* performance metrics is described in detail in [14] and in other sources such as [32] and they are not given herein.

2.4. Data Analysis

Data analysis and comparison was done based on simple graphical reporting of the values computed for the classification performance metrics. Such an approach is commonly used to evaluate the performance of ANNs and many studies have opted for this technique when comparing either the performance of AI algorithms and methods [22] or the performance of different treatments by ANN [35]. As such, the classification performance metrics were computed R times for each E, resulting in 1,458 average values that characterized the possible combinations in P. Based on these results, it was assumed that the classification performance metrics (*AUC*, *PREC* and *REC*) can be cumulated for each $P_{f \times i \times n}$ such as the values close to 5, cumulatively computed for the events *Off*, *IdleH*, *IdleS*, *Throt* and *Cut*, would have been characterizing the best outcomes. The *Overall* event was treated separately and reported as such, while for comparison, the rest of events were plotted graphically for each $P_{f \times i \times n}$. Based on the graphical assessment described above, each $P_{f \times I}$ was used to see the effect of n on the classification performance metrics. However, only the findings which met the best values of the classification performance metrics were plotted as results (nine cases), while the rest (18) were only discussed in the text.

3. Results and Discussion

3.1. Performance Metrics

3.1.1. Area Under Curve

As a metric to characterize the performance of a classifier, the area under curve (*AUC*) is often used in evaluating the performance in the area of receiver operating characteristics (ROC) graphs and it holds an important statistical property, because it is equivalent to the probability that a classifier (ANN in this work) will rank a randomly chosen positively instance highly than a randomly chosen negative instance [14]. In general, the higher the *AUC*, the better the performance of a classifier. Figure 3 shows the cumulated *AUC* for each $P_{f \times i \times n}$ taken into study. It is mentioned that values close to 5 were considered to give the best performance of the ANN. Two things may be discussed as seen in Figure 3. The first one refers to the fact that the number of iterations (i) had a high effect on the *AUC* performance. As such, those $P_{f \times i \times n}$ that were fitted using a number of i=1000 of iterations produced, in general, the best results for this classification performance metric.

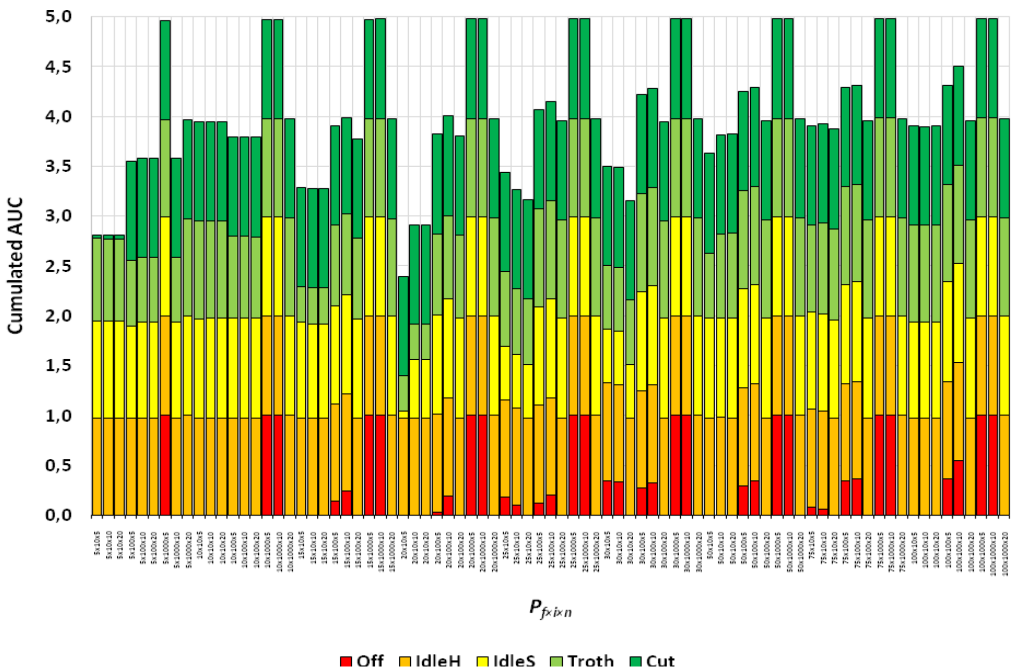

Fig. 3. *Cumulated AUC for the protocol used to train the ANN*

Nevertheless, some cases which had used an i=1000 have failed to provide good performances (Figure 3), a fact that has been associated with the number of folds used for cross-validation (f). As a fact, the data set from which the ANN was trained covered a length of 993 seconds, therefore it seems that some events were too short to enhance the training of the ANN or they were particularly distributed across the folds in such a way that prevented this attempt. In general, this was specific to f=10 and f=20. However, as the number of neurons in the hidden layer (n) increased, only f=20 has preserved this low performance. Therefore, one can assume that for better recognition performance the number of folds should be managed based on the quantity and quality of the input data and, as the number of neurons increases this can balance to some extent also the number of folds used. For i=1000 and f<20, it seems that the minimum number of neurons needed to produce good results were, in general, n≥15. For lower values used to setup the ANN, the *Off* event was either unrecognized or poorly recognized (Figure 3, left side). For such situations, the *AUC* of the *Overall* event was found to have the minimum value of 0.625 ($P_{5\times10\times5}$), while the maximum value was of 0.998 (several *P*s).

Figures 4 to 6 show the effect of n on the *AUC* for i=1000, under the attempt to present the best results of the *AUC* classification performance metric. They also consider the number of folds used for cross-validation.

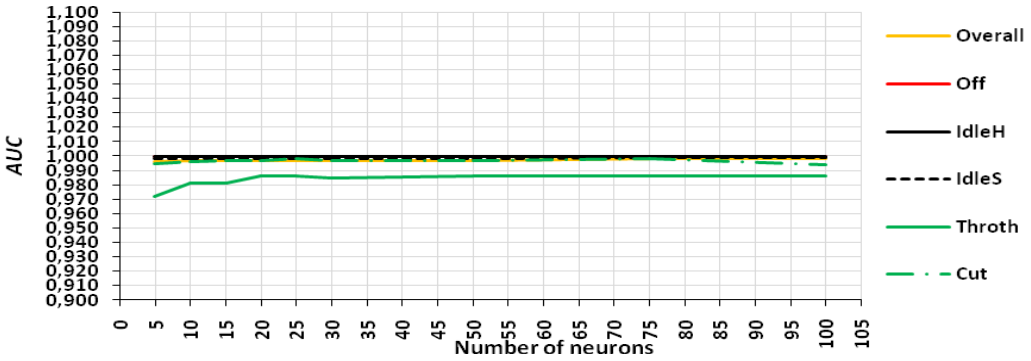

Fig. 4. *AUC for* $P_{5\times1000\times n}$

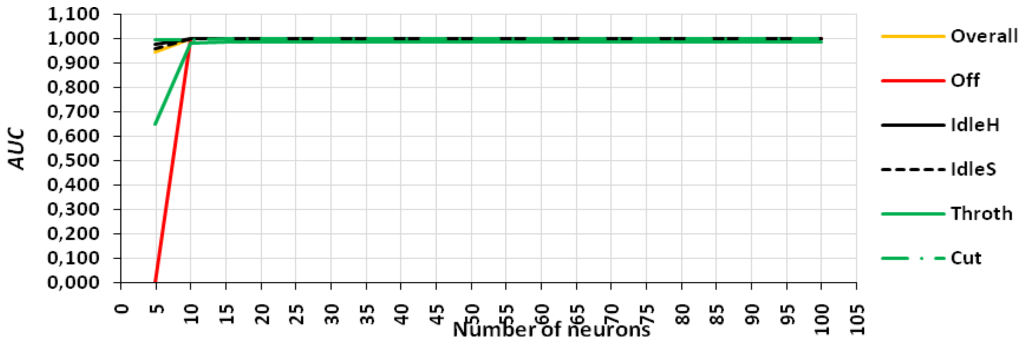

Fig. 5. *AUC for* $P_{10\times1000\times n}$

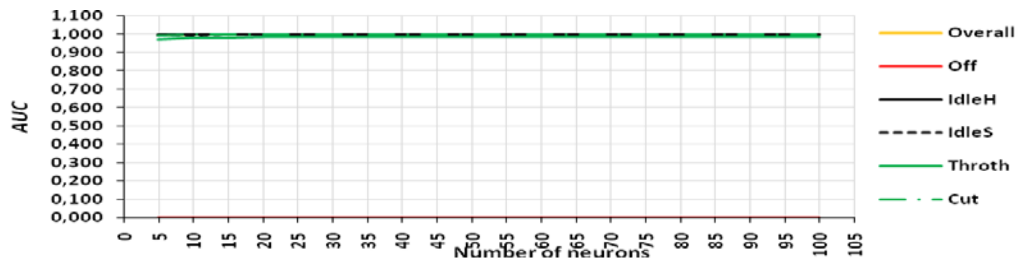

Fig. 6. *AUC for* $P_{20\times1000\times n}$

As shown, increasing the number of neurons and decreasing the number of folds used for cross-validation can contribute to the enhancement of the *AUC*. As a fact, some of the best results could be associated to f=5 and to a number of neurons n>30 where the *AUC* of the *Throt* event began to stabilize itself (Figure 4). In this case, it seems that one could also use a lower number of neurons and get a good classification performance but still, if f=10, the data shows that for n≥10, the performance in terms of *AUC* was more stable for all the events taken into study (Figure 5). In comparison, for f=20, *AUC* for the *Off* event was rated at 0 (Figure 6).

3.1.2. Precision of Classification

As a classification performance metric, precision (*PREC*) or the positive predicted value stands for the fraction of the instances identified by a classifier as true positives within the total number of positively classified instances [14]. For multi-class problems, such as that described herein, the precision is calculated by averaging among the classes [20], [32]. By taking into consideration this metric, Figure 7 shows the results at $P_{f \times i \times n}$ level for the same events as described for the *AUC* metric. In this case, however, it was quite clear that the number of iterations had the greatest effects, with i<1000, in general, giving poorer results and missing some classes.

Also, it can be observed (Figure 7, right side), that in those cases in which i was set to 1000, the number of folds (f) had also a low effect. In general, and as the number of neurons used to train the ANN increased, f=5 provided the best performance in terms of precision. For i=100, *Throt* and *Off* events were missed (*PREC*=0) irrespective of the number of neurons, with the worst cases being those specific less than 10 neurons. From this point of view, n<10 provided poor results also in the case of i=1000. Therefore, for the analyzed case, good precisions could be attained by setting the number of neurons to more than 10, holding the cross-validation folds to the minimum (see the explanations provided to *AUC*) and using at least 1000 iterations. By considering the number of iterations, some argued that this should be set as high as possible providing that it is computationally feasible and some have used as much as 1,000,000 iterations to train their ANNs [36]. However, as the value of the i parameter increases, the computational cost will increase also, a fact that has been found during the simulations taken in this study (results not shown herein). While in this study the background data was limited, under the assumption that datasets will be produced to cover longer time periods, the computational cost could be less manageable.

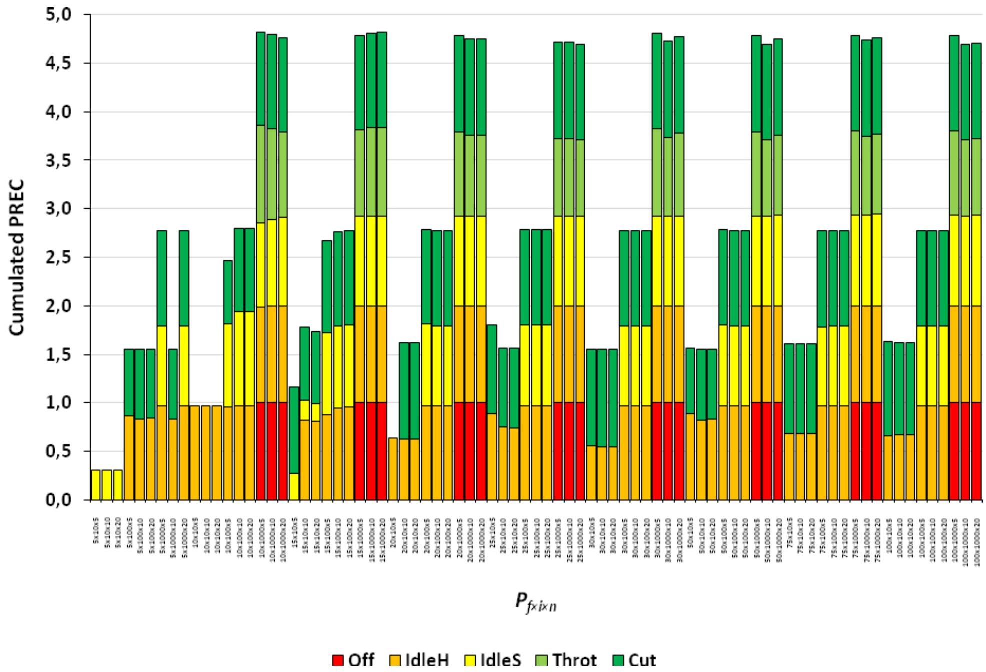

Fig. 7. *Cumulated PREC for the protocol used to train the ANN*

Figures 8 to 10 show the best results of the precision as a classification performance metric. In general, the poorest results were those associated to the *Throt* event, which were similar to the situation shown for the *AUC*. Concerning the number of neurons used, it seems that $n \geq 30$ provided the best results in the case of *PREC*, a fact that was somehow similar to the results shown for *AUC*, and which showed a better stability only for f set at 5.

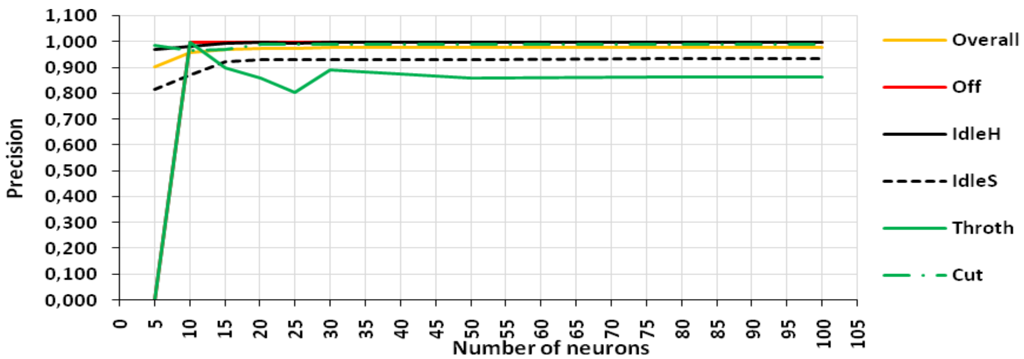

Fig. 8. *PREC for $P_{5 \times 1000 \times n}$*

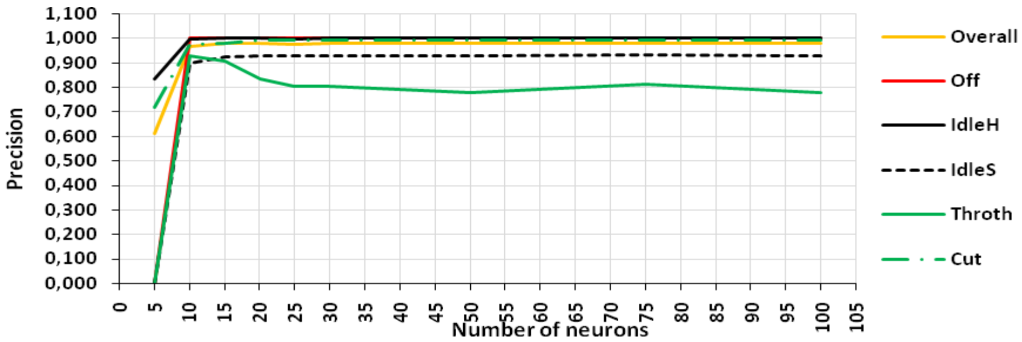

Fig. 9. *PREC for $P_{10\times1000\times n}$*

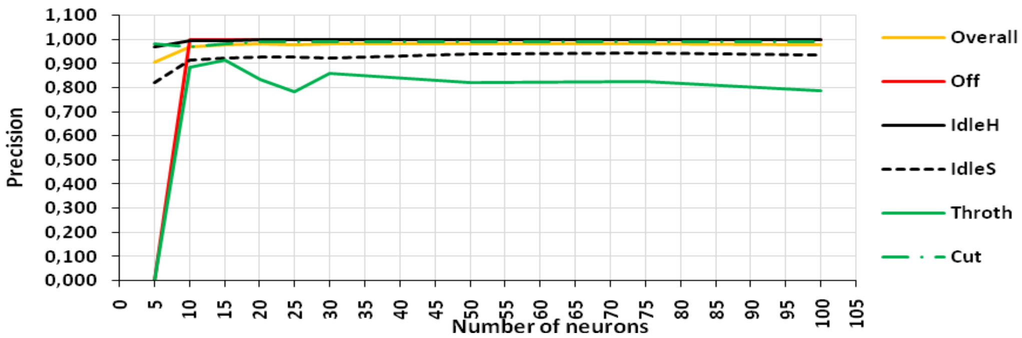

Fig. 10. *PREC for $P_{20\times1000\times n}$*

3.1.3. Classification Recall

Assuming a good performance of the *AUC*, which should not be random, probably the most important classification performance metric for studies and applications such those presented herein is the recall metric (*REC*). This is because it shows the fraction of those instances classified as true positives (those instances that are positive and were classified as such) from the total number of positive instances [14], even tough some are misclassified as negatives [20]. In short, it shows how many of the data within a true class has been correctly identified by a classifier to belong to that class. From this point of view, Figure 11 is showing the cumulated situation by considering the protocol taken into study. Similar to *AUC* and *PREC*, those *P*s that were characterized in general by *i*=1000, and *n*≥30 provided the best results. For *n*≥25 and *i*=100, *Off* and *Thort* events were missed and for *n*=5 the results were the poorest. The best overall *REC* was that of $P_{20\times1000\times75}$ while the worst was, in general, that of $P_{f\times10\times5}$. Similar to *AUC* and *PREC*, a number of more than 30 neurons provided the best *REC* results for each event taken into study, as shown in Figures 12-14. However, *Throt* event provided the worst results among the events taken into study, a fact that was similar to those shown for *PREC* metric; also, the data on this metric has shown stability for all the events excepting *Throt*, in the range of approximately 30 to 100 neurons. Therefore, and by considering the importance of this metric from the perspective of operational monitoring and provision of accurate data to complement the traditional time studies and to automate to a greater extent this activity, one should count on at least 30 neurons in the hidden layer as well as on at least 1000 iterations to train the ANN. Given the better stability of the *Thort* event in the case of f=5, one should consider also less folds for cross-validation. Nevertheless, this is dependent on the amount of data used in training and on its pattern in the time domain.

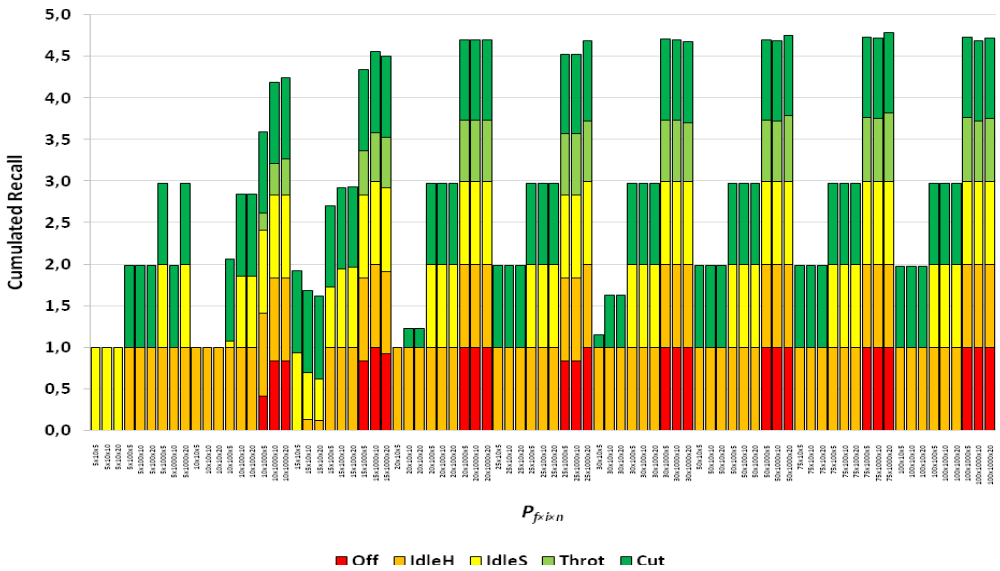

Fig. 11. *Cumulated REC for the protocol used to train the ANN*

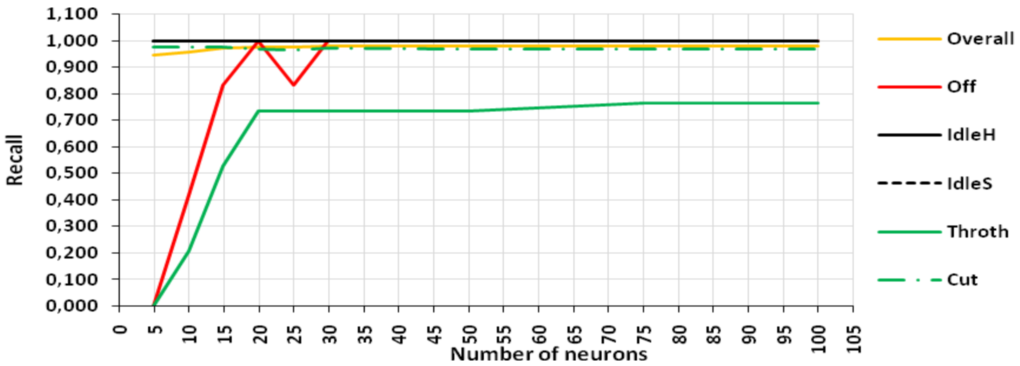

Fig. 12. *REC for $P_{5 \times 1000 \times n}$*

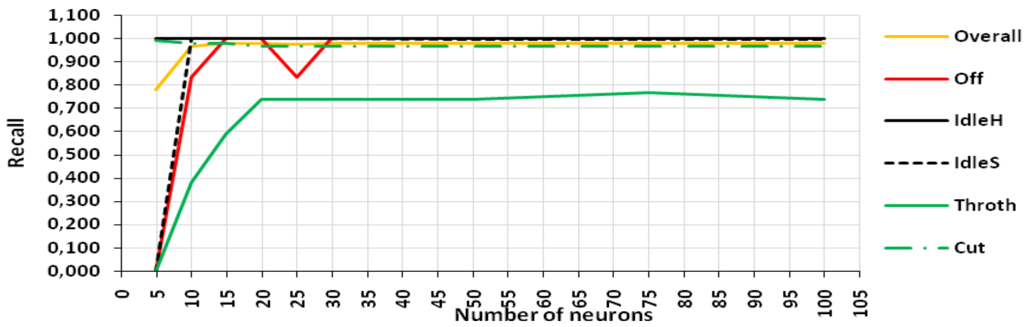

Fig. 13. *REC for* $P_{10 \times 1000 \times n}$

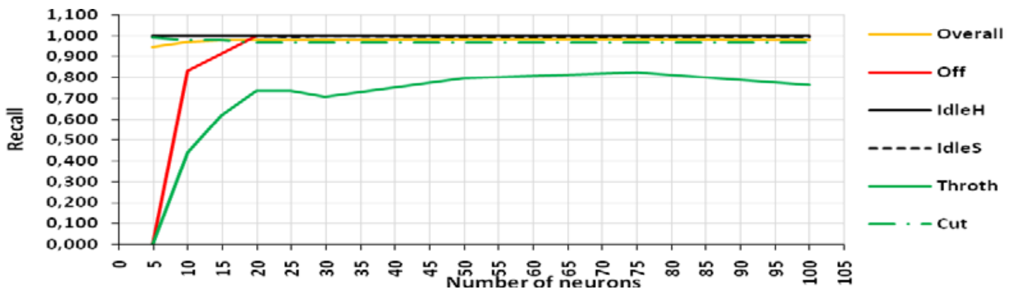

Fig. 14. *REC* for $P_{20 \times 1000 \times n}$

3.2. Overall Performance and Implications for Motor-Manual Work Monitoring

While all the metrics used in this study are important for the evaluation of classification performance, and since they stand just for a small part of the commonly used metrics (see for instance [20]), it is important for applications such as that of monitoring and getting time consumption data in motor-manual work to restrict the available set to those that bring the most important contribution. Thus, in time and motion studies the researcher tries to best describe the events and to quantify, as accurate as possible, the time consumption on distinct events [7], a fact that enables other data analysis approaches such as modelling by regression or data comparison [1]. From this point of view, the most important thing is to have a good signal as an input as well as a classifier that correctly puts the right data in the right category. Obviously, this is described by the *REC* metric of the $MF_{k=3}$ and, as such, this will be discussed further here.

The best cumulated *REC* was found in the case of $P_{20 \times 1000 \times 75}$ that corresponded to the maximum *REC* of *Overall*, *Off* and *Thort* but not to the rest of events in *E*, even though all the events were preserved and had high values for *REC*. However, the most important events for the practice are those of cutting, because they provide the conversion of tree shape and they are targeted by many studies. It is a fact also, that within the time structure of motor-manual work, other movements and tasks will account for greater time shares compared to the effective cutting.

Nevertheless, cutting itself and idle working of the engine are those events that affect the fuel intake [18], therefore, they are those for which an accurate accounting is crucial. From this point of view, the *Cut* event had the best *REC* value for $P_{10\times10\times25}$ and $P_{20\times10\times25}$, respectively. However, these situations missed largely other events.

In the analyzed *P*, the *REC* value of the *Overall* event, varied between 0.173 and 0.981 meaning that the ANN classifier had the capability to correctly classify in between 17.3 and 98.1% of the cases. These figures depended largely on the number of neurons used in the hidden layer and on the number of iterations used to train the ANN, while the number of folds used in the cross-validation process was important also. Therefore, the overall recognition was very good for n>30 and i=1000, and it is likely that by exceeding the i=1000 it will improve further. Since the best value of *REC* was of 98.1%, worth mentioning that classification performance at similar figures is rated as being high [20] or as being acceptable for 80% [22] for the classification accuracy (*CA*) metric. However, *CA* differs from *REC* [20]. Even if not explicitly given and described herein, the maximum values of *CA* were of 0.981, 1.000, 0.999, 0.989, 0.988 and 0.988 for the *Overall*, *Off*, *IdleH*, *IdleS*, *Throt* and *Cut*, respectively. However, by considering the classifier's performance by the *REC* metric which was found to be of 98.1%, one may assume that, overall, from one hour of study one will misclassify the data coming from approximately one minute of observation. Whether this is significant or not, should be checked by comparison with traditional methods. Nevertheless, it is less likely for a field researcher to be as accurate as not missing more than 8 minutes per day of study, provided that he or she will carry on the study on long term and will be affected by fatigue [37].

Taking into account the classification performance, this study has shown that it was less in the case of *Throt* event, irrespective of the chosen metric to characterize it. This is not erratic, since in this event the chainsaw was operated at high and variable speed but not when working the wood, therefore it produced acceleration data that was variable in the amplitude and in the time domain. It would have been interesting to see if finer sampling rates (more than 1Hz) would have been produced more accurate data, but at the end of the day, one should account for the trade-off between accuracy and data storage capabilities. To what extent a signal filtering approach using higher widow sizes would have been improved the results worth exploring. However, as the window size increases the data set to be used will gradually lose observations, a fact that limited the use of this approach in this study.

Last, but not least, this study's approach was that of trial-and-error, therefore the results stand within the approach and data used in it. It is to be checked if an increment in the number of iterations or neurons beyond the figures provided will improve the accuracy. However, this will also lead to an increased computational cost.

4. Conclusions

We conclude that implementing an ANN architecture to learn from filtered acceleration data has a lot of potential in long-term monitoring of motor-manual work, and this study provides empirical data on the factors that should be fine-tuned in such attempts. This study was experimental and does not resemble the typical way of doing this kind of work but it includes typical events that could occur in such work. It is likely that its replication in the real world, which provides much longer time windows of given events as well as less events, will produce better results, a fact that needs to be checked in the future. Nevertheless, one can account on a good data classification that could support the effort of reaching the requirements of Big Data Analytics;this could be achievable by designing data collection devices that could embed ANNs and by integrating them into the chainsaws, as a first step in the automation of field data collection.

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