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Development and evaluation of a weighing system for forestry cranes based on artificial neural networks

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In both log and chip logistics, important reference data for logistic purposes are often lacking, as they are usually completed with insufficiently accurate estimates. In order to obtain higher quality information on the moving timber quantities, optional crane scales can be mounted between the telescope and the grapple of the forwarder. However, this has a negative effect on the crane kinematics and manoeuvrability while at the same time machine productivity is reduced due to an interruption in the loading process necessary for measurement.

In this paper, a data-based method is presented which allows dynamic weighing in a continuous loading process for modern forestry cranes without the need to install an additional hardware component on the machine. This allows a cost-effective and comprehensive application. In the course of this method, a loading cycle is automatically detected, and the loaded mass is estimated by means of an artificial neural network (ANN). Signals from sensors installed as standard on modern forwarders serve as input variables. The Long Short-Term Memory (LSTM) architecture for the neural network has proven itself for handling these time-based sensor data. Based on LSTM cells, an appropriate network was designed, trained and subsequently optimized. The test shows an average full-scale error of 1.5% per 1,000 kg for a single loading cycle. For a fully loaded forwarder, this results in a total mass error of less than 1.2%.

Keywords
Neural networks, crane scales, forestry machines, forwarder

Different timber harvesting methods are used for the provision of raw wood, depending on the initial situation and the assortment. One case is the fully mechanized timber harvest, which is mainly used in smaller diameter classes and for the provision of short and industrial timber assortments (BERG et al. 2012). Here, a harvester cuts the trees and places them on the skid track. Then the forwarder moves the processed assortments from the logging area to the forest road for piling (HEINIMANN 1994, CACOT et al. 2006, NURMINEN et al. 2006, ERLER et al. 2010, KUPTZ et al. 2015, MANNER et al. 2016).

This machine combination offers the potential to obtain comprehensive assortment information on the current cut via the harvester data. The automatic recording of the assortment information and the additional acquisition of the spatial reference makes it possible to subsequently assign it to the forwarder (MANNER et al. 2016). This means that the information of the timber moved is available for productivity recording of the work step or for further planning purposes.

Assortments which have not been processed by the harvester and thus recorded must be additionally measured to quantify them. The proportion of unrecorded quantities becomes particularly

clear when looking at wood chip assortments for green wood chips. In addition to processed products such as energy roundwood, these assortments mainly include crown parts or entire trees with high proportions of small compartments (Deutscher Forstwirtschaftsrat e.V. und Deutscher Holzwirtschaftsrat e.V. 2015). Methods for recording the quantities of these assortments, which are inadequately or not at all documented by the harvester, are currently mostly based on estimation methods, but are usually insufficiently accurate, which in practice leads to problems in wood chip logistics (Kuptz et al. 2015).

The use of crane scales, which has already been considered for the provision of logs, therefore offers a solution for a mass determination as a dispositive measure (Bodelschwingh 2006). With the help of these scales, the weight of wood chips can also be recorded, and their volume can be deduced with high accuracy. Information about the size of the formed chip piles extends the degree of professionalization in chip logistics, whereby the increased performance of modern chippers can be achieved in the best possible way even under unfavourable storage and space situations (Kuptz et al. 2015). In addition, with sufficient accuracy of the scale, overloading of the wood chip transporting trucks could be avoided. Increasing machine and road damage, as well as potential legal consequences for driver and owner, are typical effects of overloading.

State of the art

At present, crane scales are commercially available for this area of application in wood logistics. These can be optionally mounted between the telescope and the grapple and are based on the concept of mechanical or hydraulic force transducers (Komatsu 2019, Ponsse 2010). However, the crane kinematics change negatively since the increased distance between the centre of gravity of the grapple and the telescope can lead to higher oscillating movements of the grapple.

With a crane scale, the grapple load can be measured in a dynamic loading process with a uniform, calm operation mode, whereby the accuracy is significantly reduced compared to a static measurement (Korten and Kaul 2012, Wide 2012). In conjunction with interrupted loading processes for accurate measurements, this leads to a significantly reduced overall productivity.

Several research projects investigated a payload determination in wheel loaders or front loaders, whereby the vehicles were mapped as mechanical multi-body models. Based on these multi-body models, under the modelling of friction forces, the mass in the bucket was determined (Bennett et al. 2014, Walawalkar and Heep 2016, Yung 2017, Walawalkar et al. 2018).

However, the quality of the weight determination highly depends on the level of detail of the models. Due to assumptions for model parameters such as component deformations, friction or leakages, which are based on empirical findings, the challenge is to map the non-linear system behaviour of the hydraulic system correctly. A model that reflects reality with sufficient accuracy can only be determined with extremely high effort (Frederic 2015, Fodor 2017).

Neural networks were already developed for a wheel loader to determine the bucket content (SAVIA and KOIVO 2002). Due to a lower number of degrees of freedom, reduced complexity in the hydraulic system, and the variable centre of mass, the network architectures are not transferable to forestry cranes. The high complexity of a forestry crane with a large number of degrees of freedom, all of which are subject to friction, makes the creation of mechanical replacement systems for weight determination unreasonable.

Objectives of the developed method for a data-based crane scale

With the data-based method presented in the following, a dynamic weighing process including subsequent data processing is realized in order to close the information gap in the logistics process without reducing the machine's productivity. The crane kinematics are not changed by additional components. Measurement and data post-processing are completely autonomous, so that neither an interaction between the forestry machine operator and the measurement system is necessary nor the loading behaviour has to be adapted (GEIGER et al. 2018).

The data-based approach eliminates the need for time-consuming modelling of crane kinematics, taking cylinder and joint friction into account. With the abstracted approach of mapping the crane by means of an artificial neural network, unknown parameters in the hydraulic system, such as specific leakages or friction, do not have to be modelled explicitly. For the development and verification of the weighing system, using logs in this study creates reproducible conditions in comparison to an investigation of residual forest wood.

Basic physical principle and sensory acquisition of the input variables

The weight force caused by the mass in the grapple F_G (Figure 1) correlates idealized with the force applied by the lifting cylinder (IBC) due to the equilibrium of moments around the axis of rotation of the inner boom in the following idealized way (Equation 1):

$$F_{IBC} \cdot l_{IBC} = F_G \cdot (l_G + l_{IBC}) \qquad \text{(Eq. 1)}$$

with

l_{IBC} = Distance pivot point to IBC
l_G　 = Distance IBC to grapple

Here the mass m of the grapple content can be determined analytically, based on the pressure p_{IBC} in the inner boom cylinder, as it is only connected on the piston side (Equation 2):

$$m = \frac{p_{IBC} \cdot A_{IBC}}{g} \cdot \frac{l_{IBC}}{l_G + l_{IBC}} \qquad \text{(Eq. 2)}$$

g　 = acceleration of gravity
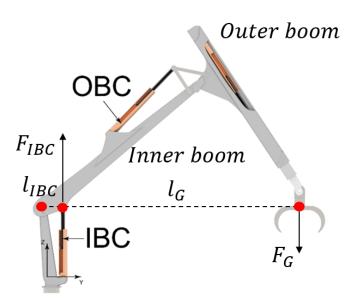A_{IBC} = piston area inner boom cylinder

Figure 1: Force application position at a forestry crane

The equations above describe an idealized analytical way of determining weight by measuring p_{IBC} as well as the grapple distance l_G. The method developed is based on this idea. Due to the high number of joints and cylinders, an analytical calculation of the grapple content is not possible because of the non-linearities. Therefore, with the help of an ANN, in which the real influencing factors are taken into account, a substitute model for weight determination is developed, which maps these non-linear correlations.

The primary input variables for the neural network are the pressure in the inner boom cylinder p_{IBC}, the kinematic conditions resulting in the variable distance l_G as well as the operator inputs. The pressure is given into the network both directly, as a time series, and filtered. In addition, the frequency spectrum of the IBC pressure resulting from a fast Fourier transform (FFT) is used as an extra input. Furthermore, in the hybrid hydraulic system (GEIGER and GEIMER 2017, HOHENLOHE 2014) of the demonstrator machine, accumulator pressure, pump pressure and valve pressures are used as input signals. CAN-capable pressure sensors record all pressures with a frequency of 50 Hz. The oil temperature is also included in the ANN.

The distance of the grapple l_G is calculated using kinematic relationships from the angles between the crane column-inner boom, inner boom-outer boom, slewing gear and the length of the telescope. The sensors required for this are standardly installed in the crane and can be read via the CAN bus. Based on this, the grapple speed and acceleration are calculated and entered into the net. The crane is controlled by two CAN bus-capable joysticks. These signals are thus located on the CAN bus as standard and can be recorded directly, which means that the operator's target specifications are recorded.

Phases in the loading process of a forestry crane

Based on an evaluation of the measurements in real forest use, a loading cycle is divided into 4 loading phases (Geiger and Geimer 2017):

I.   Extending movement of the grapple from the stanchion basket to the log
II.   Grasping and lifting the log
III. Retracting movement of the grapple with log to the middle of the stanchion basket
IV.   Positioning and depositing of the log in the stanchion basket

Figure 2 shows the individual phases in accordance with Morales et al. (2015). It makes sense to measure the weight of the grapple contents in phases II and III, as the log is usually moved over the stanchion basket without bumping surrounding trees or stanchions. Phase IV cannot be included because the log rests on already loaded logs during positioning in the stanchion basket.
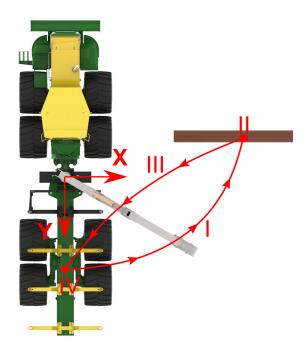

Figure 2: Loading phases (Geiger and Geimer 2017)

Measurement data acquisition on the application vehicle

The foundations of the data-based method are training data, which represent the real loading process in the forest. These enable the neural network to precisely determine the mass in the grapple from future, unknown data. In order to be able to use the real log mass as the target size in the training phase, the logs of the spruce trees were weighed individually beforehand and marked with a consecutive number (Figure 3). The scale used to determine the real mass had a measurement inaccuracy of 0.5 kg. The masses of the individual logs were in the range of 100–600 kg, the centre diameters ranged from 20–50 cm with a log length of 5.2 m. Due to the simultaneous loading of several logs, the measuring range extended up to 1,000 kg.

Figure 3: Collecting training data (© C. Geiger)

The operator of the machine was instructed to load the logs randomly. Parallel to loading, the respective log number was noted so that it could then be converted to the loading mass. The forestry machine operator was asked to load several logs simultaneously in order to reflect the process as accurately as possible in the forest. A total of 500 loading cycles were recorded using this procedure, with 25 loading cycles corresponding to a completely filled stanchion basket of 10 solid cubic metres loading volume and 11 tonnes payload.

Network architecture for the determination of the log mass

An artificial neural network maps an input vector to an output vector with the help of the hidden layer. In the training phase, the individual parameters of the ANN are adjusted to convert the input variables into the desired output. The learning algorithm of the ANN can individually adjust the weighted connections between the input neurons, the hidden layer neurons and the output neurons. This consists of a concatenation of backpropagation and the stochastic gradient method (GOODFELLOW et al. 2016).

The individual loading processes are available as time series data and represent the same process, but they show local differences and also differ in total duration. Each loading cycle is therefore unique in its signal sequence. In a classical ANN, the length of the input vector is freely selectable but cannot be changed.

Recurrent neural networks (RNN) have proven to be useful for processing sequential information. The far-reaching advantage of an RNN lies in the cyclic connections of the cells in the hidden layer. This allows the network to determine an output vector for the current time step based on the current input vector and including all previous time steps. The data from the past have a direct influence on weight determination in the present. Thus, an RNN can learn complicated, locally shifted relationships in data and generate an abstract understanding of the system (GRAVES 2012, GOODFELLOW et al. 2016). A special variant of the RNN is the Long Short-Term Memory (LSTM) architecture (HOCHREITER and SCHMIDHUBER 1997). This enables the network to amplify the memory effect over a longer period and to react ideally precisely to previous and current input variables. During the training phase, the net-

work learns which input signals it must remember and which have no influence on the target value or are only relevant in the current state (GRAVES 2012).

Figure 4 illustrates the structure of the network for determining the weight with a forestry crane based on the LSTM architecture. The input variables for the respective time step (orange) are forwarded to the LSTM cells (green). There, the outputs of the LSTM cells of the previous time step are added (red), which represent the cyclic connections of the network. At the same time, each individual LSTM cell adopts the inner state from the previous time step (grey). The cell compares these three input signals with each other (HOCHREITER and SCHMIDHUBER 1997) and then produces a signal to the hidden neuron layer (blue). This maps the outputs of the hidden layer to the output neuron (yellow) of the network for the respective time step. These steps are repeated within the data series until its end.
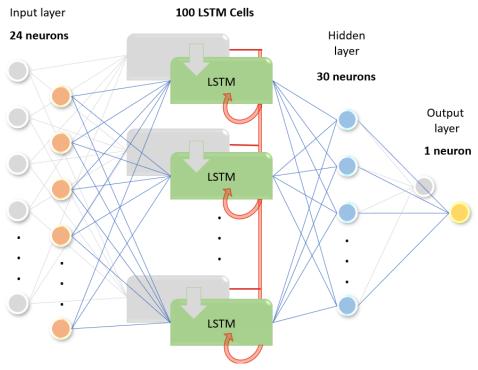

Figure 4: Used network structure including LSTM cells

Hyperparameters are parameters whose values must be determined before the start of training. They influence both the training process itself as well as the final solution quality. Apart from the hyperparameters for the data preparation of the input variables, such as filter width, the combination of possible signals or the temporal resolution of signals, there are other hyperparameters which influence the network structure, the initialization or the training phase. As a result, the network structure shown in Figure 4 turned out to be ideal, using 24 input neurons, 100 LSTM cells, 30 neurons in the hidden layer and 1 neuron as output.

Within the stochastic gradient method, the network weights are varied by averaging the gradient for randomly selected subsets of the training data (mini batches). This abrupt change of the gradient allows the algorithm to leave saddle points and converge to local minima of higher quality. The step size within the solution space along the gradient is called learning rate. The aim of the design phase is to optimally determine the hyperparameters such as learning rate or size of parallel batches. This generates a solution in which the error lies within the target range (GE et al. 2015, MASTERS and LUSCHI 2018).

In order to reduce the error on test data, a so-called dropout artificially limits the capacity of the network in the training phase (Hinton et al. 2012). Using a value of 0.5 in the network for this purpose results in half of the LSTM outputs being randomly omitted at each time step during training, thus set to zero. The purpose of this measure is to prevent co-adaptions between the individual neurons. The individual cells are therefore forced to independently obtain information from the input signals (Hinton et al. 2012).

The noted log mass serves as target value for the respective loading cycle, but the RNN requires a target value for each time step. In order to generate this vector, it is assumed that the grapple load acts with its full weight on the crane as soon as it is in the air. In the gripping phase (phase II), the mass vector, black-dashed in Figure 5, is assumed to increase linearly. Figure 5 shows the starting point of the mass vector at approximately 7 seconds and illustrates the further course based on the previous assumptions. The slope is explicitly determined by the gradient of the grapple height after gripping the log. If the grapple height exceeds a threshold value, it is assumed that the load is completely in the air. The target mass vector is linearly interpolated between the start point and the endpoint.
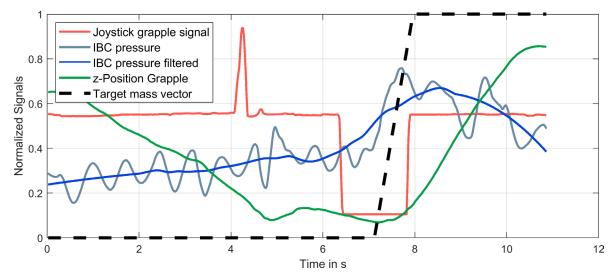

Figure 5: Mass vector including linear increase

An analysis of the input weights of the LSTM cells makes it possible to estimate the behaviour of the network. According to the physical basics, it has been shown that especially the IBC pressure, unfiltered and filtered by means of a Savitzky-Golay filter, as well as the l_G distance are relevant input variables for the network. Other significant input variables are the z-position of the grapple, the joystick signal of the inner boom cylinder and the angle between the inner boom and the crane column.

Automated weighing process in the assortment process

In order to achieve acceptance and applicability of the described method for weighing the grapple content, this method must be user-friendly. Due to the large amount of data generated during a working day, it is therefore essential to automate the individual weight estimation process. Figure 6 illustrates the sequence of the automated weighing process, in which the loaded masses of a complete working day are determined in a post-processing procedure.
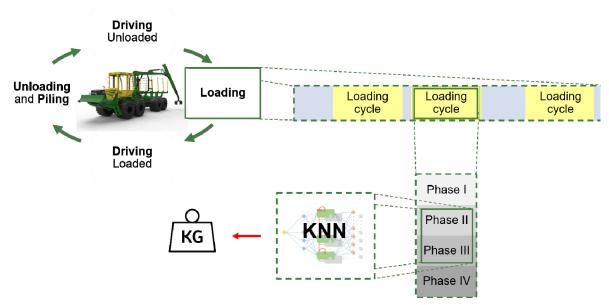
Figure 6: Flow chart of the automated weighing process for a forwarder

The forwarder is located several times in the skid track during a whole working day, which is why these periods must be extracted in the first step. The individual loading cycles are subsequently identified for each skid track. The 4 phases of the loading cycle are then determined for each detected loading cycle and all recorded signals for phase II and phase III are stored since these time series data form the inputs for the neural network. With the trained RNN, the mass is estimated for the respective loading cycle. The individual steps of the explained method are explained in detail below.

Step 1: Detection of the forwarder on skid track

The working process of loading, i.e. the period in which the forwarder is on the skid track, must be determined first in order to minimize the amount of data to be examined for the subsequent algorithms. To ensure that this process runs as quickly as possible and with minimum computational resources, only the signals of the swivel angle and the cylinder pressure of the grapple are considered. Although loading can easily be distinguished from the work processes of driving loaded and unloaded (Figure 6), a differentiation between unloading is not trivial. For this differentiation, an algorithm was developed which detects the loading cycles of the forwarder. Hereby, the cylinder pressure of the grapple is considered when swivelling the grapple towards the stanchion basket. This pressure is significantly higher during loading than unloading, as the grapple is swung back empty to the stanchion basket. After successful detection of possible loading cycles, time-related loading cycles are combined into intervals at which the forwarder is on the skid track. In these periods, all input signals are used for further evaluation for the subsequent steps.

Step 2: Detection of the individual loading cycles and the gripping phase

The individual loading cycles are detected via the grapple position, explicitly the lateral distance between the grapple and the crane column. The part of the loading cycle that is relevant for the scale begins when the stanchion basket is left. In addition, all cycles are examined according to their pressure curves in the main arm cylinder. If the pressure while leaving the basket is lower than while re-entering, there is loading.

The gripping phase and the subsequent retraction movement of the crane including the load contain the information that the recurrent neural network uses for the weighing process. The position of the gripping phase in the loading cycle is determined by an analysis of the joystick signals, the IBC pressure and the grapple position (Figure 5).

However, the raw data of the IBC pressure are not used to determine the gripping phase, as the local oscillations in the signal make a precise analysis difficult. The pressure fluctuations are reduced by filtering the signal. After detecting all filtered pressure peaks in the cycle, all positions in which the grapple is in a local minimum are checked for three conditions (Figure 5):

- Is there a pressure peak in the immediate vicinity?
- Does the grapple close in the immediate vicinity?
- Does the z coordinate rise above a threshold value immediately after the minimum?

If all three conditions are met, this minimum is marked as a possible starting point for the gripping phase. If several minima meet the requirements, the last occurring minimum is always selected. Therefore, the mass, which is ultimately loaded into the vehicle, always enters the network. This covers the practical case of collecting several small-diameter logs, which are then loaded together.

Step 3: Weighing process with neural network

After detection of the gripping phase, the corresponding part of the cycle is added to the RNN as input data. Each input signal is available in form of a time series. The trained RNN calculates a mass prediction at each time step based on all previous input data. This resulting mass vector is converted in the last step by an estimation function to a scalar value, which corresponds to the loaded log mass.

Figure 7 illustrates the prediction of the mass vector by the RNN exemplary for a cycle. Determining a scalar mass from this prediction, it is necessary to consider the appropriate section of the output vector. In this case, it starts between seconds 3 and 4 (Figure 7). To determine this point, the gradient of the mass vector is used. Starting from the beginning of the section, the symmetric trimmed mean of all subsequent data points is calculated. In comparison to the arithmetic mean, it is suitable as an estimation function because it suppresses local maxima and minima.
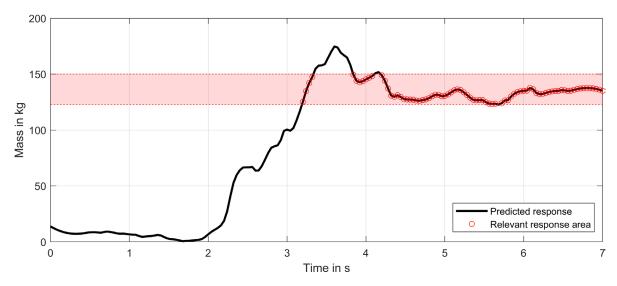

Figure 7: Prediction of the network

However, if there is an asymmetric distribution, as shown in Figure 7, a symmetrically trimmed mean is not ideal, as valid data points are hidden at one end of the data range. The determination of the log mass was therefore extended by an additional step. Unbalanced outliers are determined by a distance to the previously calculated trimmed mean by inserting a tolerance range. This is highlighted in red in Figure 7. The mean value of the data points circled in red represents the final log mass for this loading cycle.

Results from a measurement campaign

The random processes in the training phase and initialization of neural networks leads to each RNN being in a different local minimum in the solution space after the training. In order to cover the optimal solution space, 120 RNN were trained after the design phase. Since each RNN has different final weights, this leads to varying strengths and weaknesses in prediction quality. According to the theory, improved results can be achieved through a combination of the different predictions to an overall prediction (Perrone and Cooper 1995, Goodfellow et al. 2016). The trained networks were therefore tested for accuracy on a test data set consisting of 25 randomly selected cycles. This test data set was compiled under the same conditions as the training data set but was not used to train the RNN. The error on a data set unknown to the network provides information on what extent the network was able to generate an abstract understanding of the system during the training.

It is important for the quality of the dynamic weighing process that there is no continuous over- or underestimation. In addition, the variance of the individual loading cycles should be as low as possible. Figure 8 shows the error during mass determination for a varying number of networks used. The ideal estimated mass results from the arithmetic mean of the 20 networks with the smallest error (Figure 8 on the right). This is also shown by the minimum variance compared to the mean of all networks (left) or the network with the smallest error (center), visually illustrated by the smallest distance of the data area in the box plot (Figure 8). If all networks are consulted, the error range stretches considerably, which indicates the poor quality of some local optima. The comparison with the individual network with the smallest error also supports the thesis of the strengths and weaknesses of the individual networks. It should be noted here that the median of these two differs imperceptibly.
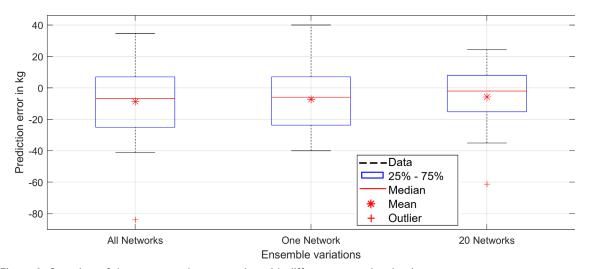

Figure 8: Overview of the errors on the test cycles with different network selection

With this network ensemble, it is possible to achieve an average accuracy of 15 kg per loading cycle on the basis of previously unknown data, which corresponds to an absolute average full-scale error of 1.5% related to 1,000 kg. Figure 9 illustrates the real log mass of the individual loading cycles and the corresponding estimated mass of the network.
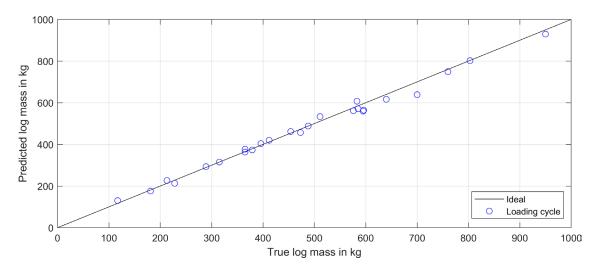

Figure 9: Result of network prediction for previously unknown test cycles

The quality of the estimates is constant over the entire range, and there is only one cycle which is not close to the ideal line. This outlier appears also in Figure 8 (right). The predicted mass of the fully-loaded forwarder with a payload of 11,974 kg thus deviates by 143 kg, which corresponds to a mass error of 1.19%.

Conclusions

On the basis of an RNN, a mass determination of the grapple contents during a dynamic loading process is possible in an offline procedure under reproducible conditions with logs. The arithmetic mean of the 20 RNN with the lowest error was best suited for an optimal determination of this mass. The databased method is suitable for obtaining information about the mass moved during the course of the day.

The crane scale was developed and tested under reproducible conditions on a flat surface with a limited number of logs. A functionality test of the scale within a real forest application with more strongly varying assortment characteristics or vehicle inclinations is still pending. For the future use of a weighing system also in the traditional volume measure, appropriate conversion factors must be provided for chips, which consider among other things the moisture content or the proportion of green biomass of the assortment and make it possible to derive the volume proportions from the weight. The presented approach is based on an evaluation of the data at the end of a working day. In future, the method will be further developed so that the current mass in the grapple can be determined online using a convolutional neural network (CNN) and the driver can thus read the weight in real time.

Using such a configured carrier vehicle, when equipping a mobile chipper, for example, enables to achieve an optimal payload in the wood chip process for trucks for onward transport. A cross-industry expansion of the system is therefore conceivable.

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