On the Methods to Predict Moisture Content on Wood: A Literature Review

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Abstract: Wood is the raw material for many manufactured goods. Charcoal, cellulose for the paper industry, laminated wood furniture, and even explosive products, such as gunpowder cotton, are possible destinations for the wood. On the other hand, the growing use of wood as a raw material has increased illegal deforestation and, as a direct consequence, it has changed the climate at a global level. The use of wood in production processes must be optimized to mitigate these adverse effects. One of the determining factors for this optimization is moisture content on wood, i.e., the ratio between the mass of water contained in the wood and dry wood mass. This article reviews the scientific literature published from 1959 to 2019 regarding the use of wood due to a better knowledge of its properties, particularly systems to explain or predict the moisture content. It contributes to the continuity of related research with the theme by ensemble the conducted studies into a single analysis.

1 INTRODUCTION

China's exponential growth and its consequent structural transformation from an essentially rural society to an urban-industrial civilization would inevitably produce demands for natural resources of all kinds. The policy of China's economy has brought about a dramatic expansion in foreign trade (Hu and Khan, 1997). Over the past twenty years, Brazil has become the largest supplier of agricultural products to the Chinese market. Exports to China accelerated and deepened technological and organizational changes in Brazilian agriculture – the base of the competitiveness of Brazilian agribusiness (Vieira et al., 2019).

Considering the wood, given its limited access to natural resources, China has increasingly resorted to external purchases for the production of its local factories. This fact led Brazil to double its exports of wood logs between 2017 and 2018. According to a survey by the *Forest2Market* consultancy, based on the Brazilian government's foreign trade data, exports of eucalyptus logs in the year 2018 increased 122% compared to 2017. Of this total, 89% was exported to China (Brazilian Society of Agriculture, 2019).

It is also necessary to add the Brazilian national demand, already have been analyzed for the medium and long term. Precisely, between 1988 and 2007, studies already presented results indicating that the variables *price of wood logs* and *installed capacity of the pulp industry* explained the Brazilian national demand (Ângelo et al., 2009).

Almost all finished products with wood as raw material go through the same stage: storing wood logs in piles. To better understand this question, Figure 1 shows a pile of wood logs in a storage yard.

The condition of the wood logs during storage is a determining factor for the quality of the finished product. The storage time of wood logs directly influences acceptance, if the wood is destined for the manufac-

Figure 1: Example of wood logs stored in a pile.

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ture of wood chips (Lima et al., 2017) or laminates of wood (Júnior and Alves, 2019), two of the essential purposes of wood in the Asian market.

Logs of wood from newly felled trees have high water content. This content is slowly reduced as the logs are exposed to the environmental conditions during storage (Rezende et al., 2010). The wood starts to dry, and its weight decrease with the loss of moisture (Tomczak et al., 2018).

Wood can absorb from 25 up to 30% of its weight in water (Dorigato et al., 2019). As the wood dries, cracks start to occur. The cracks are responsible for the large volume of wood losses during log storage (Gerwing et al., 2000). Thus, the moisture content must be observed and kept within the standards during the storage time (Estuqui Filho, 2006). Figure 2 shows examples of cross-section images of wood logs, stored in piles, with different crack conditions.

Figure 2: Cracks in wood logs.

There is a direct relationship between the moisture content and the weight of wood logs stored in the yards. Based on this premise, this work aims to research the relevant scientific literature that addresses the problem of modeling the variation in the moisture content and weight of logs. This research can be used for building different intelligent information systems, helping to create new technologies, especially that which use machine learning methods.

Machine Learning is a subarea of Artificial Intelligence (AI) (Russell and Norvig, 2002) and can be considered as an evolving branch of computational algorithms designed to emulate human intelligence, learning from the environment (El Naqa and Murphy, 2015). Machine learning allows the computer to develop models that automatically learn about a particular topic. Machine learning-based techniques have been successfully applied in many fields, from pattern recognition, computer vision, spacecraft engineering, centralized and decentralized finance, entertainment, computational biology, and medical applications.

This paper is organized as follows. We analyze two different ways to deal with the variation of wood moisture content: using machine learning-based models (Section 2) and analytical and statistical approaches (Section 3). We still present in Section 4 other methods that indirectly contribute to solving this problem. We deeply discuss some interesting studies for each method. In Section 5, we organize, summarize and categorize the literature reviewed in a timeline format, demonstrating the evolution of related research. Finally, Section 6 concludes our study and points out some future directions.

2 MACHINE LEARNING-BASED MODELS

Machine Learning (ML) is a computer program that learns from experience concerning some class of tasks, evaluating its performance when executing these tasks improves with the experience (Mitchell, 1997). ML can be understood as a subset of Artificial Intelligence (AI) that has the ability to build mathematical models for the purpose of making predictions or decisions without having to be explicitly programmed to do this (Zhang, 2020).

A moisture content modeling method, was proposed by using *Support Vector Machine* (SVM) technique (Wen et al., 2012). In this model, the input is the temperature and the equilibrium moisture content, i.e., the moisture content at which wood neither gains nor loses moisture. The moisture content is the output. The training data was obtained from a wood drying kiln with a temperature between 26.6 and 37.7 ºC and steam heating. Besides using the drying kiln, there were still heating equipment and measuring instruments, including temperature sensors, moisture content sensors, equilibrium moisture content sensors, drought fans, and controllers. Moreover, experimental parameters selection for the SVM model was investigated, and the infinite impulse response (IIR) filter technique was applied to screen noise of the training data. The results show the effectiveness of the proposed method, demonstrating that it is possible to use machine learning techniques for this purpose.

Fuzzy logic was also applied to predict moisture content (Bardak and Bardak, 2019). This work was related to the drying temperature and time. The authors have used the An air-dried *Fagus orientalis* species, which is commonly wood utilized in manufacturing. The specimens were dimensioned as 55×25×25mm. Then, the samples were kept in the moisture-conditioned room until weight gain reached equilibrium. The moisture content of 13% was achieved. Afterward, wood samples were dried in a drying oven at different temperatures (50ºC, 70ºC, 90ºC, 110ºC) and time (0.5, 1.0, 1.5, 2.0, 2.5 hours). Ten samples were prepared for each experiment. This model has two input variables (temperature, time) and one output variable (moisture content). The fitted model showed an average accuracy rate equal to 97.16%, showing that fuzzy logic can be used as a valuable tool in the wood drying process, which is an important part of the cost in the wood industry.

Machine learning algorithms were also used to predict wood volumes in trees and better allocation of wood logs for different uses, comparing them with the taper equations (Souza, 2019). These equations explain the relationship between the diameter and the height of a tree. Unlike traditional approaches in which wood volume is based on a single measure of tree diameter, taper equations use trunk taper measurements, providing considerably more accurate volume estimates, considering the changes in decreasing diameters from the base to the top of the trees. The authors compared Artificial Neural Networks (ANN), Support Vector Regression (SVR), and Random Forest (RF), trying to understand the behavior of the predictions proposed by different algorithms, in addition to specifying the best models for the studied cases. The ANN model reached the best accuracy. RF generated imprecise estimates unless the measurements are taken at smaller intervals and with large amplitudes of log size classes. The ML algorithms performed better or equal to taper equations.

To organize wood logs used as raw material in sawmills, the authors (Morin et al., 2020) demonstrate how machine learning models can provide recommendations for multiple tasks: allocation of cutting blocks, helping in the planning stage, and recommending both the wood and the mill that will process it. In this way, they exploit the processing plants' strengths and reduce losses in the process. The proposed models achieved up to 94% of the maximum theoretical gain in decision-making using Decision Trees (DT), with an average gain of 83% compared to the more usual method of historical production.

Regarding the variation in moisture content, we highlight a study that used ANN to predict the drying rates of wood kiln based on species and basic wood density information (Wu and Avramidis, 2006). Although this is not precisely a sub-area of interest in this research because of kiln-drying rather than air-drying, the contribution to estimating wood moisture content using machine learning must be considered. The neural network developed had three inputs: initial moisture content, density, and drying time. The model's output was the estimate of the average final moisture content. A back-propagation algorithm was implemented to train, validate, and test the model with 50, 25, and 25% of instances, respectively. The formation of these partitions was due to the equal spacing of the points and the original data. After obtaining the optimized configuration by varying the main hyperparameters, such as the transfer function, the learning rate, and the number of neurons and learning layers, the quality of the final model achieved a Mean Relative Absolute Error (MRAE) lower than 2%, confirming the excellent predictive capacity of this method in order to predict the drying rate.

3 ANALYTICAL, STATISTICAL, OR GENERALIZATION-BASED MODELS

In Finland, researchers estimated the ideal storage time of woodpiles kept outdoors based on moisture content changes (Raitila et al., 2015). Multivariate models were created aiming to estimate moisture content changes in different drying environments, based on testing and validating models developed for the *pinus* wood species. These models were applied to piles of *wild pinus* species destined for fuel production. In order to cover different moisture levels through the different periods of the year, the experimental data were collected over seven to fourteen months and considered the precipitation, evaporation, and wood species as main factors. The work compared regression models to estimate moisture content with the more traditional method – the periodic weight difference of logs stored in piles. The conclusion was that data logging based on load cells to estimate the change in wood moisture content proved to be a viable option to obtain the necessary data for wood drying models.

Regarding the wood drying process, there are researches directly related to the construction of metrics for different estimates. The theme has been researched since 1959, and it is known that it is ruled by some variables, such as temperature, relative humidity, wind speed, and precipitation (Kröll, 1959). In 2009, another study inserted more variables to be studied and researched, such as access to wind currents and exposure to the sun (Kofman and Kent, 2009) in the outdoor drying process (*air drying*).

In 2000, a computer simulation was developed an analytical way of estimating the natural drying times of various species of laminated wood from local meteorological data for wood piled on any day of the year (Simpson, 2000). In this study, the effect of sawn wood thickness on drying time was also included. The model presented is based on experimental times of natural drying for six wood species: *northern red oak*, *sugar maple*, *American beech*, *yellow poplar*, *pinus ponderosa* and *Douglas-fir*. The premise was that, once the parameters were found for each wood species in the geographic location of the experimental data, they could be used in drying simulation, estimating natural drying times in other locations where historical meteorological data were also available. The results show the estimated natural drying times of the six wood species, for any thickness, up to any final moisture content, on any day of the year and in any location where there are data on average temperature and relative humidity.

In 2004, a study by the same researcher (Simpson, 2004) developed a non-linear regression model to describe outdoor drying equally for two wood species. In this research, regression coefficients were developed to predict the daily loss of moisture content based on the same variables: early-day moisture content, temperature, and average daily relative humidity. The wood species used in this study were *northern red oak* and *sugar maple*. The resulting regression models are presented below:

$$\delta_M = MC^{2.38}F^{0.759}RH^{-2.91}(\textit{northern red oak})$$

$$\delta_M = MC^{2.18}F^{1.89}RH^{-3.57}(\textit{sugar maple})$$

The models can predict daily moisture loss based on almost always the same variables (*MC* is early wood moisture content, *F* is daily average temperature, and *RH* is daily average relative humidity). Therefore, having the variables in common, the equations could be used to develop curves of loss of moisture content over time, as long as local meteorological data were available, observing only the wood species. So, the research resulted in the development of an electronic spreadsheet to estimate the time needed for drying wood outdoors, based on an index called Air-Drying Estimator (Mitchell, 2019).

Corroborating the above studies, another study demonstrates that meteorological data used in natural drying models can adequately estimate the wood moisture content in logs (Erber et al., 2012). Also, considering that determining the moisture content in a log pile without measuring it frequently is an operational problem, this study aimed to model the change in the moisture content of a log pile as a function of measurable input variables. So, the periods of natural drying could be optimized, and thus, the period of transformation of wood into firewood (for energy production) could be determined.

In order to estimate these data, equipment was used to constantly measure - every ten minutes - the wood samples in logs. The data collected were: percentage of relative humidity, temperature, wind speed, and precipitation. For calculation purposes, even if it was in the form of snow - non-liquid precipitation, the precipitation was transformed into the equivalent of net precipitation. The regression model then generated was:

$$CMC = 4.691 \times 10^{-3}DP + 1.359 \times 10^{-2}P,$$

where *CMC* is the daily percentage of moisture content variation, *T* is the temperature (measured in degrees Celsius), *DP* is the percentage of potential daily relative humidity, and *P* is the sum, in millimeters, of the daily net precipitation and non-liquid.

The objective of this multiple regression model was to be based on daily averages and sums, seeking to operationalize models previously studied more easily and quickly, not requiring data from the logs themselves. An important piece of information raised by this study concerns wood species. The findings on precipitation data do not match with other previous studies, which claimed that precipitation had no significant effect on natural drying (Gigler et al., 2000). Thus, it is assumed that certain wood species, such as *wild pinus* and *willow* have only surface moisture. Furthermore, *wild pinus* can be considered more likely to retain moisture in the bark than *willow*.

4 OTHER RELATED WORKS

On the storage of wood logs, a study investigated the effect caused by the storage time of wood logs in New Zealand (Visser et al., 2014). In this work, two trials were performed representing favorable and unfavorable storage conditions: in summer, in a hot and dry location, and in winter, in a cold and relatively humid place. Twenty piles were installed, containing approximately 600 kg of wood logs each (initial wet weight). Moisture content was determined gravimetrically at the tests' beginning and end. All piles were weighed at 1 to 4-week intervals to identify weight loss trends over storage time. After twenty-four weeks of storage in the summer, the wood logs' moisture content (wet base) decreased from an initial value of 53% to values between 33 and 21%. The decrease was more significant for small uncovered logs and smaller for large covered logs. Due to the wet and cold weather conditions, logs stored in winter dried very little over seventeen weeks. Moisture content decreased from an initial value of 58% to values between 51 and 49%, with no significant treatment differences observed in the winter test. The best storage technique for the summer was the simplest:

stacking small logs without any covering. Larger logs dried more slowly but splitting accelerated their drying. Stack covering did not help decrease moisture loss, and the results indicated that log covering did not improve the drying of wet logs.

Wood can be stored in piles for a variety of purposes. One of them is for energy production. A study produced in Sweden (Thörnqvist, 1985) analyzed the relationship between moisture loss and loss in energy production. In order to measure and determine the changes in energy production due to storage, moisture and matter loss (weight loss) before and after storage were analyzed. This study concluded that if the wood stored in piles is reduced to chips instead of wood logs, the energy loss can vary between 7% and 21% for a period between six and nine months of storage.

It is known that recently felled wood has high water content and that water loss is a preponderant factor through the loss of moisture content. The study (Tomczak et al., 2018) aims to demonstrate the minimum period for wood logs stored in piles to start the natural drying process. To determine how the method and storage conditions affect weight changes and moisture loss in the wood, a plot of sixty model trees was selected, divided into two groups: in the first group, thirty whole trees; in the second group, thirty trees were cut transversely, forming logs with 2.5 m in length and stored in piles. From experimentation in this study, it was noted that wood stored in piles lost moisture more slowly than wood from trees that were left whole after felling. Comparing the weights of logs stored in a pile days after harvesting, a statistically significant difference was found only between the first and fifteenth – and last – day. Therefore, this study concluded that the two-week period is the minimum pile storage period necessary to achieve a significant degree of weight change and moisture loss.

When it comes to the production of sawn wood and wood veneer, an study investigated the potential use of different eucalyptus species (*benthamii*, *deanei*, *E. dorrigoensis*, *E. dunni* and *E. smithii*) in a region with the occurrence of frost (Walker, 2006). The trees selected for sampling were eighteen years old and were sectioned into logs of 2.1 m in length. Afterward, the samples were subdivided into classes by diameter: between 20.1 cm and 25 cm; between 25.1 cm and 30 cm; and larger than 30 cm. The cracks in the boards were measured, and then the yield on already sawn wood could be calculated. The results obtained in this study indicated that the wood species studied are of good quality, highlighting *E. dunnii*. However, the other species also showed satisfactory yields, indicating that these can be used to produce sawn wood in regions with frost occurrence. For the present research, an outstanding contribution of this work is the relationship of cracks with the yield of the wood to be laminated. This yield is expressed as a percentage obtained by the ratio between the volume of sawn wood and the volume of logs exposed to the process. For eucalyptus, this percentage varies between 40 and 65%. Among some factors that have a direct influence on wood yield, in addition to the characteristics of the species itself, there is also the quality and diameter of the logs to be processed (Tsoumis et al., 1991). For this reason, the division of logs into classes by diameter is an important strategy for the production of laminated wood with high yield.

5 A COMPARISON AMONG THE DIFFERENT APPROACHES

This section aims to compare the different approaches reviewed in this paper. Considering that we provide as much important information per study as we could (nineteen different studies), in order to ease the comprehension of the summary, we have divided the analysis into two parts, Tables 1 and 2. In each table, we provide different studies, one per row and their different characteristics per column. We highlight that the first column, ID, is related to identifying the considered study. That is, the ID that appears in Table 1 refers to the same study in Table 2.

In Table 1, we provide the year of the publication, the kind of wood related to the study, the species, the country related to the study, and the objective of each study related to moisture content. Also, considering the published studies, it is noticeable that this topic has gained attention in the last years, being a problem with an interesting research field. We can also observe that North America provides most of the studies, and the United States has around 30% of the analysis (6 cases), followed by Canada (3 cases). We highlight the different studies that were carried in Europe.

Concerning the motivations, we can observe that this is an extensive research field that has been coped with *machine learning* and mathematical problems. The objectives are economical, optimization, and study the variation in moisture content, especially air drying-based models.

The second part of the analysis is provided in Table 2. In this table, we provide the adopted method and the main contribution for each considered study. We can observe that the question related to *machine learning* and the weight of the logs are the methods most commonly used because there is a direct relationship between these two critical variables.

Table 1: Timeline and researches characteristics.

ID	Year	Kind of wood	Species	Country	Objective
1	1959	Logs	(not specified)	Germany	To study the wood drying process
2	1982	Laminated	Red Oak and Yellow Poplar	United States	To estimate the drying time
3	1985	Logs / Chips	(not specified)	Sweden	Analyze the relationship between moisture loss and energy production
4	2000	Laminated	Northern Red Oak, Sugar Maple, American Beech, Yellow Poplar, Pinus Ponderosa and Douglas-Fir	United States	To estimate the air drying time
5	2003	Logs	Pinus Ponderosa and Douglas-Fir	United States	Estimate moisture content loss through natural drying on small diameter logs
6	2004	Laminated	Northern Red Oak, Sugar Maple and Pinus Ponderosa	United States	Describe, through an equation, the air drying
7	2006	Laminated	E. Benthamii, E. Deanei, E. Dorrigoensis, E. Dunni and E. Smithii	New Zealand	The potential use of different eucalyptus species based on the cracks
8	2007	Logs	Giant-Fir and Tsuga	Canada	To predict drying rates for wood kilns
9	2009	Logs	(not specified)	Ireland	Estimate the rate of moisture loss in logs in air drying
10	2012	Logs	Pinus	Finland	Modeling the change in the moisture content of a log pile as a function of measurable input variables
11	2012	Logs	Pinus Taeda, Eucalyptus Dunni and Eucalyptus Grandis	Brazil and United States	Examine the impact of time on book income and the operating cost of losing weight
12	2012	(not specified)	Sugi	Japan	To predict the moisture content
13	2014	Logs	Pinus Radiata	New Zealand	Check the effect caused by the storage time of the wood logs
14	2015	Firewood	Pinus and Wild Pinus	Finland	Estimate the optimal storage time for wood piles stored outdoors based on changes in moisture content
15	2017	Wood chips	Pinus and Oak	France	To predict the moisture content
16	2018	Logs	Wild Pinus	Poland	Evaluate changes in mass and moisture content of wood stored in logs
17	2018	Logs	Beech	Poland	Determine the minimum period for logs stored in piles to start the natural drying process
18	2019	Wood chips	Fagus orientalis	Turkey	To predict the moisture content
19	2019	Logs / Laminated	(not specified)	Canada	Allocate wood cutting blocks in order to optimize sawmill production
20	2019	Logs (trees)	Eucalyptus Grandis	Brazil	Estimate wood volume in trees
21	2019	Logs	(not specified)	Canada	Economic waste related to wood weight loss through moisture loss by natural drying
22	2019	Laminated	Red Oak, Yellow Poplar and Sugar Maple	United States	Estimate the potential of a geographic location to dry wood

6 CONCLUSION

Wood science and technology in China is becoming a solid scientific discipline and has impacted global research and development activities. The wood drying process has a complex and non-linear system with time-varying and uncertain characteristics. Wood drying is a process of removing water, that is, the decreasing process of moisture content. This is a critical issue in applications where wood and the quality are affected directly by the change of moisture content.

The aim of this work was to survey the bibliography about the properties for better use of wood in production processes, precisely the relation between pro-

Table 2: Timeline and researches contributions.

ID	**Method**	**Contribution**
1	Studied wood drying in drying kilns	Established temperature, relative humidity, wind speed and precipitation as variables
2	Deducing daily rate of moisture loss from meteorological data	Defined a regression to estimate the daily loss of moisture content
3	Analyzing moisture and weight loss before and after storage	Concluded that if the wood stored in piles is reduced to chips, the energy loss can vary between 7% and 21% for a period between 6 and 9 months of storage
4	A computer simulation, including the effect of wood thickness on drying time	Estimated the air drying time, up to any final moisture content, on any day and in any location where there are the average temperature and relative humidity data
5	Using weather data, measuring temperature and relative humidity every 10 minutes	Two different equations, one for each species
6	Using historical records of temperature and relative humidity	Developed an equation that allows the prediction of estimated air drying time at any desired location
7	Measuring the cracks and calculating the yield on already sawn wood	Expressed the relationship between cracks and laminated wood yield and established the division of logs into classes as an important strategy
8	Machine Learning using three inputs: initial moisture content, density and drying time	Confirmed the excellent predictive capacity of this modeling method
9	Continuously weighing the logs	Established access to wind currents and exposure to the sun as determinants for the estimation of moisture
10	Measure the percentage of relative humidity, temperature, wind speed and precipitation in log wood samples	Established an equation
11	Constantly weighing	Proved that the difference between the green wood and logs with 11 weeks of cut can increase a lot the cost for the companies
12	Machine learning method is proposed by using SVM	The results of this paper show the effectiveness of the proposed method, demonstrating that it is possible to use machine learning techniques for this purpose.
13	Weighed the logs every 1 and 4 weeks	The best storage technique for the summer was just stacking small logs without any covering. Also, it concluded that larger logs dried more slowly
14	Compared regression models (estimating moisture loss) with a classic model, providing the weight of log piles	Proved that periodic weighing of wood logs is an effective method to predict the difference in moisture content
15	Continuously weighing the logs	Established that as long as is the length of logs stored in the piles, lower is the loss of moisture
16	Comparing log weights with whole trees (not cutted into logs)	Concluded that two weeks is the minimum period necessary to achieve a significant moisture loss
17	Relate machine learning models with a existing simulator	Machine Learning models reached up to 94% of the maximum theoretical gain
18	Machine learning using as input data provided by the coefficient of reflection	The result show the effectiveness of the proposed modeling methodology, allowing this solution for moisture content prediction to be suitable for direct implementation on real-time wood-to-energy industrial processes.
19	Compared taper equations with models based on Machine Learning	Methods using Machine Learning were equal to or superior to the method using taper equations
20	Continuously weighing the logs	A mathematical formulation is proposed that decides on the location of potential wood storage yards
21	Fuzzy logic, relating the moisture content with the drying temperature and time	The results of the fuzzy models showed an average accuracy rate of 97.16%, showing that it can be used as a useful tool in the wood drying process – an important part of the cost in the wood industry
22	Simulations	Outputs: the estimated date when the wood will reach the target moisture content and others

ductivity and moisture content. By carrying out this study, it will be possible to help different information systems as the data are organized and summarized.

It is also known that wood properties can vary widely, depending on storage and climatic conditions and the destination of the wood itself. Therefore, an understanding of these properties, especially those that are technically important to measure losses - such as the behavior of moisture content - can increase the potential for optimizing the use of wood, regardless of whether the destination is lamination, the chip production or even power generation. Increasing the potential for using the same wood will inevitably help mitigate the acceleration of climate change globally.

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