IDENTIFICATION OF THE LENGTH DISTRIBUTION OF LUMBER DEFECT-FREE AREAS

Mykhailo Mysyk
Associate Professor
E-mail: mmysyk@i.ua

Yaroslav Matsyshyn
Senior Teacher
Department of Automation and Computer-Integrated Technologies
The Ukrainian National Forestry University
Lviv 79057, Ukraine
E-mail: slavkomaz@yahoo.com

Volodymyr Mayevskyy
Professor
Department of Sawing Technology, Technology of Joinery
and Woody Building Products
The Ukrainian National Forestry University
Lviv 79057, Ukraine
E-mail: volodymyr_mayevskyy@nltu.edu.ua

Charles D. Ray†*
Associate Professor
Department of Ecosystem Science and Management
The Pennsylvania State University
University Park, PA 16802
E-mail: cdr14@psu.edu

Roman Kurka
Associate Professor
Department of Automation and Computer-Integrated Technologies
The Ukrainian National Forestry University
Lviv 79057, Ukraine
E-mail: kurkaroman@i.ua

Ivan Sopushynskyy
Associate Professor
Department of Botany
Wood Science and Non-Wood Forest Products
The Ukrainian National Forestry University
Lviv 79057, Ukraine
E-mail: sopushynskyy@nltu.edu.ua

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Abstract. Presented here are the results of statistical analysis of length distribution of defect-free areas (DFA) of pine, beech, and oak blanks. The investigated empirical distributions of the lengths of defect-free areas nearly always exhibit right-side asymmetry and "heavy tails," with high coefficients of

* Corresponding author
† SWST member

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variation (30% ≤ c ≤ 110%). Therefore, the arithmetic mean of these lengths is not an appropriate measure for description of any of the investigated samples, and to describe the dimensional and qualitative characteristics of blanks, not only characteristics of location must be used, but also the relative characteristics of the dispersion. It is proposed that rather than use estimates of variability, to apply an assessment of stability—the value inverse to the squared coefficient of variation, which allows, with minimal computational cost, to correctly compare the lengths of DFA obtained from different lumber and in different operating conditions. It is shown that the distribution of lengths of DFA for pine, oak, and beech blanks can be only described entirely by two theoretical distributions—the Burr and log logistic, with different parameters for different wood species and various sizes of defect-free areas.

Keywords: Wood, blank, defect-free area, distribution fitting, descriptive statistics, modeling, production process.

INTRODUCTION

Modeling of production processes and optimization of their key operating parameters as constituents of the concept of virtual manufacturing is a vital approach to effective design of these processes and their implementation in a production environment. This approach is an alternative to the traditional empirical methods of designing production processes. The traditional methods require a considerable number of physical experiments to validate the assumptions and hypotheses; therefore, they are a priori ineffective (Altintas 2015). Instead, the implementation of the virtual production concept provides an opportunity to simulate a large number of options in a virtual environment and choose the best one with less time and cost. The effectiveness of virtual production primarily depends on the adequacy and accuracy of the adopted mathematical models of manufacturing processes.

The development of statistical models of processes in the wood products industry is especially relevant. Wiedenbeck (1992) was one of the first to quantify the relationship between lumber length and grade yield, and to demonstrate the advantages as well as the shortcomings of using empirical data for simulation purposes. Buehlmann (1998) discussed the stochastic nature of parameters of wood as a raw material, and summarized the different types of statistical models used to analyze log and lumber yield. Lamb (2002) cited the distribution of lengths/widths as affecting the yield from a cutting bill, and that shortest length in the cutting controls yield—the shorter the length, the higher the yield from the same grade mix. Buehlmann et al (2008) performed statistical analysis of empirical cut up simulations demonstrating that cutting bill requirements, defined by length of parts, impacts yield. However, simulation of lumber breakdown and yield in dimension mill processing has traditionally been limited to empirical data simulation of scanned defects and their relationship to the size of the board (eg, see Thomas and Buehlmann 2002; Weiss and Thomas 2005).

Simulation modeling of production processes requires information on the statistical characteristics of the input flows and parameters. Stochastic process control models have been demonstrated to be effective in reducing lumber drying time over empirically derived kiln control schedules (Gattani et al 2005), and discrete-event simulation has been used to simulate processing flow and machine downtime to improve throughput in the context of lumber cutting variability (Ray et al 2007). Such process variability can be represented either in the form of empirical data models as

Table 1. Characteristics of the studied samples of defect-free areas.

Wood species		Width of blanks h, mm	Technologically acceptable minimum length of defect-free areas x_{min}, m	The sample size
Softwood	Pine	90	0.20	191
		50	0.20	256
		78	0.15	1057
Hardwood	Oak	90	0.20	133
		50	0.20	229
	Beech	40	0.10	285

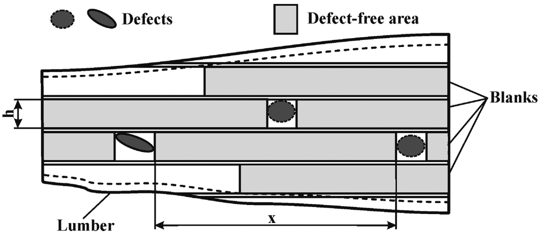

Figure 1. Lengths (*x*) of defect-free areas.

cited in the previous paragraph, or analytically in the form of theoretical distributions. In the first case, the simulation model can only reproduce the history of an actual case-studied process. Lacking any published research indicating theoretical distribution of defect-free area, Ray et al (2007) attempted to improve on the limitations of empirical simulation by using randomly generated uniform distributions to represent part production in a hardwood dimension mill. Their conclusions that cutting bill variability impacted production cycle time, work in process, and throughput were based then, on theoretical distribution assumptions of the simplest type; that distances between defects (as represented by parts produced in the simulation) could be represented accurately by uniform random numbers across species and sawing conditions.

To improve on these simplistic assumptions, a methodology is needed to determine the best theoretical distribution for the entire range of possible cutting yields, allowing the simulation of a specific range of input flow and parameters.

Table 3. Defect-free parts length empirical distribution for softwood.

Percentile	Percentile value, *m* for different width h		
	$h = 90$ mm	$h = 50$ mm	$h = 78$ mm
Minimum	0.205	0.210	0.150
5%	0.220	0.227	0.200
10%	0.237	0.260	0.230
25% (Q1)	0.290	0.355	0.290
50% (Median)	0.445	0.542	0.360
75% (Q3)	0.625	1.019	0.440
90%	1.076	3.005	0.510
95%	1.526	4.061	0.540
Max	3.690	4.670	0.640

In dimension mill processing, it can be shown that one of the most important parameters of the input flow of blanks is the distribution of lengths of defect-free areas (DFA). No published work to date has identified the relevant theoretical laws of these distances, which limits the use of simulation to empirical modeling when designing automated process flow. Therefore, our work set out to improve this situation, at least for pieces of lumber of various wood species obtained by through and through (also known as plain sawn or crown sawn) sawing methods and which are fed to the line of optimized crosscutting. In most of the prior research cited, defect parameters, such as knot type, size, density, and location are the objects of focus, because the processing algorithms are focused on identifying these defects. However, for simulation of defect-free production *rates* it is the *distance between* these defects that is of importance.

Table 2. Defect-free parts length descriptive statistics for softwood.

Statistic	Statistic value for different width h		
	$h = 90$ mm	$h = 50$ mm	$h = 78$ mm
Sample size	191	256	1057
Range, *m*	3.485	4.460	0.490
Median, *m*	0.445	0.542	0.360
Mean, *m*	0.576	1.017	0.365
Variance, m^2	0.231	1.350	0.010
Standard deviation, *m*	0.480	1.162	0.102
Coefficient of variation	0.834	1.142	0.279
Standard error	0.035	0.073	0.003
Skewness	3.266	2.002	0.109
Excess kurtosis	14.131	2.856	−0.657

Table 4. Defect-free parts length descriptive statistics for hardwood.

Statistic	Statistic value for different width *h*		
	$h = 90$ mm	$h = 50$ mm	$h = 78$ mm
Sample size	133	229	285
Range, *m*	3.814	3.81	4.377
Median, *m*	0.760	0.940	0.800
Mean, *m*	1.098	1.338	1.125
Variance, m^2	0.826	1.129	0.824
Standard deviation	0.909	1.063	0.908
Coefficient of variation	0.827	0.794	0.807
Standard error	0.079	0.070	0.054
Skewness	1.223	0.886	1.167
Excess kurtosis	0.728	−0.435	0.762

Table 5. Defect-free parts length empirical distribution for hardwood.

Percentile	Percentile value *m* for different width h		
	$h = 90$ mm	$h = 50$ mm	$h = 78$ mm
Min	0.206	0.210	0.103
5%	0.220	0.247	0.200
10%	0.260	0.291	0.246
25% (Q1)	0.357	0.462	0.415
50% (Median)	0.760	0.940	0.800
75% (Q3)	1.570	1.954	1.725
90%	2.533	3.100	2.480
95%	3.093	3.135	2.854
Max	4.020	4.020	4.480

Since the biological patterns of tree growth and crown shaping are common to trees of any species, it is possible to hypothesize about the possibility of describing the distances between the knots and other biological defects (defect-free area length) by some theoretical law of distribution with different parameters for different species and different size of defect-free areas. Unlike other studies (Sandberg and Holmberg 1996; Sandberg and Johansson 2006; Eliasson and Kifetew 2009; Eliasson 2008; Fredriksson 2011, 2012), the aim of this study was not to investigate the life cycle of lumber "from forest to finished product" (Sandberg and Johansson 2006). This research effort focused on recording the actual length of defect-free areas of the blanks, regardless of the origin and characteristics of tree stem and logs from which they were obtained. However, since the amount of biological defects and distance between them depends on the lumber processing method (Sandberg and Johansson 2006), we restricted ourselves to the blanks obtained by through and through sawing.

MATERIALS AND METHODS

Material

We used two groups of data in our study, compiled and summarized in Table 1. The first group of data, consisting of four samples (two samples for hardwood and two for softwood blanks of different widths), contains information about the virtual length of the DFA, obtained using internally developed software for simulation

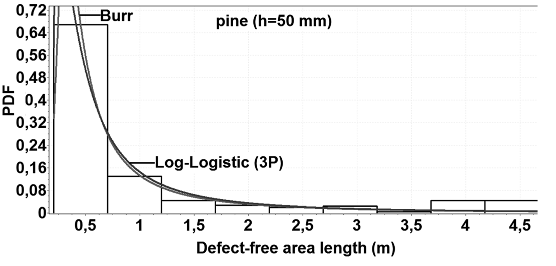

Figure 2. Example of distributions fitted for pine blanks ($h = 50$ mm) defect-free parts length.

modeling of the process of lengthwise cutting of boards (Matsyshyn et al 2012). The structure and process of verification of this software is described in detail in Matsyshyn et al 2012.

The second group of data consists of two real-world samples of DFA lengths for pine and beech blanks, obtained by lengthwise cutting of boards. The data were obtained by the authors at various factories in Ukraine by measuring the length x of defect-free areas of various widths h of standard dimension mill blanks (see Fig 1). The measurements were carried out after completing four-side milling prior to crosscutting.

Methods

To choose a theoretical distribution law based on visual analysis of the histogram of the empirical distribution, the null statistical hypothesis H_0 is traditionally used to clarify the possibility of application of a theoretical law (Law 2006). In this technique, for the chosen significance level α (mostly taken as $\alpha = 0.05$), the null hypothesis is tested with one of the statistical criteria, usually Pearson's criterion, because it accounts for the decrease in the number of degrees of freedom through the evaluation of the study sample distribution parameters. If the value of the calculated criterion does not exceed the critical one, there is no reason to reject the null hypothesis; otherwise, the null hypothesis is rejected and the alternative one is accepted because the investigated sample cannot be described by the previously accepted law of distribution. The disadvantage

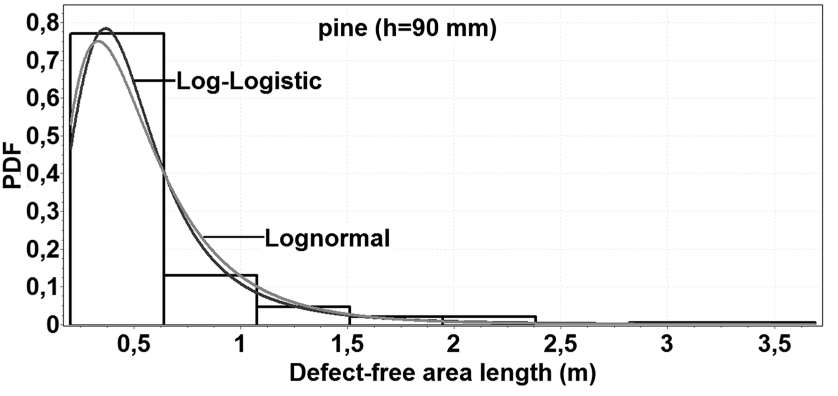

Figure 3. Example of distributions fitted for pine blanks (h = 90 mm) defect-free parts length.

of this procedure is the subjective nature of the proposal of the null hypothesis, because it relies on the researcher's personal knowledge about possible theoretical laws of distribution; moreover, graphical interpretation of the probability distribution functions (PDFs) for different theoretical distributions can be very similar and close.

Therefore, to avoid this drawback, we have used a different technique, in which none of the known laws of distribution is given preference during formulation of the null hypothesis. Instead, a series of hypotheses are consistently tested for the possibility of our data description by each of the well-known continuous theoretical distributions, then one or more are chosen from those among which there is no reason to reject the null hypothesis (at the specified significance level). Moreover, the selection criterion here is not "precision" of describing a specific sample (Law 2011), but only a formal reason not to reject the null hypothesis at a given significance level, even though Pearson's criterion is relatively close to the critical value.

For the practical implementation of this technique, there are several specialized programs (Law 2011; Mathwave 2015), from which we used the EasyFit software (Mathwave 2015). The main feature of this software is a knowledge base of almost all currently known theoretical distributions of random variables (Mathwave 2015), which makes it possible to automatically check the ability to describe data by all known distributions.

Therefore, by using Pearson's criterion (Law 2006), we check the possibility of describing empirical distribution of DFA lengths for each

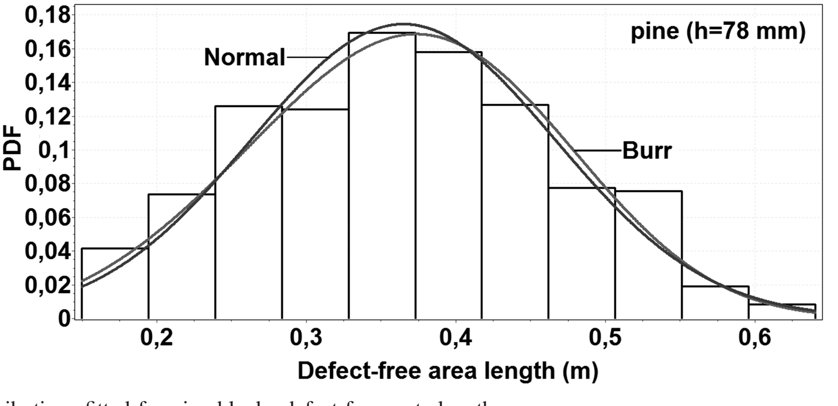

Figure 4. Distributions fitted for pine blanks defect-free parts length.

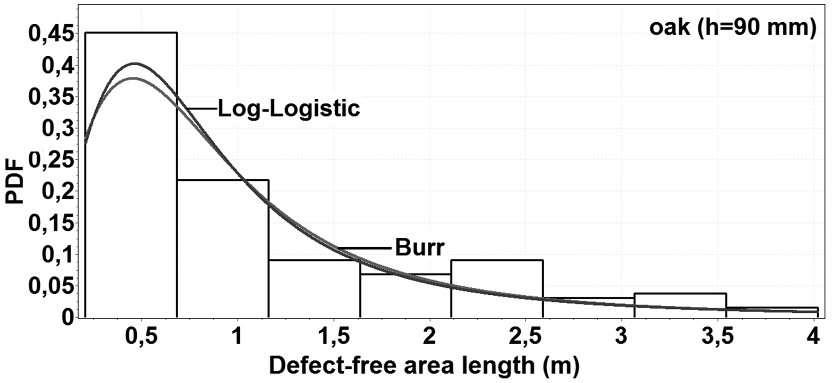

Figure 5. Example of distributions fitted for oak blanks (h = 90 mm) defect-free parts length.

sample by each of the continuous theoretical distributions. Excluded are obviously unsuitable distributions (eg, for which there is no variance). As a result, for each n^{th} (n = 1, 2, ... 6) sample we obtain a set A_n consisting of one or more theoretical distributions, the hypotheses of which are not rejected at a significance level $\alpha = 0.05$. To identify the type of distribution suitable for describing all samples, we form a new set A consisting of nonrejected theoretical distributions as the intersection of the sets of distributions suitable to describe each individual sample:

$$A = A_1 \cap A_2 \cap A_3 \cap A_4 \cap A_5 \cap A_6. \quad (1)$$

This procedure has a clear graphical interpretation in the form of Venn diagram (Weisstein 2016), as will be shown in the following Results and Discussion section.

RESULTS AND DISCUSSION

Descriptive Statistics

Statistical characteristics of the empirical samples of DFA lengths, obtained with the application of the EasyFit software, are presented in Tables 2-5 for softwoods and hardwoods, respectively. As can be seen from the tables mentioned and Figs 2-7, the investigated empirical distributions of the lengths of defect-free areas typically (with one large sample-size exception) exhibit right-side asymmetry and "heavy tails," with high coefficients of variation ($30\% \leq c \leq 110\%$). These results are confirmed by known data on the distribution of DFA lengths for pine blanks of various methods of sawing in Sandberg and Johansson (2006), providing us with acceptable theoretical possibilities for these published empirical distributions. Unfortunately, only qualitative comparison with the Sandberg

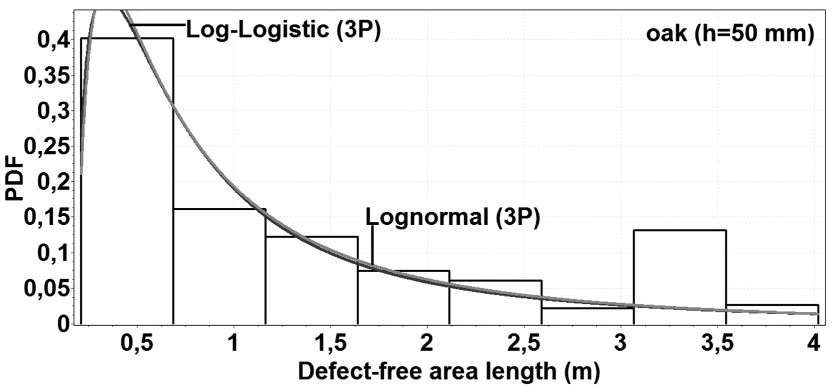

Figure 6. Example of distribution fitted for oak blanks (h = 50 mm) defect-free parts length.

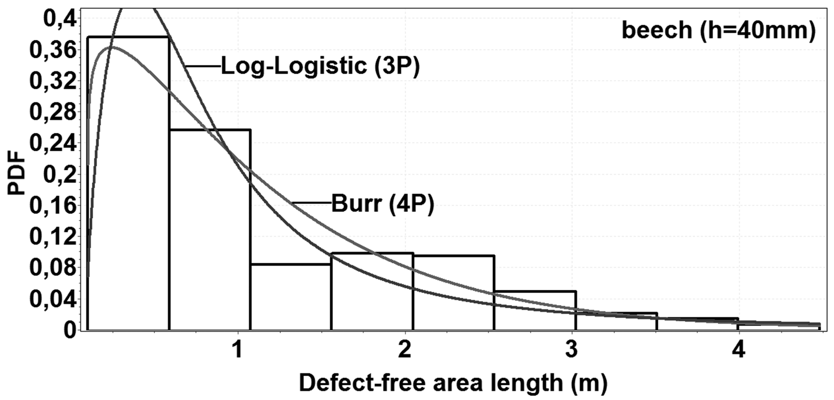

Figure 7. Example of distribution fitted for beech blanks ($h = 40$ mm) defect-free parts length.

and Johansson data is possible since it uses symmetrical confidence intervals for clearly asymmetric distributions. For example, the average length of DFAs in the previous work is more than 120-mm long obtained by "square sawn" method of 417 ± 321 mm. However, neglecting the asymmetry of the distribution leads to the fact that the confidence interval includes values which, in principle, do not exist in the sample (417–321 = 96). In addition, the use of the term "arithmetic mean" itself in the case of very asymmetric distributions (far from normal) is incorrect; in such cases, median values should be used.

A similar situation is observed in our case—the arithmetic mean of DFA lengths is not an appropriate measure for description of any of the investigated samples, except, perhaps, for the largest sample of DFA lengths of pine wood blanks of width $h = 78$ mm (Tables 1 and 3). To describe the dimensional and qualitative characteristics of blanks, not only characteristics of location must be used, but also the relative characteristics of the dispersion. Perhaps in the case of a very large sample size, the normal (or other stable) distribution will be a better fit, and the arithmetic mean may be a more appropriate estimator.

To avoid the calculation of asymmetric confidence intervals, it is possible to move from estimates of the dispersion parameters variability to inverse characteristics of stability (invariability). This assessment can be, by analogy with the Sharpe ratio (Sharpe 1992; Lo 2002; Loth 2016; Pav 2016), the value inverse of the coefficient of variation. Or, by analogy with the theory of automatic lines (Dudyuk et al 1998), the nearest large entire quantity inverse of the squared coefficient of variation (Table 6). Since the squared coefficient of variation is a measure of dispersion, variability, then it is logical to call the inverse to it as a "stability coefficient" K:

Table 6. Estimate of variability and stability of DFA length.

	Softwood			Hardwood		
	h, mm			h, mm		
Estimation	90	50	78	90	50	40
c	0834	1142	0279	0827	0794	0807
1/c	1199	0876	3584	1209	1259	1239
$\lceil 1/c^2 \rceil$	**2**	**1**	**13**	**2**	**2**	**2**

DFA = defect-free areas.

Table 7. Distribution fitted for defect-free area lengths of softwood blanks.

		Chi-squared	
Blank width h, mm	Distribution	χ^2	$\chi^2_{0.05}$
50	Burr	11.710	15.507
	Frechet (3P)	14.127	
	Log logistic (3P)	14.692	
90	Log logistic	9.647	14.067
	Lognormal	10.644	
	Weibull (3P)	11.095	
	Dagum (4P)	13.048	
78	Burr	16.174	18.307

Table 8. Verification of statistical hypothesis about the possibility of describing pine blanks defect-free area length using normal distribution.

Deg. of freedom	10				
Statistic (χ^2)	40787				
P-Value	12306E-5				
α	0,2	0,1	0,05	0,02	0,01
Critical Value χ^2_α	13442	15987	18307	21161	23209
Reject?	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

$$K = \left\lceil \frac{1}{c^2} \right\rceil = \lceil 1/(S/\bar{x}^2) \rceil = \left\lceil \frac{\bar{x}^2}{S} \right\rceil \quad (2)$$

where c is the coefficient of variation, S is the variance, x is arithmetic mean, and $\lceil \cdot \rceil$ is the nearest large integer value.

This newly defined metric K makes it particularly easy to compare the results obtained for sawn timber of different origin, with different dimensional and qualitative characteristics, obtained by different methods of sawing or of different wood species. For example, in our case, one may state that the average length of DFA obtained from pine blanks of width 78 mm (Table 2) is less than from blanks of any other width, but it is substantially more stable (by 13 times) than from blanks of width 50 and 90 mm (Table 6). This is attributable to a significantly smaller range of the sample variation, which is due to the fact that the blanks were cut out of very low-quality lumber that did not have long defect-free areas.

Distribution Identification

Here we deliberately avoid the term "distribution fitting" because our goal is not to find the theoretical distribution that "best" describes specific empirical data, but to identify the type of distribution that is equally suitable for all data studied. The procedure of selection of the theoretical distributions for each sample, as mentioned earlier, is no more than a tool to establish one or two types of suitable theoretical distributions. Following the above-described methods, let us test the hypotheses for the possibility of describing our data by every known theoretical distribution. Partial results are shown graphically in Figs 2-7.

The results are summarized in Tables 7-9, where χ^2 is the calculated value of the Pearson's criterion, and $\chi^2_{0.05}$ is the critical value of criterion for significance level $\alpha = 0.05$. It should be noted that even in the case of a very large sample with a small deviation (the lengths of DFA for pine blanks of width 78 mm), a normal distribution

Table 9. Distribution of defect-free area lengths fitted for hardwood blanks.

		Chi-squared				Chi-squared	
h, mm	Distribution	χ^2	$\chi^2_{0,05}$	*h*, mm	Distribution	χ^2	$\chi^2_{0,05}$
90	Exponential	3.8423	14067	50	Gamma (3P)	11.18	14.067
	Johnson SB	4.7514			Log logistic (3P)	13.297	
	Loglogistic (3P)	6.3441			Lognormal (3P)	13.768	
	Pearson 6 (4P)	6.5463		40	Fatigue Life	10.5	15.507
	Gen. Gamma (4P)	6.6763			Johnson SB	10.973	
	Lognormal (3P)	6.7614			Fatigue Life (3P)	10.992	
	Pearson 5 (3P)	8.0596			Dagum	12.52	
	Frechet (3P)	8.6369			Lognormal (3P)	13.729	
	Dagum	8.7995			Log logistic (3P)	13.823	
	Gamma	8.9089			Frechet (3P)	13.98	
	Gen. Gamma	9.6765			Inv. Gaussian (3P)	14.018	
	Gen. Extreme Value	11.357			Burr (4P)	14.227	
	Burr	11.59			Weibull (3P)	14.23	
	Frechet	11.743			Pearson 6 (4P)	14.792	
	Lognormal	12.825			Pearson 5	14.801	
	Erlang (3P)	13.544			Gamma (3P)	14.809	
	Exponential (2P)	13.545			Gen. Gamma (4P)	15.298	
	Log logistic	13.558			Pert	15.339	

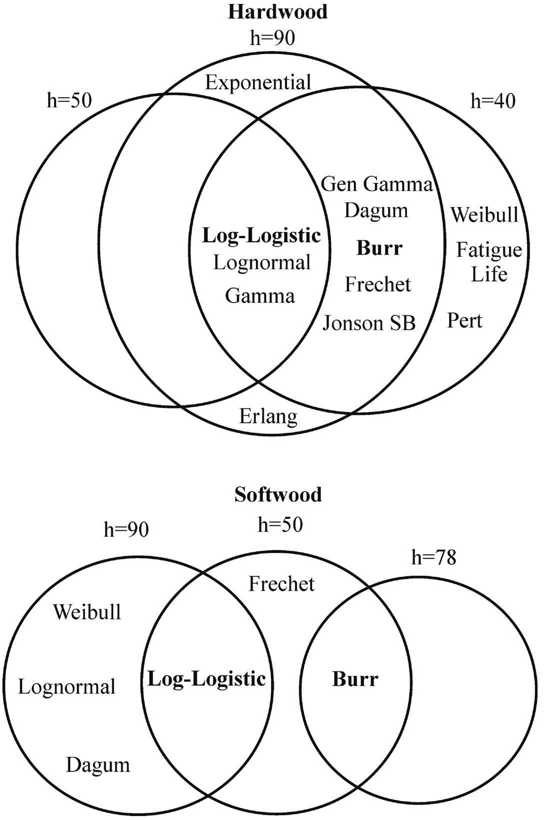

Figure 8. Venn diagram for distributions of defect-free area lengths.

(Fig 4) cannot be applied, since the calculated value of Pearson's criterion is higher than critical for any level of significance (Table 8).

Thus (Tables 7 and 9), we can detect many "suitable" theoretical distributions for each sample. On finding the intersection of these sets, it is possible to detect the distributions that are suitable for all, or at least for most of the samples. This procedure is graphically represented in Fig 8 in the form of a Venn diagram.

As can be seen from the Venn diagram (Fig 8), the log-logistic distribution and the Burr distribution (Tadikamalla 1980; Lindsay at al 1996; Al-Dayian 1999; Gove et al 2008) are always at the intersection of all (both hardwood and softwood) sets, that is why it is these distributions that should be used for theoretical description of DFA lengths. Moreover, where possible, preference should be given to the log-logistic distribution, since its parameters explicitly include minimum length of DFA. Since analytical inverse functions are known for both types of distributions (Mathwave 2015), these distributions are easy to apply for the needs of simulation modelers of crosscutting lumber into defect-free areas.

PDF of these distributions are summarized in Table 10 and distribution parameters in Table 11.

CONCLUSIONS

Large variability in the lengths of defect-free areas of blanks and different conditions of production of blanks from various species of wood perhaps make it impossible to uniquely specify only one theoretical distribution law. But the distribution of lengths of DFA for pine, oak, and beech blanks can be only described entirely by two theoretical distributions—the Burr and log logistic, with different parameters for different wood species and various sizes of defect-free areas as determined in this study and provided in Table 11.

For the average numerical characteristic of DFA lengths, it is preferable to use the median

Table 10. Distributions of defect-free area length.

Distribution	Parameters	Probability density function, f(x)
Log logistic	α: shape parameter ($\alpha > 0$) β: scale parameter ($\beta > 0$)ss γ: location parameter; $\gamma \le x < +\infty$	$\frac{\alpha}{\beta}\left(\frac{x-\gamma}{\beta}\right)^{\alpha-1}\left(1+\left(\frac{x-\gamma}{\beta}\right)^{\alpha}\right)^{-2}$
Burr	k: shape parameter ($k > 0$) α: shape parameter ($\alpha > 0$) β: scale parameter ($\beta > 0$) γ: location parameter; $\gamma \le x < +\infty$	$\frac{\alpha k\left(\frac{x-\gamma}{\beta}\right)^{\alpha-1}}{\beta\left(1+\left(\frac{x-\gamma}{\beta}\right)^{\alpha}\right)^{k+1}}$

Table 11. Defect-free area length distribution parameters.

No.	Wood species		Width of blanks h, mm	Distribution	Parameters
1	Softwood	Pine	90	Log logistic	$\alpha = 2.982$; $\beta = 0.465$; $\gamma = 0.0$
2			50	Log logistic	$\alpha = 1.210$; $\beta = 0.331$; $\gamma = 0.208$
				Burr	$k = 0.165$; $\alpha = 6.734$; $\beta = 0.278$; $\gamma = 0.0$
3			78	Burr	$k = 48.055$; $\alpha = 4.030$; $\beta = 1.049$; $\gamma = 0.0$
4	Hardwood	Oak	90	Log logistic	$\alpha = 1.189$; $\beta = 0.494$; $\gamma = 0.202$
				Burr	$k = 1.254$; $\alpha = 1.861$; $\beta = 0.936$; $\gamma = 0.0$
5			50	Log logistic	$\alpha = 1.288$; $\beta = 0.661$; $\gamma = 0.206$
6		Beech	40	Log logistic	$\alpha = 1.658$; $\beta = 0.688$; $\gamma = 0.094$
				Burr	$k = 1759.10$; $\alpha = 1.117$ $\beta = 858.05$; $\gamma = 0.102$

value and "stability coefficient" of length (the reciprocal to the squared coefficient of variation). This will enable one to correctly compare samples obtained at different enterprises and from different wood species, to evaluate the performance of lines of the optimization crosscutting and predict the structure (uniformity) of the already finished glued boards. The identified type and distribution parameters for defect-free areas are used (Matsyshyn et al 2014) for simulation modeling and optimization of lumber crosscutting operations.

Further research may be associated with parameterization of theoretical distributions of DFA in terms of recording analytical expressions for the density and distribution functions directly through the dimensional characteristics of DFA. It is obvious that the results obtained here still cannot be extended to all possible choices of the random distribution of the lengths of defect-free areas, so the collection and analysis of experimental data about the lengths of DFA blanks from other species of wood and blanks obtained by other methods of cutting should be continued. In addition, since the research concerned small sample sizes, further studies of the behavior of DFA length distributions with increasing samples are needed.

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