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Potential for improving sawing performance in low-technology environments: Insights for decision-support in Uganda's plantation sawmills

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Abstract

Optimizing sawing decisions in timber processing is a challenge due to the multiplicity of variables involved. This is more pronounced in developing countries, characterized by low-technology environments and reliance on human judgment to make sawing decision, leading to inefficiencies and reduced profitability. This study evaluated the potential for improving timber volume and value recovery in plantation forests through use of decision support tools. A quasi-experimental approach was used, analysing logs processed under normal sawmill operations. Data on log and timber sizes were collected to compare empirical and simulated outcomes, the latter being based on mathematical models that can be integrated in decision support tools. The difference in timber volume and value recovery was tested using an independent t-test at a 5% significance level. Results indicate that the simulated sawing operations yielded improved performance compared to empirical outcomes, with timber volume recovery increasing from 41% to 45% while timber value recovery rose from 218,940 UGX/m³ to 330,135 UGX/m³. This represents potential gains of 10% in volume recovery and 51% in value recovery.

These findings demonstrate that there is potential for enhancing plantation sawmilling performance through use of decision support tools. Further research is recommended to validate simulation results and to assess the cost and productivity implications of integrating decision support tools in sawing operations.

Key words: Decision-support, developing countries, sawmilling, value-recovery, volume-recovery

Introduction

The performance of sawing operations is a subject of concern worldwide owing to its impact on efficiency and sustainability of sawmilling operations. Metrics that are commonly used to assess sawing performance include timber volume recovery, timber value recovery, and throughput or processing rate (Zhang and Tong, 2005; Mendez and Pasiecznik, 2015; Quebec *et al*. 2015). Improvements in these metrics can enhance sawmill profitability owing to increased output of usable timber. Advancements in technology, such as computerized sawing systems and optimization tools, have contributed to significant improvements in sawing performance, particularly in developed countries (Howard, 2022). However, in many developing countries characterized by low-technology environments, sawing operations continue to rely on manual decision-making. This leads to use of suboptimal sawing patterns that result into higher wastage, increased pressure on forest resources, and reduced economic viability of plantation forestry (Lindner amd Wessels, 2015; FAO, 2020).

Timber value and volume recovery in sawmills depend largely on the quality of sawing decisions (Donald *et al.*, 2001; Morneau-Pereira *et al*., 2013; Vergara *et al*., 2015). Sawing decisions are influenced by numerous variables, including log quality, machine characteristics, sawyer skills, market dynamics, and timber regulations (Lindner *et al.*, 2013; Vergara *et al.*, 2015). The quantity and dynamic nature of these variables leads to a complex decision-making environment, making it challenging for sawyers to optimize sawing performance manually. However, in high-technology environments especially in developed countries, computerized decision-support tools are integral to sawmilling systems enabling sawyers to simulate sawing processes, optimize sawing patterns, and achieve timber volume recovery rates of up to 60% (Palmer, 2010; Lindner *et al.*, 2013; Lindner and Wessels, 2015; Howard, 2022). Conversely, sawmills in low-technology environments particularly in developing countries, including Uganda, lack access to such technologies. Consequently, sawing decisions rely on manual judgment, constrained by limited training and resources, resulting in poor performance with timber volume recovery rarely exceeding 40% (Mwamakimbullah, 2000; Turinawe and Mulimba, 2017; Ngobi, 2019).

Thus, the absence of decision-support tools in low-technology environments presents a significant constraint to sustainable wood utilization in developing countries. While high-technology solutions are unsuitable for such contexts due to cost and resource constraints, the potential of low-cost, accessible tools to improve sawing efficiency remains unexplored. This study evaluated the potential for improving timber volume and value recovery in plantation sawmilling in Uganda by comparing the empirical to the simulated sawmill performance. Simulated performance was based on mathematical models that can be incorporated into a decision-support tool.

Methodology

Study site

The study was conducted at a processing facility located in Mayuge District, in Eastern Uganda. With respect to the geographical demarcation of plantation forests in Uganda (SPGS, 2020), the study site is located within the Eastern Cluster with pines as the dominant trees grown. The processing facility employs a semi-permanent sawmill with an annual rated throughput of 35,000 m^3. The main processing line consists of a twin vertical bandsaw blade headrig, a single vertical bandsaw and a 6-head horizonal multi-rip while the recovery line has a 2-head horizontal resaw and an edger. At the sawmill, logs were grouped in the log yard based on top diameter. The top diameter of each individual log within a diameter class were written on the small end using a crayon. The log classes were further assorted depending on log length (4 m and 5.4 m).

Study design

The study determined and compared theoretical and empirical timber volume and value recovery of the sawmill studied, while producing a prevailing timber order comprised of timber of size 100 mm x 100 mm x 4 m with a total volume of 75 m^3 within a target period of 10 days. Empirical performance was ascertained using a quasi-experimental approach under normal sawmilling operations to meet the prevailing timber order. On the other hand, theoretical performance was deduced basing on simulation, using optimization-based decision rule, applied to the available log stock to produce the same prevailing order whilst maximizing timber volume recovery. Thus empirical and theoretical performance data were generated from independent milling strategies applied to the same log-stock and timber-order requirements and as such were treated as independent samples.

Sampling and data collection

The study sawmill was purposively selected based on ease of accessibility and resource constraints. Prevailing timber orders were obtained from the mill and categorized by customer names. The sawmill produced timber based on a pull production approach and targeted one customer at a time. The primary timber order at the time of the study was identified and the size, quantity and time required to deliver the timber were noted.

The number of logs available per diameter class with similar length to the primary ordered timber size (4m) were ascertained. The top diameter of each log empirically sawn by the sawmill to meet the order and the number of timber pieces produced for each nominal dimension were noted. The log butt end diameter and bark thickness of systematically selected logs were measured using a calliper and measuring tape. Bark thickness was measured from the log top end diameter. The sampling interval aimed at obtaining a sample of at least 90 logs over a three-day period. The sampling interval was determined using Equation 1 as in Ngobi *et al.* (2023).

$$\mathrm{SI} = \frac{\mathrm{N_q} * \mathrm{N_d}}{\mathrm{N_l}} \quad \text{.......... (1)}$$

Where:
SI = Sampling interval
N_l = Number of logs targeted for sampling
N_q = Average number of logs sawn per day
N_d = Planned study period at the sawmill

Thus, basing on an average throughput of 500 logs per day, a study period of 3 days, and a target sample of 90 logs, a sampling interval of 16 was used. The starting sample log was the first log on the log deck for the day; therefore, data on log butt end diameter and bark thickness were collected from a total of 106 logs.

The daily mill intake, unit milling cost, mill operational hours and the unit price of each timber size produced at the sample sawmill was also ascertained from the sawmill.

Data analysis

The average empirical timber volume recovery percentage (E_t) was calculated using Equation 2.

$$\mathrm{E_t} = \frac{\sum_n \frac{\mathrm{V_t}}{\mathrm{V_l}} * 100}{n} \quad \text{.......... (2)}$$

Where:
V_l = volume (m^3) of log sawn,
V_t = volume (m^3) of timber produced
n = total number of logs sawn to meet the timber order
Volume of each log sawn was determined using Smalian's formula (Equation 3).

$$V_l = \frac{\pi(s^2 + d^2) * L}{8 * q} \quad \text{......} (3)$$

Where:
V_l = volume (m^3) of each log sawn
s = small-end log diameter (cm),
d = Average butt-end log diameter of the log class (cm),
L = log length (cm),
q = units conversion factor ($1x10^6$)
Volume of each timber produced was determined using Equation 4.

$$V_t = \frac{\sum n_i w_i h_i L_i}{q} \quad \text{......} (4)$$

Where:
V_t = volume of timber (m^3)
n_i = number of pieces of timber of nominal dimension i produced,
w_i = nominal width (mm),
h_i = nominal thickness (mm),
L_i = nominal length (mm),
q = conversion factor ($1x10^9$),

Empirical timber value recovery was calculated using Equation 5.

$$E_r = \frac{\sum_n \frac{R}{V_l} * 100}{n} \quad \text{......} (5)$$

Where:
E_r = empirical timber value recovery
n = number of logs sawn
R = total timber revenue (UGX) of produced timber pieces, which was calculated using Equation 6

$$R = \sum P_i n_i \quad \text{......} (6)$$

Where:
P_i = price (UGX) per piece of timber with nominal dimension i,
n_i = number of timber pieces with nominal dimension i produced.
Simulated timber volume recovery was calculated from Equation 7.

$$S_t = \frac{\sum_k \frac{V_{tk}}{V_{lk}}}{n} * 100\% \quad \text{(7)}$$

Where:
S_t = Simulated timber volume recovery
V_{lk} = optimal volume (m^3) of logs with top diameter k sawn,
V_{tk} = simulated timber volume (m^3) produced from logs with top diameter k

The optimal log volume that had to be sawn for each top diameter to meet the timber demand while maximizing timber volume recovery was determined through a three-step simulation process as follows:

Step 1: Determining volume of log stock for each top diameter
Total log volume (V_k) per top diameter available at the sawmill was calculated from Equation 8.

$$V_k = V_{lk} * n_k \quad \text{(8)}$$

Where:
n_k = number of logs with top diameter k

Step 2: Determining optimal sawing pattern per log top diameter
Possible sawing patterns for each log top diameter were determined using sawing pattern optimizer that was developed by Ngobi *et al*. (2024). The sawing pattern optimizer generates different combinations of timber sizes that can be sawn from each log top diameter assuming a cant sawing method, which was the sawing method used by the study sawmill. For each extractable timber size, the optimizer produced the sawing pattern that maximized timber volume recovery when such a timber was extracted as a centre piece (s) and other timber as either side piece, top/bottom pieces or both.

For each log top diameter, the sawing pattern that contained the ordered timber (100 mm x 100 mm x 4 m) was noted. Where two or more sawing patterns contained the ordered timber, the sawing pattern that yielded the highest volume recovery was selected. Timber volume recovery of the ordered timber from each log top diameter was determined using Equation 9.

$$T_k = \frac{V_{dk}}{V_{lk}} * 100 \quad \text{.......} (9)$$

Where:
T_k = timber volume recovery (%) of the ordered timber from logs of top diameter k
V_{dk} = volume of ordered timber produced from log of top diameter k

Step 3: Determining the optimal log volume to saw from each top diameter
The volume of logs for each top diameter (V_{ks}) that should be sawn to produce the required quantity of the timber in the required time whilst maximizing timber volume recovery was subjected to two constraints as indicated in Equation 10: Firstly, the total volume of timber produced must be equal to the timber volume ordered; and secondly, the total time taken to mill the log volumes of the different top diameters had to be less or equal to the time required to produce the timber.

$$\sum_k T_k V_{ks} = V_d \text{ and } \sum_k \frac{V_{ks}}{P} \leq t \quad \text{.......} (10)$$

Where:
V_d = volume (m^3) of timber ordered (75 m^3)
V_{ks} = Volume of logs of top diameter k that must be sawn
P = Hourly log throughput (m^3/h) obtained by dividing the daily mill intake by the operational hours (9)
t = time (h) available for the sawmill to produce the timber.

Equation 10 was coded using PHP programming language into a module that was run iteratively to obtain all volume combinations that would meet the objective. The volume combination of log top diameters that produced the required timber in the shortest time possible was selected.

The difference in simulated and empirical timber volume recovery was tested using an independent t-test at 5% significance level. This is because the two timber volume recovery outcomes were obtained from independent milling strategies, with no one to one correspondence between individual logs, although the logs were obtained from the same sawmill log stock. Simulated timber value recovery was determined from Equation 11.

$$T_r = \sum_k \frac{n_{jk} R_{jk}}{V_{ks}} \quad \text{.......} (11)$$

Where:
T_r = timber value recovery
R_{jk} = price of timber (UGX) of size j produced from log top diameter k,
n_{ji} = number of timber of size j produced from log top diameter k.
V_{ks} = Optimal volume of logs of top diameter k obtained from Equation 10

The difference in simulated and empirical timber value recovery was tested using an independent t-test at 5% significance level.

Results

The small end diameter of the log stock at the sawmill ranged from 18 cm to 30 cm and their total volume was 641 m^3. The total volume of logs sawn by the sawmill to meet the timber order was 365 m^3 and was higher than the theoretical aggregated top diameter volumes of 271 m^3 that was obtained using simulation. The ordered timber volume comprised 53% of the empirical timber volume produced by the sawmill which was a lower proportion compared to 64% obtained theoretically. Empirical time taken to produce the ordered timber by the sawmill was longer than the theoretical time taken (Table 1).

Table 1. Descriptive summary of available sawmill log stock

Top diameter (cm)	Mean butt end diameter	Number	Volume
18	21	1048	126
19	21	723	96
20	22	326	50
21	24	375	60
23	26	338	64
24	27	341	70
25	29	135	30
27	32	113	29
28	33	281	54
29	35	171	50
30	36	38	12
		3890*	641*

* = Total

The mean empirical timber volume recovery by top log diameter ranged between 32% and 47 % with an average of 41% indicating that the mill consumed 2.4 m^3 of wood to produce one m^3 of timber under normal operating conditions. Similarly, mean empirical timber value recovery by top log diameter ranged between 200,000 UGX/m^3 and 231,000 UGX/m^3 with a sawmill average of about 219,000 UGX/m^3 indicating that each m^3 of logs processed at the sawmill translated into that amount of revenue (Table 2).

Table 2. Descriptive summary of logs empirically milled by the sawmill

Top diameter (cm)	Number	Volume	Order timber produced (m^3)	Total timber produced (m^3)	Overall volume recovery (%)	Overall value recovery (UGX/m^3)
18	1023	123	5.6	9.0	39	220,100
19	715	95	22.4	33.7	35	210,451
20	163	25	4.8	8.1	32	200,731
21	350	56	11.9	21.7	39	214,363
23	63	12	0.5	5.0	42	217,119
24	10	2	17.0	39.4	39	223,459
25	113	25	7.0	12.3	49	221,085
27	74	19	3.9	8.1	43	222,272
29	24	7	1.9	3.3	47	229,238
30	3	1	0.3	0.4	45	230,590
		365*	75*	141*	40*	218,940*

* = Total

On the other hand, the mean simulated timber volume recovery by top log diameter ranged between 29% and 67 % with an average of 45% indicating an improvement of 10% over normal operating conditions. Similarly, mean empirical timber value recovery by top log diameter ranged between 281,000 UGX/m^3 and 372,000 UGX/m^3 with a sawmill average of about 330,000 UGX/m^3 indicating an improvement of 51% over normal operating conditions (Table 3).

The standard deviations of the empirical (7.02) and theoretical timber volume recovery (7.19) were similar indicating comparable variability in the empirical and theoretical volume recoveries. The standard errors were also small (0.03, 0.08) indicating that the mean estimates were reliable. The standard deviation of the simulated timber value recovery rates was slightly higher (37,700) than empirical (32,600). However

Table 3. Simulation optimal volumes of each top diameter sawn

Top diameter (cm)	Volume recovery of order size (%)	Optimal log volume milled (m^3)	Order timber produced (m^3)	Total timber produced (m^3)	Volume recovery (%)	Value recovery (UGX/m^3)
20	27	28	7.5	10.2	34.2	280,731
21	25	30	4.0	5.5	28.8	294,363
23	21	19	7.6	10.5	37.4	317,119
24	19	31	6.0	10.5	33.8	299,459
25	36	30	10.8	14.8	49.3	341,085
27	31	29	9.0	15.7	54.3	352,272
28	29	42	12.2	21.3	50.7	343,354
29	27	50	13.6	26.3	52.5	372,238
30	38	12	4.6	8.0	66.9	370,590
		271*	75*	122*	45.3*	330,135*

* = Total

standard errors for both the empirical and simulated timber value recovery were low, indicating reliable estimate of the means (Table 4)

An independent t-test indicated a significant difference (p =0.00) between empirical timber volume recovery and theoretical timber volume recovery of the decision tool. There was also a significant difference (p = 0.00) in empirical timber value and theoretical timber value recovery (Table 5).

Table 4. Group statistics on timber volume and timber value recovery

		Mean	Std. deviation	Std. error mean
Timber volume recovery	Empirical	40	7.023	.0353
	Simulated	45	7.197	.0816
Timber value recovery	Empirical	218940	32600	976
	Simulated	330135	37700	989

Table 5. Independent t-test on timber volume recovery

		df	Sig	Mean difference	Std. error	95% Confidence Interval	
						Lower	Upper
Volume recovery	Equal variances assumed	4043	.00	-4.53	.08	-1.78	-1.92
	Equal variances not assumed	3259	.00	-4.53	.08	-1.67	-1.42
Value recovery	Equal variances assumed	4043	.00	-5100	537	-23000	-17800
	Equal variances not assumed	3259	.00	-5100	558	-22900	-16900

Discussion

A comparative evaluation between empirical and theoretical timber volume recovery indicates a 10% potential improvement in volume recovery that can be achieved when a decision support tool is used. This is like results by Vergara et al. (2015) where timber volume recovery of all the five different mathematical sawing approaches i.e., profit maximization, log number minimization, cost minimization, production time minimization and waste minimization were higher than volume recovery of the base plan. The lower empirical volume recovery can possibly be attributed to the fact that the sawmill used a higher volume of logs to produce the 75 m^3 of 4 x 4 x 13 ft that was required in 10 days. The sawmill sawed 365 m^3 of logs compared to the 271 m^3 obtained using the decision support tool. This indicates that the log volume required to produce the required timber could potentially be reduced by 26%.

The higher log volume sawn by the sawmill might be attributed to both inappropriate selection of log classes from the available pool and poor allocation of sawing patterns to some log classes. As Ngobi (2019) reported, each log class has a sawing pattern that yields the maximum volume recovery. Furthermore, each sawing pattern might yield a different volume of the ordered timber per log. A sawyer is required to ensure that the correct log class is sawed with the correct sawing pattern, a paradox that can be seldom solved manually by sawyers (Lindner, 2014).

The poor allocation of sawing patterns by the sawyer might also have resulted into underproduction of the ordered timber and overproduction of recovery timber. The ordered timber comprised only 53% of the total timber produced by the sawmill and this was a lower proportion compared to the 64% obtained by using the decision support tool. Todoroki and Rönnqvist (2002) also asserted that underproduction of demanded timber can be reduced by better allocation of sawing patterns to logs. Sawing patterns that result into overproduction of ordered timber and underproduction of recovery timber should be desired since recovery timber is often kept in stock and might eventually be sold at lower prices due to low demand. Furthermore, such sawing patterns might produce the ordered timber volume in the shortest time possible which reduces the production costs (Carvalho *et al*., 2020). The sawmill took 27 hours to saw the 365 m^3 of logs and produce the required volume of the ordered timber. On the other hand, the sawmill would have taken 20 hours if it sawed 271 m^3 of logs that was indicated by the decision support tool as being optimal thereby reducing the production time by 26%.

Given the unit milling cost of 117,700 UGX/m^3incurred by sawmill, the empirical milling cost associated with the ordered timber volume was 42,960,000 UGX. On the other hand, the sawmill would have incurred 31,896,000 UGX if it was able to minimize log volume to the 271 m^3 indicated by the decision support tool and subsequently, a 26% reduction in the production costs. The empirical timber value recovery obtained by the sawmill was 218,940 UGX/m^3 and was lower than the theoretical timber value recovery of 330,135 UGX/m^3. Similar to volume recovery, the lower value recovery can be attributed to poor allocation of sawing patterns which resulted into lower timber volumes of timber being recovered from the logs.

Conclusion

The use of a decision support tool indicated a potential improvement of 10% in timber volume recovery, 51% in timber value recovery, 11% in recovery of ordered timber, 11% reduction in log volume needed to meet timber order, 26% reduction in production time and 26% reduction in production costs. However, this study was conducted at a single sawmill, implying that the performance data were derived from milling strategies specific to that mill's operational context including log characteristics, technology used, operator skill, and workflow organization. Hence, the findings are applicable to sawmills that share similar characteristics with the study sawmill. To get more generalizable findings, future research should be conducted across multiple mills representing different technological levels, species, and production environments. Furthermore, there is need to validate the simulated results through extensive testing of other mills and to assess the feasibility of process and technology modifications necessary for adoption of a decision support tool in Uganda's plantation sawmilling operations.

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