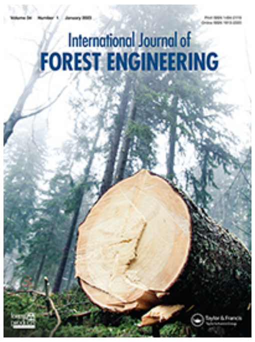

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The need for flexibility in forest harvesting services – a case study on contractors' workflow variations

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ABSTRACT

In many parts of the world, contractors account for the main share of harvesting work. Harvesting is characterized by innate complexity and volatility, and this can affect contractors' workflow and ultimately their profitability. Thus, there is certainly a need for flexibility in harvesting service provision and procedures, but our current knowledge about contractors' workflow variations are limited. This study investigates workflow variations in harvesting services by comparing monthly variations between contractors' workload in terms of harvested volumes and the time spent on operations. The data originates from 77 machines belonging to contractors and their harvesting of 6.6 million m^3 of roundwood in Sweden during a two-year period. The results indicate differences between contractors' workflow variations which can be attributed to the number of machines, machine sizes, and the workload in harvested volume and hours. These findings are relevant for guiding both the customer and contractor in this business relationship, and they could also serve as a basis for further research on the need for flexibility to effectively increase and decrease volume production in harvesting services.

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Contractor; business relationship; profitability; supply chain; harvester; forwarder

Introduction

Like many other countries (see, e.g., the work of Drolet and LeBel 2010; Mac Donagh et al. 2017; Jylhä et al. 2020), the main share of harvesting work in Sweden is done by independent contractors hired by forest companies or forest owner associations to cut and transport the trees from forest to roadside (Ager 2014; Eriksson 2016; Erlandsson 2016). In Sweden, the main part of harvesting work was outsourced by forest companies during the 1980s and 1990s, aiming for increased capacity flexibility and decreased fixed capital in machinery for the service-buying companies (Lidén 1995; Ager 2014). Moreover, competitive forces among the service-providing contractors were considered to boost the development in harvesting operations. Nowadays, the competitive market forces in harvesting services are weak (Eriksson 2016). There are only a few, albeit large, customers of harvesting services on the market (Kronholm et al. 2019). Typically, contractors rely heavily on a business relationship with a single customer (Kronholm et al. 2021), which has immense influence on the contractor's business model (Benjaminsson et al. 2019).

Contractors providing harvesting operation services play an important role in handling the volatility and complexity of wood supply. Their work affects not only the cost and availability of raw material but also the environmental and social value of forests (Ollikainen 2014). Not surprisingly, customers of harvesting service providers place high demands on their performance (Eriksson et al. 2015; Erlandsson et al. 2017). Contractors' flexibility is highly appreciated in the harvesting service but is experienced by contractors to have negative effects on their own economic viability (Johansson et al. 2021). Flexibility in harvesting operation can mean different things (see, e.g., the work of Gautam et al. 2013; Erlandsson et al. 2017). In this study, contractors' flexibility is viewed according to the Johansson et al. (2021) description as a value attribute in harvesting service, meaning that the contractor adapts to variations and changes according to customer needs. That can, for instance, be customer needs to change the contractor's cutting plan, immediate adjustment of wood assortments and shortening or lengthening of time for harvesting. These needs can result in contractors' machines being utilized in uneven and unexpected levels during the year. Due to high investment costs, a consistent utilization of the machines is important for the contractors' profitability and their ability to provide competitive harvesting services to their customers (Mäkinen 1997; Erlandsson 2016; Erlandsson and Fjeld 2017).

How wood supply is managed by the customer affects the contractors. It is possible to collect detailed information from the machines about the trees, the machine work, and productivity during harvesting. Such information can be used to anticipate the wood flow and ensure that the demanded volumes are delivered on time to the industry despite the complexity of the wood supply chain (Eriksson and Lindroos 2014; Lindroos et al. 2015; Noordermeer et al. 2021). Delivering data to the customer that is produced by the machines during operations is normally a part of the contractors' harvesting services. However, some of this data is undoubtedly sensitive in that it relates to core business activities, and thus there are legitimate concerns about business partners' right to access it; for instance, work time data from machines could be counted as personal data. Legislation and agreements between the parties are some examples of measures

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that regulate the access, right and usage of data. Issues about data protection and ownership of data processed and produced by harvesting machines currently lack clarity (Regulation EU 2016/679; Metsäteho Oy 2017; Kemmerer and Labelle 2020).

Aiming to keep the machines busy, but still with the ability to adjust the wood flow requires that the machines are used in working conditions that meet the desired output of wood quantity. Workflow can be managed in the customer's selection of stands for harvesting in the cutting plan by purposely using the differences in productivity when working in different conditions. For contractors to accept this type of management, the pricing of the work needs to be adjusted for the variations in work conditions. Payment per work time meets this requirement but might in many cases not be preferred by the customer. Payment per produced unit, on the other hand, is considered to promote work efficiency. For this pricing model to adequately compensate for work condition differences, there is a need to adequately predict the productivity of harvesting operations under various work conditions. Moreover, such business models also enable the matching of work conditions to desired wood quantities by selecting harvesting stands based on the predicted time it will take for the contractor to harvest the standing volume. With specialized machines, different conditions within thinning or final felling, respectively, can be chosen to manage the wood flow. Multipurpose machines can be used in both thinning and final felling. This gives opportunities to decrease relocation distances, as well as, rapidly increase or decrease delivered volume by changing between thinning and final felling (Andersson and Eliasson 2004; Erlandsson 2013).

Using productivity predictions to anticipate the wood supply requires accurate data about the forest to be harvested, the machines that will be used, and accurate productivity models. Data acquisition and methods to produce models are constantly being refined (Eriksson and Lindroos 2014; Liski et al. 2020). Even though the increased data quantities and improved qualities provide more reliable predictions, the outcome of a given operation may still deviate due to, for instance, large differences between machine operators (Purfürst and Erler 2011; Häggström and Lindroos 2016; Manner et al. 2016). The information about the forest that will be harvested can be insufficient (Gustafsson 2017) and the ability to handle variations in wood demand by adjusting the work conditions is also limited to the available harvestable stands during a given period (Guatam et al. 2013). Therefore, variations to the planned needs for harvesting services can be expected due to many different sources of uncertainties.

Customers can manage their varying need for harvesting services by hiring some of the contractors on short-term contracts or through spot purchases, but this increases the risk of lacking harvesting capacity when it is needed the most. Therefore, when there is a perceived lack of contractors on the market, it can be beneficial to secure the main, or even the full, share of the estimated annual capacity need on long-term contracts and then restructure the fleet of contractors to be tolerant to wood demand variations (Erlandsson 2016).

In general, profitability in the harvesting service sector is low, although it varies between different contractor groups (Kronholm et al. 2019, 2021). A study in Finland found that larger companies were more profitable in providing harvesting services. Profitability was attributed to their capacity to deliver large amounts of volume, versatile services, negotiation power and cost-effective operations (Jylhä et al. 2020). In comparison, contractors in Sweden are smaller (Häggström et al. 2013) and have, in general, weak negotiation power against their customers (Eriksson 2016; Kronholm et al. 2019). The service-buying companies also have leverage to affect the contractors' business models by influencing resource investments and their service delivery (Benjaminsson et al. 2019). Therefore, if there is a need for contractors' flexibility, then the customers should have an interest to enable it and at the same time promote contractors' profitability. Business management skills have also been cited as a reason behind contractors' profitability (Ollonqvist 2006; Jylhä et al. 2020), as well as good performance in harvesting services (Drolet and LeBel 2010). Thus, the need for flexibility in harvesting services is also a concern for the contractors themselves to handle. Success in this endeavor will lead to profitability and to the provision of competitive harvesting services to their customers.

How much flexibility different contractors actually need to manage has so far been barely investigated. Therefore, this study investigated contractors' workflow variation and identified differences between contractors. Specifically, this study measures the level of variation in contractors' workload between months in terms of wood volumes handled and time spent on the operation, and compared contractors' level of variation depending on their total workload, number of machines, and the type and size of the machines.

Materials and methods

This study was based on data from a forest company operating in central Sweden, with a large part of its harvesting work outsourced to contractors.

Data collection

Data on contractors' harvesting work during the calendar years of 2018 and 2019 were collected from the forest company's records stored in its IT system. To derive machines' monthly variation in harvesting volume, data about reported volumes were extracted per machine, stand, and date. The data was reported per day but aggregated per month in the data extraction. Moreover, information about type of operation, estimated productivity, reported time and compensation for other harvesting work, and hourly compensation rates were extracted to enable the derivation of machines' monthly variation in terms of work time. The information in the dataset also included machine size and type, and to what contractor the machine belonged (see Table 1). All data on log volumes were reported in solid cubic meters under bark (m^3).

The volumes were either automatically recorded from the machines or manually entered by the machine operator. In some cases, the reported volume was negative for a given stand in a month, which indicated a correction of previously reported volumes. All negative volumes were therefore transferred to the same machine and stand in the previous month, meaning that the reported volume for the machine and stand was reduced by the corresponding volume.

Estimated productivity was recorded for normal machine work in final felling and thinning and was used by the forest company to reimburse the contractors for the harvesting work. The productivity rate was defined as volume of logs produced per productive machine hour including downtime of a maximum 15 minutes per occasion (m^3/PMh_{15}). The estimated productivity rates used in the analysis were determined by the forest company as a mean value per stand and based on information about productivity-affecting factors, for instance mean stem size, based on data available after harvesting. Multiple productivity rate registrations for the same machine and stand occurred in 578 out of 40,546 cases. All duplicates were reduced by keeping only the latest updated value. Hours of normal work was calculated for each machine, stand and month by dividing the reported volume by the estimated productivity rate for the corresponding machine and stand.

The dataset also contained information defined as "other harvesting work," mainly about payments related to the machine-specific work of such a character that was not recorded or paid for as normal harvesting work in final felling or thinning. Such other harvesting work could be e.g. different actions for nature, cultural and social considerations, as well as salvage loggings after windstorms. This data was manually registered by the contractor either as a monetary sum or in number of work hours, and accepted by the production supervisor. Negative values in the monetary sum and number of hours were controlled with respect to associated notes. Most of the notes indicated repayments or resets for previous time reports. In such cases, the values for the stand and machine in question were reduced with the corresponding value. Normally, the time reporting for other harvesting work was done in connection with the summary for the month's invoicing, which was normally done on one of the first five workdays of the following month. Therefore, all time for other harvesting work and extra compensation reported on one of the first five workdays of a month were transferred to the previous month to represent the month in which the work had actually been carried out.

For cases in which contractors reported other harvesting work as a monetary sum, the corresponding work times were derived by dividing the sum by the hourly compensation rate unique for the specific machine, month and type of operation. Hours of other harvesting work was then derived for each machine on each stand and month. For the analysis, the reported volume and derived hours were aggregated and handled on a monthly basis.

The dataset also included information about machine sizes, classified by the service-buying forest company based on machine weight for harvesters and load capacity for forwarders. The machine weight for small, medium and large harvesters was <12 tonnes, 12–18.9 tonnes and >18.9 tonnes, respectively. The load capacity for small, medium and large forwarders was <12 tonnes, 12–16 tonnes and >16 tonnes, respectively.

Data reduction

The extracted data were, of course, initially entered into the company's systems for operational purposes and not for the purpose of this study. It was also a mix of data being manually entered into the system by different persons or automatically recorded from the machines. Thus, the occurrence of data errors was considerable, and this flaw had to be handled in order to get as reliable a reconstruction of the volume and time workflow as possible. To be able to investigate the workflow at machine level, it was important that the included machines had produced reliable data during the studied period. Therefore, the original data was refined by removing machines that did not meet the criteria of the three steps below. The aim being to minimize the effect of poor data quality on the results (Table 1).

Step 1: study time coverage

This step was to ensure that the included machines had operated for the main part of the studied period. Only machines for which volume had been reported for at least 22 of the studied 24 months were included in the analysis. Two months absence from operations was accepted due to the possibility that many machines that continuously operated for the customer could still be having long periods of inactivity. For instance, the risk of forest fires was exceptionally high during summer 2018, and machine operation in the forest was therefore not allowed at many locations. It was also taken into account that some contractors and their operators may have four continuous weeks of vacation per year, without hiring any substitute operators. Step 1 resulted in more than half of the machines, just about one-fifth of the total volume and one-fourth of the total time being removed from the dataset.

Table 1. Data quantities before and after data reduction.

Variable	Before reduction	After reduction	Description
Types of operations (n)	3	3	Final felling, Thinning, Other harvesting work.
Machine type (n)	2	2	Harvester, Forwarder
Machine size (n)	3	2	Small, Medium, Large
Months (n)	24	24	January 2018–December 2019
Forest stands (n)	9,700	4,300	Number of different stand identification numbers (rounded to hundreds).
Machines (n)	408	77	Number of different machine identification numbers.
Contractors (n)	130	39	Number of different contractors.
Volume (million m^3)	17.5	6.6	Cubic meters of solid wood under bark in total for all machines the whole study period.
Work time (million PMh_{15})	1.1	0.4	Estimated productive machine hours including downtime of maximum 15 minutes per occasion in total for all machines throughout the whole study period.

Step 2: completeness of work time estimations

The second step was to ensure that it was possible to determine the total number of worked hours. In some cases, the productivity rate and/or hours of other work was missing although volumes were reported. The reasons for the missing data could be, for instance, pure errors but also because of deliberate unconventional data recording for solving operational matters. The missing data meant that worked time by a machine would be either impossible to determine or seriously underestimated. Therefore, it was decided that the data completeness regarding estimated productivity rate and/or hours of other harvesting work on the reported volume for the machines should be high in order to keep them in the dataset.

Due to different productivities in the different types of operations (Table 1) it was considered to be insufficient to solely reduce machines based on the proportion of volume without an estimated productivity rate and/or hours of other harvesting work. Therefore, the time for the volumes with missing data was estimated in each month by dividing the volume, distributed on types of operations by the machine's mean volume weighted productivity during the total period for the corresponding types of operations (Table 1). If the total estimated missing time for a month corresponded to more than 10% of the reported estimated time for the month, the machine was excluded from the study. The estimated missing time was handled on a monthly basis because of the risk that a substantial amount of the unreliable time occurred during one or a few months, with a high impact on specific months. The level of 10% was set due to the observation that the main part of machines had been treated with a "special solution" resulting in the absence of some estimated productivity data and/or reported hours during the studied period. That can be explained by the long period, and the fact that all machines harvested many stands during this period. In normal operations, it is likely that situations which need "special solutions" will be encountered. Thus, tolerating up to 10% of unreliable time per month resulted in a set of machines with a relatively low and similar proportion of unreliable time. Step 2 resulted in almost half of the machines, volume and time remaining from step 1 removed from the dataset.

Step 3: quality of reported data

The third step of data reduction focused on ensuring good quality in terms of the reporting of data used to derive monthly volume and time for the machines. This reduction step consists of four parts.

Step 3, part 1, was set to ensure that the reported volume from the machines corresponded with the volume from the independent measurement organizations. That was done by comparing the reported volume for each machine with the volume recorded by industry or at a terminal by an independent wood measurement organization and registered for legal and payment purposes. Reported volumes were almost always lower than the volumes registered at the terminal or industry (see Figure 1). One possible reason for this may be that the contractors prefer to get an additional payment at a later stage, rather than incur a debt with the customer. Due to this frequent and systematic difference, up to 15% higher volume registered by industry than finally reported was accepted. All machines with 16% and higher differences were excluded. Step 3, part 1, resulted in 7% of the machines (Figure 1), and 4% of the volume and time remaining from step 2 removed from the dataset.

Step 3, part 2, was to ensure that the estimated time to harvest or extract the reported volume was realistic. Each machine's volume weighted mean productivity for the study period was calculated and compared to each other. This indicated the existence of some outliers. Hence, based on the observed clustering of mean productivities and comparison with documented long-term productivity levels (e.g. Eriksson and Lindroos 2014), machines with mean productivities of more than 40 m^3/PMh_{15} were excluded. Step 3, part 2, resulted in 6% of the machines (Figure 1), 6% of the volume and 5% of the time remaining from step 3, part 1, removed from the dataset.

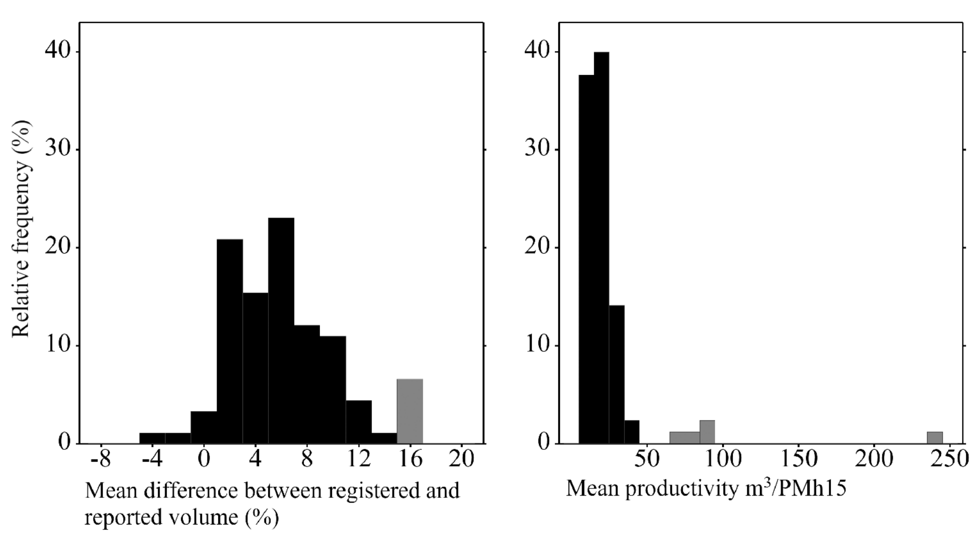

Figure 1. Data reduction of machines based on difference between volume registered by industry in relation to reported volume (N = 91 machines before outlier reduction) and mean productivity (N = 85 machines before outlier reduction, which also represent the number of machines after reduction based on mean correction). The gray bars illustrate the outliers of machines that were removed from the dataset.

Step 3, part 3, was conducted to ensure the reliability in the time report for the hours of other harvesting work. Two of the remaining machines from step 3, part 2, had unknown negative values in this time report and were therefore excluded from the dataset.

Step 3, part 4, was performed so that the time variation was realistic for the remaining machines from step 3, part 3. One machine deviated with an unusually high work time for one month (661 PMh_{15}) compared to the machine's mean monthly work time (170 PMh_{15}). That machine was not close to that amount of time during any other month. Moreover, the high work time would basically require the machine to work continuously for the whole month, since 24 hours of work during 30 days gives 720 hours. Hence, the recording was considered unrealistic and the machine was excluded.

The remaining dataset

The 77 remaining machines accounted for 19% of the machines, 38% of the total harvested volume and 36% of the total time in the original dataset (Table 1). In the original dataset, 3.4% of the machines were of small size, 67.4% of medium size and 29.2% of large size. All small size machines had been reduced in the first data reduction step because none of them operated continuously for the customer, and, thus, the remaining machines were of medium and large sizes. Medium machines operated mainly in thinning, but some were also put to final felling, while large size machines worked mainly in final felling. The volume in different types of operations (Table 1) also differed between machines. The analysis had to account for the machines' different workflows in volume and time in order to make their variations comparable.

Data analysis

The analysis was done with two main variation focuses (Performance variation and Workflow variation) and on two main aggregation levels (individual machines and contractor). For analysis at the contractor level, the volume and time on the machines owned by the same contractor were aggregated per month for the corresponding contractor. The statistical analysis was carried out in Minitab 18, with the significance level set to 5%.

Performance variation

Relative monthly performance variation for a machine was calculated by comparing monthly values with the mean value for the studied period, for both volume and time as well as for individual machines and for contractors. This created monthly performance variation values that were normalized to the performance of individual machines or contractors and were therefore comparable between machines or contractors.

Seasonal differences in relative performance variation in volume and in time were analyzed by one-way Analysis of Variance (ANOVA) with Tukey pairwise comparisons, with months as fixed main effect (with 24 levels). Relationships between relative volume and time variation were analyzed by use of Pearson correlations.

Workflow variation

The coefficient of variation (CV) was used to establish a single value per machine or contractor for the workflow variation during the studied period. CV is a relative measure of variation, in which the standard deviation is put in relation to the mean value. This created workflow variation values that were normalized to the workflow of the individual machine or contractor and were therefore comparable between machines or contractors. The workflow variation in volume will from hereon be expressed as CV_{volume} and workflow variation in time as CV_{time}.

A Pearson correlation was used to analyze relationships between CV_{volume} and CV_{time}, for all machines, as well as within groups based on machine size and type. Similarly, relationships between CV_{volume} and CV_{time} were also analyzed for all contractors, as well as within groups based on how many and what type of machines the contractor owned. Moreover, a Pearson correlation was used to analyze relationships between CV_{volume} and total work time and total volume, respectively, for the whole studied period. One-way ANOVA with Tukey pairwise comparisons were used to analyze differences in CV_{volume} and CV_{time}, respectively, between contractors having one, two or more than two machines (i.e. contractor size as fixed effect, with three levels).

Results

Performance variation

When analyzing the performance variation between months within the 77 machines, there was a large dispersion in both worked time and volume produced. It ranged from the lowest possible relative variation value of −100%, indicating that the machine had not been used or produced any volume at all, to more than 100% – which indicated a value more than double the machine's mean performance during the observed 24 months (Table 2). For all of the studied 24 months, there were many machines that substantially deviated from their mean values. Nevertheless, there were seasonal patterns during which most of the machines

Table 2. Distribution of relative monthly variation within individual machines or for all machines a contractor owned. Since the variation is reported relative to the mean value, the relative mean value is zero for all aggregation levels and variables. The lowest possible relative variation value −100% indicates that the machine had not been used or produced any volume at all that month. N = number of observations, where one observation represents one machine or contractor and one month.

Aggregation level	Variable	N	SD	Min.	Quartile 1	Median	Quartile 3	Max.
Machine	Volume	1,848	37.9	−100	−23.9	0.7	22.4	182.4
	Time	1,848	34.3	−100	−18.9	2.0	21.1	149.2
Contractor	Volume	936	35.4	−100	−21.2	1.9	21.8	152.0
	Time	936	32.5	−100	−16.7	3.4	19.7	130.7

performed above or below their mean volume and time values, with the most notable being the lower relative performances during the spring and summer months (May–July) (Figure 2). The observed significant differences between months (Tukey test, $p < 0.001$) were mainly observed for months in different seasons. However, the largest difference between all 24 months was observed between July and August 2018. For only two months, the machine performances were significantly different between years; performance in both time and volume were significantly higher in May 2018 compared to May 2019, whereas time performance was significantly higher in August 2018 compared to August 2019.

The relative variation of time and volume within months for all of the 77 machines pooled was positively correlated ($r(1848) = 0.78$, $p < 0.001$). The correlation was significant ($p < 0.001$) for all four combinations of machine types and sizes, but with the lowest correlation coefficient value for medium size harvesters and the highest value for large forwarders. Large harvesters and medium size forwarders had both correlation coefficient values similar to the large forwarders. It should be noted that the range of dispersion was considerably smaller for negative values compared to positive values of relative variation (Figure 3).

The dispersion of relative variation decreased when aggregating the machines on the 39 contractors that owned them. The dispersion was highest for the relative volume values, for both machine and contractor levels. The widest dispersion was observed for volume variation on machine level, in terms of standard deviation values, range between minimum and maximum values as well as in terms of range between the first and third quartile values. The lowest dispersion was found for the relative time variation on the contractor level (Table 2).

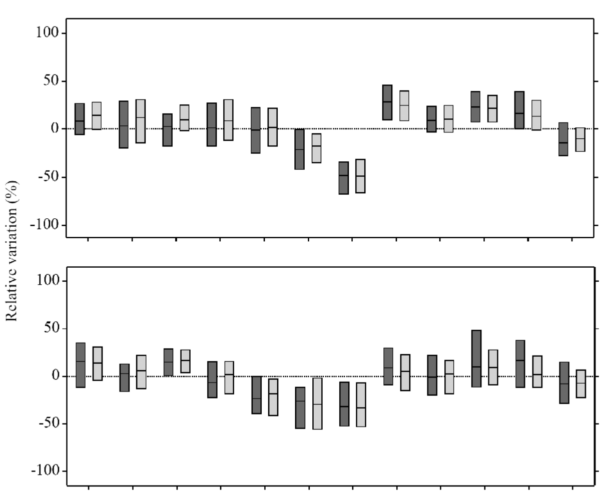

Figure 2. Relative variation in the machines' volume produced (dark gray) and worked time (light gray) over months for 2018 (upper panel) and 2019 (lower panel). Boxes indicate median and quartile values. A relative variation value of 0% indicates that the value for that month was the same as the mean value for the machine's performance during the observed 24 months. The lowest possible relative variation value −100% indicates that the machine had not been used or produced any volume at all that month. N = 77 machines per month.

Workflow variation

Machines' and contractors' workflow variation was indicated by their CV of volume produced and worked time over the studied 24 months. When analyzing and comparing workflow variation in volume (CV_{volume}) and time (CV_{time}) within and between aggregation levels, a range of differences were observed (see Table 3). There was a wide dispersion between the 77 machines' CV_{volume} and CV_{time}, which indicated differences between machines in their workflow variation in both volume and time.

The mean CV_{volume} was higher than CV_{time} at both aggregation levels. The standard deviation on CV_{volume} and CV_{time} was higher, and mean CV_{volume} and CV_{time} lower, for contractors than for machines, indicating bigger differences between contractors than between machines (Table 3). The distribution of CV_{volume} differed from the distribution of CV_{time}. CV_{time} had a more concentrated distribution for both machines and contractors compared to CV_{volume}. When aggregating to contractors, the CV_{time} was shifted to lower values, with a similar but less distinct effect on the $CV_{volume.}$ (Figure 4).

In general, there was a strong positive correlation between CV_{volume} and CV_{time} at both machine (Figure 5) and contractor (Figure 6) levels. However, there were also examples of substantial deviations between CV_{volume} and CV_{time} at both levels. The examples were especially common for medium size harvesters and forwarders (Figure 5) and contractors with medium size machines (Figure 6). Consequently, the correlation was low and not significant for medium harvesters ($r(20) = 0.39$, $p = 0.093$). For medium forwarders, there was a significant correlation, but less strong ($r(16) = 0.66$, $p < 0.001$) compared to big harvesters ($r(17) = 0.94$, $p < 0.001$) and big forwarders ($r(24) = 0.97$, $p < 0.001$).

It should be noted that most of the large correlation deviations were below the line that represents a perfect correlation (Figure 5 and 6). This indicates that in general there was a higher CV_{volume} than CV_{time}. Contractors with two medium size machines had the weakest correlation between CV_{volume} and CV_{time}. However, CV_{volume} and CV_{time} did not seem to only depend on machine size, since all machine sizes showed both low and high CV values (Figure 5 and 6). In contrast, number of machines seemed to matter, since contractors with more than two machines all had relatively low values in both CV_{volume} and CV_{time} (Figure 6).

Both CV_{volume} and CV_{time} were negatively correlated to the machine's total work time and total volume produced for the 24 month study period (Table 4). Thus, CV_{volume} and CV_{time} decreased with increased amount of work time and increased amount of volume produced. These observed correlations were not strong, and there were also differences between the machine types and sizes. For instance, CV_{volume} and total work time was correlated for all machines except for medium size harvesters. CV_{volume} and total volume was correlated for the large but not for the medium machines. CV_{time} and total work time was correlated for all machine sizes and types, so also with CV_{time} and total volume, with the strongest correlation for the forwarders.

Total time and total volume at contractor level depended both on the number of machines and total time, respectively, on the machines. The mean value for CV_{volume} and CV_{time}

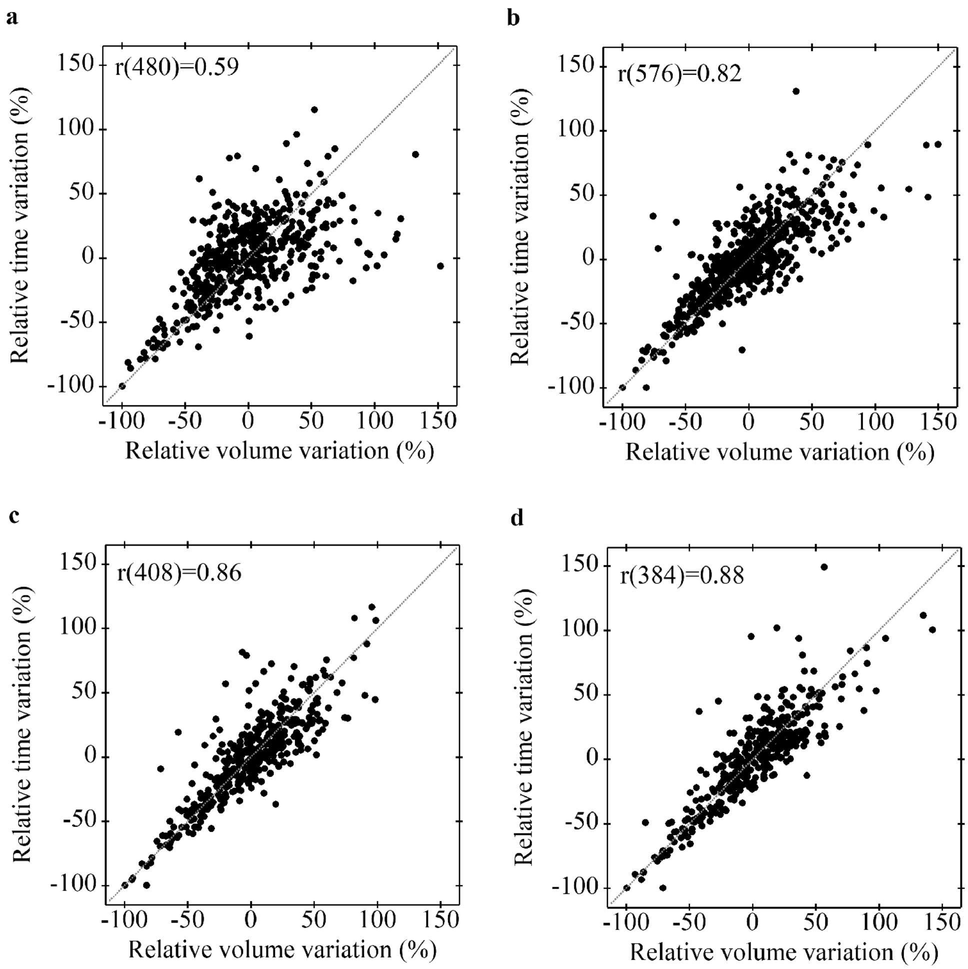

Figure 3. Relative monthly volume variation plotted against relative monthly time variation for the four combinations of machine sizes and types (a. = medium harvester, b. = medium forwarder, c. = large harvester, and d. = large forwarder). A relative variation value of 0% indicates that the value for that month was the same as the mean value for the machine's performance during the observed 24 months. The lowest possible relative variation value −100% indicates that the machine had not been used or produced any volume at all that month. The gray line indicates a perfect correlation between time and volume variation. r = Pearson correlation coefficient. The numbers in parentheses represent the number of observations, with an observation representing one machine and one month.

Table 3. Distribution of CV (%) for machines and contractors on their performance in terms of monthly volume and work time. N = number of observations, where one observation represents one machine on machine level or one contractor on contractor level. For each observation, the mean and SD values were based on the 24 values of volume produced or worked time within each machine or contractor.

Aggregation level	Variable	N	Mean	SD	Min.	Quartile 1	Median	Quartile 3	Max.
Machine	CV_{volume}	77	37.4	10.3	19.7	29.6	35.1	44.0	73.9
	CV_{time}	77	33.8	9.4	14.5	27.7	31.1	36.4	69.8
Contractor	CV_{volume}	39	34.4	11.2	17.1	26.4	31.7	40.3	73.9
	CV_{time}	39	31.5	10.4	18.5	25.4	29.4	36.3	69.8

decreased the more machines a contractor owned (Table 5). Contractors with three or more machines had significantly lower CV_{volume} and CV_{time} compared to contractors with one machine (Tukey test, p-value = 0.032 (volume) and 0.018 (time). The dispersion in both CV_{volume} and CV_{time} between contractors owning a certain number of machines decreased with the number of machines owned (Figure 7). From one, two to three or more machines, the standard deviation decreased (Table 5).

The near-lack of observations above the perfect correlation line in Figure 8 indicates both CV_{volume} and CV_{time} were in general lower at the contractor level than at the machine level. For the few exceptions, the difference was small (i.e. observations close to the perfect correlation line). The exceptions were eight forwarders of both medium and large sizes for which the CV_{volume} was lower at the machine level than when aggregated at the contractor level. For $CV_{time,}$ three harvesters that had a lower CV_{time} than the contractor owning them.

Discussion

The need for flexibility

The results showed a seasonal variation in harvesting activity (Figure 2), which is in line with other studies (Carlsson and Rönnqvist 2005; Uusitalo 2005; Audy et al. 2012; Erlandsson 2013, 2016). Typically, in Sweden demand and harvested volumes decrease during the spring and summer months,

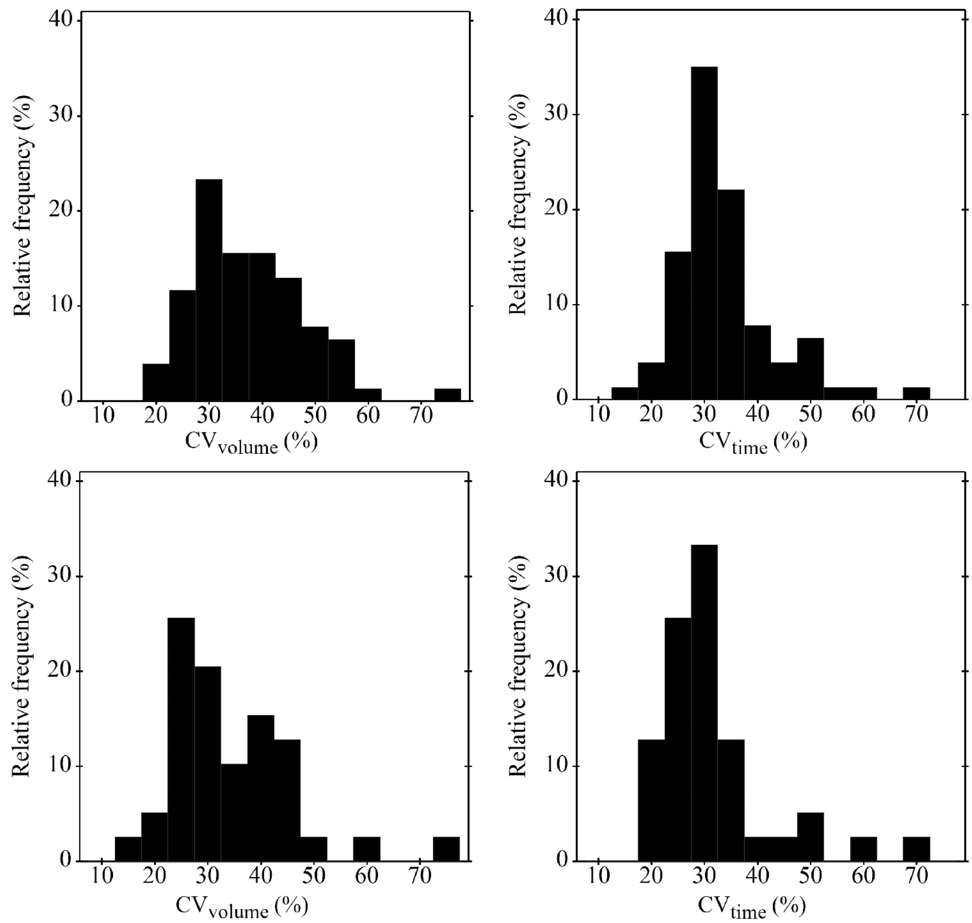

Figure 4. Relative distribution of volume and time coefficient of variation for the machines (upper panels, N = 77) and contractors (lower panels, N = 39).

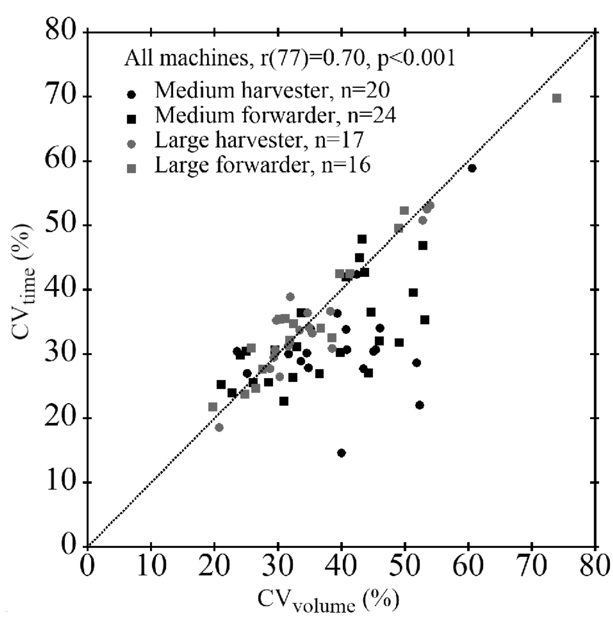

Figure 5. Relationship between the machines' CV$_{volume}$ and CV$_{time}$, distributed over machine type and size. The closer to the line, the more equal CV$_{volume}$ and CV$_{time}$. Machines under (to the right of) the line have a lower CV$_{time}$ than CV$_{volume}$. r = Pearson correlation coefficient. The number in parenthesis represents the total number of machines. n = number of machines in each combination of machine size and type.

only to increase again in autumn. Even if the pattern of seasonal variations is well known, the study showed that there can still be differences between months in different years. For instance, differences were found between May 2018 and 2019 and between August 2018 and 2019. These are the months when the amount of harvesting operations typically starts to decrease and increase, respectively, and this is often related to the current levels of market demand, weather conditions and stock levels in the industry as a whole (Carlsson and Rönnqvist 2005; Uusitalo 2005). There were notably weather differences between the two years, with considerably more rainfall in May 2019 compared to 2018 and a drought during the summer of 2018. This drought resulted in decreased and halted operations due to the risk for starting fires during June and July. To compensate for the production loss, it is possible that many machines operated on extra time during August 2018. More extreme and unexpected weather contiditons are likely to influence the need for flexibility in workflow. Such changes should motivate further research into the relationships between harvesting operations efficiencies and the impact of the changing environmental conditions and climate.

This study investigated actual volumes delivered by contractors, and not the actual or predicted wood demand from the customer. As shown by Erlandsson (2016), the outcome can differ significantly from the prediction of delivered volume. Thus, there is an uncertainty and a need for flexibility due to changes in and from predicted production plans, as well as due to the fact that delivered volume may differ from the volume demanded. Wood demand also varies and thus managers at the

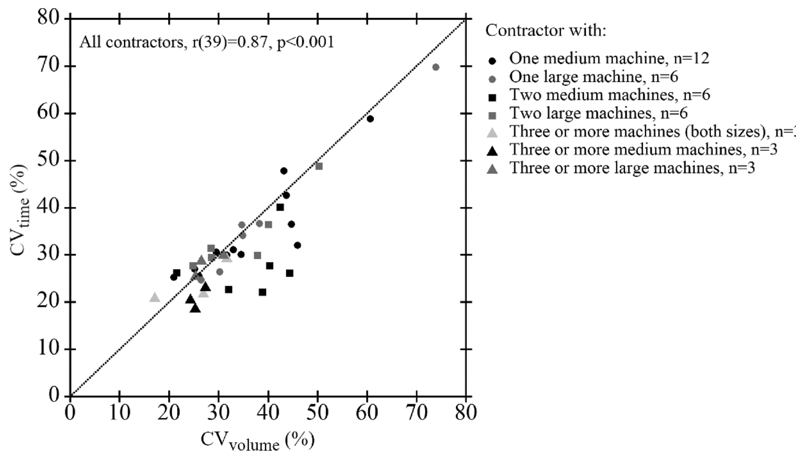

Figure 6. The contractors' machines' CV_{volume} and CV_{time} with information about machine size and number of their machines. The closer to the line, the more equal CV_{volume} and CV_{time}. Contractors under (to the right of) the line have a lower CV_{time} than CV_{volume}. r = Pearson correlation coefficient. The number in parenthesis represents the total number of contractors. n = number of contractors in each combination of number and sizes of machines.

Table 4. The relationship between CV_{volume} and CV_{time}, respectively, with total work time and total volume distributed over machine sizes and types. r = Pearson correlation coefficient. n = number of machines.

	Medium sized				Large sized					
	Harvester (n = 20)		Forwarder (n = 24)		Harvester (n = 17)		Forwarder (n = 16)		All machines (n = 77)	
Variable	r	p-value	r	p-value	r	p-value	r	p-value	r	p-value
Correlation between CV_{volume} and;										
Total work time	−0.22	0.355	−0.50	0.012	−0.67	0.004	−0.73	0.001	−0.55	<0.001
Total volume	0.02	0.930	−0.38	0.065	−0.64	0.005	−0.73	0.001	−0.44	<0.001
Correlation between CV_{time} and;										
Total work time	−0.48	0.032	−0.68	<0.001	−0.61	0.009	−0.77	<0.001	−0.66	<0.001
Total volume	−0.50	0.024	−0.63	0.001	−0.63	0.007	−0.78	<0.001	−0.28	0.012

Table 5. Mean coefficient of variation (CV) on volume and time for contractors depending on number of machines the contractors have in the dataset. N = number of contractors with the number of machines.

		CV_{volume}		CV_{time}	
Number of machines	N	Mean	SD	Mean	SD
1	18	37.6	13.1	35.8	12.2
2	12	35.8	8.6	30.7	7.7
≥3	9	26.1	4.2	24.1	4.3
–All pooled	*39*	*34.4*	*11.1*	*31.5*	*10.4*

customer companies steer production to correspond to actual demanded wood volume, which can affect utilization of contractor resources (Erlandsson 2013).

In the case of the present study, the customer used productivity prediction models to direct the wood flow toward satisfying demand, while at same time trying to enable the contractors to utilize their resources at a high and consistent level through the year. Indeed, if the customer is able to achieve

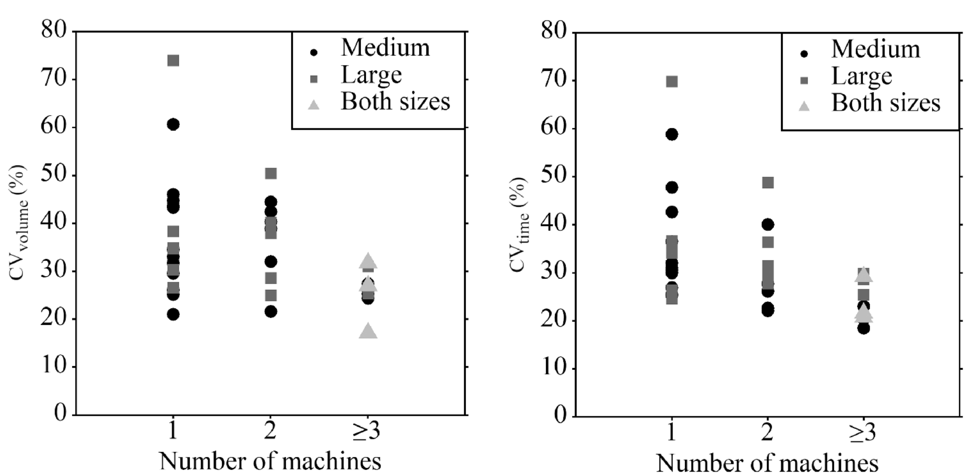

Figure 7. CV_{volume} and respective CV_{time} in relation to the contractors' number of machines in the dataset.

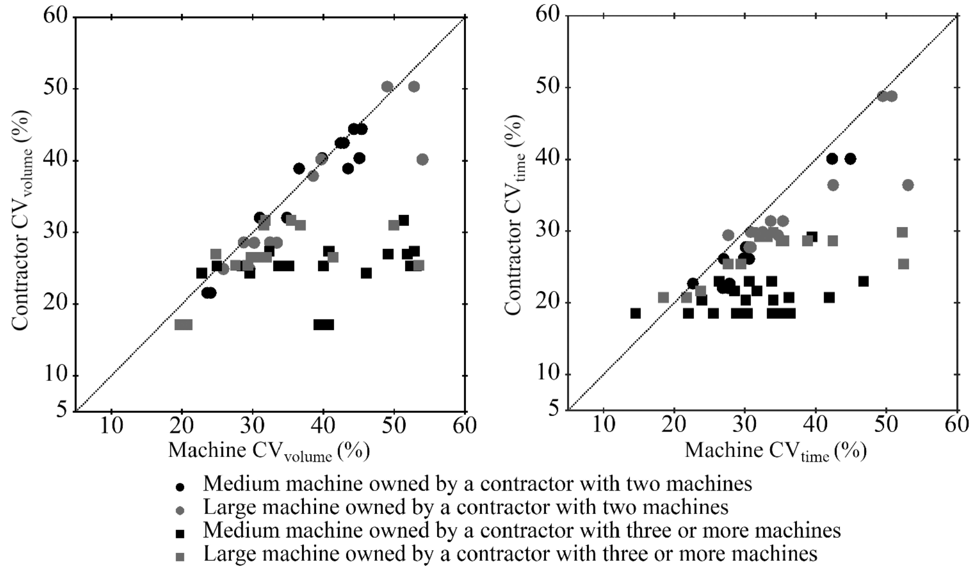

Figure 8. CV_{volume} and CV_{time} on the machines in relation to when machines are aggregated on the contractor that owns them. The closer to the line, the more equal the CV on the machine and contractor level. Machines under (to the right of) the line have a higher CV than they have aggregated on the contractor.

that goal, it has positive effects on contractor profitability and satisfaction (Erlandsson and Fjeld 2017). It will also reduce the cost of unused machines and manpower for which the customer may have to compensate contractors according to the common standard for agreements between customers and forest contractors (Skogforsk 2020). The assumption was therefore that the time would vary less than the volume. However, this study shows a significant correlation between volume and time-relative performance variation (see Figure 3). Therefore, the need for contractors' flexibility probably means variations for contractors in both delivered volume and their work time. Since the range of dispersion was considerably smaller for negative values compared to positive values of relative variation (Figure 3), the result indicates that flexibility to increase volume produced would be desirable, without the same need of flexibility in work time. If the need is for contractors' flexibility to decrease volume produced it would probably mean a need of contractors' flexibility in decreasing work time to manage as well.

Customer's opportunities to manage the need for flexibility

The findings of the CV_{volume} and CV_{time} for machines and contractors in the present study indicate that it is challenging to maintain an even workflow throughout the year, and the results also indicate that all contractors have demonstrated flexibility over the study time frame. In other words, their machines are utilized to a different extent each month, which can be caused by varying wood demands and weather conditions (Uusitalo 2005). Another factor that may influence the contractors' need to be flexible is the customer's management of their contractor crew: for example, the type of contract agreements they apply, the harvesting stands that are assigned, the quality of the information about stands to be harvested, how far in advance the information about stands is provided to the contractor, distances between harvesting sites and so on (Erlandsson et al. 2017; Gustavsson 2017). This study found differences between contractors in both CV_{volume} and CV_{time}, as well as the correlation between CV_{volume} and CV_{time}, which could be attributable to the size of their machines, the amount of total work time and total volume produced on the machines and how many machines the contractor had.

Many of the medium machines had a relatively high CV_{volume} while still having relatively low CV_{time} (Figure 5). It is possible to use those machines in both thinning and final felling, which gives the opportunity to rapidly increase or decrease volume production (Erlandsson 2013) without the need to increase or decrease the time on the machines (Eriksson and Lindroos 2014). Since it is the customer that provides stands for harvesting to the contractors, the contractors with medium size machines may need to be flexible in changing between types of operations (Table 1). As can be noted from Figure 3, the difference between relative variation in volume and time is smaller in negative values compared to positive values of relative variation. An explanation for this may be that the medium size machines are normally used in thinning, but when wood demand increases some of the medium machines are instead used in final felling to increase delivered volume. Increasing the woodflow in this way can be an effective way to rapidly handle a temporary increase in wood demand without requiring more work time.

It can also be effective to increase work time on the machines to meet increased wood demand and use the machines in the most suitable type of operation (Table 1). That may mean more variation in work time on the machines. Thus, it should be taken into account that large machines have higher productivity in final felling, even if the difference in productivity between the machine sizes decreases with smaller stem sizes and shorter extraction distances (Eriksson and Lindroos 2014). Final felling stands with small stem sizes can thus be used to either increase or decrease productivity in a short time depending on what machine size is used.

The hours that a machine can be used per day are limited, and with a high utilization rate there is consequently less time left to use for meeting temporary increases of volume production. This can be a part of the explanation as to why CV_{time} was correlated with both total work time and total volume produced (Table 4). A possibility to increase the production is, then, to provide stands in which the machines are expected to have high productivity. The results indicate just such success for some of the medium machines is due to high CV_{volume} with low CV_{time}, especially for the harvesters (Figure 5).

As discussed, medium size machines can be used in both thinning and final felling, which enables rapid adaption to variations in volume demand. Due to the machines' different suitability for thinning and final felling, and differences in productivity depending on stand characteristics (Eriksson and Lindroos 2014), it may be possible to reach a more cost-effective flexibility by improving stand selection in final felling for large machines and in thinning for medium machines. That possibility may be limited to available stands to be thinned or harvested (Gautam et al. 2013), and the study does not investigate how much of the potential to manage variations in volume demand with stand selection was achieved in this case. Therefore, more research is needed on the potential to manage the needs for flexibility from the customer's side by improving stand information and selection based on the attempt to maintain even workflow in time for the machines, even when external factors such as wood demand and weather conditions vary.

Contractors' opportunities to manage the need for flexibility

As indicated by the results, contractors' flexibility can have negative effects on their profitability and their ability to provide competitive harvesting services (Mäkinen 1997; Erlandsson 2016; Erlandsson and Fjeld 2017). As highlighted in Johansson et al. (2021), adaptability, including flexibility, is highly appreciated in harvesting services. Given the observed CV_{volume} and CV_{time}, this is not surprising since there is obviously a need for contractors' flexibility. Contractors seem to take different opportunities to manage the need for their flexibility (Figure 6).

It seems as though contractors can level their workflow between their machines (Figure 8), and that this possibility increases with more machines (Figure 7). The need to prioritize the use of the harvester or forwarder may differ over time due to, for instance, the difference between harvester and forwarder productivity varying between stand conditions and machine operators (Eriksson and Lindroos 2014; Liski et al. 2020). With more machines, the contractor also has increased opportunities to use them to compensate for each other when needed, for instance when a machine is unavailable due to repairs or being serviced.

That contractors may try to utilize their operators more evenly than their machines could explain why aggregation on contractor level had lower CV_{volume} and CV_{time} than the individual machines (Figure 8). Lack of machine operators is the main obstacle for high harvesting performance and business expansion (Kronholm et al. 2019), and it is also due to this that it can be expected that contractors will steer their operators to use the machine which is most needed at a given moment. Having many machines and employed operators also provides more possibilities for the operators to compensate for each other if needed. That requires good management skills by the contractor as well as skilled operators who are able to manage different types of machines and types of operations (Table 1).

Contractors with less work may take opportunities to increase the time on the machine when needed, and thus temporarily contribute with additional volumes in short-term agreements, as discussed by Erlandsson (2016). Also, contractors with only one or two machines may increase their chances of effectively managing the need for flexibility by cooperating with other contractors, and by that means maintaining a more cost-effective utilization of the machines and machine operators.

It is proposed that more research is needed on how machine operators and machines can be utilized to effectively manage flexibility. In this analysis, it seems the more medium-sized machines a contractor has, the more opportunities to effectively adapt the resources to varying wood demand. Most contractors in Sweden own just one, or a few, machines. Therefore, more research is needed about how cooperation models between contractors can be used to increase their opportunities to effectively respond to varying demands on their services. Contractors are competing for contracts and it should also be considered how such contractor-to-contractor relationships may affect the competitive forces to respond to varying demands.

Strengths and weaknesses

This study focused on contractor-owned machines that operated continuously for the same customer during the whole study period. The study did not represent the whole spectrum of the customer's need for contractors' flexibility. Instead, the study provided details in how contractors' workflow can vary, as indications of how much flexibility contractors operating continuously for the same customer need to manage. The first data reduction step was to remove machines without continuous work for the customer. Thus, all small machines, and also a large component of the medium and large size machines were removed from the original dataset. In this case, there were only a few small size machines in the original dataset and their potential to capture flexibility in volume production was therefore considered to be low. It is possible, but not investigated in this study, that the few small machines were used in special services requested by the customer.

The high share of machines being removed from the dataset due to not operating continuously during the whole study period is worth notice, since they probably account for some part of the flexibility in harvesting service. It is likely, but not shown in the study, that some of the customer's management of varying need of harvesting capacity lies in the temporary contracting of some of the machines that were removed in that step. Even if the contractors often receive the majority of their income from one customer (Benjaminsson et al. 2019; Kronholm et al. 2021), it is still possible that some contractors in this dataset also provided harvesting services to other customers. The study does not show if contractors level out the work between different customers, which can be a possible way to manage varying demands for their services.

What the result show is the variation for a part of the harvesting service, both in terms of the work of single machines and for machines owned by the same contractor that continuously operate for the same customer. When comparing the delivered volume and worked time on the contractor level the result only represents the work from the machines in the dataset. Some of the contractors had additional machines operating for the customer during the two-year period which were excluded during the data reduction process. Even though the results do not represent the complete extent of harvesting services at the contractor level, it still indicates what can happen with the workflow when the work is compiled over more than one task. The results in this study are built on the same 77 machines with relatively reliable information about their operations each month over the two-year study period. That made it possible to investigate and compare how the workload of individual machines differed over time on a monthly scale.

The estimated time in this study was calculated based on a productivity model used by the customer, taking different productivity-affecting factors into account at each stand. That is not the same as actual productivity, and it is likely that it is down to individual differences between machine operators to account for the difference between actual productivity and the estimated productivity (Purfürst and Erler 2011; Häggström and Lindroos 2016; Manner et al. 2016) – which affects the reliability of the estimated time result in relation to the real time. Therefore, it would also be beneficial to investigate CV_{time} for machines and contractors derived from operational monitoring data (e.g. drf files) as, for instance Purfürst and Erler (2011) and Eriksson and Lindroos et al. (2014) did for productivity modeling. In this study, the results represent the time that the contractor got paid for and the customer's expectation of how much time the contractors need to deliver the volumes. Therefore, the estimations could be expected to be reliable in the sense that they are approved by both parties as part of their business relationship.

In this kind of business relationship, the reliability of the productivity model and the accuracy of the included data is important for both the contractors' profitability and the customer's estimation of the required harvesting resources. Data collection and quality can be improved by use of modern data collection methods from forest operations. The utilization and availability of such real big data is limited due to regulations of data protection and data ownership (Regulation EU 2016/679). It should be considered how big data can be utilized in aiming to improve management of the customer's need for contractors' flexibility in a way that favors both parties in the business relationship.

Conclusions

Contractors' workflow vary in both volume and time. The level of unevenness in workflow differs between contractors, which can be attributed to the number of machines, machine sizes and total workload of harvesting services. It seems as if contractors with more machines can level out the workflow between their machines, resulting in a more even workflow at the company level than on the individual machines. In general, workflow variation in volume and time are correlated. An exception was found for medium size machines and especially harvesters, which in this study had a relatively high variation in volume while still having a relatively low variation in time. Contractors with a larger workload had, in general, lower workflow variation than contractors with a smaller workload. One explanation can be limited opportunities to lengthening time on the machines when demand increases. These findings are relevant for both parties in the business relationship when considering the need for flexibility to increase and decrease volume production and still promote contractor profitability.

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