

Quantifying the Influence of Geo-spatial Forest Distribution on Machinery Management

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Abstract

Modern forest machines are highly effective but their availability is reduced through frequent relocation. Relocation has been estimated to constitute between 6-20% of the delivered roadside cost of cut-to-length (CTL) timber. Machine utilisation is increased when relocation frequency is reduced (larger stands), and when relocation distances are shorter. The geo-spatial structure of forests at a stand and landscape level is therefore assumed to play a role in setting the efficiency threshold of modern harvesting systems. It is further assumed that this effect varies between regions and forest ownership patterns, and that the extent of the effect is quantifiable.

Testing this assumption, the size and mutual distance between 29 000 coniferous stands constituting some 70,000 ha and divided into 4 machinery management regions in Denmark was analysed using single-linkage cluster analysis. Furthermore, benefits of using the shortest path algorithm to schedule machine deployment in an optimal way were compared with a fully randomised (customer-oriented) deployment in a simulated environment. Finally, a comparison of the advantage of sandwiching multiple (3) years of scheduled thinnings into 1 package were compared with the re-deploying of machines across the region every year.

Results showed that the geo-spatial structure at landscape level mean distances between clusters ranging from 49 km in region East, to 90 km in region North. Weighting clusters with stand size reversed this ranking, where the mean distance in North was reduced from 90 km to 17 km. This highlights the importance of using the correct statistic in planning. Furthermore, when comparing a fully randomised relocation with shortest path scheduling, the mean relocation distance in region East was reduced from approximately 49 km to under 5 km, increasing productivity for a single machine set by 900 m³ a⁻¹. This increase was slightly larger when 3 years of thinnings were grouped into one planning parcel as compared to deploying across the whole region every year. Finally, proper scheduling of relocation was shown to be of increasing importance with increasing machine productivity.

Findings are considered to have important connotations for both the layout of administrative forest areas, and the manner in which machines are deployed. The clustering method used proved a powerful tool for generating packages of stands, for e.g. a tendering process, for finding an appropriate number of machine systems to cover a region, and for using as a method to evaluate the performance of harvesting systems, and the effectiveness of machinery managers and machine operators within these regions.

Key words: Machinery management, spatial planning, forest topology, cluster analysis, simulation

Introduction

The degree of spatial dispersion of work tasks distinguishes the production planning environment in forest operations from the most industrial production settings. The necessity of having to frequently relocate production units between forest stands incurs a transaction cost (including inspection), a direct transport cost, a start-up cost through the familiarisation phase in a new stand, as well as the subsequent indirect cost of reduced effective machine utilisation.

The relocation of forest machines is a recognised cost driver. Väättäinen et al. (2006) found that reloca-

tion contributed a considerable 6-10 % of total logging costs in the contiguous boreal forests of Finland. Spinelli and Magagnotti (2011) suggest that relocation could account for as much as 20 % of harvesting costs in the more challenging topology of the Italian Alps. As relocation is classified as a supportive work task (Björheden et al. 1995), it is generally ignored in the reporting of productivity studies, or handled as a fixed cost per move, e.g. Asikainen (2004). The inclusion of forest fuels as a commodity product is set to increase the amount of machine relocation taking place, as even more specialised machinery will visit each site. Therefore there is a need to quantify the underlying driv-

ers of relocation costs in an attempt to reduce their impact on the delivered cost of forest products.

One method to reduce relocation costs is to improve spatial aspects of harvest planning procedures when deploying forest machines, both at strategic, tactical and operational levels. The majority of spatial planning literature in forestry is applied to issues of harvest scheduling from the aspect of aesthetics, silviculture and biodiversity, where extensive work deals with the latter (Gustafson 1998). Studies that group harvesting through periodic blocks, using algorithms, which minimise 'interior edges' or adjacency (e.g. Gustafson 1996, Tarp and Helles 1997, Boston and Bettinger 2001), generally take departure in longer term effects on biodiversity constraints or forest economics and not operations economy.

More closely related to the problem at hand are the procurement studies that apply explicit spatial analysis in dealing with machines and transport, e.g. Graham et al. (1997). However, dealing more specifically with tactical timber harvest planning, Karlsson et al. (2004) include various levels of seasonal access to different stands in an optimisation setting, thereby handling dynamic issues facing operational forest planning. Nelson et al. (1991) generate spatially feasible tactical solutions from long term strategic harvesting plans using both optimisation and simulation, while Daust and Nelson (1993) investigate the effect of spatial constraints on longer range scheduling. Öhman and Eriksson (2010) developed a model that essentially minimises relocation by generating large aggregate harvest sites. However, these would often need to be dis-aggregated in meeting ecological and aesthetic constraints, thereby once again increasing complexity (Murray 1999). Both Laamanen and Kangas (2011) and Nilson et al. (2013) highlight the need for improved utilisation of spatially explicit data in operational planning in the forestry industry, while Calvert (2011) provides a valuable overview of the literature, methodologies and challenges involved in addressing the utilisation of such data.

The present paper attempts to provide more insight into how the landscape level structure of forests predetermines machine availability expressed in terms of the proportion of relocation time to workplace time, building on the work of Smaltschinski et al. (2012). Well established methods including cluster analysis, shortest-path optimisation, and simulation are applied in verifying whether such a difference is quantifiable.

Materials and Methods

A number of consecutive analyses were necessary in completing the evaluation. Firstly, four regions were

delineated and descriptive statistics of their forest structures was provided. Secondly, the geo-spatial structure of each region was measured and described in terms of stand sizes and mutual distances between stands, using network- and cluster analysis. Thirdly, the work of a CTL harvesting system, including relocation, was simulated in each region to evaluate differences in machine availability due to relocation. Finally, a case study was done in one region to investigate the benefits of optimising the relocation distance using the shortest route algorithm. This was tested both for 1 year of thinning activity, and the merging of three years of thinning activity into one management parcel.

Delineation of Regions

Four machine-regions, administered by the Forest and Nature Agency, were used as the administrative units of analysis. These machine-rings service all state forests in the country, and are divided into four geographic regions referred to here as NORTH, MID, SOUTH (all on the Jutlandic peninsula and island of Funen) and EAST, which covers the island of Zealand (Figure 1).

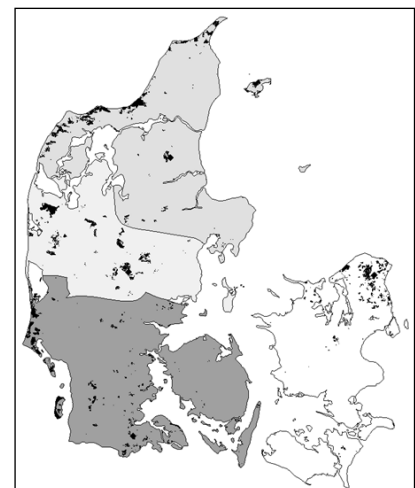


Figure 1. The four operational areas covered by state-owned machine rings in Denmark. The blackened polygons represent coniferous stands included in the study

Descriptive statistics of each of the regions are provided in Table 1. Only coniferous stands were considered, as fully mechanised cut-to-length (CTL) operations are not commonplace in hardwood stands.

Stand data

Stand sizes were obtained from the central planning database, where the mean ranged from 1.7 ha in EAST to 3.05 ha in MID and the number of stands ranged from 5068 in EAST and 9172 in NORTH. The stand sizes were fitted with a Weibull distribution for later stand generation in the simulation phase, where the parameters are given in Table 2 and shown in Figure 2. The threshold parameter was set at zero for all regions.

Table 1. Total area, forest area, coniferous forest area and density of coniferous forest in four regions

Region		NORTH	MID	SOUTH	EAST
Total area	(km ²)	11 559	8 491	13 093	9 251
Total forest area	(ha)	50 290	40 395	41 635	37 606
Coniferous forest area	(ha)	23 897	23 488	13 731	8 611
Density of coniferous forest	(%)	2.07	2.77	1.05	0.93

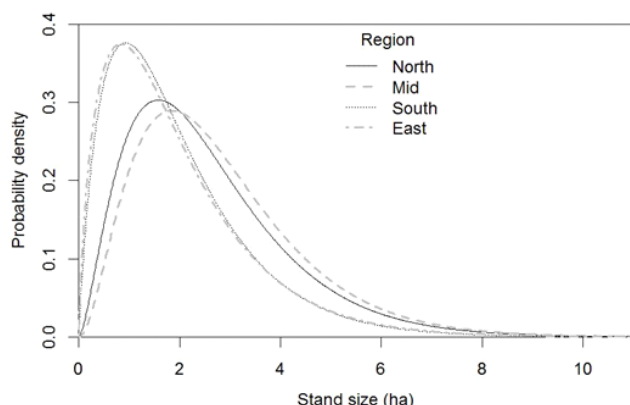


Figure 2. Stand size distribution curves by region

Table 2. Parameters of empirical stand size distributions, by region

Parameter	NORTH	MID	SOUTH	EAST
Number of coniferous stands	9 172	7 698	7 231	5 068
Mean size (ha)	2.61	3.05	1.89	1.70
Shape parameter: Weibull	2.592	2.962	1.912	1.766
Scale parameter: Weibull	0.990	0.943	1.015	1.095
Threshold parameter: Weibull	0	0	0	0

Relocation distances

Relocation distances between all geographic units were calculated from the national road database using Network Analysis in the ArcView™ GIS. In order to reduce problem complexity resulting from a very high number of stands and the unique shortest routes between all pairs of stands, a grid of 1 km² cells was draped over the entire country. The centroids of all coniferous stands were then accrued to the mid-point of a grid cell. The mid-point of each grid cell was in turn linked by straight line coverage to the nearest node of a public road in the national road database. Because of the very high public road density in the country (1,000-1,500 m km⁻²), misrepresentation associated with this approach, on a regional level, was considered minimal. Establishing the grid system reduce the complexity of the problem from 5068-9172 stands to 576-722 grid cells. The number of the unique shortest routes between all pairs of stands is equal to the matrix of $(n^2-n)/2$, and is given in Table 3.

The resultant road distance distributions were multimodal due to multiple natural clusters within each

Table 3. Statistics on stands, grid cells and pairwise distances

Parameter	NORTH	MID	SOUTH	EAST
Number of stands	9172	7698	7231	5068
Number of grid cells	722	639	663	576
Unique pairs of shortest route between all pairs of stands (x1000)	42058	29625	26140	12840
Unique pairs of shortest route between all pairs of grid cells	260 281	203 841	219453	165600

region, and the cumulative density functions were therefore plotted and used in the simulation phase (Figure 3).

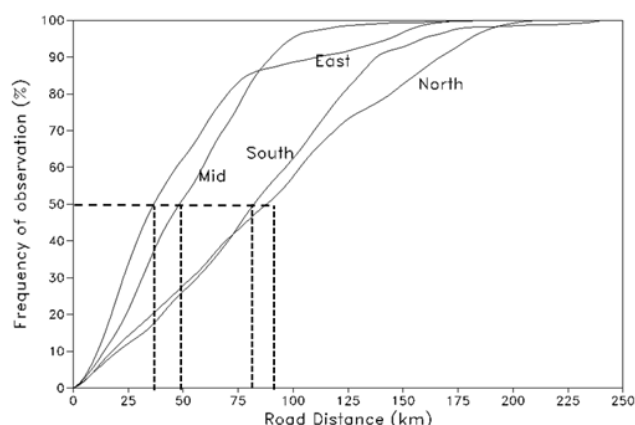


Figure 3. Cumulative density functions for relocation distances for each region. The 50th percentile is used in finding the median relocation distance for each region

Cluster analysis

Hierarchical cluster analysis was carried out on the road distance matrices using the Cluster procedure in the statistical analysis software, SAS®. This procedure is commonly used in similarity analyses using Euclidean coordinate data. However, because of anticipated variation in the difference between Euclidean and road distances within and between regions (Figure 1), the analysis was done using the road distance table developed above. The single-linkage method of clustering was chosen as it was considered most relevant to the purpose of the study, i.e. it classifies the effect of distance between stands themselves, and not, for example, between cluster centroids. The single-linkage method can be defined by:

$$D_{KL} = \min_{i \in C_K} \min_{j \in C_L} d(x_i, x_j), \tag{1}$$

which states that the distance between any two clusters (K, L) is given by the shortest distance of all possible combinations of elements in those clusters – and its use for this problem is substantiated by Smaltschinski et al. (2012). In effect it links each stand with the closest one in the next cluster. In a second analysis, the distance matrix was weighted by the in-

verse of the area at the destination stand. Thus, grid cells with small concentrations of coniferous forest area are penalised in a way that reflects the disadvantage of relocating forest machines to close, small stands, or large but distant stands.

Case study

In order to assess the consequences of the geo-spatial structure in an operational setting, a Monte-Carlo type simulation was carried out for EAST, where grid cells containing one or more activated stands are shown in Figure 4. The simulation was run in SAS and involved generating stands and distances between stands, performing mechanised harvesting and forwarding, and relocating the machines to the next stand. Time consumption was calculated for each activity (harvesting, forwarding, and relocation). The process was repeated through the entire set of stands 100 times, with the output being averaged to a single record at each iteration. The cumulative production and utilisation output figures for the machines were standardised to a single operating year of 2,000 work place hours on the harvester. Each element of the simulation is described separately below.

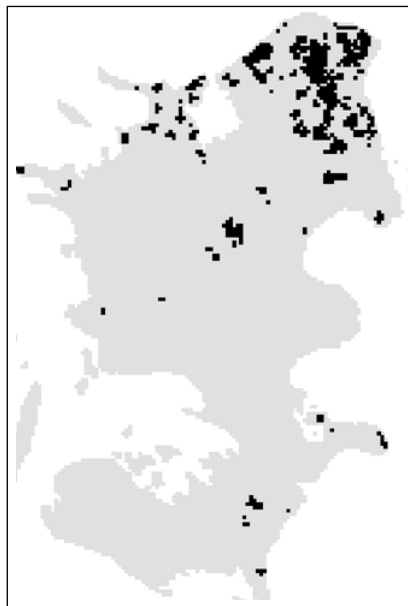


Figure 4. A map of region 'East' (1:1 200 000), the black quadrants represent the 1 km² active grid cells that include at least one coniferous stand

Harvesting system time consumption model

A regression model for time consumption for a CTL harvesting system comprising a harvester and forwarder, with thinning type variable parameters, was utilised from an earlier study (Talbot et al. 2003) and implemented directly in the simulation (Eq. 2). Mean extraction distances used in the forwarding model were cal-

culated simply as the square root of the size of the stand generated by the Weibull stand function, as suggested by Aedo-Ortiz et al. (1997). The standard deviation of extraction distance was arbitrarily set at 20% of the mean simply to increase variation. Individual tree volumes and the number of stems removed per hectare differed for each of three thinning types that were included in the simulation, and were derived from the Swedish guidelines (Anon. 2001). In first thinnings, tree volumes were normally distributed around 0.05 m³ stem⁻¹ (remove 1050 stems ha⁻¹) incrementing through 0.16 m³ stem⁻¹ (remove 560 stems ha⁻¹) to 0.27 m³ stem⁻¹ (remove 390 stems ha⁻¹) in the third thinning. The thinning number itself was determined from a uniform distribution, implying an equal probability of each thinning level.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3, \quad (2)$$

where: Y = System time-consumption (min m⁻³); X1 = Harvest volume (m³ ha⁻¹); X2 = Stem-volume (m³); X3 = Lead distance (m).

The respective intercepts and coefficients are given in Table 4.

Table 4. Parameters for the harvesting system time consumption model

Thinning	β_0	β_1	β_2	β_3
1st	25.72	-0.07023	-119.3	0.002776
2nd	12.95	-0.02026	-16.34	0.002793
3rd	9.820	-0.01507	-4.137	0.002782

Relocation distances

Because of their being multimodal, the relocation distance functions could not be fitted to a common distribution for generating distances in the simulation. This was resolved by using the cumulative density functions and applying the inverse transformation method described by Hillier and Lieberman (2010). This method involves generating a random, uniformly distributed number, which represents the probability of an observation on the y-axis, then reading the corresponding distance value from the x-axis (see Figure 3). The density functions were based on 1 km interval histograms plotted from the original distance matrices. To be able to run the analysis at a stand – and not grid cell – level, Euclidean distances between active grid cell centroids and the centroids of the stands within the grid cell were generated randomly ranging from 0 to half the diagonal length ($\sqrt{2}/2$) of the 1 km × 1 km cell. This allowed for distances to be generated on the fly for any stand combination distance being analysed, without the need for large intermediate datasets.

Relocation modelling

Relocation refers to the movement of machines from one working tract (object) to another, and allows for specific time consumption (min.m³) to be calculated. This highlights the negative effects of long distances or small volumes (object volumes) on machine utilisation rates. The relocation model is taken from an earlier simulation (Talbot et al. 2003) and made explicit in Figure 5. At distances under 20 km, relocation always occurs under own power, while between 20 and 40 km, 50% of the relocations are done by low-bed truck, which also accounts for all relocations exceeding 40 km. Movement on road happens at an average velocity of 15 km hr⁻¹(under own power) alternatively 60 km hr⁻¹(low-bed truck), and each move incurs a fixed time penalty of 30 minutes per machine. The start-up time is constant irrespective of relocation distance, and includes preparing to relocate as well as orientation on arrival in the new stand. Relocating outside of normal working hours does not influence machine utilisation. A random timestamp ranging between 10:00 and 19:00 was used to generate task-completion time. A variable was used to retain the frequency and distance of low-bed truck relocations.

In the simulation, the time consumption models, together with time lost to relocation, are used in determining utilisation rates on the machines. Equation (2) essentially feeds into the calculation of E₁₅ hours, which are equated to Productive Work Time (PW) (Björheden et al. 1995). This allows for a comparison

at Work Time (WT) level, which comprises both PW and Supportive Work Time (SW) here only measured as relocation. Thus utilisation can be measured as the ratio of PW to WT.

Testing of sequencing method and pre-grouping of stands

A complementary method of assessing the stand topology would be to investigate the proportion of relocation time arising from fully randomised movement of machines at the landscape level, as well as comparing this with an optimised, shortest path sequence. Another option available to the operations manager is to group thinning operations in time, delaying some while moving others forward, thereby ensuring a higher spatial density of active stands. Each of these methods, and the interaction of both, was tested in the case study setting in region EAST under the scenarios described in Table 5.

Table 5. Description of the 2x2 scenarios used in testing both sequencing method and pre-grouping of thinnings

Pre-grouping of thinnings (no. of stands)	Sequencing method	
	Shortest path	Random
Single year, (208) ONE	SHORTEST- ONE	RANDOM- ONE
Three years, (658) THREE	SHORTEST- THREE	RANDOM- THREE

The RANDOM sequencing scenarios simulate fully customer-oriented harvesting (meeting customer requests irrespective of location or sequence), and machines are relocated at random across the entire operational area. The SHORTEST scenarios use the shortest route between all the stands, derived using the shortest path algorithm in ArcView's Network Analyst®. The route visits each stand once and returns to the origin, having sequenced the stands according to the shortest total path. The differences in density distributions of relocation distances arising from the RANDOM and SHORTEST methods are shown in Figure 6. These distributions were fed into the relocation model in the simulation.

To test the effect of pre-grouping of thinnings, stands were selected for thinning from the database on the basis of suitable age. For scenario ONE, three stand establishment years were chosen to emulate three distinct groups of thinnings (the 1st, 2nd and 3rd thinning). The result was a sample size of n = 208 stands (Figure 7 -left).

For scenario THREE, the preceding and succeeding establishment years from those selected in scenario ONE were added to those of scenario ONE. This gave a sample size of n = 658.

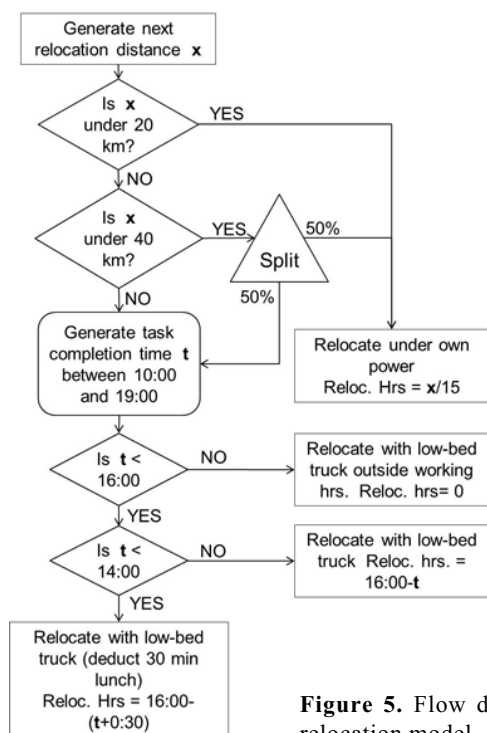


Figure 5. Flow diagram of the relocation model

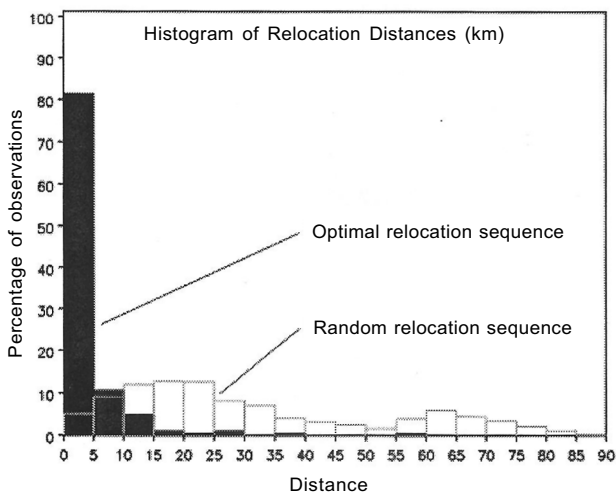


Figure 6. Resultant relocation distance distributions in EAST using the shortest path algorithm (black) and a random relocation sequence (white)

NORTH and SOUTH and smaller in the two smaller regions MID and EAST. The inclusion of the area-weighting changes the absolute numbers and ranking, as the large stands in NORTH and MID result in a smaller area-weighted mean distance as compared to the small stands in SOUTH and EAST. Mean distance estimation does not include any aspects of optimising relocation.

The non-weighted single linkage cluster analysis can also provide other important information about the

Table 6. Mean distance between stands: non-weighted and area weighted

Region	NORTH	MID	SOUTH	EAST
Mean distance between stands non-weighted (km)	90.2	52.5	84.9	49.4
Mean distance between stands area weighted (km ha ⁻¹)	17.7	19.2	39.4	38.7

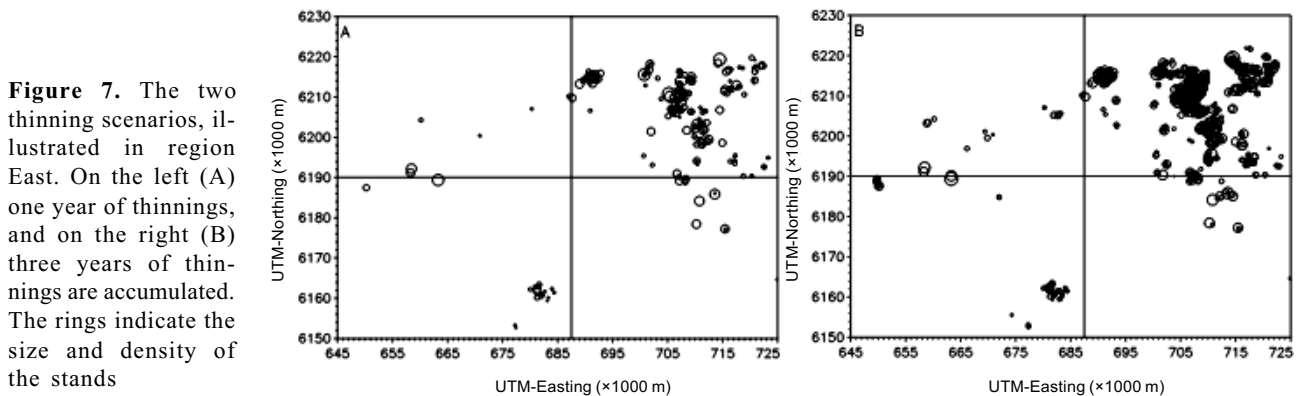


Figure 7. The two thinning scenarios, illustrated in region East. On the left (A) one year of thinnings, and on the right (B) three years of thinnings are accumulated. The rings indicate the size and density of the stands

Results

General results

The simplest way of quantifying the geo-spatial structure of coniferous forests at landscape level was using the summary statistics such as the coniferous forest area within the region and the density. The density was the highest in the heath plantations in NORTH and MID and the lowest in the old forests in SOUTH and EAST. The total area of coniferous was much larger in NORTH and MID as compared to SOUTH and EAST, while the size of the mean individual stands also varied considerably (Table 1).

The geo-spatial distribution of stands was also described in terms of the mean distance between all the stands and the area-weighted mean distance between stands, both of which are effectively measured through the clustering procedure (Table 6). The mean distance both non-weighted and weighted is indicative of the spatial distribution, but is highly influenced by the total area of the region. The non-weighted average distance is bigger in the two large regions

geo-spatial structure. Figure 8 shows a graphical expression of a non-weighted single linkage cluster analysis of the four regions. By selecting a certain distance for example a minimum distance for low-bed truck transportation it can be seen how many clusters the stands are divided into and how many low-bed truck transportations that are necessary if all parts of region should be reached. The cluster analysis gives information, about which stands should preferably be treated together. Isolated stands should be treated simultaneously so the long transportation should only be performed once. An example is seen in EAST, some stands at the right side of the graph in Figure 8 are located quite close to each other, but almost 70 km away from the main part of the region.

Results from a case study of EAST the Optimal Sequence vs. Customised Service

Results were standardised to 2,000 work-place hours for the harvester. The effect of geospatial structure and the application of a sequencing algorithm on annual production was relatively limited, with between

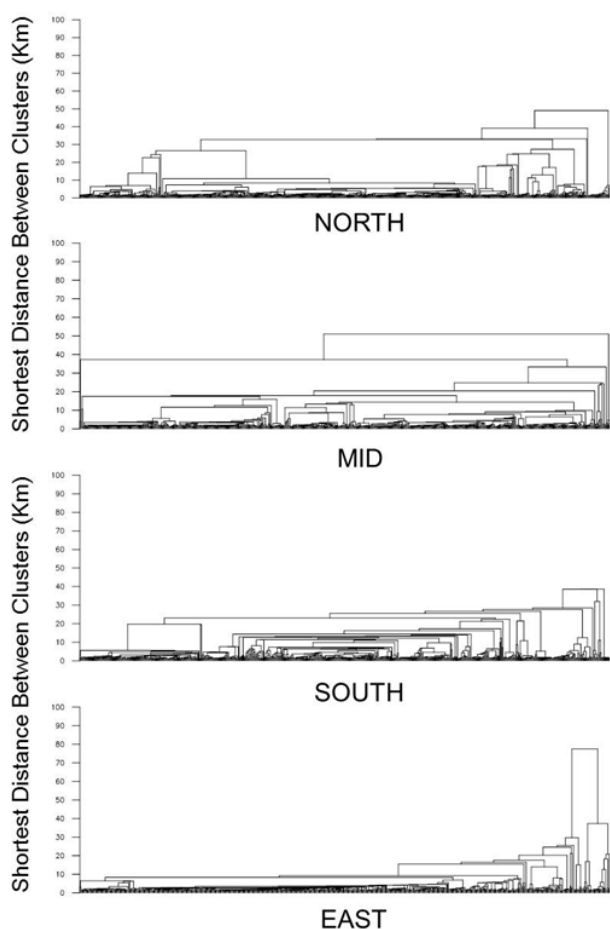


Figure 8. A graphic representation of the results of a non-weighted single linkage cluster analysis

500 m³ (ONE) and 900 m³ (THREE) difference on an annual level – corresponding to roughly 100 productive hours on the harvester. Effective utilisation of the harvester ranges between 0.92 for RANDOM-THREE (the worst possible combination) and 0.97 for SHORTEST-THREE (the best possible combination). Forwarder utilisation was significantly lower, given the higher productivity of the forwarder (Table 7). Machine utilisation rates refer only to inefficiencies arising from relocation. Relocation time (as a part of work place time) increases from 57 hrs per year to 158 hrs per year, when looking at RANDOM-THREE. The direct cost of relocation is not considered, but frequency of relocation with a low-bed truck increases from 0.8-1.5 for the shortest route up to between 44 and 47 times per year under the random relocation scenario.

Discussion

This study attempted to find indices that could be used to quantify and rank the geo-spatial structure

Table 3. Results of the sequencing and pre-grouping scenarios, standardized to 2000 hrs on the harvester

Descriptor	RANDOM		SHORTEST	
	ONE	THREE	ONE	THREE
Annual volume (m ³)	18 080	17 943	18 580	18 862
Harvester (E15 hrs)	1 868	1 843	1 925	1 942
Forwarder (E15 hrs)	1 284	1 273	1 329	1 344
Relocation (hrs)	131.6	158.4	74.7	57.8
Relocation (km)	3186	3 526	390	236
Low bed frequency	46.8	44.7	1.53	0.83
Harvester availability	0.93	0.92	0.96	0.97

of forest regions. Descriptive statistics, road distance tables, stand-size weighted cluster analysis, and a simulation of relocation time were used as methods to find such indices.

Cluster analysis

Cluster analysis appears to provide an elegant and powerful solution to the analysis of large datasets providing both total and summary distance tables, for area-weighted and non-weighted solutions. The graphic output provides useful interpretations of cluster sizes and frees the operations manager from the concentric ring distance approach to procurement management.

Forest administration areas that have been fixed for decades or centuries along natural boundaries could essentially be restructured on the basis of economic savings based on the application of such a method, which effectively shows both density and distance between stands.

Especially the interpretation of complicated winding road routes as absolute (Euclidean) distances makes for a fast visual overview of the geo-spatial structure. The decision maker could use the cluster tree to select sub-clusters in awarding contracts, or in balancing the administrative or technical workload between multiple machine systems.

The option of using Euclidean distance clustering, which requires GIS data only, was not tested against the utility of the pairwise distance tables, and the latter might have been unnecessary in a country like Denmark, which is both flat and without any major topographic inhibitors to assuming linear distances. In e.g. Alpine conditions, differences in altitude, or obstructions such as lakes and fjords, are not easily handled in the 2-dimensional Euclidean space, and it would be essential to have a distance, energy use, or time based table for comparison.

Stratification on the basis of specific age classes, species, or operations (eg. thinning, chipping, re-establishment) could be a useful way of generating less

dense clusters for specific management use (Daust and Nelson 1993).

Mosaics of disperse forest ownership patterns even in contiguous forests can be deceptive when using vector based analysis, while clustering essentially ignores the intermediate areas. The use of state owned forests provided an excellent platform for analysis as it could be done on a sub-national level, and importantly, that the machines are in fact relocated across the whole region. Private forest owners with similar spatial dispersion, would likely hire in local contractors in various parts of the region.

Converting stand size and forest attributes to task completion times would, together with good distance based relocation models, make it possible to use cluster analysis in deciding exactly the number of machine systems required for any given region.

Relocation modelling

The simulation failed to show significant differences in the effect forest topology might have on machine utilisation alone. This is partly explained by (i) the design of the relocation model, which does not count relocation time outside of work place time, and (ii) the relatively high threshold on driving under own power (20km) the set-up time at each stand (30 min.). Smaltschinski et al. (2012) give a corresponding distance of 15 km as the break even distance for deciding whether to drive the machine or relocate it using a truck.

Also, the actual relocation distances used are not well known and the operations manager would likely always be stratifying and clustering tasks at a more general level. Actual relocation would be expected to lie closer to the optimal solution than the random one. Road surface and other parameters (e.g. bearing capacity) were not included in the network analysis and all roads were considered to be accessible to machine utilisation. Such an assumption might be important in determining between the shortest path and the lowest cost solution in settings, where a difference between the two could be expected.

The cumulative relocation distances had a median (50% likelihood) of ranging between 30 (EAST) and 90 km (NORTH). An operations manager needing to inspect the stands before deploying machines would therefore be at a severe disadvantage in the latter case, as such a visit is not sensitive to stand size, i.e. must be carried out irrespectively. Relocation becomes relatively more important with increasing machine productivity in that more hrs. per year will be used on this. This has important connotations for modern highly effective harvesting systems, including large chippers, which would typically relocate on a daily or more frequent basis, and would benefit from optimised scheduling.

More sophisticated models need to be developed for describing relocation but these are made complex by the combination of management (in or outside of working time) and quantitative (distance) parameters. In Finland, many contractors own low-bed trucks and relocation unavoidably becomes part of their working time (Väättäinen et al. 2006). This both reduces the operator availability, and likely increases the cost, due to a low utilisation of such a truck. In Denmark, independent transport contractors would invariably be used and the model developed here reflects that.

Machines in this study worked only single shift days, a double shift schedule would imply a higher share of relocation during work time, and a higher frequency of relocation as stands would be harvested at roughly twice the speed.

Real world applicability

The production models used in this study were developed for three levels of thinnings, where early thinnings show very low productivity. This does reduce the effect of the relocation aspect of the paper, as it is shown how the importance of relocation planning increases with increasing productivity levels. The real applicability of work in this paper is likely to be in the large and centrally owned plantation companies in the S. Hemisphere, this is made apparent by the work of Smaltschinski et al. (2012). However, some larger companies and forest owner associations in N. Europe have access to good geographical and stand data, and do carry out centralised operational planning. Two recent papers addressing knowledge needs in large Scandinavian forest companies, Finnish Metsähallitus with 3.5 million ha (Laamanen and Kangas 2011) and Swedish Sveaskog with 3.3 million productive ha. Nilsson et al. (2013) point to the need for improved utilisation of spatially explicit data in operational planning.

Conclusions

There were quantifiable differences in topology between forest operations management regions. The consequences of these differ depending on whether the task is administrative (insensitive to stand size) or operational (influenced by stand size).

The evaluation of operational areas is a complex task, and significantly more research could be done on developing methods and indicators for making rapid assessments.

Cluster analysis could be more widely applied in forest operations management given the ease of application, the size of the datasets that can be handled, and the utility of the information that it provides.

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References

- Aedo-Ortiz, D. M., Olsen, E. D. and Kellogg, L. D. 1997. Simulating a harvester-forwarder softwood thinning: A software evaluation *Forest Products Journal* 47(5): 36-41.
- Anon. 2001. Gallringsmallar, Södra Sverige [Thinning prescriptions for Southern Sweden] Skogsstyrelsen (p. 1-35).
- Asikainen, A. 2004. Integration of Work Tasks and Supply Chains in Wood Harvesting – Cost Savings or Complex Solutions? *International Journal of Forest Engineering* 15(2): 11-17
- Björheden, R., Thompson, M. and Rickards, J. 1995. Forest Work Study Nomenclature. IUFRO/Swed. (p. 16): Univ. Agric. Sci, Dept. of Operational Efficiency.
- Boston, K. and Bettinger, P. 2001. Development of spatially feasible forest plans: a comparison of two modeling approaches. *Silva Fennica* 35(4): 425-435
- Calvert, K. 2011. Geomatics and bioenergy feasibility assessments: Taking stock and looking forward. *Renewable and Sustainable Energy Reviews* 15(2): 1117-1124, <http://dx.doi.org/10.1016/j.rser.2010.11.014>
- Daust, D. K. and Nelson, J. D. 1993. Spatial Reduction Factors for Strata-Based Harvest Schedules. *Forest Science* 39(1): 152-165.
- Graham, R. L., Liu, W., Downing, M., Noon, C. E., Daly, M. and Moore, A. 1997. The effect of location and facility demand on the marginal cost of delivered wood chips from energy crops: A case study of the state of Tennessee. *Biomass and Bioenergy* 13(3): 117-123, [10.1016/S0961-9534\(97\)00022-6](http://dx.doi.org/10.1016/S0961-9534(97)00022-6)
- Gustafson, E. J. 1996. Expanding the scale of forest management: allocating timber harvests in time and space. *Forest Ecology and Management* 87(1-3): 27-39, [http://dx.doi.org/10.1016/S0378-1127\(96\)03838-8](http://dx.doi.org/10.1016/S0378-1127(96)03838-8)
- Gustafson, E. J. 1998. Quantifying Landscape Spatial Pattern: What Is the State of the Art? *Ecosystems* 1(2): 143-156, doi: 10.1007/s100219900011
- Hillier, F. S. and Lieberman, G. J. 2010. *Introduction to Operations Research* (9th ed.). Singapore: McGraw-Hill. 1045 pp.
- Karlsson, J., Rönnqvist, M. and Bergström, J. 2004. An optimization model for annual harvest planning. *Canadian Journal of Forest Research* 34(8): 1747-1754, doi: 10.1139/x04-043
- Laamanen, R. and Kangas, A. 2011. Large-Scale Forest Owner's Information Needs in Operational Planning of Timber Harvesting – Some Practical Views in Metsähallitus, Finnish State-Owned Enterprise. *Silva Fennica* 45(4): 711-727.
- Murray, A. T. 1999. Spatial Restrictions in Harvest Scheduling. *Forest Science* 45(1): 45-52.
- Nelson, J., Brodie, J. D. and Sessions, J. 1991. Integrating Short-Term, Area-Based Logging Plans with Long-Term Harvest Schedules. *Forest Science* 37(1): 101-122.
- Nilson, M., Wästerlund, D. S., Wahlberg, O., and Eriksson, L. O. 2013. Forest Planning in a Swedish Company - a Knowledge Management Analysis of Forest Information. *Silva Fennica* 46(5): 717-731.
- Smaltschinski, T., Seeling, U. and Becker, G. 2012. Clustering forest harvest stands on spatial networks for optimised harvest scheduling. *Annals of Forest Science* 69(5): 651-657, doi: 10.1007/s13595-012-0182-7
- Spinelli, R. and Magagnotti, N. 2011. The effects of introducing modern technology on the financial, labour and energy performance of forest operations in the Italian Alps. *Forest Policy and Economics* 13(7): 520-524. doi: <http://dx.doi.org/10.1016/j.forpol.2011.06.009>
- Talbot, B., Nordfjell, T. and Suadicani, K. 2003. Assessing the Utility of Two Integrated Harvester-Forwarder Machine Concepts Through Stand-Level Simulation. *International Journal of Forest Engineering* 14(2): 31-43
- Tarp, P. and Helles, F. 1997. Spatial optimization by simulated annealing and linear programming. *Scandinavian Journal of Forest Research* 12(4): 390-402, doi: 10.1080/02827589709355428
- Väätäinen, K., Asikainen, A., Sikanen, L. and Ala-Fossi, A. 2006. The cost effect of forest machine relocations on logging costs in Finland. *Forestry Studies | Metsäntuotteen Uurimused* 45: 135-141.
- Öhman, K. and Eriksson, L. O. 2010. Aggregating harvest activities in long term forest planning by minimizing harvest area perimeters. *Silva Fennica* 44(1): 77-89.

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