Journal of Forestry Research (2025) 36:79
https://doi.org/10.1007/s11676-025-01876-1

ORIGINAL PAPER

A two-level optimization approach to tree-level planning in continuous cover forest management

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Received: 19 October 2024 / Accepted: 25 February 2025

Abstract The current trends in forestry in Europe include the increased use of continuous cover forestry (CCF) and the increased availability of tree-level forest inventory data. Accordingly, recent literature suggests methodologies for optimizing the harvest decisions at the tree level. Using tree-level optimization for all trees of the stand is computationally demanding. This study proposed a two-level optimization method for CCF where the harvest prescriptions are optimized at the tree level for only a part of the trees or the first cuttings. The higher-level algorithm optimizes the cutting years and the harvest rates of those diameter classes for which tree-level optimization is not used. The lower-level algorithm allocates the individually optimized trees to different cutting events. The most detailed problem formulations, employing much tree-level optimization, resulted in the highest net present value and longest optimization time. However, restricting tree-level optimization to the largest trees and first cuttings did not significantly alter the time, intensity, or type of first cutting. Computing times could also be shortened by applying accumulated knowledge from previous optimizations, implementing learning aspects in heuristic search, and optimizing the search algorithms for short computing time and good-quality solutions.

Keywords Management optimization · Forest planning · Differential evolution · Simulated annealing

Introduction

With the increased use of airborne and terrestrial laser scanning and various drone applications, tree-level inventory data are increasingly available for forest management planning (Chen et al. 2006; Leite et al. 2020; de Paula Pires et al. 2022Lopatin et al. 2023). This makes it possible to optimize harvest decisions at the tree level. Several methods have already been suggested for formulating and solving these optimization problems (Pukkala and Miina 1998; Fransson et al. 2020; Pascual 2021; Sun et al. 2022a). Many other previous studies optimize the harvest rates or tree frequencies for different diameter classes (e.g. Haight 1987; Haight and Getz 1987; Hyytiäinen and Tahvonen 2001; Pukkala et al. 2014). However, these studies do not represent tree-level optimization because harvest prescriptions are not obtained for individual trees.

The approaches suggested for tree-level optimization fall into two categories. The first approach is to optimize a rule for selecting the harvested trees (Pukkala and Miina 1998; Pukkala et al. 2015). The other approach, which has been used more in recent studies, is to employ combinatorial optimization to select the harvested trees or allocate the trees to different cutting events (e.g., Packalen et al. 2020; Fransson et al. 2020; Pascual 2021).

Project funding: This study was supported by the KESTO project (Planning and implementation of the harvesting of climate-resilient continuous cover forests (CCF) using digitalization in North Karelia), Grant Number 41007-00241901. The project is funded by the European Regional Development Fund (ERDF).

The online version is available at https://link.springer.com/

Corresponding editor: Lei Yu.

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Every tree of a stand occupies a small area of the forest, and this area can be equated with a stand where only one tree is growing. After making this parallelism, it becomes clear that many methods commonly used in forest planning can be straightforwardly used in cases where the simulation and calculation units are individual trees. For example, Packalen et al. (2020) divided the forest into Voronoi polygons, each polygon occupied by one tree. Then, a cellular automaton was used in spatial optimization to select those one-tree polygons that should be cut. The same method was used earlier in forest planning applications where the calculation units are traditional stand compartments (Heinonen and Pukkala 2007). Pascual (2021) used mixed integer programming to select the trees that should be removed in a thinning treatment.

Methods developed for combinatorial optimization have also been used in problems where a sequence of cuttings is optimized at the tree level instead of just one thinning. For example, Fransson et al. (2020) used a genetic algorithm and Sun et al. (2022a) used simulated annealing to allocate the trees to different cutting events. The problem with this approach, especially in the boreal zone where rotations are long, is the large size of the decision space. This is because the number of potential cutting years (thinning and final felling) is high, resulting in many combinations. To alleviate this problem, Sun et al. (2022a) suggested a two-level hierarchical optimization approach, in which the cutting years are optimized at a higher level. The lower-level optimization problem allocates the trees to these cutting years in an optimal way.

Another difficulty, compared to traditional stand-based planning, is that all combinations of the cutting events of trees must be simulated. This is because the development of an individual tree depends on the removal and growth of adjacent trees. This also rules out the use of linear programming or integer programming for solving the lower-level allocation problem. In stand-based planning, it is possible to use a two-stage approach where the first stage simulates alternative treatment schedules for the stands and the second stage finds the optimal combination of the simulated treatment schedules (e.g., Heinonen and Pukkala 2007). In many cases, it is possible to use linear programming or other exact methods to find the optimal combination of treatment schedules.

In most forest planning cases the starting point of the calculations is an existing stand (Kangas et al. 2015). If the profitability of forest management is maximized, the net present values (NPV) of the inspected cutting schedules need to be predicted to infinity. In even-aged forestry, management may be optimized until clear-felling and bare land value can be added to the incomes of the final felling year. This approach does not work in CCF where there is no clear-felling. One option is to formulate fixed-endpoint or equilibrium-endpoint problems where the stand reaches a steady state after a certain number of cuttings (Haight and Getz 1987; Tahvonen 2011; Pukkala 2015). The steady-state forest is harvested similarly at regular intervals, which makes it possible to estimate the NPV to infinity.

However, fixed or equilibrium endpoint formulations may be too restrictive, and reaching the optimal steady state may require long periods, especially in mixed stands or fertile pine or broadleaf-dominated stands where the species composition gradually develops towards spruce dominance. Requiring a steady state stand structure too early decreases the profitability of forest management (Haight 1987).

Another possibility is to optimize a certain number of cuttings or a certain period and use a predictive model to calculate the value of the ending growing stock (Pukkala et al. 2014). Models for predicting the net present value of a forest stand have been presented in the literature (e.g., Pukkala 2022, Supplementary Information). Due to discounting, the effect of the model-based estimate of the NPV of the ending growing stock is not large if the optimized period is long enough.

When drones and laser scanning applications are used in forest inventories, the usual outcome is that only part of the trees are detected (Peuhkurinen et al. 2011; Vauhkonen et al. 2012; Sun et al. 2022b). On the other hand, the complete diameter distribution of the trees can be estimated by using data imputation or other methods (Næsset 2002; Gobakken and Næsset 2004; Maltamo et al. 2006; Packalén and Maltamo 2008; Hao et al. 2022). In these situations, it is possible to optimize the harvest decisions only for the detected trees and use an optimized harvest intensity model for the non-detected trees. The harvest intensity model shows the proportion of harvested trees for different diameter classes.

Compared to even-aged management, CCF has the additional difficulty that the gradual regeneration (ingrowth) needs to be considered in management optimization. The amount of regeneration can be predicted using ingrowth models (e.g., Lappi and Pukkala 2020; Pukkala et al. 2021) but the locations of the ingrowth trees are unknown when distance-independent ingrowth models are used. Although the cutting events of trees that belong to ingrowth could be optimized at the tree level (Sun et al. 2022a), there is usually no point in doing that since the prescriptions and the trees cannot be matched in the forest. Tree-level cutting prescriptions for ingrowth do not provide better advice for cutting, compared to optimal harvest intensities in different diameter classes.

In forest planning, simulations and optimizations are often conducted for several decades. This does not mean that the optimal management schedule should be followed for so long. Decision support is required mainly for the next cutting. The main role of longer-term calculations is to verify that short-term decisions do not have harmful long-term consequences. Since long-term calculations involve much uncertainty related to forest development, timber prices, regulations, and even management objectives, forest inventories and management planning are often repeated at clearly shorter intervals than the time horizon of forest planning calculations.

The largest trees of the stand are financially the most mature and are usually removed in economically optimal thinning (e.g., Pukkala et al. 2015). Therefore, for practical decision support, it is important to optimize the harvest decisions correctly for the dominant trees of the stand.

The objective of this study was to develop, test, and demonstrate a flexible two-level method for optimizing harvest decisions of individual trees in CCF. CCF corresponds to the German Dauerwald concept, which means that steady-state stand structures are not required. The only requirement is that the tree cover is continuous, both spatially and temporally (Möller 1922; Helliwell 1997; Knoke 2012). The method is based on alternating use of two optimization levels and methods. The higher level optimizes the cutting years and harvesting rates for those trees for which harvest decisions are not optimized individually. The lower level allocates the individually optimized trees to the cutting events, the years of which are optimized at the higher level. The method can deal with ingrowth, and the optimization does not require a steady-state stand structure at the end of the simulation period. Any number of future cuttings can be optimized.

Since tree-level optimization is time-consuming, special effort was put into analyzing the effect of computational simplifications on the time consumption of the optimization process and the quality (net present value) of the solution. The tested simplifications were: using tree-level optimization only in the first or a few first cuttings; optimizing harvest decisions individually only for large trees; using accumulated knowledge from previous optimizations; implementing learning aspects in heuristic search; optimizing the heuristic search for short computing time and good-quality solutions. The similarity of alternative solutions in the first cutting was examined, corresponding to the assumption that the main role of optimization is to provide decision support for the next cutting.

Materials

A 40 m by 50 m sample plot in the Tuupovaara village of Joensuu and a 40 m by 40 m sample plot in Revonkylä (also Joensuu) were used in this study (Table 1, Fig. 1). The plots belong to the research plots of the KESTO project, which investigates the implementation of alternative CCF variants and harvesting costs of CCF, as well as soil compaction and

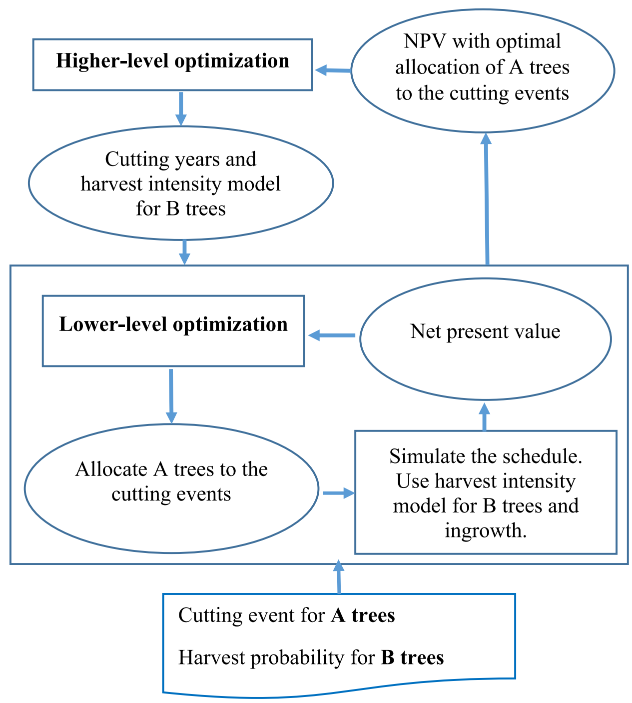

Fig. 1 Flow chart of the two-step method for optimizing the cutting schedule in continuous cover forestry. **A trees** are trees for which the cutting event (cutting in which the tree is harvested) is optimized individually. **B trees** are harvested based on the harvest intensity model, which shows the thinning rate as a function of diameter

Table 1 Species composition of the sample plots of Tuupovaara and Revonkylä

	Tuupovaara							Revonkylä						
	N	G	D	D_{min}	Q1	Q3	D_{max}	N	G	D	D_{min}	Q1	Q3	D_{max}
Scots pine	245	25.2	37.7	11.2	31.6	38.0	53.9	150	4.7	22.5	2.3	17.5	23.1	29.6
Norway spruce	630	7.5	26.6	3.0	4.0	9.8	45.9	2888	10.4	13.9	0.8	2.3	6.5	29.0
Silver birch	215	5.6	19.7	7.3	15.5	20.9	25.5	0	0	-	-	-	-	-
Downy birch	380	5.3	16.0	4.4	8.4	14.9	26.2	806	8.8	17.1	0.9	2.1	15.7	25.5
Total	1470	43.6	30.8	3.0	6.3	21.3	53.9	3869	24.0	16.7	0.8	2.3	8.5	29.6

N = number of trees per hectare, G = basal area (m^2 ha^{-1}), D = basal-area-weighted mean diameter (cm), D_{min} = minimum diameter (cm), D_{max} = maximum diameter, Q1 = 1st quantile (25% percentile), Q3 = 3rd quantile (75% percentile) of the diameter distribution (cm) logging damages to remaining trees. The KESTO plots are 20 m wide and 40 m or 50 m long. The two plots used in this study were obtained by joining two adjacent 20-m-wide plots. The EUREF-FIN-TM35FIN coordinates of the plots were: Tuupovaara 6927496 (N), 686373 (E); Revonkylä 6953432 (N), 678946 (E).

The plots were measured in stands where the landowner has decided to use CCF. All trees taller than 1.4 m were measured before the thinning treatment for species, diameter at 1.3 m (dbh), and location (Table 1). Tree height was measured for every fourth tree. The Cartesian coordinates of the trees were determined by a distance from a reference point and an angle from a reference direction (north). For this study, the distances and angles were converted into x and y coordinates.

The plots represent medium site fertility (mesic). The mesic site is the most common site fertility class in Finland. All main tree species of Finland grow on mesic sites, namely Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* (L.) H. Karst.), silver birch (*Betula pendula* Roth), and downy birch (*B. pubescens* Ehrh.). The stand structures of the plots were typical of naturally developed stands; pines and birches, which are pioneer species, were larger than the spruces, and the spruce layer was uneven-aged and uneven-sized (Table 1). The Clark and Evans (1954) aggregation index was 0.93 for both plots, suggesting that the spatial distribution of trees was slightly more aggregated than a random (Poisson) distribution.

Methods

Harvest intensity model

The method developed and tested in this study was based on the alternate use of two optimization methods (Fig. 1). The higher-level method optimized the cutting intervals and the harvest intensity model for trees for which the harvest decision was not optimized individually. The formula of the harvest intensity model was (Pukkala et al. 2014):

$$TI(d) = \frac{1}{\left[1 + a_1 \exp\left(-a_2(d - a_3)\right)\right]^{\left(\frac{1}{a_1}\right)}} \tag{1}$$

where $TI(d)$ is the proportion of removed trees for breast height diameter (dbh) d, and a_1, a_2 and a_3 are parameters. The higher-level method optimized the number of years to each cutting (from the beginning or previous cutting), and three parameters of the harvest intensity model. The ranges of parameters were not constrained which means, for example, that thinning from above, thinning from below, and uniform thinning (the same harvest intensity in all diameter classes) were all possible optimization outcomes. The initial cutting intervals, used to generate starting values for optimization, ranged from 5 or 30 years except for the first cutting for which the range was 0–30 years. The minimum accepted interval between cuttings was 5 years. However, the optimization was allowed to go beyond the 30-year cutting interval.

Optimization algorithms

The algorithm used at the higher level was differential evolution (DE) which is a suitable method for optimizing continuous decision variables (Storn and Price 1997; Pukkala 2009; Jin et al. 2018). DE is a population-based method operating with several solution vectors (several combinations of optimized variables). In this study, the number of variables in each solution vector was six because three cuttings were optimized (three cutting intervals and three parameters of the harvest intensity model).

The DE algorithm begins with the generation of initial solution vectors. For each vector, the initial values of optimized variables were drawn randomly from uniform distributions. Then, the solution vectors were improved for several iterations. A so-called noise vector was generated for each solution vector and iteration as follows:

$$y_i = x_{Ci} + \lambda\left(x_{Ai} - x_{Bi}\right) \tag{2}$$

where λ is a parameter (0.5 used in this study), y_i is element i of the noise vector, and x_{Ai}, x_{Bi} and x_{Ci} are the values of element i in three, randomly selected solution vectors. An element of a solution vector was replaced by the noise vector value with a certain probability (0.5 used in this study). However, in one, randomly selected solution vector, all elements were replaced by the noise vector value. If the modified solution vector improved the objective function value, it replaced the non-modified vector. Otherwise, the non-modified vector was maintained, and the modified version was discarded.

The number of solution vectors used in this study was 20 and the number of iterations was 10. The parameters used in the DE algorithm were based partly on earlier studies (Jin et al. 2018) and partly on preliminary optimization runs.

The lower-level problem was a combinatorial problem and, therefore, a different optimization algorithm was used. This algorithm allocated the individually optimized trees to the cutting events, the years of which were optimized at the higher level. When the number of optimized cuttings was three, each tree had four possible decisions: (1) removed in the first cutting, (2) removed in the second cutting, (3) removed in the third cutting and (4) not removed in any of these three cuttings. Many methods are available for solving combinatorial problems. We used simulated annealing (e.g., Bettinger et al. 2002), but the genetic algorithm (Fransson et al. 2020), tabu search, and cellular automata (Packalen et al. 2020), among others, could be used as well.

Simulated annealing (SA) begins by randomly selecting the cutting event for each tree. Then, a random tree is selected, and its cutting event is changed. If the change improves the NPV of the cutting schedule, the change is accepted. Changes that do not improve the NPV are accepted with the following probability:

$$p = \left[\frac{NPV_{\text{AfterChange}} - NPV_{\text{BeforeChange}}}{T} \right] \quad (3)$$

where T is a parameter ("temperature") that affects the probability of accepting changes that do not improve the NPV of the cutting schedule. The value of parameter T was decreased gradually, which reduced the probability of accepting non-improving changes. In SA terminology, decreasing the value of T is called cooling.

The number of changes evaluated at each temperature was 0.1 times the number of trees (within the plot) optimized at the tree level times the number of cuttings. For example, if 150 trees were optimized at the tree level, and there were three cuttings, the number of candidates was $0.1 \times 150 \times 3 = 45$. A new temperature was obtained by multiplying the previous temperature by 0.9. The starting temperature was 10,000 divided by the number of trees for which the cutting event was optimized individually. The search was stopped when the temperature reached a freezing point, which was 0.01 times the starting temperature. All parameters were adopted from previous studies where the parameter values were optimized (Pukkala and Heinonen 2006; Jin et al. 2016). According to Pukkala and Heinonen (2006), a suitable value for the initial temperature is the maximum effect of one change in the solution (cutting event of a tree) on the objective function value.

Time reduction methods

The combinatorial optimization problem was simplified by reducing the number of cuttings or the number of trees optimized at the tree level. In alternative problem formulations, tree-level optimization was used only for trees larger than 10, 15, or 20 cm in dbh in Revonkylä, or larger than 10, 20, or 30 cm in Tuupovaara. The reason for using different limits was that the trees were substantially larger in the Tuupovaara plot. For each dbh limit, one, two, or three cuttings were optimized at the tree level. The harvest intensity model optimized at the higher level was used for the other trees and cuttings.

Each combination of cutting years and harvest intensity model tested by the higher-level algorithm (DE) was passed to the lower level (Fig. 1), i.e., all members of the DE population were passed to the SA algorithm at every iteration. The lower-level algorithm (SA) allocated the trees selected for tree-level optimization to different cutting events (including the no-cut option).

Three additional ways to shorten computing times were analyzed. The first was to employ results from earlier optimizations (Pukkala 2022) to find near-optimal starting values for the cutting years. Pukkala (2022) optimized the cutting schedule of 1487 Finnish stands when they were managed without clear-felling. These results were used for a predictive model for the optimal number of years to the first, second, and third cutting. These predictions were used to generate the cutting intervals for the initial solution vectors of the DE search; the initial value was a uniform random number ranging from $x-5$ to $x+5$, where x is the cutting interval obtained from the model.

The second tested way to shorten search times was a learning element implemented in SA. Since the lower-level SA search is repeated many times during the two-stage search process, it was possible to use earlier SA results from the same optimization run to initialize each new SA search with cutting events that resembled earlier SA solutions. For this, the cutting events of the trees in previous SA searches were kept in the memory. When the starting solution for a new SA search was generated, each tree was allocated to a cutting event that had been most often optimal for the tree. Because the starting solutions gradually became more and more optimal, the SA algorithm used smaller changes when generating new candidate solutions. The original SA algorithm randomly selected a new cutting event for a tree from all possible events. The learning SA version changed the cutting event only by one when it generated new candidate solutions. For example, if the cutting event of a tree was 2, it was changed to 1 or 3.

The third way to shorten optimization times was to use SA parameters optimized for quick search. This was done by adding the four SA parameters (initial temperature, cooling rate, freezing temperature, and search intensity) to the set of parameters optimized by DE at the higher level. In this case, the variables passed from DE to SA (see Fig. 1) consisted of three cutting intervals, three parameters of the thinning intensity model, and four parameters of the SA algorithm. Because it is known (Pukkala and Heinonen 2006) that maximizing NPV as the only objective would lead to a slow SA search, the SA solution was penalized if the search lasted longer than 10 s. As a result, such SA parameters were obtained that found profitable cutting schedules in a short time. SA was optimized for a search that employed the two previous learning elements (knowledge from previous optimizations and learning SA).

Simulation

Each combination inspected at the lower level was simulated, taking the cutting years and the harvest intensity model from the higher-level solution. The simulation computed the objective function value (Eq. 4) of the cutting schedule. When net present value was maximized, the net income of a cutting event was calculated as the difference between the roadside value of the harvested trees and harvesting costs. Harvesting costs were calculated using time consumption functions for the harvester and forwarder (Rummukainen et al. 1995).

The functions of Rummukainen et al. (1995) gave the harvester time for each harvested tree as a function of tree size (stem volume) and cutting type (clear felling or partial cutting). The time consumption of the forwarder depended on the total removal (m^3/ha, converted into cubic meters per 100 m of strip road, assuming a 20-m distance between strip roads), cutting type (partial cutting or clear-felling), terrain class (assumed normal) and forwarding distance (200 m assumed). The harvester and forwarded times were multiplied by the hourly cost of the machine (130 €/h for the harvester and 90 €/h for the forwarder). The roadside values were 72 €/m^3 for conifer saw logs, 60 €/m^3 for birch saw logs, and 40 €/m^3 for conifer and birch pulpwood. The third assortment was energy wood with a roadside price of 35 €/m^3.

The taper models of Laasasenaho (1982) were used to calculate assortment volumes. The over-bark minimum top diameter of the saw log was 15 cm for pine, 16 cm for spruce, and 18 cm for birch. The top diameter was 8 cm for pulpwood logs and 3 cm for energy wood logs. The minimum piece length was 4.3 m for conifer saw logs, 3.4 m for birch saw logs, and 3 m for pulpwood and energy wood logs.

The smallest accepted harvest removal was 50 m^3 ha^{-1} per thinning since timber buyers may not be interested in buying the timber if the removal is smaller. The maximum removal was 150 m^3 ha^{-1} in Revonkylä and 200 m^3 ha^{-1} in Tuupovaara because very high removals would make the remaining stand vulnerable to wind throws (Pukkala et al. 2016) and may cause much damage to advance regeneration. The lowest accepted post-cutting basal area was 12 m^2ha^{-1}, to guarantee that the optimized cutting schedule fulfills the legal requirements set for CCF.

The objective function maximized at both levels of the two-level hybrid method was net present value (NPV), predicted to infinity with a three percent discount rate. The net incomes of the three optimized cuttings were calculated from the simulation results, and the NPV of the remaining growing stock after the third cutting was estimated with a predictive model:

$$NPV = \sum_{k=1}^{3} \frac{NI_k}{1.03^{t_k}} + \frac{NPV_{\text{end}}}{1.03^{t_3}} \tag{4}$$

where NI_k is the net income of cutting k and t_k is the number of years from the starting year to the year of cutting k. NPV_{end} is the predicted NPV of all cuttings from year t_3 onwards, discounted to year t_3. The NPV of the ending growing stock (remaining growing stock after simulating the last cutting) was calculated with the following predictive model, adopted from Pukkala (2022, Supplementary Information):

$$NPV_{\text{end}} = \exp(5.7723 + 0.47156 \times \ln(D \times G \times LogPrice)) \tag{5}$$

where NPV_{end} is the net present value (€ ha^{-1}), D is the basal-area-weighted mean diameter of trees (cm), G is the stand basal area (m^2ha^{-1}), and *LogPrice* is the roadside price of conifer saw log (€ m^{-3}). The model is based on long-term simulations of optimized management schedules for 437 stands, located on mesic sites in different parts of Finland. The model explains 91.4% of the variation of the NPVs of the simulated management schedules.

The distance-independent individual-tree models of Pukkala et al. (2021) were used to simulate the diameter increment and survival of the trees, and the ingrowth of the stand. In these models, competition is described by the stand basal area and by the basal area of trees that are larger than the subject tree. Ingrowth is predicted by species, and it depends on the basal area and species composition of the stand. The time step of the simulation was 5 years, corresponding to the time step of the models. The simulation was conducted at the tree level, i.e., diameter increment and survival of each tree of the plot were simulated individually. The ingrowth model predicted the number of trees per hectare that will pass the 1.3 height during the next five years. This prediction was converted to the number of trees in the plot. For example, 50 ingrowth trees per hectare correspond to 8 new trees in a 0.16-ha plot. These new trees were placed in the plot in random locations.

The survival model is a logistic model showing the probability that a tree survives for 5 years. Survival was simulated by comparing the survival probability to a uniform random number (U[0,1]). Simulating survival in this way is stochastic, which is not ideal in optimization because the same set of optimized variables may result in different NPVs in different simulations. This would make it more difficult for the optimization algorithm to locate the optimum. To avoid this problem, a single uniformly distributed random number (U[0,1]) was generated for each tree and 5-year period at the beginning of the optimization, and this number was kept unchanged for the whole search process. The survival probability was compared to this random number.

The harvest intensity model (Eq. 1), when applied at the individual tree level, gives also a probability (probability of removal). Therefore, another uniformly distributed random number was generated for each tree and cutting event at the beginning of the optimization. This number was compared to the value obtained from the thinning intensity model to decide whether the trees should be removed.

The calculations were done with a Lenovo laptop computer (DESKTOP-K89L8SR, Intel(R) Core(TM) i7-8550U CPU @ 1.80 GHz 1.99 GHz).

Results

NPV and computing time

The first question analyzed was the effect of using tree-level optimization only for the largest trees or only for the first cuttings. Three cuttings were always optimized. In Revonkylä, the most detailed optimization always produced the highest NPV. In Tuupovaara, the differences between problem formulations were small (Fig. 2). The effect of increasing the diameter limit for tree-level optimization reduced the NPV most when tree-level optimization was used in all four cuttings (Fig. 2).

The time consumption of the optimization decreased significantly when fewer cuttings or fewer trees were optimized at the tree level (Fig. 3). In Tuupovaara, for example, the computing time of the most detailed optimization (tree level optimization in three cuttings for all trees larger than 10 cm) was 7.2 times longer than in the most simplified problem (tree level optimization was used in one cutting for trees larger than 30 cm). The time consumption for solving the most simplified problem was 0.8 h in Tuupovaara and 1.3 h in Revonkylä. These are still long computing times considering that the management of small plots was optimized.

The optimal cutting type was always thinning from above, irrespective of problem formulation. Figure 4 shows the optimized harvest intensity models for Tuupovaara when one, two, or three cuttings were optimized at the tree level. The models show that only a few trees had to be removed from small diameter classes.

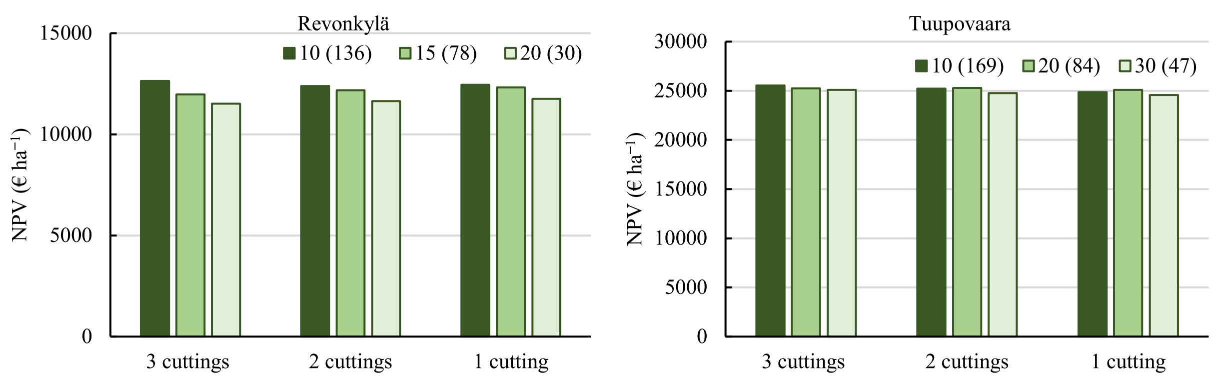

Fig. 2 Net present value of the optimized management schedule when tree-level optimization was used in 3, 2, or 1 cuttings (out of three optimized cuttings), and tree-level optimization was used for trees larger than 10, 15, or 20 cm in Revonkylä, and 10, 20 or 30 cm in Tuupovaara. The numbers in the parentheses are the number of trees for which the cutting event was optimized at the tree level. The total number of trees within the plot was 619 in Revonkylä and 294 in Tuupovaara

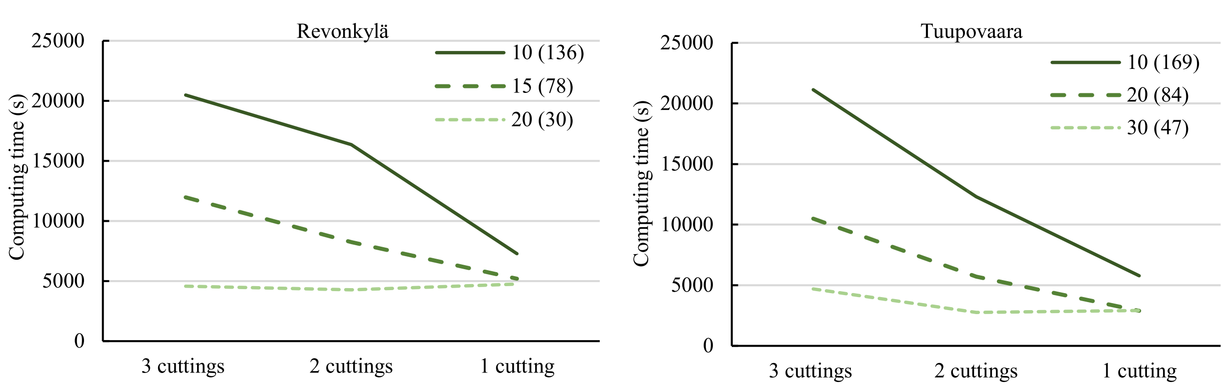

Fig. 3 Computing time of the optimization, when tree-level optimization was used in 3, 2 or 1 cuttings (out of three optimized cuttings), and tree-level optimization was used for trees larger than 10, 15, or 20 cm in Revonkylä and 10, 20, or 30 cm in Tuupovaara. The numbers in the parentheses are the number of trees for which the cutting event was optimized at the tree level

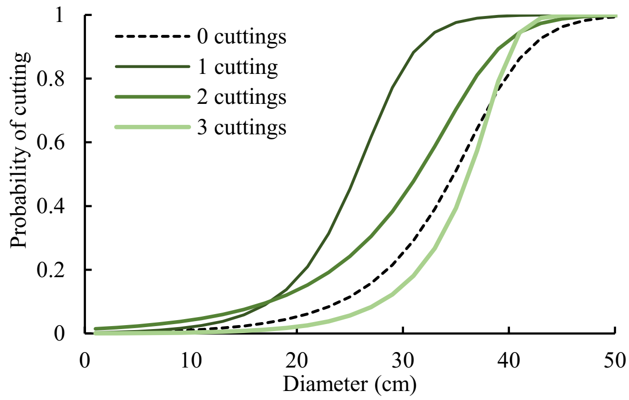

Fig. 4 Optimized harvest intensity models in Tuupovaara when three cuttings were optimized, tree-level optimization was used in 0, 1, 2, or 3 cuttings, and tree-level optimization was used for trees whose initial diameter (dbh) was larger than 20 cm. The same thinning intensity model was used in all three cuttings

Figure 4 also shows the optimized harvest intensity model when no trees were optimized at the tree level (the "0 cuttings" model of Fig. 4). In this formulation, the time consumption of optimization was 19 s Tuupovaara and 10 s in Revonkylä. Compared to the most detailed optimization, the NPV decreased significantly, by 11.9% in Tuupovaara and 7.5% in Revonkylä**.**

Optimal cutting schedules

The optimized three-cutting schedules, obtained from the most detailed problem formulations (all trees larger than 10 cm optimized at the tree level in all three cuttings) are shown in Figs. 5 and 6. In Revonkylä, the first cutting was in year 2 and removed 100 m^3 ha^{-1}. The second cutting removed 83 m^3 ha^{-1} in year 15 and the third 129 m^3 ha^{-1} in year 35. Most of the trees removed in the third cutting were initially smaller than 10 cm (yellow symbols in the bottom right tree maps of Fig. 5). The presence of spruce increased when the stand developed. The sizes of the tree symbols in Figs. 5 and 6, and all other tree maps are based on the crown radius models of Pretzsch et al. (2015).

In Tuupovaara, the optimal cutting schedule removed 199 m^3 ha^{-1} immediately, another 146 m^3 ha^{-1} five years later, and 66 m^3 ha^{-1} in year 15 (Fig. 6). The maximum accepted removal was 200 m^3 ha^{-1}. Without this constraint, the first cutting would have likely been stronger, and the time interval between the first and second thinning longer. It also seems that the minimum accepted post-cutting basal area, 12 m^2 ha^{-1}, affected the optimal solution in both Revonkylä and Tuupovaara.

The effect of prior knowledge and learning

The models fitted for the optimal cutting years, based on optimizations from a previous study (Pukkala 2022), have the following form

$$Y = a_0 + a_1TS + a_2SubXeric + a_3Xeric + a_4D + a_5G \quad (6)$$

where Y is ln(cutting year + 1), TS is the temperature sum of the growing season (accumulated sum of mean daily temperatures minus five °C), $SubXeric$ is an indicator variable for sub-xeric sites (1 in sub-xeric sites, and otherwise 0), $Xeric$ is an indicator variable for xeric sites, D is the mean diameter calculated using tree basal area as the weight (cm) and G is the stand basal area (m^2 ha^{-1}).

The models (Table 2) indicate that the optimal cutting years are earlier when the stand basal area or mean tree diameter increases (Fig. 7). In Tuupovaara, where the basal area was 43.6 m^2 ha^{-1} and the mean diameter was 30.8 cm, the first cutting should be conducted immediately, the second after 3 years and the third after 6 years. In Revonkylä, where the basal area and mean tree diameter were smaller, the predicted optimal cutting years were 2, 9, and 14.

The knowledge incorporated in the models of Table 2 was used to solve the problems where three cuttings were optimized at the tree level and the minimum diameter for tree-level optimization was 20 cm in Tuupovaara and 15 cm in Revonkylä (Fig. 8). In Tuupovaara, the NPV decreased by 0.4%, and in Revonkylä it increased by 2.0% compared to the optimization where prior knowledge was not used. Computing time decreased by 32% in Tuupovaara and 40% in Revonkylä (Fig. 8).

Implementing the learning process in the SA algorithm improved the NPV of the optimal solution by 1.5% in Tuupovaara and 2.4% in Revonkylä. The computing time decreased as much as 67% in Tuupovaara but only 6% in Revonkylä. When prior knowledge and learning were used simultaneously, the NPVs improved slightly, and the computing time decreased by 65% in Tuupovaara and 46% in Revonkylä.

The third inspected way to shorten the optimization time was to optimize the SA search for a case where both prior knowledge and learning SA were used. In addition, the DE algorithm used at the higher level was slightly modified. Figure 9 shows the development of the NPV for the 20 solution vectors used in DE in the baseline optimization (learning and knowledge not used) and in a case where prior knowledge was used. As the NPVs of the solution vectors converged more rapidly with prior knowledge being used, the number of iterations on the DE search was reduced from 10 to 7.

When the same problem was solved using optimized SA parameters, prior knowledge, and learning SA, the computing times of the search process were greatly

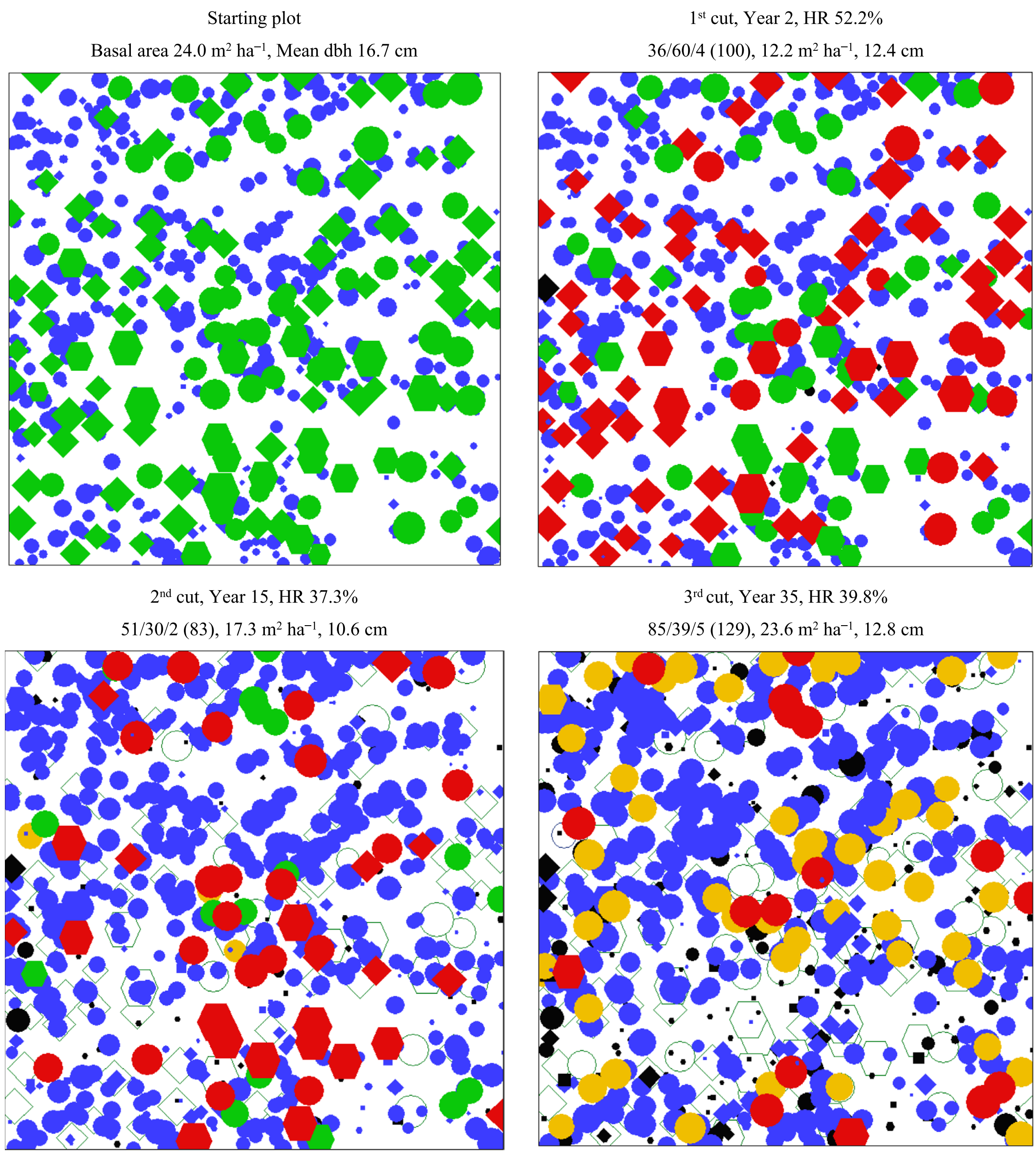

Fig. 5 Optimal cutting schedule in Revonkylä when the diameter limit for tree-level optimization was 10 cm, and 3 cuttings were optimized at the tree level. The numbers on top of the cutting maps are: cutting year (since the beginning): removals of saw log/pulpwood/energy wood and (total) in m^3ha^{-1}, post-cutting basal area, and post-cutting mean diameter. HR is the percentage of removed basal area. Green = remaining tree optimized at the tree level; Blue = remaining tree not optimized at the tree level; Red = removed tree optimized at the tree level; Yellow = tree removed based on the harvest intensity model; Circle = Norway spruce; Hexagon = Scots pine; Diamond = birch (silver birch or downy birch). Non-filled symbols are for trees removed in earlier cuttings. Black symbols are dead trees

reduced, 96% in Tuupovaara, and 95% in Revonkylä. The computing time was 6.8 min in Tuupovaara and 9.4 min in Revonkylä. These time consumptions were 30 to 56 times longer than in a formulation where tree-level optimization was not used. The NPVs of the optimal cutting schedule decreased by 0.5% in Tuupovaara and 1% in Revonkylä (Fig. 9) compared to the case where prior knowledge, learning SA and optimized SA parameters were not used (‘Basic’ in Fig. 9).

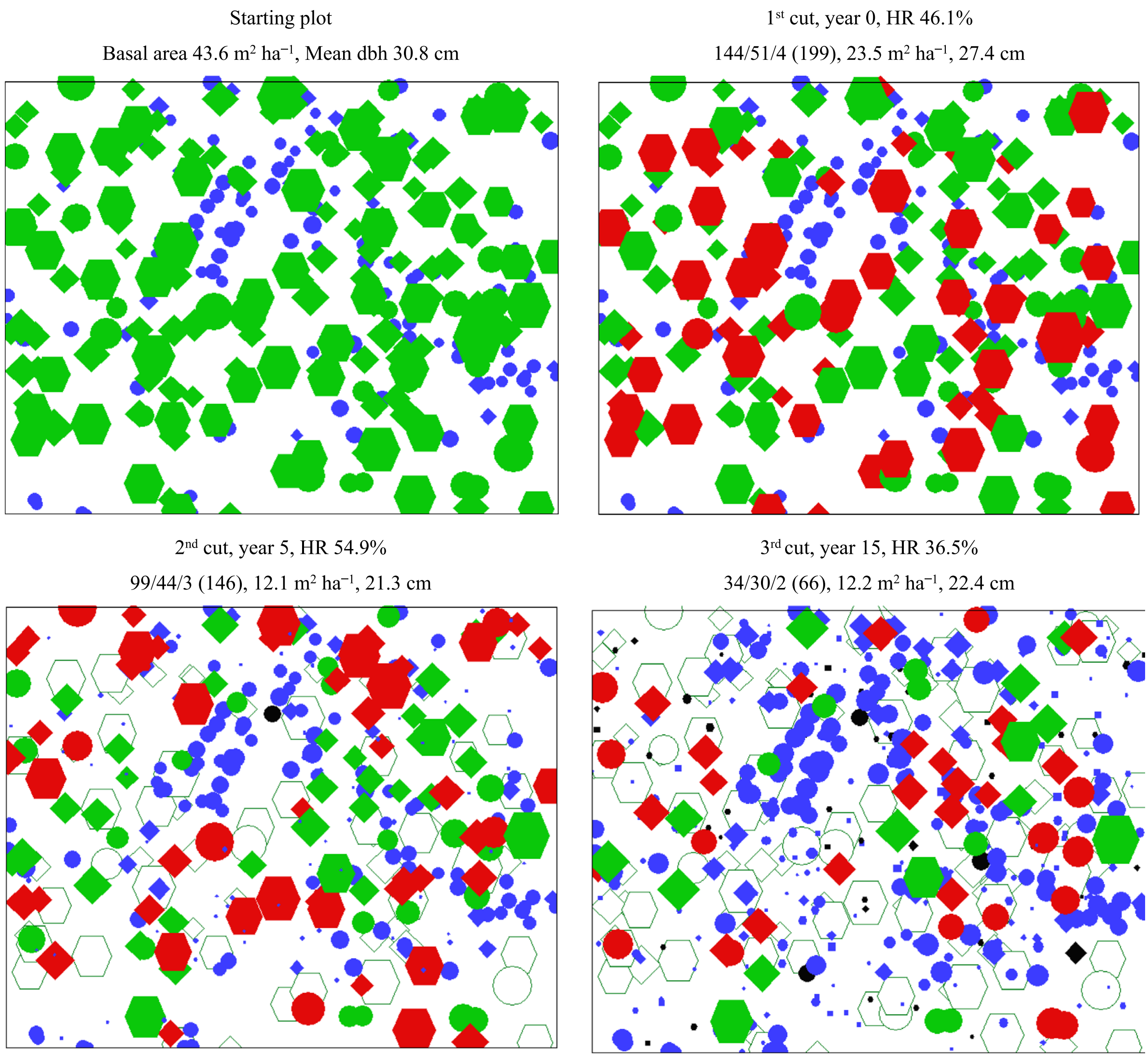

Fig. 6 Optimal cutting schedule in Tuupovaara when the diameter limit for tree-level optimization was 10 cm, and three cuttings were optimized at the tree level. The numbers on top of the cutting maps are: cutting year (since the beginning): removals of saw log/pulpwood/energy wood and (total) in m^3 ha^{-1}, post-cutting basal area, and post-cutting mean diameter. HR is the percentage of removed basal area. Green = remaining tree optimized at the tree level; Blue = remaining tree not optimized at the tree level; Red = removed tree optimized at the tree level; Circle = Norway spruce; Hexagon = Scots pine; Diamond = birch (silver birch or downy birch). Non-filled symbols are for trees removed in earlier cuttings. Black symbols are dead trees

Table 2 Parameters of the model for the optimal number of years to the first, second, and third cutting in the CCF management of Finnish forests

Variable	Parameter	1st cutting	2nd cutting	3rd cutting
Intercept	a_0	5.30386	4.723122	4.731939
TS	a_1	−0.00017	−0.00027	−0.00026
SubXeric	a_2	−0.23397	−0.149	−0.11587
Xeric	a_3	−0.45072	−0.14385	−0.03575
D	a_4	−0.0869	−0.03103	−0.00801
G	a_5	−0.08028	−0.04861	−0.04831

Similarity of the first cutting

If the main purpose of optimization is to provide decision support for the first (next) harvest decision, it is relevant to analyze the similarity of the prescriptions for the first cutting in different problem formulations. In Revonkylä, the first cutting was prescribed after 0–3 years in the fast solutions visualized in Fig. 10 whereas it was in year 2 in the most detailed formulation (Fig. 5). The computing time of these faster solutions was 2.3–55.0% of the time used to solve the most detailed problem. The removal of the first cutting ranged from 58 to 105 m^3 ha^{-1} (100 m^3 ha^{-1} in the most

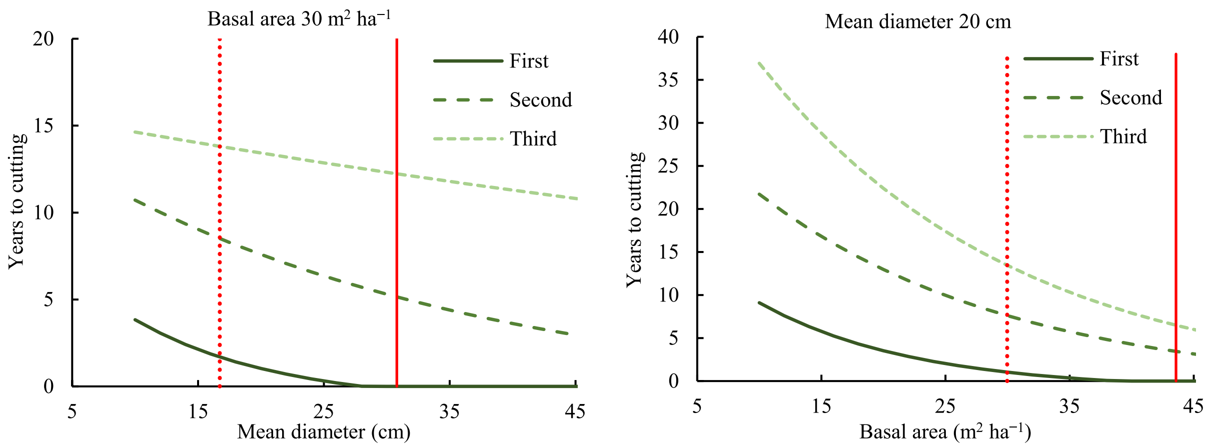

Fig. 7 The optimal year of the first, second, and third cutting as predicted with a model (Eq. 6). The predictions are for a mesic site and temperature sum of 1300 d.d. The vertical lines show the stand basal area and mean tree diameter for the Revonkylä (dotted line) and Tuupovaara (solid line) plots

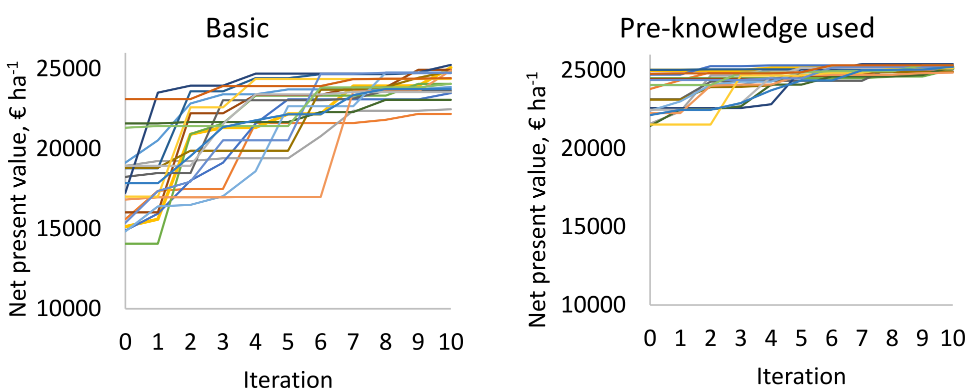

Fig. 8 Development of the net present value during 10 iterations for the 20 solution vectors used in the differential evolution algorithm. The right diagram shows the development of the solutions when prior knowledge about the optimal cutting years was used. The left diagram shows a case where prior knowledge was not used. The diagrams are for the Tuupovaara plot when tree-level optimization was used in three cuttings for trees larger than 20 cm in dbh

detailed formulation, Fig. 5 top right) and the post-cutting basal area was 12.4–16.4 $m^2\ ha^{-1}$ (12.4 $m^2\ a^{-1}$ in the most detailed formulation). The thinning was always from above. Therefore, all solutions were rather similar in terms of the timing and type of cutting, but there was some variation in the removed volume.

In Tuupovaara, all solutions proposed an immediate cutting (Fig. 6, Fig. 11) and the removed volume was always about 200 $m^3\ ha^{-1}$, i.e., the largest allowed removal. The thinning was always from above. The solutions of all formulations suggested similar management, although tree-level cutting prescriptions varied. Possible reasons for the tree-level differences were the use of distance-independent growth models and optimizing the cuttings without spatial management objectives. If one of the objectives had been a certain type of post-cutting spatial distribution of trees, the tree-level prescriptions would probably have been more similar. The tree-level prescription would also have been more similar if the cutting had aimed at removing those large trees first that overtop smaller trees.

Discussion

The article described an optimization method that includes two levels of detail and two optimization algorithms. The method used differential evolution at the higher level and simulated annealing at the lower level. However, any algorithm that optimizes continuous variables could be used at the higher level, and any method suitable for combinatorial optimization could be employed at the lower level (Sun et al. 2022a).

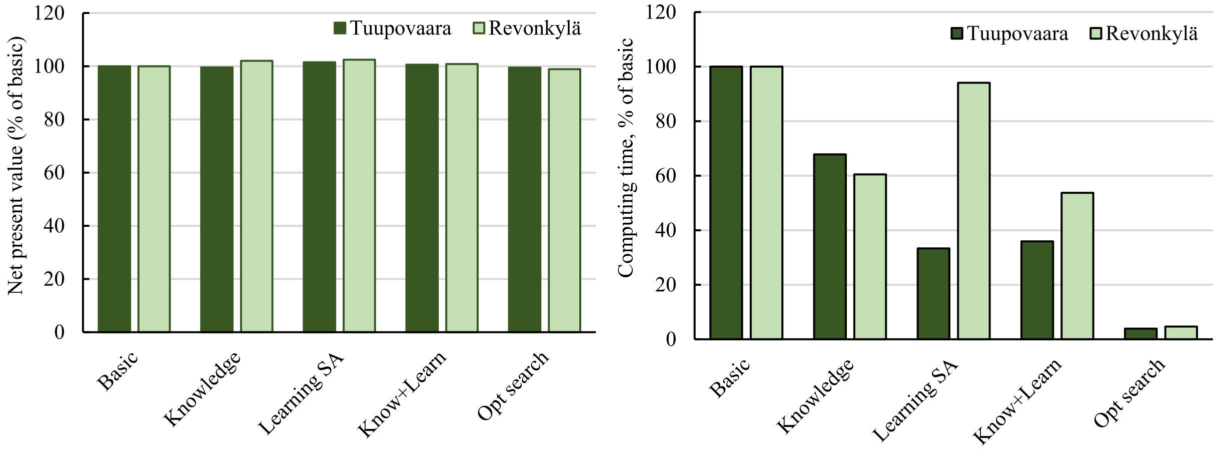

Fig. 9 Relative net present value and computing time ("Basic" = 100) when prior knowledge, learning SA algorithm (simulated annealing), or optimized SA search (Opt search) was used. Know + Learn means that both prior knowledge and learning SA were used. Simulated annealing was optimized for a search process where both prior knowledge and learning SA were used

The method allows flexible choices between detailed tree-level optimization and less detailed or diameter-class-level optimization. The method can be used always when tree-level data is available for part of the trees. As it is known that, in CCF, economically optimal thinning treatments remove predominantly large trees (e.g., Pukkala et al. 2015), it is often enough to optimize the harvest decisions individually only for the dominant trees. From the implementation point of view, it makes sense to optimize those trees individually whose location is known. The solution can be passed to the computer of the harvester so that the driver can see from a map the locations of the trees that should be removed.

The differential evolution and simulated annealing algorithms include stochastic elements meaning that repeated optimizations do not produce the same result. To analyze the effect of algorithm stochasticity, one problem was solved 10 times (Tuupovaara plot, three cuttings, trees larger than 20 cm optimized at the tree level, learning implemented in simulated annealing). The standard deviation of the NPVs of the 10 solutions was 0.88% of the mean, and the smallest NPV was 97% of the largest NPV. For the time consumption, the relative differences between repeated optimizations were smaller because the same number of candidates was evaluated in repeated optimizations. Because our results for time consumption of different problem formulations were systematic and clear (Figs. 3 and 10), the stochasticity of the used algorithms does not invalidate the study's main conclusions.

Both case study stands used in the study have been harvested. In both cases, the actual thinning resembles the optimal solution. In Revonkylä, the landowner thinned the stand from above (in year 0), removing 73 m^3 ha^{-1}. The percentage of pine, spruce and birch of the removed volume were 37%, 45% and 18%. The most detailed optimization suggested removing 100 m^3 ha^{-1} two years later, and large trees of all tree species were removed (Fig. 5, top right). Another problem formulation (Fig. 10, bottom left) suggested removing 72 m^3 ha^{-1} in year 0, which is almost the same as the realized removal.

In Tuupovaara, the landowner harvested 230 m^3 ha^{-1} immediately (year 0) and all optimizations suggested a removal of about 200 m^3 ha^{-1} in year 0. The reason for the slightly smaller removal in the optimization was the constraint that prevented removing more than 200 m^3 ha^{-1}. Most of the removal (80%) consisted of large pines, both in the optimizations and actual thinning.

The method developed in this study is technically ready for practical use. However, in forestry practice, harvest decisions are optimized for stands instead of small plots, which causes computational challenges. The computing time needed to solve the planning problem increases exponentially with the increasing number of trees for which the cutting prescription is optimized individually. This calls for delineating small stands and restricting tree-level optimization to the largest trees and first cuttings.

Fortunately, using prior knowledge, learning, and optimized search algorithms makes it possible to greatly shorten computing times, which is a prerequisite for the real-life use of the method. When tree-level optimization is used to a larger extent, the results and the optimized search parameters can be saved in a database. Then, this database can be utilized for instance via machine learning or modeling to start new optimizations from near-optimal solutions. Because the optimal cutting years, cutting types, and even the optimal search parameters depend on management objectives and stand type, many optimizations are needed for a useful prior knowledge database.

Forest planning problems may include forest-wide constraints related to, for example, annual or periodical

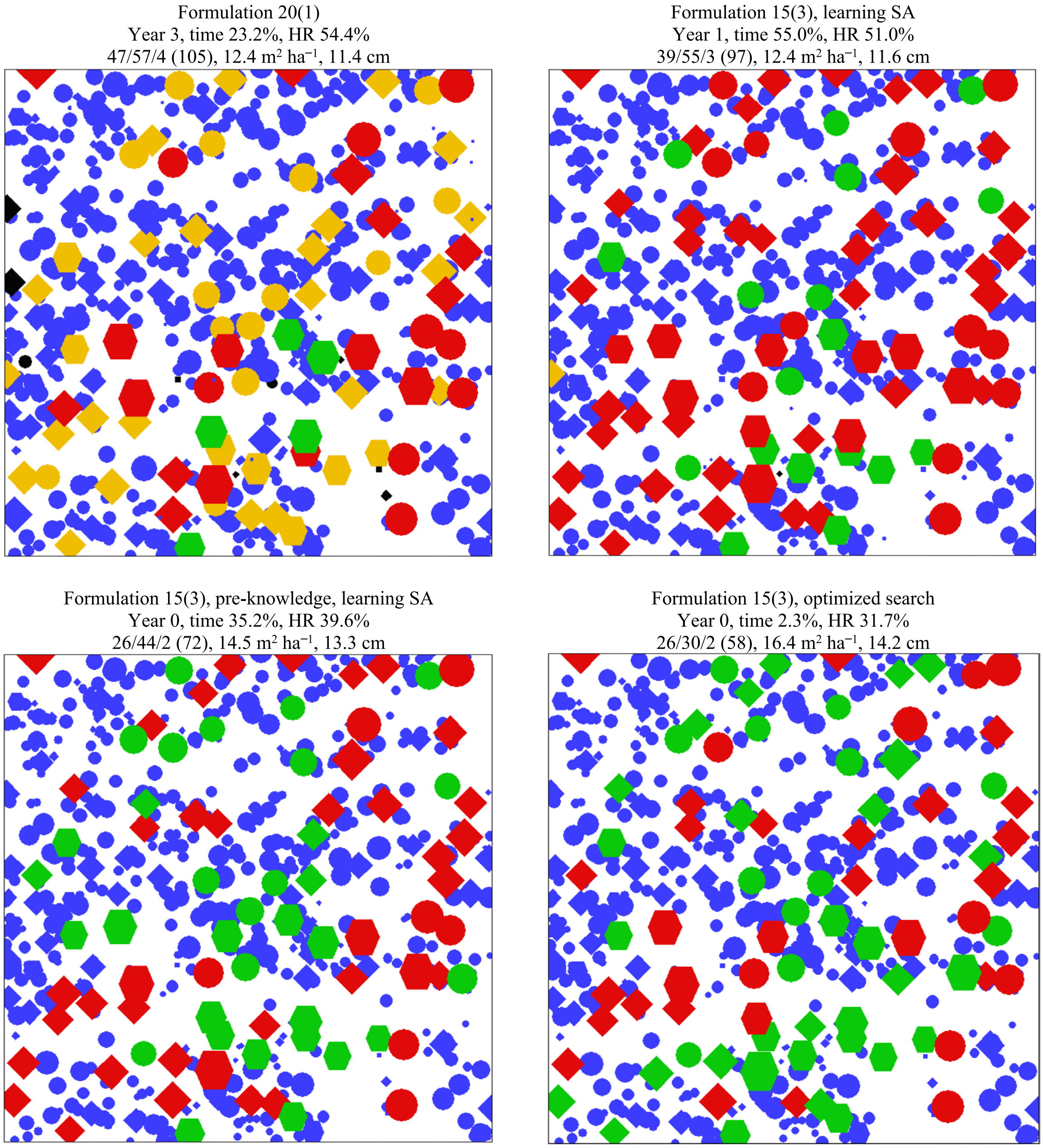

Fig. 10 Remaining and harvested trees in the first cutting of the Revonkylä plot in different problem formulations. In the abbreviation $x(y)$, x is the minimum diameter for tree-level optimization, and y is the number of cuttings in which tree-level optimization was used. The numbers above tree maps indicate the cutting year; relative computing time as a percentage of the most time-consuming problem; removals of saw logs/pulpwood/energy wood (total); post-cutting basal area and basal-area-weighted mean diameter. HR is the percentage of removed basal area. Green = remaining tree optimized at the tree level; Blue = remaining tree not optimized at the tree level; Red = removed tree optimized at the tree level; Yellow = tree removed based on the harvest intensity model; Circle = Norway spruce; Hexagon = Scots pine; Diamond = birch

removals, areas of certain habitat types, or amounts of ecologically important tree species (Kangas et al. 2015). There are methods available that facilitate forest-level constraints in stand-level optimization. The method developed by Hoganson and Rose (1984) and extended to spatial problems by Pukkala et al. (2008) uses a penalty function based on the dual prices of the forest-level constraints. The use of this method requires that the stand-level optimization problems be solved several times, by gradually adjusting the penalty function until the forest-level constraints are met. This would make the optimization process very

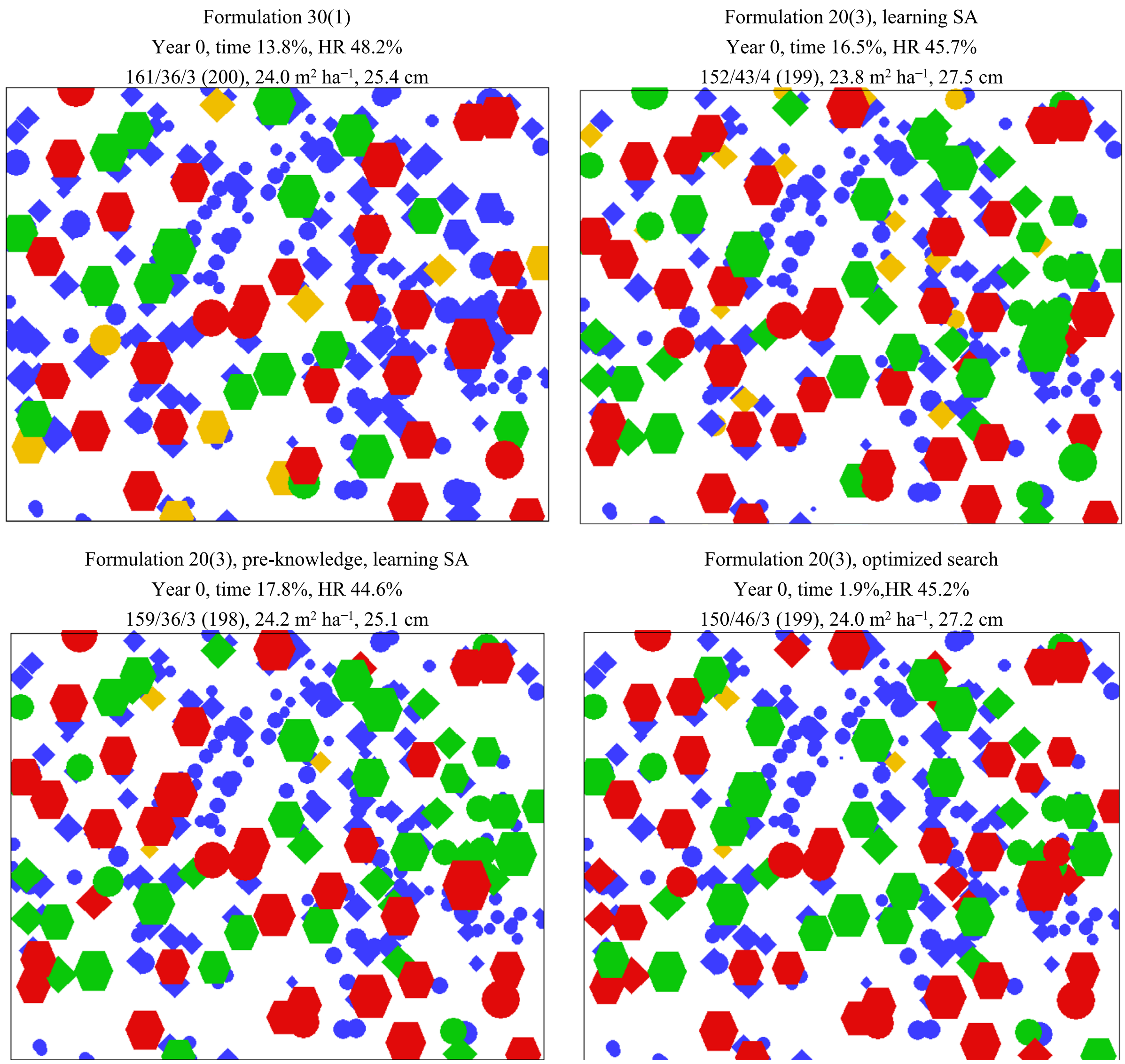

Fig. 11 Remaining and harvested trees in the first cutting of the Tuupovaara plot in different problem formulations. In the abbreviation $x(y)$, x is the minimum diameter for tree-level optimization, and y is the number of cuttings in which tree-level optimization was used. The numbers above tree maps indicate the cutting year; relative computing time as a percentage of the most time-consuming problem; removals of saw logs/pulpwood/energy wood (total); post-cutting basal area and basal-area-weighted mean diameter. HR is the percentage of removed basal area. Green = remaining tree optimized at the tree level; Blue = remaining trees not optimized at the tree level; Red = removed tree optimized at the tree level; Yellow = tree removed based on the harvest intensity model; Circle = Norway spruce; Hexagon = Scots pine; Diamond = birch

time-consuming, which increases the importance of fast methods for solving stand-level management problems.

Optimizing the cutting schedule without tree-level optimization decreased the NPV by about 10%, which verifies the worth of tree-level optimization. A possible way to decrease the importance of tree-level optimization would be to optimize the harvest intensity model separately for each cutting and tree species. Diversity-related management objectives (Thompson et al. 2009; Jactel et al. 2017; Pardos et al. 2021) may also increase the need to optimize harvest intensities separately for different tree species. However, a previous study (Pukkala et al. 2014), where four different harvest rate functions were optimized for 200 stands, showed that species-specific harvest intensity models optimized separately for each cutting, increased the net present value by only 1–2%. Using more flexible, six-parameter harvest rate functions increased the NPV by 1–7%.

On the other hand, using species- and cutting-specific harvest intensity models would multiply the number of optimized parameters with the consequence that the optimization time would also become many-fold. The time gained from avoiding the tree-level optimization would be largely lost. In addition, ecological goals related to the complexity of the stand structure (Seidl and Lexer 2013; Messier et al. 2019), the presence of large trees, and the spatial distribution of trees can be easily addressed in the tree-level approach but may be hard or impossible to incorporate into problem formulations that do not use tree-level optimization. Therefore, it seems likely that methods that support tree-level management decisions will be developed and used increasingly in the future.

Conclusions

Tree-level harvest optimization is straightforward combinatorial optimization, for which many methods are available. However, the size of the decision space is often so large that computational limitations usually prevent the practical use of the methods. This study showed that there are several possibilities to shorten the computing times. These possibilities include restricting tree-level optimization to the largest trees and first cuttings, using prior knowledge, integrating learning aspects into the optimization process, and optimizing the search algorithms. The study showed that these simplifications do not deteriorate the cutting prescriptions significantly when net present value is used as the criterion. The fastest variant of the solution method involves using optimized heuristic search, prior knowledge, learning aspects, and a hybrid approach where tree-level optimization is used only for a part of trees and cuttings. It is envisioned that tree-level optimization will be used increasingly because it can easily deal with management objectives related to the diversity and complexity of the stand structure. Our study makes it possible to accelerate the shift to tree-level management optimization.

Author contributions TP: calculations, writing; YN: planning of the experiment, funding acquisition, field measurements, writing; TM: planning of the experiment, field measurements, writing.

Funding Open access funding provided by University of Eastern Finland (including Kuopio University Hospital).

Data availability The sample plot data is available upon reasonable request from YN.

Code availability Upon reasonable request from TP.

Declarations

Conflict of interest The authors declare that they have no conflicts of interest.

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