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Optimizing continuous cover management of boreal forest when timber prices and tree growth are stochastic

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Abstract

Background: Decisions on forest management are made under risk and uncertainty because the stand development cannot be predicted exactly and future timber prices are unknown. Deterministic calculations may lead to biased advice on optimal forest management. The study optimized continuous cover management of boreal forest in a situation where tree growth, regeneration, and timber prices include uncertainty.

Methods: Both anticipatory and adaptive optimization approaches were used. The adaptive approach optimized the reservation price function instead of fixed cutting years. The future prices of different timber assortments were described by cross-correlated auto-regressive models. The high variation around ingrowth model was simulated using a model that describes the cross- and autocorrelations of the regeneration results of different species and years. Tree growth was predicted with individual tree models, the predictions of which were adjusted on the basis of a climate-induced growth trend, which was stochastic. Residuals of the deterministic diameter growth model were also simulated. They consisted of random tree factors and cross- and autocorrelated temporal terms.

Results: Of the analyzed factors, timber price caused most uncertainty in the calculation of the net present value of a certain management schedule. Ingrowth and climate trend were less significant sources of risk and uncertainty than tree growth. Stochastic anticipatory optimization led to more diverse post-cutting stand structures than obtained in deterministic optimization. Cutting interval was shorter when risk and uncertainty were included in the analyses.

Conclusions: Adaptive optimization and management led to 6%–14% higher net present values than obtained in management that was based on anticipatory optimization. Increasing risk aversion of the forest landowner led to earlier cuttings in a mature stand. The effect of risk attitude on optimization results was small.

Keywords: Adaptive optimization; Anticipatory optimization; Stochastic optimization; Risk preferences; Risk; Uncertainty; Reservation price

Background

Maximizing the economic benefits from timber production is equal to maximizing the net present value of future net incomes. Unfortunately, the future net incomes are unknown at the moment when management decision should be made. Future net incomes depend on future timber prices, which show substantial temporal variation (Leskinen and Kangas 1998).

Also the growth and development of trees and stands are poorly known. Deterministic models explain only a part of the growth variation between years, stands and trees. Measurements of past growth show that there are periods of good growth while in other years or during longer periods trees grow less than the long-term average (e.g. Pasanen 1998). In addition to these weather-related seasonal variations in annual growth, there are also between-tree growth differences which cannot be explained by deterministic models. Another factor causing uncertainty in growth prediction is climate change. It is usually assumed that the growth rate will increase in the boreal forests of North Europe (e.g. Pukkala and

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Kellomäki 2012), but the estimated growth trends represent very uncertain knowledge.

Flowering, pollination, seed production and germination are sub-processes of the regeneration process of trees and stands. All these sub-processes are very sensitive to weather conditions such as temperature and rainfall. In addition, the eventual size of the seed crop depends on the fluctuations of seed predators and seed diseases. Since many sub-processes critical to regeneration success depend on weather conditions, it is impossible to predict the exact amount of regeneration in a certain year in the future, even when there are plenty of empirical regeneration data to fit models. The best that can be done is to predict the distribution of regeneration results or the probability of successful regeneration. Mortality is also hard to predict exactly. However, the so-called regular mortality (competition-related mortality) is very low in regularly thinned managed boreal forest. Therefore, if catastrophic events are excluded from the analysis (like in this study) uncertainty in mortality does not add much to the total degree of uncertainty in the prediction of stand development. For an attempt to include catastrophic events see Zhou and Buongiorno (2006).

The above discussion shows that decisions on future forest management must be made under risk and uncertainty. Risk is usually understood to be a situation in which the probabilities of different states of nature are known, which makes it possible to calculate the distribution of outcomes for a certain decision alternative. Uncertainty refers to situations in which the probabilities are unknown. The prevailing situation is uncertainty. However, to make analyses easier, the situation is transformed from uncertainty to risk, by assuming some distributions for the uncertain factors. This allows the analyst to calculate the probabilities of different outcomes of decision alternatives.

Forest landowners have different attitudes toward risk and uncertainty. Most people are risk avoiders, especially in "big" decisions with a major potential impact on their livelihood. A risk-averse person seeks decision alternatives, which are at least reasonable when the states of nature develop in an unfavorable way. Risk avoiders tend to select decision alternatives for which the lower end of the distribution of outcomes is as good as possible (Pukkala and Kangas 1996). They may also minimize the "regret", i.e. the maximum loss compared to the best decision alternative under certain states on nature. On the contrary, risk takers are optimistic and favor decision alternatives that are good under favorable states of nature, even though the probability of such an outcome may be low.

There are two basic approaches to the optimization of stand management in a risk situation: anticipatory and adaptive optimization. Anticipatory optimization seeks a single management schedule, which produces the most favorable distribution of net present values or some other objective function (Valsta 1992). Risk neutral decision makers select management schedules which produce high average net present values. Risk takers often select management schedules for which the best outcomes are good whereas risk avoiders tend to maximize the worst outcomes of alternative management schedules.

Adaptive optimization does not try to find a single management prescription for the stand. Instead, it aims at finding rules that help the landowner to make right decisions in changing environment (Lohmander 2007). A well-known rule is the reservation price function indicating the minimum price that the seller should obtain from timber (Brazee and Mendelsohn 1988; Lohmander 1995; Gong and Yin 2004). A more general approach is the Markov decision process model (Lembersky and Johnson 1975; Kaya and Buongiorno 1987).

It can be assumed that reservation price decreases with increasing financial maturity of the stand: the lower the relative value increment of the stand, the lower is the minimum selling price of a certain timber assortment. Since the relative value increment decreases with increasing stand density and mean tree size, it can be assumed that reservation price is negatively correlated with stand basal area and mean tree diameter (Lohmander 1995; Gong 1998; Lu and Gong 2003).

The aim of this study was to describe a system for stochastic optimization of the management of boreal forests in a situation where future timber prices, tree growth and regeneration are not known exactly. The developed simulation–optimization system was used to compare deterministic and stochastic optima, as well as the results of anticipatory and adaptive optimization approaches. Pukkala and Kellomäki (2012) compared anticipatory and adaptive management in even-aged forestry and Zhou et al. (2008) compared adaptive and anticipatory policies in uneven-aged forests. In this study, continuous cover management of both even-and uneven-aged initial stands was optimized. Continuous cover management refers to any sequence of cuttings that keep a minimum post-cutting residual stand basal area. Regeneration by planting or sowing is not used.

Based on previous studies, it was hypothesized that in a risk situation it is optimal to grow more diverse stands than under certainty (Rollin et al. 2005). Risk avoiders were assumed to maintain more diverse stand structures than risk seekers (Pukkala and Kellomäki 2012). The third hypothesis was that adaptive optimization and management results in higher average net present value than anticipatory optimization (Gong 1998; Lu and Gong 2003).

Methods

Growth and yield model

The set of models that was used to simulate stand development (Pukkala et al. 2013) consists of individual-tree model for diameter increment, individual-tree survival function, and an ingrowth model (Vanclay 1994). To calculate the assortment volumes of removed trees, the height model of Pukkala et al. (2009) and the taper models of Laasasenaho (1982) were used. The article of Pukkala et al. (2013) reports also methods for simulating the residual variation around the diameter increment and ingrowth models. The deviation of diameter increment from deterministic model prediction was modelled as follows (Miina 1993):

$$dev_{it} = a_i + v_{it} \tag{1}$$

$$v_{it} = \rho v_{it-1} + e_{it} \tag{2}$$

where dev_{it} is the deviation from model prediction for tree i and 5-year period t, a_i is normally distributed random tree factor for tree i, v_{it} is random autocorrelated residual for tree i and period t, ρ is correlation coefficient between the residuals of consecutive 5-year periods and e_{it} is normally distributed random number, $\mathrm{var}[e_i] = \mathrm{var}[v_{it}](1 - \rho_i^2)$. It was assumed that 1/3 of dev is accounted for by the tree factors (a_i) and the rest is accounted for by autocorrelated residuals (v_{it}). It has been found that the correlation between the residuals of consecutive 1-year periods is 0.4–0.7 and the correlation between 5-year residuals is about half of it (Henttonen 1990; Miina 1993; Kangas 1997; Pasanen 1998). In this study, the autocorrelation coefficient of residuals (ρ) was assumed to be 0.300 for all species. The total variance of residual was 0.254 for pine, 0.283 for spruce and 0.228 for birch (Pukkala et al. 2013). The random numbers (e_{it}) generated for the trees in a particular 5-year growth period were assumed to be correlated (Pasanen 1998), resulting in both auto- and cross-correlated time series of growth residuals (Figure 1). In simulation, the stochastic residuals were added to the predicted diameter increment. As a result, the simulated differentiation of tree size was faster than it would be in deterministic simulation.

The diameter increments obtained from the diameter increment model were multiplied with a multiplier that describes the effect of climate change on tree growth (Pukkala and Kellomäki 2012). The climate-induced growth trend is based on a process-based model (Kellomäki and Väisänen 1997; Ge et al. 2010) and corresponds to climate change scenario A1B. The effect of changing climate on diameter increment depends on tree species and growing site. The trends are linear and growth will improve approximately 20% in 50 years. In this study it was assumed that the influence of climate change on diameter increment is not known with certainty. Therefore, the slope of the trend line was assumed to be stochastic, with standard deviation equal to 0.1 times the slope coefficient.

Ingrowth was defined as the number of new trees per hectare that reach the 1.3 m height during a 5-year period. Pukkala et al. (2013) modelled the residuals of the ingrowth model as follows

$$dev_{s,t} = \rho_s dev_{s,t-1} + se_s e_{s,t} \tag{3}$$

where $dev_{s,t}$ is the deviation from the deterministic logarithmic model for species s and 5-year period t, ρ_s is the autocorrelation coefficient of successive 5-year periods for species s, se_s is the standard deviation of the stochastic annual component and $e_{s,t}$ are multi-normally distributed correlated random numbers (N(0,1)) for pine, spruce, birch and hardwood other than birch. Correlated random numbers ($e_{s,t}$) were obtained by using the Cholesky decomposition of the covariance matrix of the residuals of the species-specific ingrowth models (Pukkala et al. 2013). Correlations between the residuals of different species are not high, but for instance the unexplained variation in the ingrowth of spruce is positively correlated with the residual for birch. On the contrary, the correlations between successive five year periods are rather high, 0.670 for pine, 0.577 for spruce, 0.657 for birch and 0.637 for hardwood other than birch. The main reason for the positive autocorrelation is most

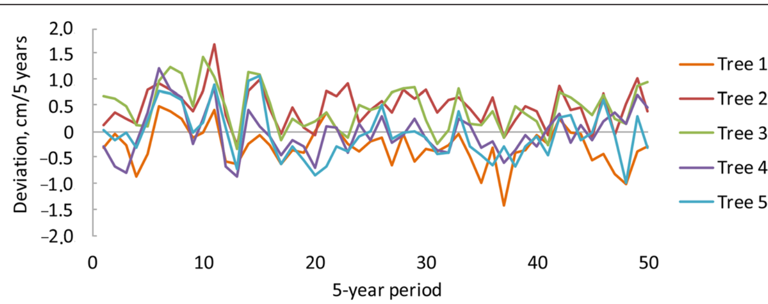

Figure 1 A diameter increment scenario. Sequences of stochastic deviations from deterministic model prediction for five trees and fifty 5-year periods. Each sequence consists of a tree factor and cross- and autocorrelated stochastic temporal components. Tree 2 is a fast-growing individual and Tree 1 is a slow-growing individual.

probably that a single good regeneration year (good seed crop with low seed predation and high germination rate) increases the ingrowth in several coming years. The standard deviation of the stochastic annual component (*se*) is 0.526 for pine, 0.990 for spruce, 1.027 for birch and 0.938 for hardwood other than birch. Stochastic ingrowth scenarios are produced by adding the simulated residuals to the deterministic logarithmic ingrowth model and converting the result to a non-logarithmic value. Figure 2 shows examples of ingrowth scenarios when the model prediction is 10 new trees per hectare. It can be seen that the resulting ingrowth scenarios are very erratic, reflecting to what happens in reality.

Leskinen and Kangas (1998) described the annual variation in timber prices with a set of models where the logarithmic price of a certain timber assortment depends on the price of the previous year plus a stochastic annual component

$$p_t - \bar{p} = \alpha(p_{t-1} - \bar{p}) + e_t \tag{4}$$

where p_t is the logarithmic price in year t, α is parameter ranging from 0.45 to 0.89 for different timber assortments and e is normally distributed random number. Correlated random numbers for different assortments were produced with the help of Cholesky decomposition. The model has been estimated from the historical timber price statistics of Finland. Figure 3 shows an example timber price scenario for six assortments. It can be seen that the prices of successive years are positively correlated and the prices of different assortments are also correlated.

Case study stands

Calculations were done for an uneven-aged spruce stand, mixed stands of pine, spruce and birch, and pure pine and spruce stands (Table 1). Each stand was assumed to grow on a typical growing site for the species. The stands represent typical and common stand structures in the managed forests of Finland. The stands were assumed to grow in Central Finland.

Each species and canopy layer was initially described by basal area, mean diameter, mean height and minimum and maximum of the diameter distribution. Stand basal area and the three diameters were used to predict the diameter distribution of each stratum (species or canopy layer) present in the stand. The predicted diameter distribution was divided into 10 classes of equal width, and 5 trees were taken to represent each class. The random tree factors of the residuals of the diameter increment model were generated at this point (a_i of Equation 1). As a result, each stratum of the stand was represented by 50 “representative trees” varying in size and inherent growth potential.

Growth, survival and ingrowth were simulated using 5-year time steps. If there was ingrowth, a new representative tree was generated for every 10 new conifers or 50 hardwoods (each new tree represented 10 or 50 trees per hectare). The random tree factors of the residuals of diameter growth models were drawn from normal distribution for each new representative tree. Mortality was

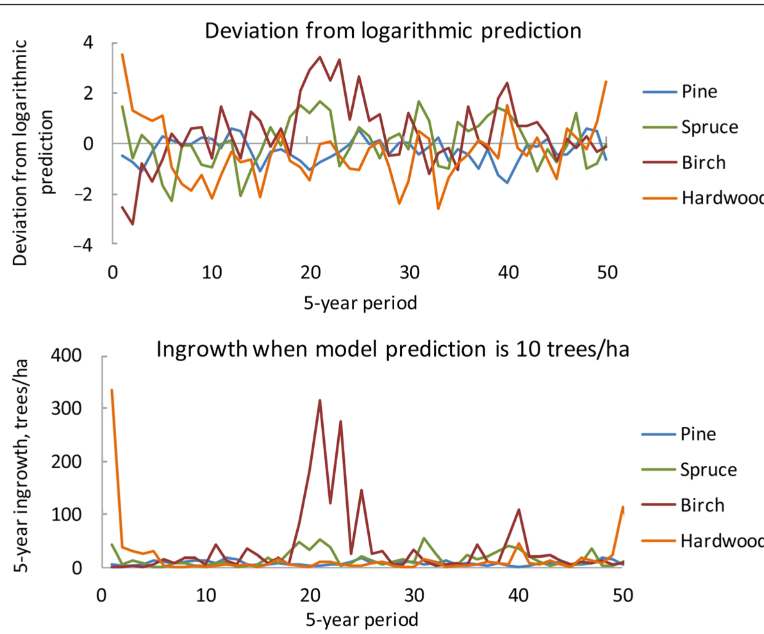

Figure 2 A stochastic ingrowth scenario. Cross- and autocorrelated logarithmic residuals are generated (top) and added to the logarithmic ingrowth prediction, which is then converted to non-logarithmic value (bottom).

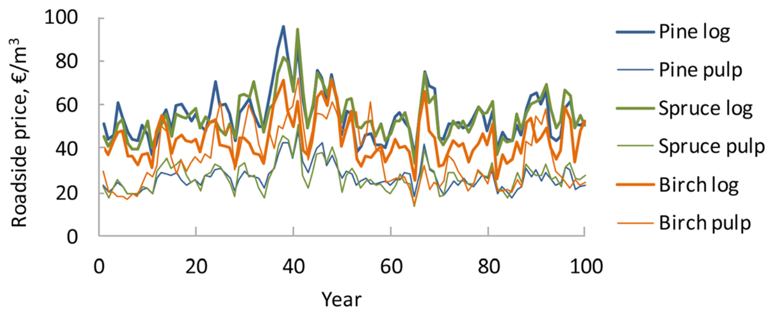

Figure 3 A stochastic timber price scenario for 100 years. The prices of different assortments are auto- and cross-correlated.

simulated by multiplying the frequency of the representative tree by its survival probability.

Optimization

The objective variable was the net present value of all future net incomes, calculated with 3% discount rate. The next three cuttings were optimized for all stands. The net present value of the remaining growing stock (after the 3rd cutting) was calculated with species-specific models using stand basal area, mean dbh, discount rate, site variables and timber prices as predictors (Pukkala 2005). These models explain 90%–95% of the variation of the NPV of the optimal management schedule, depending on tree species. Because of discounting, the value of the ending growing stock, i.e. the discounted value of predicted net present value of all cuttings conducted later than the third cutting, had only a small effect on the total NPV. Preliminary tests indicated that optimizing three first cuttings was enough to have a reliable estimate of the total NPV and to know how the stand should be managed in the near future (Figure 4). For example, when optimizing one to five next cuttings and using model prediction to calculate the NPV of the residual stand, the following total NPVs (calculated with 3% discount rate) were obtained for an uneven-aged spruce stand: 11426 €·ha^{-1} (1 cutting optimized), 11897 €·ha^{-1} (2 cuttings optimized), 11917 €·ha^{-1} (3 cuttings optimized), 11884 €·ha^{-1} (4 cuttings optimized), 11879 €·ha^{-1} (5 cuttings optimized).

In anticipatory optimization the decision variables for each cutting were as follows:

- Cutting year (exactly: number of years since the start or since previous cutting)
- Parameters of the thinning intensity curve, which was defined separately for each species present in the initial stand

Thinning intensity was first described with the following logistic function (Pukkala et al. 2014):

$$h(d) = \frac{1}{1 + a_3 \times \exp[a_1(a_2 - d)]^{1/a_3}} \qquad (5)$$

where $h(d)$ is the proportion of harvested trees at dbh d and a_1, a_2 and a_3 are parameters to be optimized. This simple function has been found to result in almost as good solutions (in terms of NPV) as optimizing the

Table 1 Case study stands

Stand	Site	Strata	BA	Height	D_{min}	D_{mean}	D_{max}
Uneven spruce	MT	Spruce	18	21	17	22	28
		Spruce	7.6	6	1	8	16
Mature mixed	MT	Pine	6	21	13	22	28
		Spruce	6	14	3	16	22
		Birch	6	20	13	21	27
Young mixed	MT	Pine	4	17	13	18	22
		Spruce	3	14	3	16	22
		Birch	4	16	13	17	20
Young spruce	OMT	Spruce	15	11	5	12	18
Mature spruce	OMT	Spruce	28	21	15	23	29
Young pine	VT	Pine	15	11	5	12	18
Mature pine	VT	Pine	25	20	15	21	27

MT = mesic site; OMT = herb-rich site; VT = sub-xeric site; BA = stand basal area (m^2·ha^{-1}); Height = mean tree height (m); D_{min} = minimum diameter (cm); D_{mean} = mean diameter (cm); D_{max} = maximum diameter (cm).

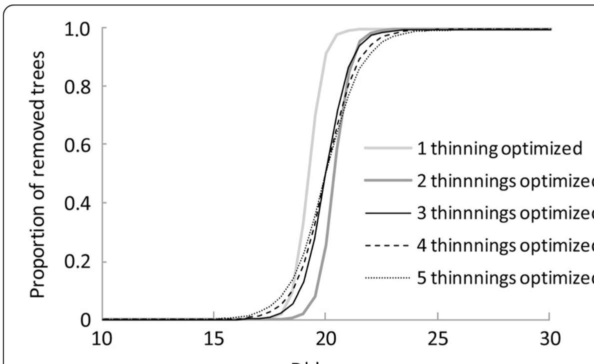

Figure 4 Effect of optimizing 1 to 5 next cuttings on the optimal thinning intensity curve of the first cutting in an uneven-aged spruce stand.

harvest intensities of different diameter classes separately (Pukkala et al. 2014). Moreover, preliminary analyses showed that parameter a_3 could be fixed to $a_3 = 1$ (i.e. a_3 could be removed) without any notable deterioration of the NPV of the optimal solution. Therefore, the following simplified thinning intensity model was used in this study:

$$h(d) = \frac{1}{1 + \exp[a_1(a_2 - d)]} \tag{6}$$

Parameter a_2 gives the diameter at which thinning intensity is 0.5, and a_1 defines the type of thinning. If a_1 is negative, small trees are thinned more than large ones, resulting in low thinning. When a_1 is positive, the thinning represents high thinning while $a_1$equal to 0 results in uniform thinning. As a result, the number of optimized variables was $3(1 + 2) = 9$ for one-species stand and $3(1 + 3 \times 2) = 21$ for a mixture of pine, spruce and birch.

In adaptive optimization, cutting years were replaced by a reservation price function. The following form was assumed, based on previous research (e.g. Pukkala and Kellomäki 2012), preliminary analyses and known relationships between stand basal area, mean tree diameter and financial maturity:

$$RP = \exp\left(b_1 + b_2\sqrt{D} + b_3\sqrt{G}\right) \tag{7}$$

where RP is the price of saw log (roadside price) that activates a cutting treatment and b_1, b_2 and b_3 are optimized parameters that define how the reservation price depends of stand basal area and mean tree diameter. The same reservation price was used in all cuttings. In a mixed stand the current timber price, which was compared to the reservation price, was computed as the weighted average of the saw log prices of all species present in the stand, using basal area as the weight variable.

The intensity and type of cutting were defined with the same logistic function that was used in anticipatory optimization. However, in adaptive optimization cutting may be postponed if timber price is not good enough. Using the same thinning intensity curve with varying cutting years may lead to situations in which the thinning is too heavy or too light, depending on how much and to which direction the cutting year is moved. To avoid this from happening, the problem formulation was changed so that parameter a_2 (location of thinning intensity curve) was calculated with a model, and only parameter a_1 (thinning type) was optimized. This resulted in problem formulations containing $3 + 3 \times 1 = 6$ decision variables in one-species stands, and $3 + 3 \times 3 \times 1 = 12$ decision variables in the mixture on pine, spruce and birch (the type of thinning was optimized separately for each species).

Several deterministic optimizations were conducted for different species on different growing sites to find the relationship between parameter a_2 (location) of the thinning intensity curve and the stand characteristics (Figure 5). On the basis of these optimizations, the following model was fitted to the diameter at which thinning intensity is 50%:

$$a_2 = 8.738 - 0.156G + 0.771D - 1.906CT \tag{8}$$

where D is basal-area-weighted mean diameter of the trees (cm), G is stand basal area ($m^2 \cdot ha^{-1}$) and CT is an indicator variable for xeric growing sites ($CT = 1$ for *Calluna* type and poorer sites, and 0 otherwise). The model explained 82% of the variation of a_2.

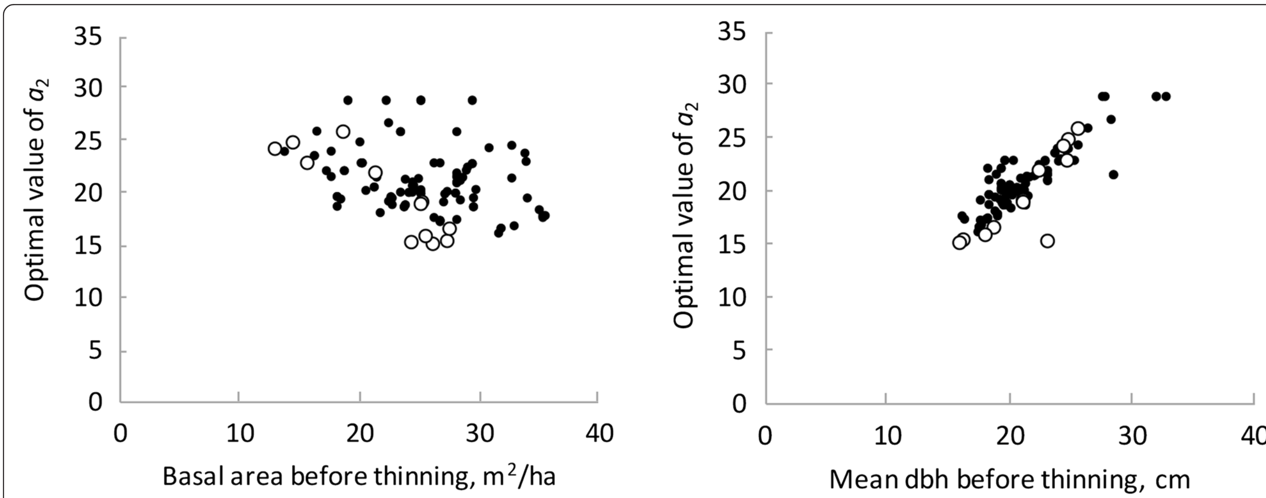

Figure 5 Dependence of parameter a_2 of the thinning intensity curve (Equation 5) on stand basal area and mean tree diameter. Open circles represent xeric (dry) growing sites.

The current forestry legislation of Finland does not allow the landowner to thin the stand below a certain minimum residual basal area (typically around 10 $m^2 \cdot ha^{-1}$). If the minimum basal area requirement is not met, the landowner is obliged to regenerate the stand within a certain time frame. In this study, any solution in which the minimum basal area was not met was penalized with the consequence that the selected schedules were better in line with the current forestry legislation.

Each management schedule evaluated during an optimisation run was simulated 600 times, and the mean NPV of the 600 stochastic outcomes was passed to the optimization algorithm. The results therefore represent the optimal management for risk neutral decision makers. When the effect of risk attitude was analysed the 10% accumulation point of the distribution of outcomes was used as the objective variable for a risk avoider, leading to the selection of such a management schedule for which the worst outcomes are as good as possible (Pukkala and Kangas 1996). The corresponding accumulation point for a risk seeker was 90%. The used optimization method was the direct search algorithm of Hooke and Jeeves (1961). Afterwards, all optimal solutions – also the deterministic ones – were simulated 1000 times with stochastic variation in tree growth, growth trend, in growth and timber price. The reported results on NPV, removals etc. are based on these simulations.

Results and discussion

Effect of risk factors

The effect of adding different stochastic components to simulation and anticipatory optimization was inspected in the uneven-aged spruce stand. Management was optimized without any stochasticity and with stochasticity in growth, ingrowth or timber price. The distributions of net present values produced by the optimal anticipatory solution are shown in Figure 6. It can be seen that when only ingrowth or only climate-induced growth trend is stochastic the distribution of outcomes is very narrow, indicating that these factors do not bring much uncertainty to decision-making. Stochastic variation in tree growth brought much more uncertainty in NPV than stochasticity in ingrowth or climate-induced growth trend. When timber price was stochastic the distribution of outcomes was much wider indicating that timber price is a more significant source of uncertainty than the biological growth process of trees.

Deterministic optimization and simulation resulted in the NPV of 11775 $€ \cdot ha^{-1}$. The average NPVs of the outcomes of stochastic anticipatory optima were almost the same. Also the optimal cutting years of the uneven-aged spruce stand were the same in all optimizations: the first cutting immediately, the second after 15 years and the third 10 years later. However, the way in which cuttings were conducted depended on the degree of stochasticity. The deterministic optimum advised the landowner to remove all trees larger than 20.2 cm in dbh. When stochastic factors were added to simulation and optimization, more and more trees larger than 20 cm were retained, and more and more trees less than 20 cm in dbh were removed, which means that stochastic optimization leads to higher dbh-variation in the post-cutting stand (Figure 7). The same trend was observed also in pure even-aged conifer stands, except mature pine stand (Figure 8). However, also in this stand the second and third thinnings showed similar differences between deterministic and stochastic optima as obtained for the other stands. Similar differences between deterministic and stochastic optima were obtained also for the mixed stands (results not shown). Rollin et al. (2005) found that counting for risk leads to clearly more diverse stand structures than suggested by deterministic solutions.

The total removal of the three cuttings was 6%–23% lower in the stochastic anticipatory optima than in the deterministic optima. The interval between the 1st and the 3rd cutting was 5–20 years shorter in the stochastic optima. These are indications of risk sharing behavior: in a risky situation it is optimal to cut more often but remove a smaller volume at a time.

Figure 7 shows that the cutting intensity curve is located at larger diameters in mature stands. Because the mature stands are to be cut immediately, the result suggests that the cutting may already be late. Another partial explanation for the difference between young and mature stands is that the basal area of the young stands would increase too much without cutting, decreasing the relative value increment of the stand (see Figure 5). Table 2 shows that the stand basal area at cutting is larger for the young initial stands but the mean tree diameter is smaller, suggesting that high stand densities call for earlier cuttings, which is a logical result. In general, the higher was the mean tree size the lower was the pre- and post-cutting stand basal area.

Effect of risk attitude

The effect of risk attitude on optimal management was analyzed in the mixed stands with the hypothesis that a risk avoider maintains a more diverse stand structure than a risk seeker. However, the thinning intensity curves were very similar for both risk attitudes suggesting that the post-cutting diameter distributions were also similar for both attitudes. The same difference as in pure stands was observed between deterministic and stochastic anticipatory optima: the deterministic optima proposed diameter-limit cutting with a narrower post-cutting diameter distribution than obtained in stochastic anticipatory optimization.

The proportions of different species after the first cutting were more uniform for risk avoider than for risk seeker (Figure 9), i.e. risk aversion led to more

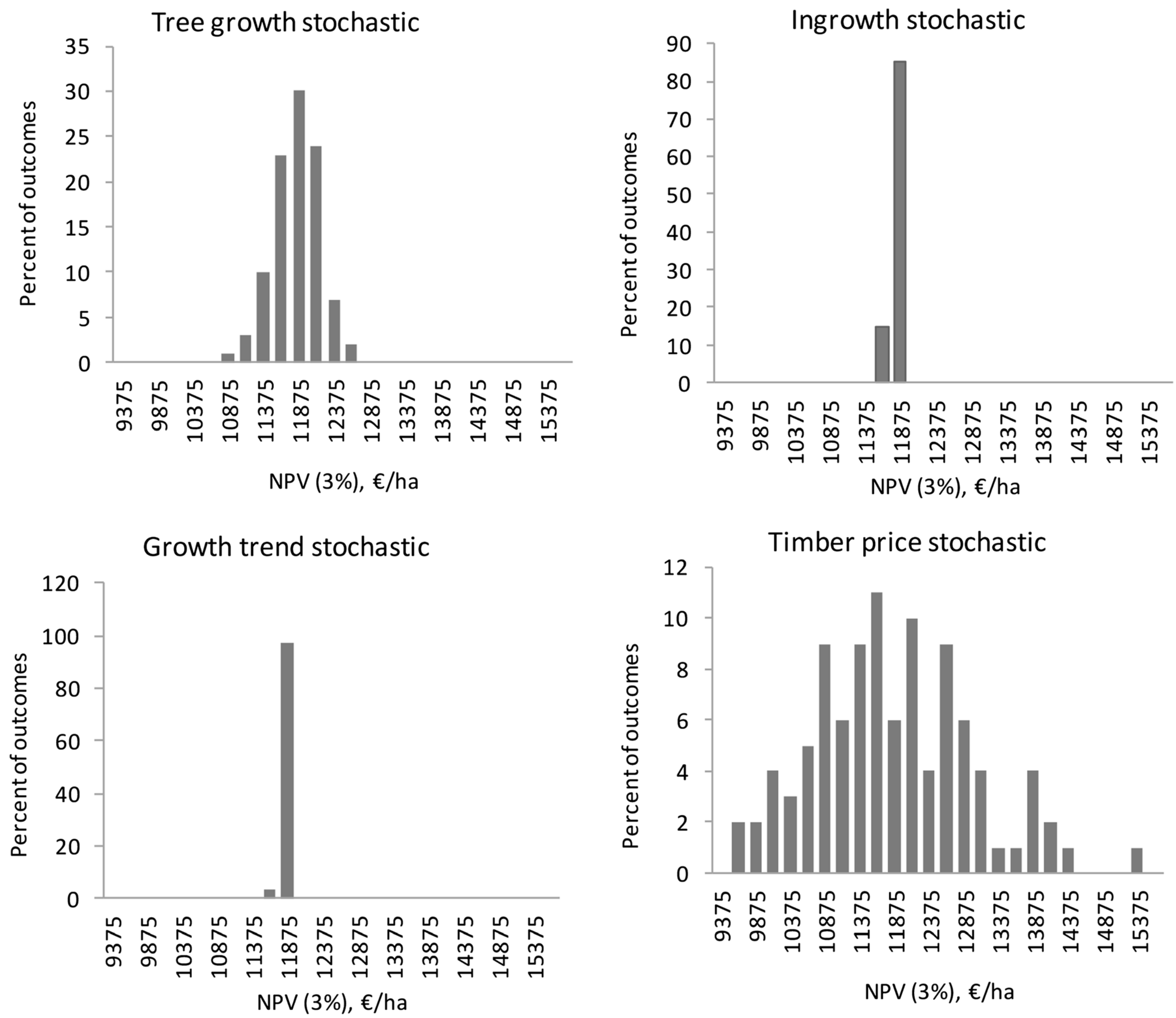

Figure 6 **Distributions of net present value in the optimal solution when one factor at a time is stochastic (growth, ingrowth, growth trend, or timber price).**

mixed stand. In the young mixed stand the risk seeker removed all pines in the first cutting whereas the risk avoider left all species in the residual stand. In the mature stand the post-cutting stand was more spruce dominated for the risk seeker, the risk avoider maintaining more birch and slightly more pines than the risk seeker. The differences were in line with the hypothesis, but they were small. The reason for the small differences may be that the legal limits force the landowner to keep more than species in the first cutting since otherwise the stand balsa area would be too low. Another reason is the fact that since pines and birches were clearly larger than spruces, it was optimal to gradually remove them irrespective of risk attitude. In addition, since the prices of different tree species correlate (Figure 3), increasing species diversity does not decrease the financial risk very much.

In the mature mixed stand, the cuttings were the earlier the more risk-averse the decision-maker was (Table 3). This is in line with Gong (1998) who concluded that risk avoiders should have the final felling earlier than risk-neutral forest landowners. The removed volume increased towards increasing risk tolerance (Gong 1998; Lu and Gong 2003). In the young mixed stand the removal was larger for the risk-neutral decision-maker than for risk avoider, but the seeker cuts less, most probably because the third cutting was 10 years earlier for the risk seeker than for other risk attitudes.

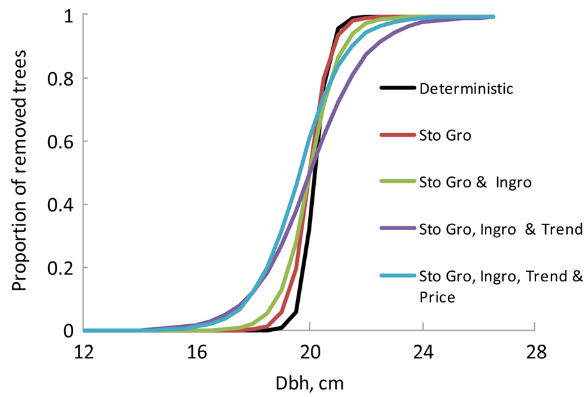

Figure 7 Optimal first cutting in deterministic solution and in stochastic anticiparoty optima with different sources of stochasticity (Gro = growth, Ingro = ingrowth, Trend = climate-induced growth trend, Price = timber price).

Adaptive optima

In adaptive optimization, cutting years were replaced by the reservation price function, resulting in cutting years that may be different in repeated stochastic simulations, depending on the realized stand development and timber price. To make the thinning intensity curve sensitive to changes in cutting year, the "location" parameter of the curve (a_2, dbh at which thinning intensity is 0.5) was calculated with a model (Equation 8) and only the type of thinning (low, uniform or high depending on parameter a_1 of Equation 6) was optimized.

The optimal reservation price functions were very similar for all initial stands (examples shown in Figure 10). As expected, the mean net present values of several repeated stochastic simulations with the optimal parameters were clearly better for the adaptive optima (Figure 11), the advantage of adaptive optimization and management being 6%–14%. There were no systematic differences in the average cutting years or removals between anticipatory and adaptive optima (Table 2). In mature stands, the average cutting year suggested by the adaptive optima was about 5 years later than in the anticipatory optima. However, the reason for this difference is most probably technical: it was possible to only postpone the first cutting from year zero, not have it earlier.

The solutions of the adaptive optimization problems were also simulated so that the optimized value of parameter a_1 (thinning type) of the thinning intensity curve (Equation 6) was replaced by 1, corresponding to high thinning. The average NPVs of 1000 simulations were nearly the same as obtained with the optimized values of parameter a_2, except for the mature mixed stand. The result indicates that nearly optimal adaptive management can be found when optimizing only the reservation price function and calculating the thinning intensity curve with model, fixing parameter a_1 to 1. The whole management schedule can be defined and optimized only by three decision variables, namely the parameters of the reservation price function. In the anticipatory optima for mixed stands there are 21 decision variables and yet the expected NPV is clearly better for the adaptive solution defined by only 3 decision variables.

The average roadside price obtained from saw log was about 20% higher in adaptive optima than in deterministic or stochastic anticipatory optima (Table 2). The difference was smaller in the first cutting of the mature stands, due to the high opportunity cost of the growing stock (high financial maturity of the initial stand). The results are in agreement with the assumptions made about the shape of the reservation price function.

Conclusions

All the hypotheses of the study were supported by the results. However, the effect of risk attitude on optimal management was very small, which may be related to the current forestry legislation which ruled out a part on the management options. Another reason may be the size differences of the species of mixed stands, which

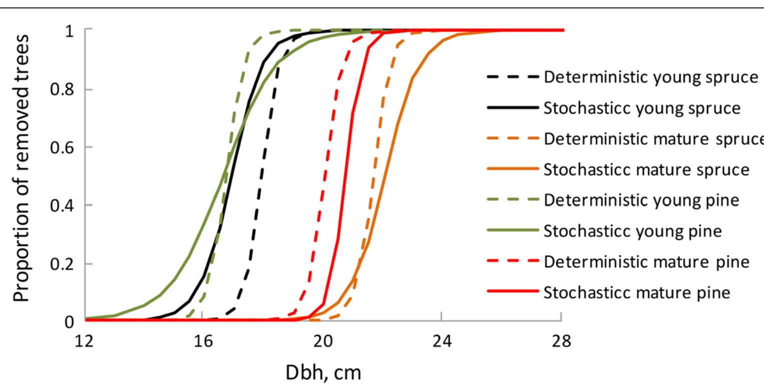

Figure 8 Thinning intensity curves in the first cutting of pure conifer stands in deterministic (dashed lines) and stochastic anticipatory optimization (solid line).

Table 2 Results calculated from 1000 stochastic simulations with the optimal values of decision variables for a risk neutral decision maker in different problem formulations when tree growth, ingrowth and timber price are stochastic (Det = deterministic optimization, Anti = stochastic anticipatory optimization, Ada = stochastic adaptive optimization)

Number of the cutting	Young spruce			Mature spruce			Young pine			Mature pine		
	Det	Anti	Ada	Det	Anti	Ada	Det	Anti	Ada	Det	Anti	Ada
	Cutting year											
1st	20	20	21.9	0	0	4.6	20	20	25.3	0	0	5.6
2nd	35	35	42.1	20	15	19.6	35	35	47.4	15	15	21.2
3rd	55	50	62.9	55	45	30.8	55	50	70.3	45	25	39.2
	Diameter before cutting (cm)											
1st	19.1	19.1	19.6	23.0	23.0	24.4	17.5	17.6	18.6	21.0	21.0	22.2
2nd	19.9	19.7	21.9	28.3	26.6	27.7	17.8	18.9	20.0	23.5	23.5	23.8
3rd	23.3	22.3	25.3	31.5	30.5	29.9	19.9	19.1	21.6	24.8	24.3	23.7
	Basal area before cutting ($m^2 \cdot ha^{-1}$)											
1st	35.7	35.7	37.1	28.1	28.1	31.3	32.1	32.2	35.8	25.1	25.1	28.1
2nd	29.5	27.1	33.6	21.6	19.8	19.7	26.7	26.6	33.2	16.4	19.4	19.5
3rd	27.6	25.7	29.0	26.7	21.6	14.9	27.6	26.0	32.0	23.9	14.1	19.6
	Basal area after cutting ($m^2 \cdot ha^{-1}$)											
1st	14.6	12.4	14.5	9.8	10.8	11.1	13.5	13.4	14.4	9.3	11.8	11.5
2nd	10.6	12.7	12.5	6.4	5.5	9.2	10.5	12.8	12.5	7.1	9.4	8.7
3rd	10.5	12.6	10.1	11.6	7.2	5.1	11.3	12.1	11.2	9.2	6.2	9.3
	Removed volume ($m^3 \cdot ha^{-1}$)											
1st	176	192	192	197	187	219	140	141	167	150	126	162
2nd	163	126	190	164	153	113	129	111	175	93	99	109
3rd	160	122	182	167	157	109	141	118	181	153	78	93
Total	499	440	564	528	497	441	410	370	523	396	303	364
	Average roadside saw log price obtained (€ $\cdot m^{-3}$)											
1st	56.8	55.8	64.6	56.1	56.3	61.9	56.7	56.4	66.8	55.7	56.3	62.9
2nd	56.2	56.5	65.0	56.5	56.4	66.2	56.1	55.8	67.0	56.2	56.5	67.5
3rd	56.5	55.6	65.1	54.5	55.1	67.4	55.6	55.8	65.2	54.5	55.7	68.1

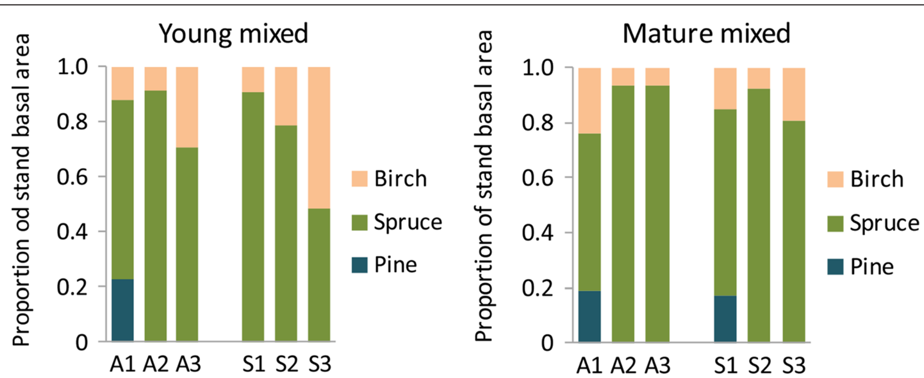

Figure 9 Proportions of different tree species in the post-cutting stands according to stochastic anticipatory optima for risk avoider (A) and risk seeker (S). The number after A or S is the number of the cutting.

Table 3 Optimal cutting years in anticipatory stochastic optima for different risk attitudes

No. of the cutting	Young mixed stand			Mature mixed stand		
	Avoider	Neutral	Seeker	Avoider	Neutral	Seeker
	Cutting year					
1st	20	20	20	0	5	10
2nd	35	35	35	15	20	25
3rd	65	65	55	45	50	55
	Removed volume ($m^3 \cdot ha^{-1}$)					
1st	142	145	162	77	107	139
2nd	110	107	83	102	130	115
3rd	193	215	127	229	210	243
Total	446	467	372	408	448	497

had a greater impact on the results than risk attitude. Positive correlation between timber prices of different tree species (Figure 3) also decreases the possibilities to reduce financial risk by increased species diversity. Roessiger et al. (2011) concluded that the optimal management for a cautious risk-avoiding forest landowner uses tree species diversification, avoiding clear-cutting and mono-species forest composition.

All thinnings of all solutions were high thinnings. The very high stochastic variation of ingrowth did not affect the expected NPV of the management schedule and it did not bring much uncertainty in decision-making. This is because the removals and incomes of the first three cuttings were obtained from trees that already existed in the initial stands. Ingrowth affects the incomes of distant cuttings whose effect on NPV is very small when the discount rate is 3% or higher. In addition, infrequent regeneration and ingrowth, combined with uneven growth rate of the ingrowth trees may provide a continuous enough supply of trees to larger diameter classes.

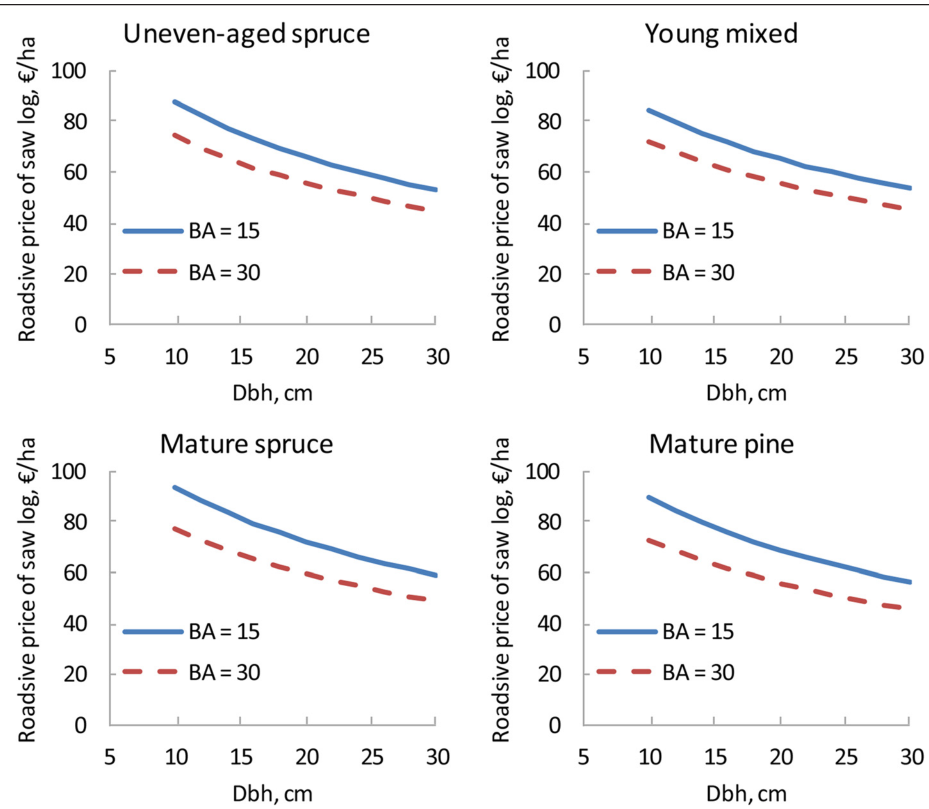

Figure 10 Examples of optimal reservation price functions obtained in adaptive optimization. Reservation price is the minimum price (in this case the minimum roadside price of saw log) which must be obtained to sell timber.

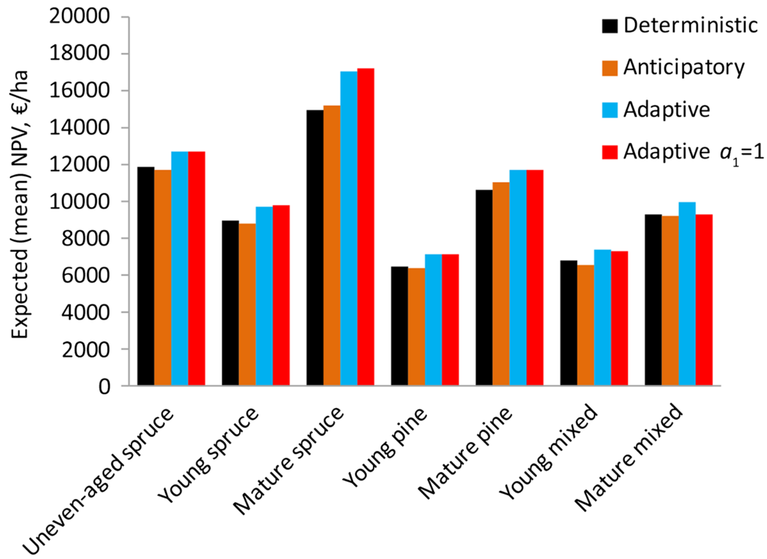

Figure 11 Average net present values of 1000 stochastic simulations with the optimal values of decision variables obtained in different problem formulations. "Adaptive a1 = 1" is a simulation in which the optimized value of parameter a_1 of the tinning intensity curve was replaced by a constant value ($a_1 = 1$).

Timber price was by far the most significant source of risk and uncertainty.

By looking at the average NPVs of 1000 stochastic simulations conducted with different optimal solutions (Figure 11) it can be concluded that there is also some uncertainty related to the optimality of the found solutions. Theoretically, stochastic anticipatory optima should produce better results than 1000 stochastic simulations with the deterministic optima, but this was not always the case. Correspondingly, fixing parameter a_1 to 1 should decrease the simulated NPVs, compared to adaptive solutions where a_1 was optimized, but this did not happen always. The results suggest that stochastic problems are more difficult to solve than the deterministic ones. Simulating each schedule clearly more than 600 times in optimization (600 realizations were used in optimization runs) would most probably partially solve the problem, but with a high computational cost. An alternative approach, namely the Markovian decision process model, would be better from the computational point of view (Kaya and Buongiorno 1987).

Corresponding to the hypotheses and previous studies (Gong 1998; Lu and Gong 2003; Pukkala and Kellomäki 2012), adaptive optimization led to higher NPVs than anticipatory optima. However, the differences were smaller than what could be expected on the basis of some earlier studies (Gong and Yin 2004; Pukkala and Kellomäki 2012). This was partly because the growth interval was always 5 years although the truly optimal cutting year might be one of the years within the 5-year time step used in simulation. This most probably decreased the NPVs more in adaptive optimization since it was not possible to pick the year of the 5-year period that had the highest timber price. Therefore, the results of this study can be interpreted so that the benefit of adaptive optimization is at least 6%–14% but it can be also higher. Zhou et al. (2008) found a 17% higher NPV for adaptive strategy compared to fixed strategy, with little difference in length of cutting cycle.

The adaptive approach facilitates very simple management rules. The optimal future management can be described with only 3 parameters, namely the coefficients of the reservation price function. A thinning treatment should be conducted when the actual price is higher than the reservation price. The thinning intensity of different diameter classes is calculated with Equation 6. Parameter a_1 of the equation can be taken as 1, and parameter a_2 is calculated with Equation 8. If the use of equations is difficult to the forest manager, the equations can be converted to diagrams that show the optimal management in a changing environment.

Competing interests

The author declares that he has no competing interests.

Authors' contributions

TP conducted the analyses and wrote the manuscript. The author read and approved the final manuscript.

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References

Brazee R, Mendelsohn R (1988) Timber harvesting with fluctuating prices. For Sci 34(2):359–372

Ge Z-M, Zhou X, Kellomäki S, Wang K-Y, Peltola H, Väisänen H, Strandman H (2010) Effects of changing climate on water and nitrogen availability with implications on the productivity of Norway spruce stands in southern Finland. Ecol Modell 221(13–14):1731–1743

Gong P (1998) Risk preferences and adaptive harvest policies for even-aged stands management. For Sci 44(4):496–506
Gong P, Yin R (2004) Optimal harvest strategy for slash pine plantations: the impact of autocorrelated prices for multiple products. For Sci 50(1):10–19
Henttonen H (1990) Kuusen rinnankorkeusläpimitan kasvun vaihtelu Etelä-Suomessa. Summary: Variation in the diameter growth of Norway spruce in Southern Finland. University of Helsinki, Department of Forest Mensuration and Management. Res Notes 25:1–88
Hooke R, Jeeves TA (1961) "Direct search" solution of numerical and statistical problems. J Assoc Comput Mach 8:212–229
Kangas A (1997) On the prediction bias and variance in long-term growth projections. For Ecol Manage 96:207–216
Kaya I, Buongiorno J (1987) Economic harvesting of uneven-aged northern hardwood stands under risk: a Markovian decision model. For Sci 33(4):889–907
Kellomäki S, Väisänen H (1997) Modelling the dynamics of the forest ecosystem for climate change studies in the boreal conditions. Ecol Model 97:121–140
Laasasenaho J (1982) Taper curve and volume equations for pine spruce and birch. Communicationes Instuti Forestalis Fenniae 108:1–74
Lembersky MR, Johnson KN (1975) Optimal policies for managed stands: an infinite horizon Markov decision process approach. For Sci 21(2):109–122
Leskinen P, Kangas J (1998) Modelling and simulation of timber prices for forest planning calculations. Scand J For Res 13:469–476
Lohmander P (1995) Reservation price models in forest management: errors in the estimation of probability density function parameters and optimal adjustment of the bias free point estimates. Management systems for a global forest economy with global resource concerns. Society of American Foresters, USA, pp 439–456
Lohmander P (2007) Adaptive optimization of forest management in a stochastic world. In: Weintraib A, Romero C, Bjørndal T, Epstein R, Miranda J (eds) Handbook of operations research in natural resources. International Series in Operations Research and Management Science, Vol. 99. Springer Science + Business Media B.V., pp 525–543.
Lu F, Gong P (2003) Optimal stocking level and final harvest age with stochastic prices. J For Econ 9:119–136
Miina J (1993) Residual variation in diameter growth in a stand of Scots pine and Norway spruce. For Ecol Manage 58:111–128
Pasanen K (1998) Integrating variation in tree growth into forest planning. Silva Fennica 32(1):11–25
Pukkala T (2005) Metsikön tuottoarvon ennustemallit kivennäismaan männiköille, kuusikoille ja rauduskoivikoillle. Metsätieteen aikakauskirja 3(2005):311–322
Pukkala T, Kangas J (1996) A method for integrating risk and attitude toward risk into forest planning. For Sci 42(2):198–205
Pukkala T, Kellomäki S (2012) Anticipatory vs. adaptive optimization of stand management when tree growth and timber prices are stochastic. Forestry 85 (4):463–472
Pukkala T, Lähde E, Laiho O (2009) Growth and yield models for uneven-sized forest stands in Finland. For Ecol Manage 258:207–216
Pukkala T, Lähde E, Laiho O (2013) Species interactions in the dynamics of even- and uneven-aged boreal forests. J Sustainable For 32:1–33
Pukkala T, Lähde E, Laiho O (2014) Optimizing any-aged management of mixed boreal forest under residual basal area constraint. J For Res 25(3):627–636
Roessiger J, Griess VC, Knoke T (2011) May risk aversion lead to near-natural forestry? A simulation study. Forestry 84(5):527–537
Rollin F, Buongiorno J, Zhou M, Peyron J-L (2005) Management of mixed-species, uneven-aged forests in the French Jura: from stochastic growth and price models to decision tables. For Sci 51(1):64–75
Valsta L (1992) A scenario approach to stochastic anticipatory optimization in stand management. For Sci 38:430–447
Vanclay JK (1994) Modelling forest growth and yield: applications to mixed tropical forests. CAB International, United Kingdom
Zhou M, Buongiorno J (2006) Forest landscape management in a stochastic environment, with an application to mixed loblolly pine–hardwood forests. For Ecol Manage 223:170–182
Zhou M, Liang J, Buongiorno J (2008) Adaptive versus fixed policies for economic or ecological objectives in forest management. For Ecol Manage 254:178–187