# Integrating Timber Price Scenario Modeling with Tactical Management Planning of Private Forestry at Forest Holding Level

Jyrki Kangas, Pekka Leskinen and Timo Pukkala

**Kangas, J., Leskinen, P. & Pukkala, T.** 2000. Integrating timber price scenario modeling with tactical management planning of private forestry at forest holding level. Silva Fennica 34(4): 399–409.

In forest management planning, deterministic timber prices are typically assumed. However, real-life timber prices vary in the course of time, and also price peaks, i.e. exceptionally high timber prices, might occur. If land-owners can utilise the price variation by selling timber with the high prices, they are able to increase their net revenues correspondingly. In this study, an approach is presented to study the timber price variation and its significance in the optimization of forest management. The approach utilizes stochastic timber price scenario modelling, simulation of forest development, and optimization of forest management. The approach is presented and illustrated by means of a case study. It is shown how the degree of uncertainty due to variation in timber prices can be analyzed in tactical forest planning of private forestry, and how the potential benefits of adaptive timber-selling behaviour for a forest landowner can be computed by using the approach. The effects of stochastic timber prices on the choice of forest plan are studied at the forest holding level considering also the spacing and type of cuttings and the optimal cutting order. A forest plan prepared under the assumption of constant timber price very seldom results in optimal forest management. Through studying the effects of stochastic timber prices, forest landowners and other decision makers obtain valuable information about the significance of adaptive timber selling behaviour. The presented methodology can also be used in analysing the land-owners' economic risks as a function of time-price structure.

**Keywords** adaptive behaviour, decision support, non-industrial private forestry, optimization, tactical planning, timber price modelling
**Authors´ addresses** *Kangas* & *Leskinen* Finnish Forest Research Institute, Kannus Research Station, Box 44, FIN-69101 Kannus, Finland. *Pukkala*: University of Joensuu, Faculty of Forestry, Box 111, FIN-80101 Joensuu, Finland
**Fax** +358 6 874 3201 **E-mail** jyrki.kangas@metla.fi
**Received** 27 January 2000 **Accepted** 26 September 2000

# 1 Introduction

Variation in timber prices is a major source of uncertainty in forest planning; prices can change rapidly, and they are difficult to predict. The longer the time horizon in planning calculations the more difficult it is to forecast the development of timber prices. Although present-day forestry is more and more frequently multi-objective, net income from timber production or net present value is often the most important criterion in decision making concerning commercially managed forests. Timber prices, forecasting them, and reliability of the price forecasts are therefore still of central importance in forest management planning.

Typical time horizons in tactical forest planning range from 5 to 20 years. Timber price predictions even for only two or three years often prove to be erroneous. Prices can change quickly due to changes in supply and demand and to the world market for timber and wood products. Forest land-owners can obtain substantial benefits if they manage to cut and sell their timber when prices are high. However, success in adaptive timber selling behaviour requires knowledge about the process of timber price variation with time.

A recommendation as to the action plan for the forest area under study is an important result of tactical forest planning. In the forest plan, treatment recommendations are given for each forest stand within the area. For every cutting operation or other treatment, a time schedule is also proposed. An action plan recommendation can be compiled on the basis of optimization calculations. Usually, an even timber price scenario having deterministic prices is assumed in calculations.

There are plenty of studies concerning variation in timber prices. So far, the studies have mostly been econometrically oriented (e.g. Kaya and Buongiorno 1987, Gong 1992, Forboseh et al. 1996). In this study, the focus is on tactical forest management planning. In the Nordic Countries, planning calculations are widely applied in the guidance and decision support of private forest land-owners, as well as in the State and industrial forestry. Forest management planning has been seen as an important tool in forest policy, too. Unfortunately, implementation of econometric results in forest planning has gained only limited attention, especially with regard to considerations of adaptive forest management. On the other hand, forest planning has suffered from too simplified assumptions regarding timber prices.

The aim of this study was to develop an approach, and a corresponding methodological framework, for integrating timber price scenario modeling with forest-holding level management planning. The approach makes use of stochastic timber price modeling, simulation of forest development under different management alternatives, and numerical optimization.

The approach is presented and illustrated by means of a case study in order to give a practical expression of the approach, methods, and their application possibilities. In the case study, the modelling technique of Leskinen and Kangas (1998) was used to produce price scenarios. The simulation program, needed for predicting stand development and drain, was developed from the program called MONSU, presented by Pukkala (1993). A heuristic optimization method HERO (Pukkala and Kangas 1993) was used to find the optimal forest management regimes under different price scenarios. The HERO method iteratively maximizes an additive utility function estimated following the forest land-owner's objectives and preferences.

Using the approach, for example, the benefits which the forest land-owner might gain through adaptive timber selling by reacting to the variation in timber prices can be studied, as is done in the case example. In that, distributions of the values of decision variables in the adaptive optima under variable prices were compared to the optimal solution under constant and deterministic timber price (anticipatory optimum). Differences between the anticipatory optimum and the mean value of adaptive optima were used as measures of the potential gain due to adaptive timber sales. Variation of the optimum value of a decision variable served as a measure of the sensitivity of optimal forest management to timber prices.

## 2 Case Study Framework

The methodological framework developed was tested and illustrated, and the study problem was investigated, in a forest holding of 95 ha, which had been divided into 50 forest stands, i.e. compartments. The forest holding located in north Karelia, eastern Finland, and was owned by a private nonindustrial forest landowner.

The standing volume of the forest was about 15 000 $m^3$ out of which almost 8800 $m^3$ consisted of Scots pine (*Pinus sylvestris*). The sawlog volume was 8800 $m^3$. Most sites represented medium fertility (*Myrtillus* site type). One-third of the stands were so old (80 years and older) that immediate regeneration cutting was permissible according to the present forestry regulations, and another 15 hectares were approaching this stage. Thinning treatment was possible in many of the younger stands.

The iterative optimization technique called HERO, proposed by Pukkala and Kangas (1993), was used in optimization. With HERO, optimization can be divided into two main phases: (1) estimation of the utility function, and (2) maximization of the utility function. The maximization procedure finds the optimal treatment schedule for each compartment among the simulated space of treatment alternatives by applying a heuristic search procedure. The optimality is determined with respect to the objectives set for the whole forest holding or area under planning, and the result is a recommendation as to the optimal combination of forest-stand-wise treatment schedules.

An additive utility function form is assumed in the basic version of HERO, i.e.

$$U = \sum_{i=1}^{m} a_i u_i(q_i) \tag{1}$$

where $U$ is the total utility, $m$ is the number of objectives, $a_i$ is the relative importance of objective $i$, $u_i$ is the partial utility function, i.e. the sub-utility or sub-priority function, of objective $i$, and $q_i$ is the quantity that the plan produces or consumes objective variable $i$. Objectives are either forest products and values, such as timber, amenity and biodiversity, or resources, such as costs and labour requirement.

Also interaction terms and multiplicative parts, for instance, could be added into the utility model (Kangas and Kangas 1998), but for the purposes of this study the standard version was suitable. There are several alternative techniques for estimating the coefficients $a_i$ of the utility function, as well as the sub-priority functions. For details of the HERO method and the estimation of the utility function readers are referred to Pukkala and Kangas (1993, 1996) and Kangas and Kangas (1998).

The criteria applied for comparing alternative 20-year forest management plans were chosen by the forest land-owner. The criteria were: net present value of the income and costs of the first 10-year period ($NPV_1$), net present value of the income and costs of the second 10-year period ($NPV_2$), volume of the growing stock at the end of the second 10-year period ($VOL_2$), and volume of sawlog at the end of the second 10-year period ($LOG_2$).

The land-owner found these criteria equally important, i.e. the utility function of the forest owner was:

$$\begin{aligned} U = 0.25u_1(NPV_1) + 0.25u_2(NPV_2) + \\ 0.25u_3(VOL_2) + 0.25u_4(LOG_2) \end{aligned} \tag{2}$$

Piecewisely linear sub-utility functions were applied to each decision variable. For each decision variable, a minimum satisfactory value was determined by the landowner, henceforth referred to as the target level. The target level of $NPV_1$ and $NPV_2$ was 1.5 million FIM, and that of $VOL_2$ and $LOG_2$ 10 000 $m^3$ and 5000 $m^3$, respectively. The sub-utilities ($u_1 - u_4$) through the criterion variables increased rapidly up to these levels, and slower thereafter (Fig. 1). When producing forest plans for individual forest holdings, the model (decision variables, coefficients, sub-utility functions) should be estimated separately for each forest landowner following his or her objectives and preferences.

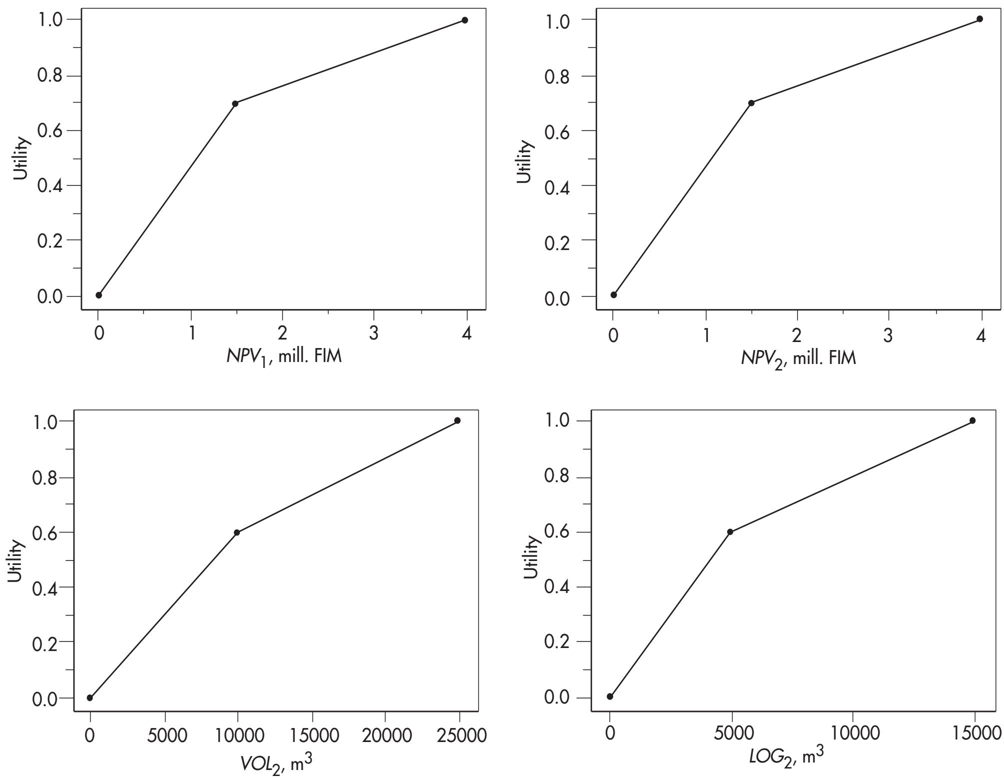


**Fig. 1.** Sub-utilities for criteria $NPV_1$, $NPV_2$, $VOL_2$, and $LOG_2$.

# 3 Price Scenarios

Leskinen and Kangas (1998) constructed a model for logging-year-specific average timber prices in Finland for sawlog and pulpwood of different tree species (Figs. 2 and 3). A special feature of Finnish timber prices, like in many other countries, is the occurrence of price peaks, i.e. exceptionally high timber prices in the early 1950s and mid-1970s. Leskinen and Kangas (1998) divided the variation in timber prices into two different processes, one for price peaks, and the other for rest-of-the-time series (prices without the effect of peaks). The variation in the rest-of-the-time series is henceforth referred to as normal price variation.

The occurrence of a price peak was supposed to be a case of a Bernoulli trial, i.e. a price peak occurs in year $t$ with probability $p$, or does not occur with probability $1 - p$ (Leskinen and Kangas 1998). The effect of a price peak was assumed to have a normal distribution. The possibility that price peaks have effects over several years was taken into account by allowing price peaks to have a decreasing effect during the next two years.

Let $X_t$ be the logarithmic timber price in year $t$ after eliminating the price peaks and lag effects. Leskinen and Kangas (1998) used AR(1) model for the normal price variation, i.e.

$$X_t - \overline{X} = \alpha(X_{t-1} - \overline{X}) + Z_t \tag{3}$$

where $\overline{X}$ is the average of $X_t$ and $Z_t \sim \mathrm{NID}(0, \sigma^2)$, or the $Z_t$ are independently and normally distributed residuals with a mean zero and variance $\sigma^2$. If $|\alpha| < 1$, the process is stationary. If $\alpha = 1$, the AR(1) model becomes random walk model.

The empirical estimates of the AR(1) coefficients are based on a small number of observa-

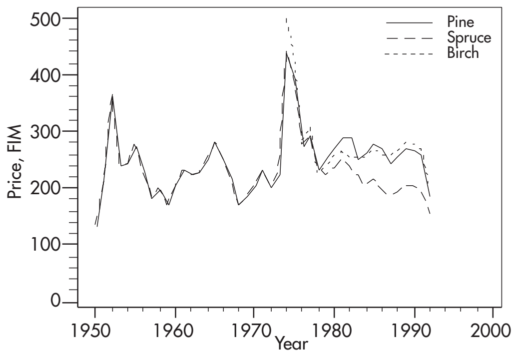


**Fig. 2.** Real timber prices for sawlog species (index of cost of living, base year 1991). The year 1974, for example, refers to the logging year 1.7.1973–30.6.1974. Pine and spruce sawlogs are not separated prior to year 1979.

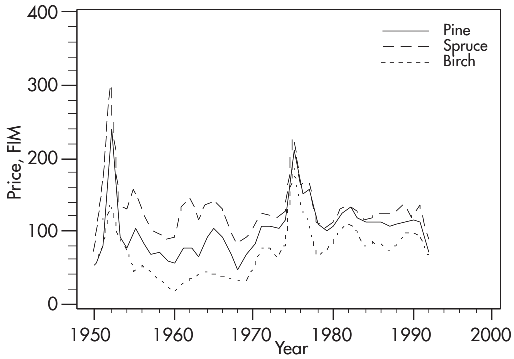


**Fig. 3.** Real timber prices for pulpwood species (index of cost of living, base year 1991). The year 1974, for example, refers to the logging year 1.7.1973–30.6.1974.

tions and are therefore uncertain. Thus, also the subjective estimates of AR(1) coefficients were given (Leskinen and Kangas 1998). These were based on the subjective statement of the variance of timber prices, and residual variance estimated from the random-walk model. The cross-correlation structure of the residuals of different types of timber at lag zero was simulated using the Cholesky decomposition (Ripley 1987).

The above model presented by Leskinen and Kangas (1998) was used to produce price scenarios for the planning horizon of 20 years. The estimates of the residual variances used were from the random-walk model from the estimation period 1950–1992 with the exception that the estimate for spruce sawlogs was used for birch sawlogs (Table 1). The first price observation for birch sawlogs was from the year 1976. The estimates of AR(1) coefficients were obtained subjectively by using residual variance estimated from the random-walk model, upper and lower limits being based on observed minimum and maximum values of normal price variation and subjective probability of 0.97 for timber prices remaining within the upper and the lower limits (Leskinen and Kangas 1998). The last observed timber prices in the data (year 1992) were used as the starting values of the simulated AR(1) processes. The means of normal price variation of the different types of timber were obtained directly from the data with the exception of birch sawlogs, for which the mean of pine sawlogs was used. The cross-correlation structure of residuals at lag zero were based on the residuals of the random-walk model.

**Table 1.** Estimates of AR(1) coefficients and residual variances used in simulation.

| | Pine sawlog | Spruce sawlog | Birch sawlog | Pine pulpwood | Spruce pulpwood | Birch pulpwood |
|---|---|---|---|---|---|---|
| $\hat{\alpha}$ | 0.610 | 0.640 | 0.590 | 0.609 | 0.450 | 0.860 |
| $\hat{\sigma}^2$ | 0.020 | 0.019 | 0.019 | 0.034 | 0.028 | 0.048 |

The estimates for price peak parameters were obtained from the empirical data (Leskinen and Kangas 1998) with the exception of the frequency of price peaks, i.e. the probability $p$, for which three different values were used: $p = 0$, $p = 1/22$, and $p = 3/22$. The first one means that there were no price peaks in the price scenarios; the second one was the estimate obtained from the data, and the third one represented three times observed frequency of price peaks. For each value of $p$, 100 scenarios were produced. Furthermore, a deterministic scenario was computed by using the mean of normal price variation for every year. More detailed description of the model can be found in Leskinen and Kangas (1998).

**Table 2.** Values of criterion variables in anticipatory deterministic optimum and the means of adaptive optima with three price peak frequencies.

| Variable | Anticipatory optimum | Adaptive optima No peaks | 1 peak / 22 a | 3 peaks / 22 a |
|---|---|---|---|---|
| $NPV_1$, mill. FIM | 1.241 | 1.414 | 1.481 | 1.692 |
| $NPV_2$, mill. FIM | 1.492 | 1.497 | 1.638 | 1.816 |
| $VOL_2$, $m^3$ | 11020 | 11747 | 13210 | 15621 |
| $LOG_2$, $m^3$ | 5005 | 5599 | 6520 | 8094 |
| Utility index (Eq. 1) | 0.6257 | 0.6572 | 0.6861 | 0.7326 |

# 4 Forest Simulation and Optimization

Alternative treatment schedules were simulated for the 50 compartments over the 20-year planning period. The 20-year period was divided into two 10-year management periods. The program developed by Pukkala (1993) was modified and used as follows. If the treatment schedule did not contain cuttings, all the treatments were simulated in the middle of the 10-year period, i.e. after 5 or 15 years. If a cutting belonged to the schedule, it was simulated in all years of the 10-year management period, resulting in ten schedules. The income from cutting was computed using the timber prices of that year. The total number of schedules for the 50 compartments was 1430. This simulation was first carried out with constant (deterministic) timber price.

Simulation of the 1430 treatment schedules was repeated under all the price scenarios which were produced as realizations of the stochastic timber price model. Because three different assumptions of stochasticity were tested (no peaks, one peak/22 years, and 3 peaks/22 years), this resulted in 301 sets of 1430 treatment schedules (one with constant prices and three times 100 sets with variable timber prices).

The utility function of the forest owner (Eq. 1) was maximized under every timber price scenario. The optimum with a constant price is here referred to as the anticipatory optimum and the other 300 as adaptive optima. The anticipatory optimum corresponds to the present forest planning practice, and it is used as a reference to which the adaptive optima were compared.

**Table 3.** Relative values of the means of adaptive optima (as percent of the anticipatory deterministic optimum).

| Variable | Adaptive optima No peaks | 1 peak / 22 a | 3 peaks / 22 a |
|---|---|---|---|
| $NPV_1$ | 114 | 119 | 136 |
| $NPV_2$ | 100 | 110 | 122 |
| $VOL_2$ | 107 | 120 | 142 |
| $LOG_2$ | 112 | 130 | 162 |
| Utility index (Eq. 1) | 105 | 110 | 117 |

In the case study calculations, the means of the adaptive optima of criterion variables were systematically higher than the anticipatory optimum (Table 2). The difference between anticipatory optimum and mean of adaptive optima was the expected maximum gain achievable by adaptive timber selling. Peaks in timber prices increased both mean and variation of timber prices. Therefore, additional gains were possible. With the present utility function, it was usually optimal to decrease cuttings with increasing possibilities to sell timber with good price.

Out of the four criterion variables, the mean optimum value of $LOG_2$ was the most sensitive to the amount of variation in timber prices, while the mean optimum value of $NPV_2$ changed the least (Table 3). Because the sub-utility functions were concave, and the target levels of $VOL_2$ and $LOG_2$ were reached already in the anticipatory optimum, the change in the mean utility index of adaptive optima was relatively small. When there were no price peaks, the mean utility index of the adaptive optima was 5 % higher than the anticipatory op-

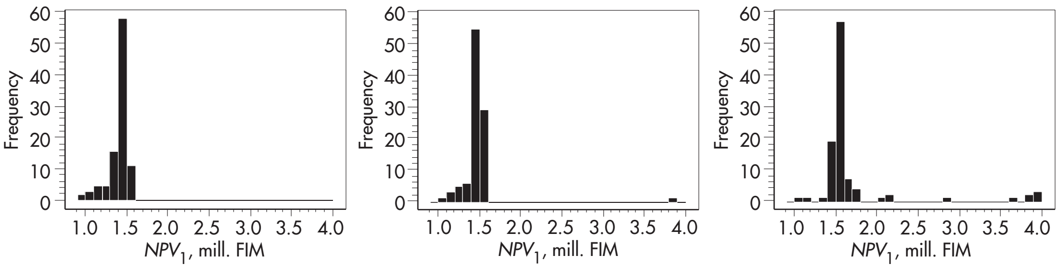


**Fig. 4.** Distribution of $NPV_1$ with price peak probabilities left) 0, center) 1/22, and right) 3/22.

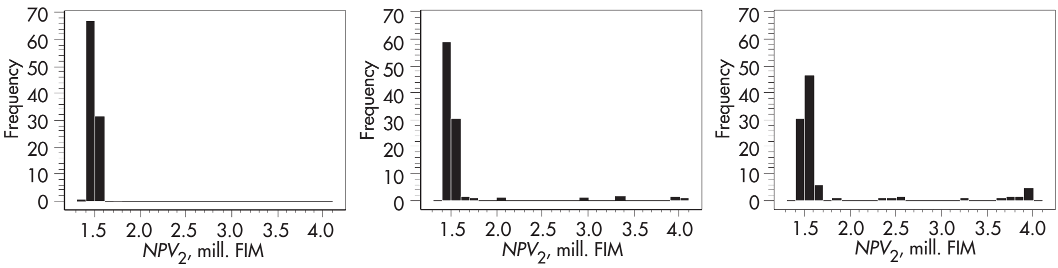


**Fig. 5.** Distribution of $NPV_2$ with price peak probabilities left) 0, center) 1/22, and right) 3/22.

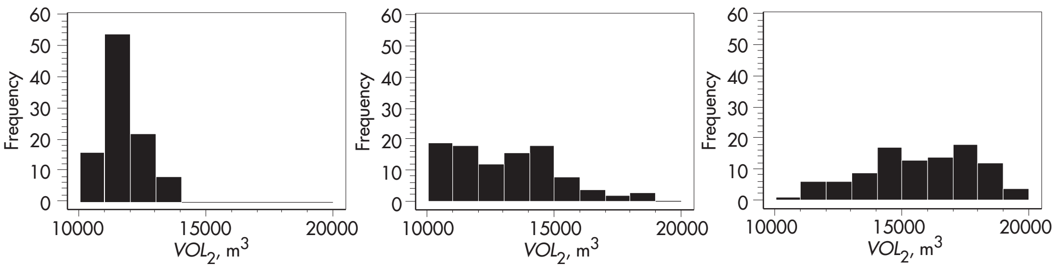


**Fig. 6.** Distribution of $VOL_2$ with price peak probabilities left) 0, center) 1/22, and right) 3/22.

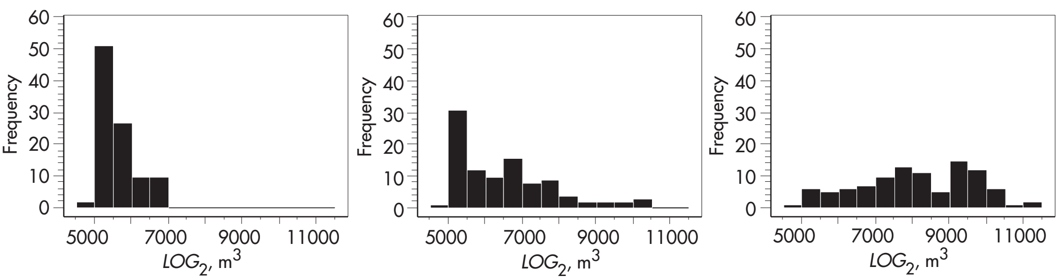


**Fig. 7.** Distribution of $LOG_2$ with price peak probabilities left) 0, center) 1/22, and right) 3/22.

timum, and 10 % or 17 % higher if the peak frequency was one or three times per 22 years, respectively.

Variation in the optimal values of objective variables was very large, and it increased with the frequency of price peaks (Figs. 4–7). For example, $VOL_2$ ranged from about 10 000 to 14 000 $m^3$ if there were no price peaks, from about 10 000 to 19 000 $m^3$ with one peak per 22 years, and from about 10 000 to 20 000 $m^3$ with

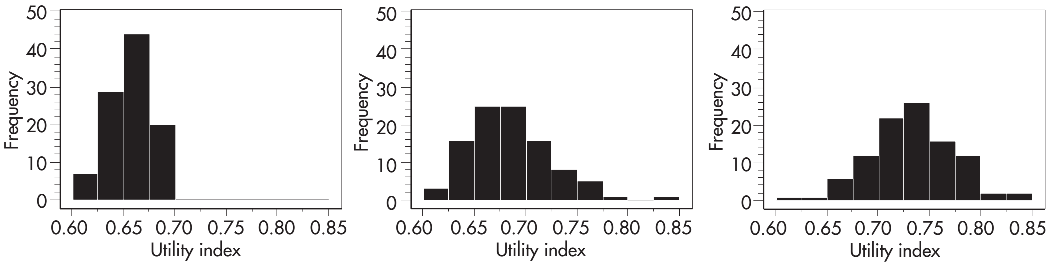


**Fig. 8.** Distribution of utility index with price peak probabilities left) 0, center) 1/22, and right) 3/22.

three peaks per 22 years. The distributions of the optimal values of decision criteria had a high frequency near the target value of the criterion (near the bend in the sub-utility function of Fig. 1) especially when there were no price peaks. If there happened to be peaks in the price scenario that was used in optimization, practically all cuttings were done in the peak years. With scenarios without peaks the 10-year cuttings tended to concentrate near both ends of the period, but this of course depended on the structure of the initial stands.

The variation in the utility index (Fig. 8) was smaller than in the decision criteria; the coefficient of variation was 4.8 % for utility index (the average of three different peak categories), whereas the corresponding percentages varied from 12.2 % to 24.3 % for the four sub-criteria. This was due to the shapes of the sub-utility functions. A drastic change in the plan did not necessarily change the utility index much and several combinations of decision criteria could produce nearly the same utility. With the poorest price outcome the utility from the adaptive optimum was slightly less than in the anticipatory optimum, even with the peak frequency of three per 22 years. The highest utility indices with peak probabilities 0, 1/22, and 3/22 were 11.0 %, 34.7 %, and 34.9 % higher than the anticipatory optimum.

The probabilities that the anticipatory deterministic optimum was smaller than the adaptive optimum were computed in order to measure the uncertainty related to the results of anticipatory planning (Table 4). According to the results, anticipatory planning usually lead to lower utility indices. For example, in the case of $NPV_1$ and no price peaks, the simulated adaptive optima were bigger than anticipatory optimum 89 times out of total 100, which was more than would have been expected randomly.

**Table 4.** Probabilities that anticipatory deterministic optimum is smaller than adaptive optimum.

| Variable | No peaks | 1 peak / 22 a | 3 peaks / 22 a |
|---|---|---|---|
| $NPV_1$ | 0.89 | 0.94 | 0.98 |
| $NPV_2$ | 0.92 | 0.93 | 1 |
| $VOL_2$ | 0.83 | 0.81 | 0.99 |
| $LOG_2$ | 0.96 | 0.95 | 0.98 |

It could be concluded from the remaining volumes of anticipatory and adaptive optima that the additional incomes of adaptive optima, as compared to anticipatory optimum, were not due to higher harvested volumes. On the contrary, the drain was less in the adaptive optima. Thence, in the present forest, it was very likely that anticipatory optimization proposed cutting levels higher than would have been best for the decision maker sensitive to timber prices.

# 5 Discussion

Choosing management options for forest stands under uncertainty has long been a frequently addressed topic in forest science. Methods have been developed for analysing the risks and uncertainty involved in forestry decisions as well as for comparing different management regimes with respect to different decision criteria. Recently, also techniques for clarifying the decision maker's attitude toward risk and for taking it into account in the comparison of forestry choice alternatives have been presented (e.g., Brumelle et al. 1990, Kangas 1992, Valsta 1992, Pukkala and Kangas 1996). Less attention has been paid on studying the possible benefits gained from risk analysis and managing risk and uncertainty. This holds also for timber price forecasts and utilisation of the variation in timber prices through adaptive behaviour.

A methodological framework was developed in this study for integrating timber price modeling with forestry planning, the price models including both the normal variation in time but also price peaks as observed in the past price developments. The timber price model used also includes dependence over time as well as cross correlations of different timber assortments. Thus, the presented approach makes it possible to study timber price developments in optimization calculations of tactical forest management planning in a realistic way, and by imitating the real-life features of them. The aims of the case study were related to testing and illustrating purposes only, not to producing empirical results. Correspondingly, no generalization can be made on grounds of the case study. As in any single forest planning experiment, the optimization results are strictly case-wise.

HERO heuristic optimization method, integrated with the forestry simulation program MONSU, was used in the case study because of its flexibility, and because it is relatively easy to interpret and understand. The approach can be applied using other appropriate optimization methods and planning packages as well. However, in practical forestry, econometric considerations should be taken into account at the level of forest holding or a forest area consisting of several different forest stands. Applying modern planning methods enables this. Using HERO, the adaptive management approach can be integrated with planning of multi-functional forestry with nonlinear non-monetary objectives, for instance. Via HERO, the presented approach is directly applicable in forest planning practice.

Previous studies on the effects of uncertain timber prices on the optimal choice of management options have mainly been made at the level of a single forest stand. Forboseh et al. (1996), for example, showed that accounting for multiple products with uncertain future prices can lead to dramatic changes in a cutting strategy and significant improvements in expected land values. A movement from stand-level studies to forest-level studies, however, has been seen as an important future direction of forest economics research on risk and uncertainty (e.g., Brazee and Newman 1999).

The effects on standwise choices, and also on potential benefits of adaptive timber selling behaviour, are more significant, and more complex, in the context of forest holding – or forest area – consisting of plenty of forest stands each having several treatment schedule alternatives to be chosen among. This is because of the possibility to change not only the timing and types of cuttings within a single stand but also the placing of cuttings within the forest holding. Moreover, on a long run, adaptivity can have effects not only on the cutting decisions but also on the optimality of silvicultural treatments. The area-level solution of optimization of forest management consists of a combination of standwise treatment schedules. The optimal choice within an invidual forest stand is affected by the characteristics and cutting potentials of other stands belonging to the same forest holding. Our approach makes it possible to study also the placing of treatments as well as the combinations of cuttings in different stands. Dealing with all the stands instead of only one stand, as often is the case with theoretical and methodologically complicated studies, is especially important in practical applications (see also, e.g., Gong 1999).

Ollonqvist and Heikkinen (1994) divided forest owners into four groups according to their motives of timber selling and found out the differences between groups with respect to the economic profitability of timber sales transactions. Thus, some forest owners are more interested in income than the others, and they also succeed in selling timber when prices are high. In the reality of timber prices changing with time, the assumption of even timber prices may lead to non-optimal treatment recommendations particularly with these land-owners (see also e.g. Brazee and Mendelsohn 1988, Gong 1992, Forboseh et al. 1996). Due to adaptive timber selling behaviour, assuming even timber prices will lead to under-estimation of the possibilities to obtain timber harvesting incomes, if the forest owner manages to time his/her timber sales transactions better than in the case of random behaviour.

The distributions of utility index and decision criteria computed in this study (Figs. 4–8) give the distribution of *the maximum output achievable* from the forest area under planning. In practice, the maximum is hard – if not impossible – to achieve, because future timber prices are unknown. However, the distribution of the maximum output gives, as additional decision support, an interesting insight into the complex decision situation. It shows that forest landowners can gain substantial benefits by utilizing timber price variation in time. It also emphasizes the value of information. Potential benefits could be realized by the more greater probability the more reliable timber price forecasts are available. Expert estimates of the future development of international timber markets, for instance, might be utilized in producing the forecasts.

If it is supposed that the timber price variation in the future will be like in the past, the use of the simulation model based on observed prices to produce future price scenarios – as was done in this study, and has been done also in previous studies on the topic – is justified. Unfortunately, there is no guarantee for this happening. Utilization of the model together with expert knowledge would be a potential improvement, when producing price scenarios for forestry practice. The integration of expert opinion with the time series model is an important topic for future research.

Prices that forest owners face in real-life markets vary to considerable extent also due to, for example, quality and amount of timber to be sold, season of the year, and harvesting conditions. In operational planning with horizon of 1 to 3 years, tactical forest plan is adjusted on the basis of more accurate and actual information on timber prices. Matters of real-life markets should be taken into account when final decisions on forestry operations are made. However, also operational decisions are made under some assumptions about future price development. In this sense, estimations of timber prices as presented in this study are of value in operational planning, too.

# 6 Conclusion

Within a forest holding consisting of plenty of forest stands, variation in timber prices has effects on the optimality of both the placing and the timing of cuttings, as well as on the choice of the types of cuttings. These, further, affect the net incomes gained during the planning period and the state of the forest in the end of the period. Correspondingly, if some target level of net income has been adopted, variation in timber prices have effects on the optimal amounts of timber to be felled during the period. Price variation is crucial especially if the magnitude and direction of changes in the prices are different with different tree species and timber assortments.

Adaptive optimization can be taken as a realistic imitation of practical decision making behaviour (Lessard 1998). This is the case particularly with timber price variation and price peaks. Any private forest landowner would prefer selling timber by as high prices as possible. Variation in prices occur in reality, and it is possible to utilise the exceptionally high prices.

All forest planning is made under uncertainty, and, as a consequence, no absolutely optimal recommendations can be given. However, by studying the effects of stochastic prices, decision makers get valuable information on the significance of their timber selling behaviour, and they can be shown how the incorporation of "realistic uncertainty" into calculations affect the optimality of different cutting budgets. More important than to try to find any real optimum solution (because this is often impossible) is to learn about the decision situation, future production possibilities and trade-offs, and the effects of different assumptions and factors on the optimal forest plan.

The aim of forest planning is not to show 'right' decisions, but to give solid decision support and deep and versatile insight into the planning problem. The final decision is always made by a human decision maker. Studying the potential benefits of adaptive timber selling behaviour is an enlightening additional decision support for any forestry decision maker. Using our approach, this can be incorporated in calculations of tactical planning as typically performed in forestry practice.

# References


Brazee, R.J. & Mendelsohn, R. 1988. Timber harvesting with fluctuating prices. Forest Science 34: 521–528.

— & Newman, D.H. 1999. Observations on recent forest economics research on risk and uncertainty. Journal of Forest Economics 5: 193–200.

Brumelle, S., Stanbury, W.T., Thompson, W.A., Vertinsky, I. & Wehrung, D. 1990. Framework for the analysis of risks in forest management and silvicultural investments. Forest Ecology and Management 35: 279–299.

Forboseh, P.F., Brazee, R.J. & Pickens, J.B. 1996. A strategy for multiproduct stand management with uncertain future prices. Forest Science 42: 58–66.

Gong, P. 1992. Adaptive decisions in even aged stand management. Scandinavian Forest Economics 33: 170–187.

— 1999. Diversification of harvest decisions for even-aged stand management. Journal of Forest Economics 5: 123–138.

Kangas, A. & Kangas, J. 1998. Ekologiset mallit ja ekologisten riskien hallinta metsäsuunnittelussa. Metsätieteen Aikakauskirja – Folia Forestalia 2/1998: 207–222.

Kangas, J. 1992. Choosing the reforestation alternative in a forest stand: A decision analysis model based on multiattribute utility theory. University of Joensuu. Publications in Sciences 24: 1–230.

Kaya, I. & Buongiorno, J. 1987. Economic harvesting of uneven-aged northern hardwood stands under risk: A Markovian decision model. Forest Science 33: 889–907.

Leskinen, P. & Kangas, J. 1998. Modelling and simulation of timber prices for forest planning calculations. Scandinavian Journal of Forest Research 13: 470–477.

Lessard, G. 1998. An adaptive approach to planning and decision-making. Landscape and Urban Planning 40: 81–87.

Ollonqvist, P. & Heikkinen, V.-P. 1994. Kantohinnat ja yksityismetsänomistajien puunmyynnin ajoitus. Metsäntutkimuslaitoksen tiedonantoja – Finnish Forest Research Institute. Research Notes 526.

Pukkala, T. 1993. Monikäytön suunnitteluohjelmisto MONSU. University of Joensuu, Joensuu, Finland. Mimeograph. 42 p.

— & Kangas, J. 1993. A heuristic optimization method for forest planning and decision-making. Scandinavian Journal of Forest Research 8: 560–570.

— & Kangas, J. 1996. A method for integrating risk and attitude toward risk into forest planning. Forest Science 42: 198–205.

Ripley, B.D. 1987. Stochastic simulation. Wiley. New York. 237 p.

Valsta. L. 1992. A scenario approach to stochastic anticipatory optimization in stand management. Forest Science 38: 430–447.

*Total of 17 references*