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Interactive decision support and trade-off analysis for sustainable forest landscape planning under deep uncertainty

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Abstract

Sustainable environmental management often involves long-term time horizons, multiple conflicting objectives, and by nature, is affected by different sources of uncertainty. Many sources of uncertainty, such as climate change or government policies, cannot be addressed using probabilistic models, and, therefore, they can be seen to contain deep uncertainty. In this setting, the variety of possible future states is represented as a set of scenarios lacking any information about the likelihood of occurring. Integrating deep uncertainty into multiobjective decision support increases complexity, calling for the elaboration of appropriate methods and tools. This paper proposes a novel interactive multi-scenario multiobjective approach to support decision-making and trade-off analysis in sustainable forest landscape planning under multiple sources of uncertainty. It includes new preference simulation models aimed at reducing the decision-maker's cognitive load and supporting the preference elicitation process. The proposed approach is applied in a case study of long-term forest landscape planning with four sustainability objectives in twelve scenarios and a forestry expert as the decision-maker. The approach is demonstrated to be efficient in exploring trade-offs in different scenarios, helping the expert gain deep insights into the problem, understand the consequences of alternative strategies, and find the most preferred robust strategy.

Keywords: Forest management; Climate change; Multiobjective optimization; Scenario planning; Partially known preferences

21 1 Introduction

22 We study problems of sustainable environmental management, in particular forest landscape
23 planning, with a long-term time horizon and multiple conflicting objectives (such as timber
24 revenue, carbon storage and biodiversity). Conflicts between objectives imply that a solution
25 does not exist which would be optimal with respect to all objectives simultaneously. Instead,
26 the solution must be sought among the set of so-called *Pareto optimal solutions* with various
27 trade-offs between the objectives that brings the requirement of a domain expert (e.g., the
28 manager or the decision-maker (DM)) to choose the final solution among various compro-
29 mises. This set is unknown a priori, and each individual solution needs to be generated
30 using mathematical methods. Therefore, the DM needs additional support to study these
31 trade-offs and find the best balance between conflicting objectives. This typically is based on
32 his/her preferences. Multiobjective optimization methods have been developed to provide
33 this kind of support to DMs over the years in a wide range of real-life applications, including
34 various aspects of forest planning. Some examples of decision support methods and case
35 studies in forest planning can be found in Kangas et al. (2001), Eyvindson et al. (2018),
36 Marques et al. (2021a), and Marques et al. (2021b) (see also references therein). Papers
37 Mönkkönen et al. (2014), Kangas et al. (2015), and Triviño et al. (2017) develop various
38 multiobjective models of forest landscape planning for analyzing trade-offs between different
39 objectives. Some examples of mathematical methods for solving multiobjective problems of
40 forest management can be found in Tóth and McDill (2009) and references.

41 The DM may provide preferences before, after, or during the solution process. These
42 three ways of providing preferences give raise to three types of multiobjective optimiza-
43 tion methods: *a priori*, *a posteriori*, and *interactive*, respectively (Hwang and Masud, 1979;
44 Buchanan, 1986; Miettinen, 1999). The effectiveness of *a priori* methods highly depends
45 on the level of qualification and prior knowledge of the DM about the problem. Otherwise,
46 the preferences provided before the solution process may be overly optimistic or pessimistic.
47 In contrast, *a posteriori* methods aim at generating a large, diverse set representing Pareto
48 optimal solutions. This is a barrier when applying to computationally complex problems
49 and gets cognitively more and more challenging for the DM as the number of objectives
50 grows. *Interactive* methods aim at, to some extent, avoiding the disadvantages mentioned
51 above. They involve an iterative solutions process that allows the DM to gain insight into the
52 problem, explore trade-offs between objectives, and learn about the feasibility of preferences.
53 Interactive methods save computation resources and reduce cognitive load by focusing only
54 on solutions that are interesting to the DM. Interactive methods have proved their poten-
55 tial for multiobjective decision support in different environmental and forest management

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56 applications (e.g., Teclé et al., 1994; Hartikainen et al., 2015, 2016; Eyvindson et al., 2018;
57 Saccani et al., 2020).

58 Like many real-life problems, environmental management problems such as forest plan-
59 ning face different sources of uncertainty due to the unknown future states of the world, e.g.,
60 climate and environmental change, production demand, government policy changes, and nat-
61 ural hazards. Due to the lack of models and/or insufficient data, such types of uncertainty
62 cannot necessarily be framed in probabilistic terms or even described parametrically. This
63 situation is often referred to as *deep uncertainty*, i.e., when researchers do not know or cannot
64 agree upon some aspects of the systems and/or outcomes such as their probability distribu-
65 tions, boundaries, or related preferences (Lempert et al., 2003; Walker et al., 2013). In such
66 cases, however, the future states of the world can be represented as *scenarios*. More specifi-
67 cally, one can enumerate plausible future states of the world and corresponding outcomes of
68 planning but cannot define their occurrence probabilities or ranking with enough accuracy
69 because of the complexity and the lack of evidence (Lempert et al., 2006; Shavazipour and
70 Stewart, 2021).

71 Deep uncertainties, in particular those related to climate change, significantly affect the
72 performance of forest management strategies. Thus, taking them into account is vital for ro-
73 bust and sustainable forest planning (Seidl et al., 2017; Augustynczyk and Yousefpour, 2019).
74 It is worth noting that the ecosystem management activities need to be started decades be-
75 fore the realization of the uncertain factors (Spittlehouse and Stewart, 2003; Millar et al.,
76 2007; Petr et al., 2019). This necessitates the integration of deep uncertainty aspects into
77 the planning process, bringing significant challenges to environmental DMs. Scenario plan-
78 ning has been widely applied in handling uncertainty in decision-making (see, e.g., Van der
79 Heijden (1996)). It provides a framework for thinking, planning, and concrete discussions
80 of uncertainty (Durbach and Stewart, 2012). Since planning outcomes may be sensitive to
81 the consequences of uncertainty, one crucial aspect of decision-making under uncertainty
82 is identifying decisions that perform relatively well in a broader range of scenarios (called
83 robust decisions) (Lempert et al., 2006).

84 The multiobjective nature of environmental planning problems combined with their
85 dependence on deep uncertainty brings more complexity (and introduces an additional
86 dimension) to the solution process, making the DM's task cognitively more demanding
87 (Shavazipour et al., 2021b). Recently, different approaches integrated multiobjective op-
88 timization and scenario planning to cope with deep uncertainty and help the DM analyze
89 trade-offs between objectives under various scenarios and find the most preferred robust
90 solution (e.g., Watson and Kasprzyk (2017); Eker and Kwakkel (2018); Shavazipour and
91 Stewart (2021); Shavazipour et al. (2021a)), forming a class of decision problems called

92 *multi-scenario multiobjective optimization*. The issue of cognitive complexity needs to be
93 addressed by creating easy-to-understand preference handling techniques and graphical vi-
94 sualizations. Existing decision support tools in forest management rarely consider both
95 multiple objectives and deep uncertainty aspects (Yousefpour and Hanewinkel, 2016; Radke
96 et al., 2017, 2020; Hörl et al., 2020). This study is an effort to fill this vital gap in the
97 literature.

98 In this paper, we propose a novel interactive multi-scenario multiobjective optimization
99 approach as a decision support tool for environmental planning problems under deep uncer-
100 tainty and in particular, sustainable forest management. Our decision support tool includes
101 advanced visualization techniques recently developed for multi-scenario multiobjective op-
102 timization problems (Shavazipour et al., 2021b) to analyze trade-offs between objectives in
103 various scenarios. To the best of our knowledge, this is the first study of interactive environ-
104 mental decision support combining multiobjective trade-offs exploration with multi-scenario
105 considerations, such as optimality/feasibility in any given scenario and robustness over the
106 set of future scenarios.

107 As mentioned earlier, interactive methods for solving multiobjective problems rely on
108 DM's preferences. Different methods enable a DM to express preferences in different ways
109 (Miettinen et al., 2016). We concentrate on the class of methods which utilize preference
110 information provided as *reference points*. A *reference point* is a vector composed of so-
111 called *aspiration levels*, which are desirable values of the objective functions. This type of
112 preference information is in line with the concept of "satisficing" (Simon (1956); Wierzbicki
113 (1982)), which is regarded as cognitively undemanding for the DM. Reference point-based
114 methods have been widely used in practice, including environmental and forest management
115 (e.g., Krcmar-Nozic et al. (1998); Eyvindson et al. (2018); Shavazipour et al. (2021a)).

116 In multi-scenario multiobjective optimization problems, each objective in each scenario
117 is represented by an individual objective function. Thus, the DM is expected to provide
118 aspiration levels for all combinations of objectives and scenarios (Shavazipour et al., 2020;
119 Shavazipour and Stewart, 2021). This can impose a high cognitive load on the DM, even
120 for problems of moderate sizes. For example, for a problem with 3 to 5 objectives and 4 to
121 7 scenarios, the required number of aspiration levels is from 12 to 35. It is far beyond the
122 "magical number" 7 ± 2 proposed by Miller (1956) as the estimation of short-term memory
123 capacity. Thus, setting all required aspiration levels can be difficult or beyond human capa-
124 bilities. In practice, we cannot expect the preferences for all objectives in all scenarios to be
125 available from the DM and, thus, in many cases, we have to deal with incomplete preferences.
126 Therefore, our approach to interactive decision support allows expressing partial preference
127 information and includes a tool to simulate missing preferences of the DM.

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128 To illustrate our novel approach, we consider a large-scale forest landscape management
 129 problem with tens of thousands of forest stands and a 50-year planning horizon. The prob-
 130 lem is formulated as a multi-scenario multiobjective mixed-integer optimization problem
 131 with four objective functions: (i) maximizing timber harvest revenue as net present value
 132 (NPV), (ii) maximizing carbon storage, (iii) maximizing deadwood, and (iv) maximizing a
 133 combined index of species habitat availability. The formulation includes 12 scenarios based
 134 on three different sources of deep uncertainty: (a) climate change, (b) forest thinning subsi-
 135 dies, and (c) compensations for forest landscape conservation, that construct a 48-objective
 136 optimization model to be solved. We solve this complex, large-scale problem utilizing the
 137 proposed interactive multi-scenario multiobjective approach guided by a forestry expert DM.
 138 We analyze trade-offs between objectives under various scenarios with the help of advanced
 139 visualizations.

140 The rest of this paper is structured as follows. Section 2 contains a concise statement of
 141 multi-scenario multiobjective optimization problems and related definitions, followed by the
 142 proposed preference simulation method, the proposed interactive multi-scenario multiobjec-
 143 tive approach, and the visualizations utilized for trade-off analysis. The detailed description
 144 and problem formulation of the case study of forest landscape planning can be found in Sec-
 145 tion 3. In Section 4, we demonstrate our experiment of applying the proposed approach with
 146 a DM in the case study and the relevant trade-off analysis. Finally, after further discussions
 147 in Section 5, we conclude in Section 6.

148 2 Methodology

149 2.1 Multi-scenario multiobjective optimization

A multi-scenario multiobjective optimization problem can be formulated as follows (Shavazipour et al., 2021a):

$$\begin{aligned} & \text{minimize } \{f_{1t}(\mathbf{x}), \dots, f_{kt}(\mathbf{x})\}, \quad t = 1, \dots, s, \\ & \text{subject to } \mathbf{x} \in S \subseteq \mathbb{R}^n, \end{aligned} \quad (1)$$

150 where s is the number of scenarios; k is the number of objective functions, and we assume that
 151 the number of objectives is the same in all scenarios; f_{it} is the objective function defined
 152 in scenario t ; $\mathbf{x} = (x_1, \dots, x_n)^T$ is a feasible solution represented by a vector of decision
 153 variables, and $S \subseteq \mathbb{R}^n$ is the set of feasible solutions in the so called *decision space* \mathbb{R}^n .

154 Given a feasible solution \mathbf{x} and scenario $t \in \{1, \dots, s\}$, we introduce the *objective vector*
 155 $\mathbf{z}_t = (f_{1t}(\mathbf{x}), \dots, f_{kt}(\mathbf{x}))^T$ as the image of a solution \mathbf{x} under the conditions of scenario t in
 156 the *objective space* \mathbb{R}^k . A feasible solution (decision vector) $\mathbf{x} \in S$ is called *Pareto optimal*

157 if there does not exist another feasible solution with a smaller value of at least one objective
158 function in one scenario and no greater values of any objective functions in any scenarios.

We introduce a so-called *ideal* vector \mathbf{z}^{ideal} with components z_{it}^{ideal} , $i = 1, \dots, k$, $t = 1, \dots, s$ and a *nadir* vector \mathbf{z}^{nadir} with components z_{it}^{nadir} , $i = 1, \dots, k$, $t = 1, \dots, s$ composed, respectively, of the best and the worst values of the individual objective functions among the set of Pareto optimal solutions. Ideal values can be directly computed by solving the corresponding single-objective single-scenario optimization problems separately for each objective in each scenario. Nadir values are much more difficult to obtain, therefore they are usually approximated (see, e.g., Miettinen (1999)). Without loss of generality, we assume

$$z_{it}^{ideal} < z_{it}^{nadir}, \quad i = 1, \dots, k, \quad t = 1, \dots, s,$$

159 since the equality between ideal and nadir values for some i and t would mean that the i -th
160 objective function in scenario t is constant for all Pareto optimal solutions, and therefore it
161 can be excluded from the consideration. For any scenario t , we also introduce ideal and nadir
162 vectors in the objective space that are composed of the corresponding values in this scenario,
163 respectively: $\mathbf{z}_t^{ideal} = (z_{1t}^{ideal}, z_{2t}^{ideal}, \dots, z_{kt}^{ideal})$ and $\mathbf{z}_t^{nadir} = (z_{1t}^{nadir}, z_{2t}^{nadir}, \dots, z_{kt}^{nadir})$.

One way of deriving solutions to multiobjective optimization problems is to use a so-called *scalarizing function* to transform the multiobjective problem into a single-objective problem incorporating the DM's preferences (see, e.g., Miettinen (1999); Miettinen and Mäkelä (2002); Ruiz et al. (2009)). An extended version of a so-called achievement scalarizing function (Wierzbicki, 1986) has been recently introduced to solve multi-scenario multiobjective optimization problems (Shavazipour et al., 2020, 2021a). In this paper, we use the multi-scenario version of an achievement scalarizing function formulated by Shavazipour et al. (2021a) as follows:

$$\begin{aligned} & \text{minimize} && \max_{i=1, \dots, k; t=1, \dots, s} [w_{it}(f_{it}(\mathbf{x}) - \bar{z}_{it})] + \epsilon \sum_{i=1}^k \sum_{t=1}^s w_{it}(f_{it}(\mathbf{x}) - \bar{z}_{it}) \\ & \text{subject to} && \mathbf{x} \in S, \end{aligned} \quad (2)$$

164 where \bar{z}_{it} with $z_{it}^{ideal} \leq \bar{z}_{it} \leq z_{it}^{nadir}$, is an *aspiration level* representing a DM's preferences
165 in terms of a desirable value for the i -th objective function under the t -th scenario, and
166 w_{it} is the corresponding weight that can be used, e.g., for normalization purposes. The
167 augmentation term $\epsilon \sum_{i=1}^k \sum_{t=1}^s w_{it}(f_{it}(\mathbf{x}) - \bar{z}_{it})$ guarantees that the solution to (2) is Pareto
168 optimal, where ϵ is a small positive scalar (for details of the augmentation term, see, e.g.,
169 Miettinen (1999)).

170 A vector including aspiration levels for all objectives and all scenarios is called a *reference*
171 *point*. By solving (2) with different reference points, the DM can obtain different Pareto

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172 optimal solutions, although sometimes the same Pareto optimal solution may be associated
 173 with multiple reference points. A simple interactive multiobjective optimization method
 174 based on this concept can be described as follows:

175 Step 0. Initialization of the method. Present information about the ideal and nadir vectors to
 176 the DM.

177 Step 1. Ask the DM to specify preference information as a reference point.

178 Step 2. Derive a Pareto optimal solution by solving (2) and present it to the DM.

179 Step 3. Ask the DM if this or one of the previously derived solutions is satisfactory as a final
 180 solution to the problem. If yes, stop; otherwise, go to Step 1.

181 2.2 Simulation of incomplete preferences

182 If we apply the simple interactive method presented in the previous subsection directly, the
 183 DM must specify aspiration levels for all objectives and scenarios. In order to reduce the
 184 cognitive load of expressing preferences in all scenarios, we allow the DM to set aspiration
 185 levels only for some scenarios, and then we fill in missing information by simulating the
 186 DM's preferences. Assume that the DM has provided aspiration levels \bar{z}_{it} for all k objective
 187 functions, but only in q ($q < s$) scenarios (without loss of generality, we assume that these
 188 q scenarios are ordered as the first q scenarios—i.e., $\{1, 2, \dots, q, q + 1, \dots, s\}$), so, here,
 189 $t = 1, \dots, q$. The main idea of simulating the unknown preferences (the aspiration levels for
 190 the remaining $s - q$ scenarios) is to analyze the relationships between the available preference
 191 information and the ideal and nadir vectors. These relationships are represented in terms of
 192 so-called *distance-based ratios* defined below.

193 For each scenario t , $t = 1, \dots, s$, and objective i , $i = 1, \dots, k$, we define a distance-based
 194 ratio γ_i^t based on the distances between the aspiration level and the corresponding ideal and
 195 nadir values:

$$196 \gamma_i^t = \frac{\bar{z}_{it} - z_{it}^{ideal}}{z_{it}^{nadir} - z_{it}^{ideal}}. \quad (3)$$

196 It is easy to see that $0 \leq \gamma_i^t \leq 1$.

For each scenario t , $t = q + 1, \dots, s$, and each objective function i , $i = 1, \dots, k$, we calculate q candidates for aspiration levels based on the ratios obtained for the first q scenarios:

$$g_{it}^u = z_{it}^{ideal} + \gamma_i^u (z_{it}^{nadir} - z_{it}^{ideal}), \quad u = 1, \dots, q.$$

197 Thus, we obtain q candidate vectors in the objective space for the t -th scenario: $\mathbf{g}_t^u =$
 198 $(g_{1t}^u, \dots, g_{kt}^u)$, $u = 1, \dots, q$.

199 Let us denote an estimation of the vector of aspiration levels in scenario t by $\tilde{\mathbf{z}}_t =$
 200 $(\tilde{z}_{1t}, \dots, \tilde{z}_{kt})$. In order to derive this estimation of a reference point, we limit the search area
 201 in the objective space to the convex hull of those q candidate vectors. Figure 1 shows an
 202 example of the estimation process in case of a bi-objective problem ($k = 2$). The convex hull
 203 of four candidate vectors is outlined by blue lines; the area between the ideal and the nadir
 204 vectors is outlined by red dashed lines.

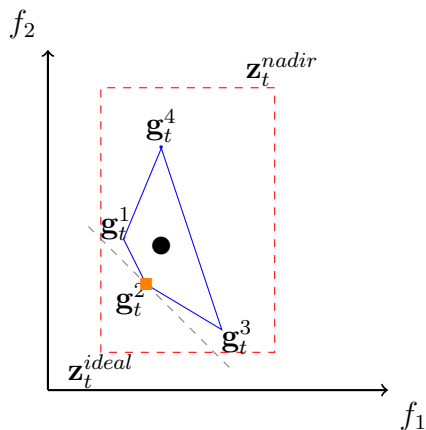


Figure 1: An example of estimating aspiration levels based on four candidates and the convex hull in a bi-objective problem including the idealistic (‘■’) and moderate (‘●’) simulated reference points.

205 We consider two styles of setting preference by a DM, namely *moderate* and *idealistic*,
 206 and for each style, propose an optimization model to estimate the unknown preferences. If
 207 the DM’s style is closer to *moderate*, (s)he may avoid the extremes and cautiously choose a
 208 vector in the center of the convex hull (e.g., the vector minimizing the sum of distances to
 209 all q candidates). This vector (represented by ‘●’ in Figure 1) can be found by solving the
 210 following optimization problem:

$$\begin{aligned}
 &\text{minimize} && \sum_{u=1}^q \sum_{i=1}^k |\tilde{z}_{it} - g_{it}^u| \\
 &\text{subject to} && \tilde{z}_{it} \geq \sum_{u=1}^q \lambda_u g_{it}^u, && i = 1, \dots, k \\
 &&& \sum_{u=1}^q \lambda_u = 1, \\
 &&& \lambda_u \geq 0, && u = 1, \dots, q.
 \end{aligned} \tag{4}$$

211 where $|\cdot|$ returns the absolute value.

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212 To estimate all the unknown aspiration levels, problem (4) needs to be solved for each
 213 of $(s - q)$ scenarios. Note that problem (4) is not computationally complex and can be
 214 solved very fast. Solving all $(s - q)$ problems could be done in seconds even for a large
 215 number of scenarios. Also, problem (4) is always feasible and bounded (see Appendix B
 216 for a mathematical proof). So, by using this model, we are always able to find simulated
 217 preferences. If the objective functions in the original problem have different scales, model (4)
 218 should be normalized, e.g., by replacing the objective function by $\sum_{u=1}^q \sum_{i=1}^k \frac{|\tilde{z}_{it} - g_{it}^u|}{z_{it}^{nadir} - z_{it}^{ideal}}$.

219 If the DM's style is closer to idealistic, e.g., (s)he has high expectations, the vector of
 220 aspiration levels can be estimated as the point of the convex hull which is closest to the ideal
 221 vector. In the case of l_1 distance, it is equivalent to the candidate vector which is closest to
 222 the ideal vector:

$$\begin{aligned} & \text{minimize} \quad \sum_{i=1}^k |\tilde{z}_{it} - z_{it}^{ideal}| \\ & \text{subject to} \quad u = 1, \dots, q. \end{aligned} \quad (5)$$

223 The '■' point in Figure 1 represents the idealistic choice. As above, the model should be
 224 normalized if there are objective functions with different scales.

225 2.3 The proposed approach for multi-scenario multiobjective de- 226 cision support

227 We incorporate the method of simulating incomplete preferences with the interactive mul-
 228 tiobjective optimization method described in Subsection 2.1. The resulting approach for
 229 multi-scenario multiobjective decision support is presented in Figure 2, while the steps are
 230 described in Algorithm 1.

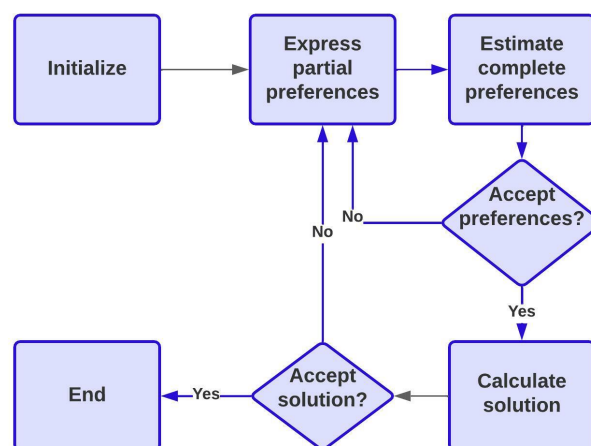


Figure 2: The general flowchart of the proposed interactive approach for multi-scenario multiobjective decision support.

Algorithm 1. The steps of multi-scenario multiobjective decision support approach

1. Initialization. Calculate and present to the DM the ideal and nadir values for all $k \times s$ combinations of objectives and scenarios (as described in subsection 2.1).
 2. Ask the DM to specify preferences in one of the following two ways:
 - (a) Provide aspiration levels for all k objectives in a freely chosen non-empty subset of scenarios;
 - (b) (From second iteration onward) Update aspiration levels, obtained from the previous iteration, for all objectives under all scenarios. The update may include changing aspiration levels and/or removing aspiration levels for a chosen subset of scenarios.
 3. Estimate missing preference information if incomplete, as described in Subsection 2.2.
 4. If the preference information has been estimated in the previous step and if the DM wishes to review it, show it to the DM. If the DM is not satisfied with the estimation result, go to step 2.
 5. Derive a Pareto optimal solution corresponding to the DM's preferences by solving problem (2), and present this solution to the DM.
 6. If the DM is not ready to accept the presented solution as the final solution to the problem, go to step 2.
 7. Stop. The Pareto optimal solution derived in Step 5 is the final solution to the problem.
-

2.4 Visual support for trade-off analysis

A scenario-based empirical attainment function (SB-EAF) has been proposed by Shavazipour et al. (2021b) to support decision-making in multi-scenario multiobjective optimization problems. This function is constructed in the objective space for analyzing a finite set of Pareto optimal solutions. The value of SB-EAF, at each point of the objective space, is the number (or the percentage) of scenarios that could attain these objective values by at least one solution. Here, by attaining, we mean that each objective function value of the solution under the given scenario is at least as small as the corresponding component of the point. SB-EAF is visualized on a plane for a selected pair of objective functions, limiting the attainability to this pair. Each region of the same attainment function value is filled with a different color.

For each solution, the SB-EAF value is constructed from s objective vectors, each corresponding to a different scenario (see Shavazipour et al. (2021b) for details). SB-EAFs are utilized to visually distinguish different regions of the objective space that may be attained by a given number (percentage) of scenarios (also called attainment surface) for each considered solution. If we compute and visualize the combination of the SB-EAF values of multiple solutions (with corresponding decision vectors) in a single plot, the visualization is called an all-in-one SB-EAF. This visualization gives the DM an opportunity of comparing different attainment surfaces of multiple solutions at a glance. We refer the reader to Shavazipour et al. (2021b) for the details and various illustrative examples. We use the SB-EAF concept and relevant visualizations to analyze the results of our case study in Section 4.

3 Case study

The forest landscape management problem considered here aims at selecting a management regime for each forest stand to optimize predicted long-term outcomes in terms of ecosystem services provided by the landscape. To be more specific, we consider a real four-objective forest management problem from Triviño et al. (2017) and extend it to a multi-scenario multiobjective optimization problem. Next, we briefly describe the problem and real-life data collected in Triviño et al. (2017). Then, we describe our modification and present the mathematical problem formulation.

3.1 Study area and source data

The study area considered in Triviño et al. (2017) is a forest landscape located in Central Finland with 68 700 hectares. The landscape is divided into 29 666 forest stands. Up to 7 possible management regimes can be independently applied to each stand. Each regime defines rules for conducting operations in the forest such as final harvest, thinning, planting or seeding trees, and site preparation. The recommended management regime, referred to as *business as usual (BAU)*, aims at increasing revenue. Most of the other regimes are modifications of this BAU regime and, contradictory, aim to increase the forest's conservation value. The considered regimes are briefly described below (for details, see Mönkkönen et al. (2014); Triviño et al. (2017)).

- *Business as usual (BAU)* – the recommended management regime in Finland aimed at optimizing timber production, with an average rotation length of 80 years.
- *Green tree retention (GTR30)* – BAU with the additional rule that 30 green trees per hectare are retained during final harvest.
- *Extended rotation for 10 years (EXT10)* – BAU with final harvest postponed by ten years.
- *Extended rotation for 30 years (EXT30)* – BAU with final harvest postponed by thirty years.
- *No thinning long rotation (NTLR)* – BAU with no thinning operations (which results in slightly longer rotation length compared to BAU).
- *No thinning short rotation (NTSR)* – a modification of BAU with no thinning, and final harvest criteria adjusted in order to obtain similar rotation length as in BAU.
- *Set aside (SA)* – the conservation strategy where no management activities are carried out during the planning horizon.

283 Using forest inventory data and forest growth simulator MOTTI (Hynynen et al., 2005),
 284 values of essential parameters of forest growth were predicted for each stand under each man-
 285 agement regime for a 50-year planning period. For each stand and each regime, these 50-year
 286 time series of parameter values were aggregated into four different quantities representing
 287 different types of characteristics of good forest management:

- 288 1. *timber harvest revenues* as the net present value discounted at 3% interest rate;
- 289 2. *carbon storage* in living and dead wood as well as extracted and residual timber;
- 290 3. *volume of deadwood*, which is an essential biodiversity indicator;
- 291 4. *habitat availability indicator* combination of habitat availability indices for six verte-
 292 brate species representing various types of habitat – three-toed woodpecker (*Picoides*
 293 *tridactylus*), lesser-spotted woodpecker (*Dendrocopos minor*), flying squirrel (*Pteromys*
 294 *Volans*), capercaillie (*Tetrao urogallus*), long-tailed tit (*Aegithalos caudatus*), and hazel
 295 grouse (*Bonasia Bonasa*).

296 Given a combination of management regimes selected across stands (one regime for each
 297 stand), the values of the above-mentioned characteristics for the whole forest landscape are
 298 calculated as sums of corresponding values for each stand. These values constitute four
 299 objective functions of our forest landscape management problem, where each objective is to
 300 be maximized.

301 The problem data published in Triviño et al. (2017) includes four matrices playing the
 302 role of coefficients of the corresponding objective functions. In each matrix, rows are forest
 303 stands, columns are regimes, and each element is the value of the corresponding characteristic
 304 for this stand under this regime.

305 3.2 Scenarios and data generation

306 We consider three sources of deep uncertainty that are independent of each other: (1) climate
 307 change, (2) forest thinning subsidies, and (3) compensation for forest landscape conservation.
 308 For each source, we consider so-called “partial scenarios” that represent future possibilities
 309 related to this source. Each combination of the partial scenarios forms one scenario in terms
 310 of the problem formulation. We consider three, two, and two partial scenarios, respectively,
 311 for the above-mentioned uncertainty sources resulting with $3 \times 2 \times 2 = 12$ scenarios in total.
 312 The partial scenarios are listed below.

- 313 • *Climate change*: in addition to the *stationary climate* scenario (i.e., no climate change),
 314 we consider two climate change scenarios established by the Intergovernmental Panel

on Climate Change (IPCC) based on the amount of greenhouse gas emissions: B1 (low emissions) and A2 (high emissions) (see, e.g., Nakicenovic et al., 2000).

- *Forest thinning subsidies*: a forest owner in Finland can apply for government subsidies related to young forest management. This results in two partial scenarios (subsidies are granted or not).
- *Landscape conservation compensations*: a Finnish forest owner can also apply for voluntary agreement programs providing compensation payments for nature conservation. This results in two partial scenarios (the application is accepted or not).

The original problem data corresponds to the scenario composed of stationary climate and the negative decisions on both thinning subsidies and compensation for landscape conservation. Generating the coefficient matrices for the rest of the scenarios was done by modifying the original matrices. First, all four matrices were modified to account for climate change, and then the elements of the timber revenue matrix were increased by adding values corresponding to thinning subsidies and/or compensation for landscape conservation. Thus, the climate change uncertainty influences all the coefficient matrices, while the other two uncertainties influence only the timber revenue matrix.

There is no data concerning the effects of the above scenarios explicitly collected for the considered forest landscape. However, we did not aim at making a decision to be implemented in practice. Rather than that, we tried to create a problem that looks realistic for an expert on forest management planning. Therefore, we did all the modifications using relevant information published in the literature, and filling in information gaps based on realistic assumptions. The process of modifying the coefficient matrices is described in detail in Appendix A.

3.3 Mathematical problem formulation

The forest management problem is formulated as a special case of the multi-scenario multiobjective optimization problem (1), where the objective functions and the set of feasible solutions are defined, respectively, as follows:

$$\begin{aligned}
 &\text{minimize} && f_{it}(\mathbf{x}) = - \sum_{h=1}^p \sum_{j \in \rho_h} a_{hj}^{it} x_{hj}, \quad i = 1, \dots, k, \quad t = 1, \dots, s, \\
 &\text{subject to} && \sum_{j \in \rho_h} x_{hj} = 1, && h = 1, \dots, p, \\
 &&& x_{hj} \in \{0, 1\} && h = 1, \dots, p, \quad j \in \rho_h,
 \end{aligned} \tag{6}$$

342 where, the number of objectives is $k = 4$, the number of scenarios is $s = 12$, and $p = 29\,666$
 343 is the number of forest stands. For each stand h , $\rho_h \subseteq \{1, \dots, r\}$ denotes the subset of
 344 management regimes that can be applied to this stand, where $r = 7$ denotes the number
 345 of management regimes. Each coefficient a_{hj}^{it} represents the outcome of applying regime j
 346 to stand h in terms of the i -th objective under the t -th scenario. The components x_{hj} of
 347 the feasible solution \mathbf{x} are binary variables defined for all pairs (h, j) , $h = 1, \dots, p$, $j \in \rho_h$.
 348 Thus, the dimension of the decision space is $n = \sum_{h=1}^p |\rho_h|$. This problem can be classified as a
 349 mixed-integer linear optimization problem, namely a multiobjective multiple choice knapsack
 350 problem.

351 In terms of the above notation, the problem data is represented by matrices A^{it} , $i =$
 352 $1, \dots, k$, $t = 1, \dots, s$, with missing elements $A^{it} = (a_{hj}^{it})$, where the elements are defined for
 353 $h \in \{1, \dots, p\}$, $j \in \rho_h$. Matrices A^{i1} , $i = 1, \dots, k$, represent the original problem data and
 354 for the rest of scenarios $t = 2, \dots, s$, the matrices are generated as described in Subsection
 355 3.2.

356 4 Results

357 4.1 Interactive decision-making process

358 We have implemented the decision support environment in a Jupyter Notebook and used a
 359 Microsoft Excel worksheet as an interface for exchanging information with the DM. In our ex-
 360 periment, the DM was an expert in forest management. To solve the mixed-integer optimiza-
 361 tion problem, we utilized Gurobi optimizer. The code and data are freely accessible at <https://github.com/industrial-optimization-group/Interactive-decision-support-and-trade-off-analysis-for-sustainable-forest-landscape-planning-under->.

364 Following the proposed Algorithm 1, the solution process was started by calculating
 365 the ideal and nadir values for all objectives and scenarios and presenting them to the DM
 366 (*step 1 in Algorithm 1*). These values are shown in Table 1. The table also contains
 367 numbers assigned to scenarios for quick reference. The scenarios are grouped based on
 368 the climate change partial scenarios, since this source of uncertainty is the most influential
 369 on the objective function values.

370 Iteration 1.

371 First, the DM was asked to choose a few scenarios for which he was willing and able
 372 to provide aspiration levels (for all objective functions) and fill in the corresponding cells
 373 in the Microsoft Excel table (*step 2a in Algorithm 1*). The DM sought to compare trade-
 374 offs between the stationary climate scenario and the high-emission (A2) climate scenario by
 375 choosing the *1st* and *4th* scenario from the former group, and *9th* and *11th* scenario from the

4.1 Interactive decision-making process

16

Table 1: Ideal and nadir values for each objective in each scenario. M: million, K: thousand.

Scenario		No.	Nadir/Ideal	Revenues	Habitat availabil- ity	Carbon storage	Deadwood volume
Stationary climate	No compens. No Thin. Sub.	1	Nadir	31.77 M	10.81 K	2.83 M	66.93 K
			Ideal	249.97 M	20.23 K	4.45 M	218.15 K
	Compens. gained No Thin. Sub.	2	Nadir	127.09 M	10.81 K	2.83 M	66.93 K
			Ideal	272.68 M	20.23 K	4.45 M	218.15 K
	No compens. Thin. Sub. gained	3	Nadir	34.07 M	10.81 K	2.83 M	66.93 K
			Ideal	283.05 M	20.23 K	4.45 M	218.15 K
	Compens. gained Thin. Sub. gained	4	Nadir	127.74 M	10.81 K	2.83 M	66.93 K
			Ideal	301.46 M	20.23 K	4.45 M	218.15 K
B1 Climate change	No compens. No Thin. Sub.	5	Nadir	33.87 M	10.69 K	3.01 M	78.03 K
			Ideal	272.69 M	20.24 K	4.89 M	279.94 K
	Compens. gained No Thin. Sub.	6	Nadir	130.53 M	10.69 K	3.01 M	78.03 K
			Ideal	291.94 M	20.24 K	4.89 M	279.94 K
	No compens. Thin. Sub. gained	7	Nadir	36.16 M	10.69 K	3.01 M	78.03 K
			Ideal	297.26 M	20.24 K	4.89 M	279.94 K
	Compens. gained Thin. Sub. gained	8	Nadir	131.18 M	10.69 K	3.01 M	78.03 K
			Ideal	314.58 M	20.24 K	4.89 M	279.94 K
A2 Climate change	No compens. No Thin. Sub.	9	Nadir	35.96 M	10.59 K	3.17 M	89.19 K
			Ideal	296.54 M	20.29 K	5.34 M	341.39 K
	Compens. gained No Thin. Sub.	10	Nadir	133.96 M	10.59 K	3.17 M	89.19 K
			Ideal	312.76 M	20.29 K	5.34 M	341.39 K
	No compens. Thin. Sub. gained	11	Nadir	38.25 M	10.59 K	3.17 M	89.19 K
			Ideal	314.38 M	20.29 K	5.34 M	341.39 K
	Compens. gained Thin. Sub. gained	12	Nadir	134.60 M	10.59 K	3.17 M	89.19 K
			Ideal	330.40 M	20.29 K	5.34 M	341.39 K

376 latter group. The DM's reasoning was to keep the timber revenue moderate while seeking
 377 more enhanced environmental benefits in the high-emission (A2) climate scenarios compared
 378 to the stationary climate scenarios. His preferences are highlighted in blue in the resulting
 379 matrix of aspiration levels shown in Table 2.

380 To get missing preferences, we calculated simulated preferences based on the moderate
 381 style (problem (4)) according to the DM's choice (*step 3 in Algorithm 1*). They can be seen
 382 in Table 2 in black. The DM wished to skip the step of reviewing the simulated preferences
 383 (*step 4 in Algorithm 1*). Therefore, we proceeded to the next step of deriving a Pareto
 384 optimal solution to the 48-objective problem (1) by minimizing the achievement scalarizing
 385 function (2). Then, the obtained solution (illustrated in a parallel coordinate plot in Figure
 386 3) was presented to the DM (*step 5 in Algorithm 1*).

387 It turned out that the trade-offs between objectives in various climate change scenarios
 388 are more intensive than the DM expected. Comparing the objective function values in various
 389 scenarios exposed trade-offs between revenue, habitat availability, and carbon storage in the
 390 Stationary climate scenarios and the high-emission (A2) climate scenarios. Furthermore, it
 391 seemed that the DM was too optimistic about environmental objectives, in particular, for
 392 the deadwood and habitat availability objective functions whose values were significantly
 393 lower than what the DM desired. Learning about this fact, the DM decided to lower his
 394 expectations related to these two objectives in all scenarios (*step 6 in Algorithm 1*).

Table 2: Aspiration levels in the first iteration. Actual aspiration levels (set by the DM) are highlighted in blue, while the simulated ones are shown in black (M: million, K: thousand).

Scenario	Revenues	Habitat availability	Carbon storage	Deadwood volume
s_1	170.00 M	15.00 K	3.70 M	140.00 K
s_2	219.32 M	17.52 K	3.90 M	175.34 K
s_3	191.80 M	17.52 K	3.90 M	175.34 K
s_4	170.00 M	16.00 K	3.90 M	160.00 K
s_5	185.16 M	17.50 K	4.25 M	222.79 K
s_6	232.79 M	17.50 K	4.25 M	222.79 K
s_7	201.57 M	17.50 K	4.25 M	222.79 K
s_8	247.36 M	17.50 K	4.25 M	222.79 K
s_9	180.00 M	17.00 K	4.20 M	250.00 K
s_{10}	247.23 M	17.50 K	4.60 M	270.00 K
s_{11}	180.00 M	17.50 K	4.40 M	270.00 K
s_{12}	258.64 M	17.50 K	4.60 M	270.00 K

4 RESULTS

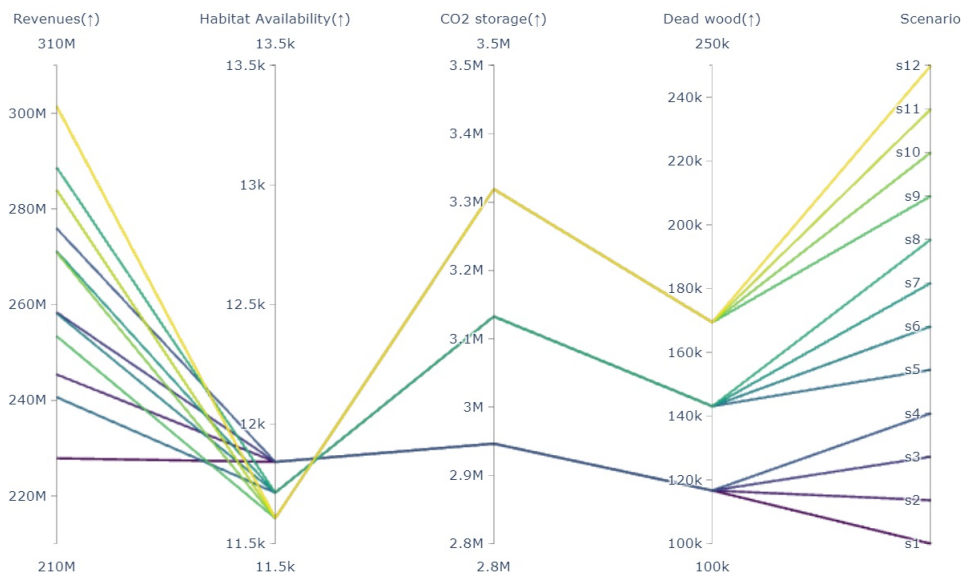


Figure 3: Pareto optimal solution generated by the simulated reference point (moderate style) in the first iteration. Each line represents the objective values in a scenario (s1-s12)—different colors are used to distinguish the achievements in different scenarios. M: million, K: thousand.

395 **Iteration 2.** As a result of learning about the problem in the first iteration, the DM set
 396 his desired habitat availability values at 10 000 in all the scenarios, reduced the aspiration
 397 level for deadwood, and kept the rest of aspiration levels as the previous iteration, which
 398 resulted in an updated matrix of aspiration levels shown in Table 3 (*step 2b in Algorithm 1*).
 399 We derived the Pareto optimal solution corresponding to the aspiration levels and showed it
 400 to the DM (*step 5 in Algorithm 1*). The solution is presented in Figure 4.

401 This time, the solution had higher environmental values at the expense of a few million
 402 EUR lower revenues in various scenarios. For example, in the best-case revenue scenarios
 403 (when both compensations and thinning subsidies were included), the revenue decreased by
 404 approximately 3–5 million EUR, while in the worst-case revenue scenarios (neither extra
 405 compensations nor thinning subsidies were obtained), the decrease was in the range of 14–
 406 16 million EUR. However, according to the DM's opinion, the environmental benefits were
 407 worth the revenue losses, and he was more satisfied with the obtained solution. Nonetheless,
 408 he was curious to check what would happen if he increased the aspiration levels for the third
 409 objective (carbon storage) by a few percent, and decided to continue the decision-making
 410 process for one more iteration (*step 6 in Algorithm 1*).

411 **Iteration 3.** This time, in order to check the potential of increasing the carbon storage
 412 objective and analyze the trade-offs between this objective and the other ones in various
 413 scenarios, the DM increased the aspiration levels for carbon storage in all scenarios by 5%
 414 while keeping the other aspiration levels the same as in the previous iteration, shown in Table
 415 4, (*step 2b in Algorithm 1*). The obtained Pareto optimal solution (*step 6 in Algorithm 1*)

4.1 Interactive decision-making process

Table 3: Aspiration levels in the second iteration. Actual aspiration levels (set by the DM) are highlighted in blue, while the simulated ones are shown in black (M: million, K: thousand).

Scenario	Revenues	Habitat availability	Carbon storage	Deadwood volume
s_1	170.00 M	10.00 K	3.70 M	100.00 K
s_2	219.32 M	10.00 K	3.90 M	100.00 K
s_3	191.80 M	10.00 K	3.90 M	100.00 K
s_4	170.00 M	10.00 K	3.90 M	100.00 K
s_5	185.16 M	10.00 K	4.25 M	110.00 K
s_6	232.79 M	10.00 K	4.25 M	110.00 K
s_7	201.57 M	10.00 K	4.25 M	110.00 K
s_8	247.36 M	10.00 K	4.25 M	110.00 K
s_9	180.00 M	10.00 K	4.20 M	130.00 K
s_{10}	247.23 M	10.00 K	4.60 M	130.00 K
s_{11}	180.00 M	10.00 K	4.40 M	130.00 K
s_{12}	258.64 M	10.00 K	4.60 M	130.00 K

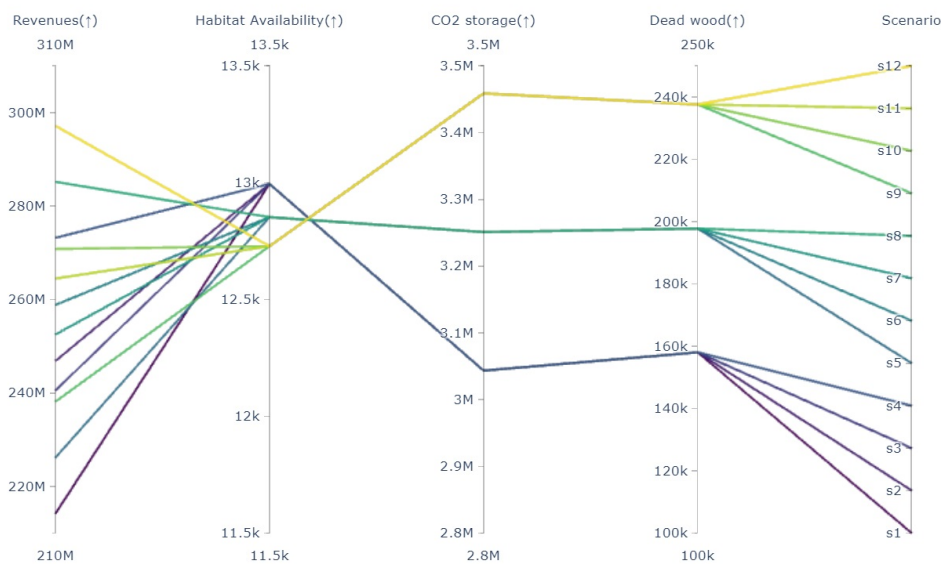


Figure 4: Pareto optimal solution in the second and third (final) iterations. Each line represents the objective values in a scenario (s1-s12)—different colors are used to distinguish the achievements in different scenarios. M: million, K: thousand. M: million, K: thousand.

416 coincided with the one from the previous iteration, suggesting that the previous solution was
 417 stable for such a slight change of preferences. Therefore, the DM concluded that the last
 418 Pareto optimal solution can be considered the final one, and the decision-making process
 419 was stopped (*step 7 in Algorithm 1*).

Table 4: Aspiration levels in the third iteration

Scenario	Revenues	Habitat availability	Carbon storage	Deadwood volume
s_1	170.00 M	10.00 K	3.89 M	100.00 K
s_2	219.32 M	10.00 K	4.10 M	100.00 K
s_3	191.80 M	10.00 K	4.10 M	100.00 K
s_4	170.00 M	10.00 K	4.10 M	100.00 K
s_5	185.16 M	10.00 K	4.47 M	110.00 K
s_6	232.79 M	10.00 K	4.47 M	110.00 K
s_7	201.57 M	10.00 K	4.47 M	110.00 K
s_8	247.36 M	10.00 K	4.47 M	110.00 K
s_9	180.00 M	10.00 K	4.41 M	130.00 K
s_{10}	247.23 M	10.00 K	4.83 M	130.00 K
s_{11}	180.00 M	10.00 K	4.62 M	130.00 K
s_{12}	258.64 M	10.00 K	4.83 M	130.00 K

420 4.2 Trade-off analysis through visualizations

421 To get more insight into the problem and provide better support for the DM in our com-
 422 plex problem, we use the visualization methods proposed by Shavazipour et al. (2021b) for
 423 decision support in scenario-based multiobjective optimization. Therefore, as proposed by
 424 Shavazipour et al. (2021b), we start with the *all-in-one SB-EAF* visualization. We refer to
 425 the Pareto optimal solutions obtained in the first and the second iteration as solutions 1 and
 426 2, respectively. We selected the first two objectives (timber revenue and habitat availability)
 427 for comparison because their conflict was the most important from the DM's perspective.
 428 This visualization is presented in Figure 5. One can clearly see the trade-offs between the
 429 two objectives and the performance of the solutions in different scenarios.

430 The dark purple area (■) represents the worst attainment surface that guarantees the
 431 objective values achievable in all scenarios. This worst attainment surface for solution 1 is
 432 bounded by 228.118 million EUR revenue and 11.6 thousand habitat availability indicator
 433 value. For solution 2, the worst attainment surface shrinks to 214.128 million EUR in
 434 revenue but expands to 12.729 thousand in habitat availability, highlighting the trade-offs

435 between these two objectives. This means that solution 2 provides higher environmental
 436 values (+1.129 thousand in habitat availability) at the expense of about 14 million EUR lower
 437 revenues in the worst-case scenario compared to solution 1. In contrast, the yellow area (■)
 438 corresponds to the best possible attainment surface (that only can happen in one scenario—
 439 the best-case scenario). Other colors describe the attainment surfaces corresponding to some
 440 other ranges of a percentage of scenarios. For example, if the DM sets aspiration levels at 250
 441 million EUR for revenue and 12.5 thousand for habitat availability, he can simply compare
 442 how well these two solutions can reach his desired values by taking a glance at Figure 5.
 443 Comparing the solutions in this figure shows that the desired revenue can be obtained in at
 444 least 75% or 50% of scenarios if the DM chooses solution 1 or 2, respectively. However, it is
 445 not possible to reach the 12 thousand value for habitat availability by choosing solution 1,
 446 while reaching this value is guaranteed under the conditions of any scenario for solution 2.

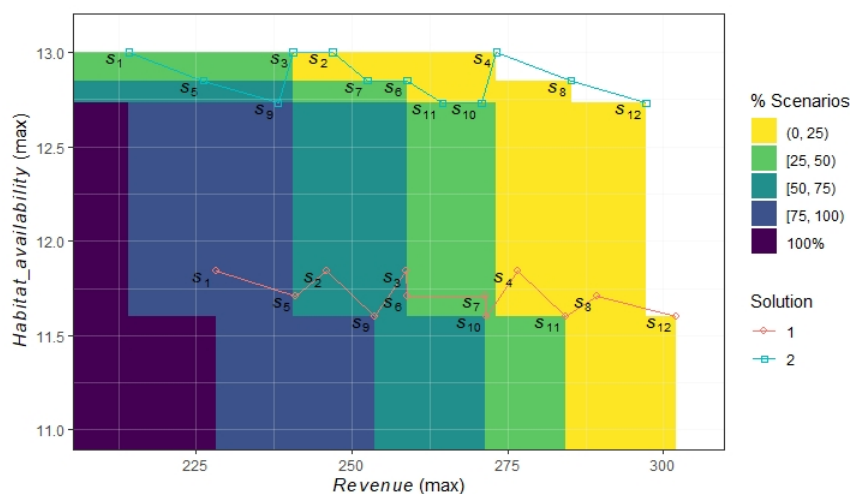


Figure 5: All-in-one SB-EAF visualization of two solutions for timber revenue and habitat availability under 12 scenarios. Points connected by a line denote a solution evaluated on different scenarios. Colored areas show regions of the objective space that can be attained within a particular percentage of scenarios by a solution.

447 As mentioned in the introduction, the SB-EAF visualization discussed above is only
 448 suitable for comparing two objectives at a time. In Figure 6, we utilize the scenario-based
 449 heatmaps visualization (Shavazipour et al., 2021b) to compare the two Pareto optimal so-
 450 lutions with regard to all four objectives under all scenarios. Darker colors represent higher
 451 objective function values. It can be seen that solution 2 provides higher values for the last
 452 three objectives (i.e., carbon storage, deadwood, and habitat availability). Regarding the
 453 first objective (timber revenue), solution 1 gives higher values except for the 2nd and 6th
 454 scenario.

455 The visual analysis confirms the result obtained by Triviño et al. (2017), stating the
 456 possibility of significant improvements of the multifunctionality of the forest landscape (in
 457 terms of the biodiversity objectives) at the expense of a slight revenue reduction. Moreover,

5 DISCUSSION

458 in the 2nd and 6th scenarios, solution 2 provides better values for all four objective functions
 459 than solution 1. In other words, if one of these two scenarios happens, the improvements of
 460 the multifunctionality of the forest landscape (in terms of the biodiversity objectives) can
 461 also bring more revenue than the revenue-focused solution (i.e., solution 1) in our problem.
 462 This valuable insight could not be gained without separate consideration of scenarios and
 463 studying trade-offs between them, as proposed in this study. However, generalizing this fact
 464 needs more in-depth investigations in various real cases.

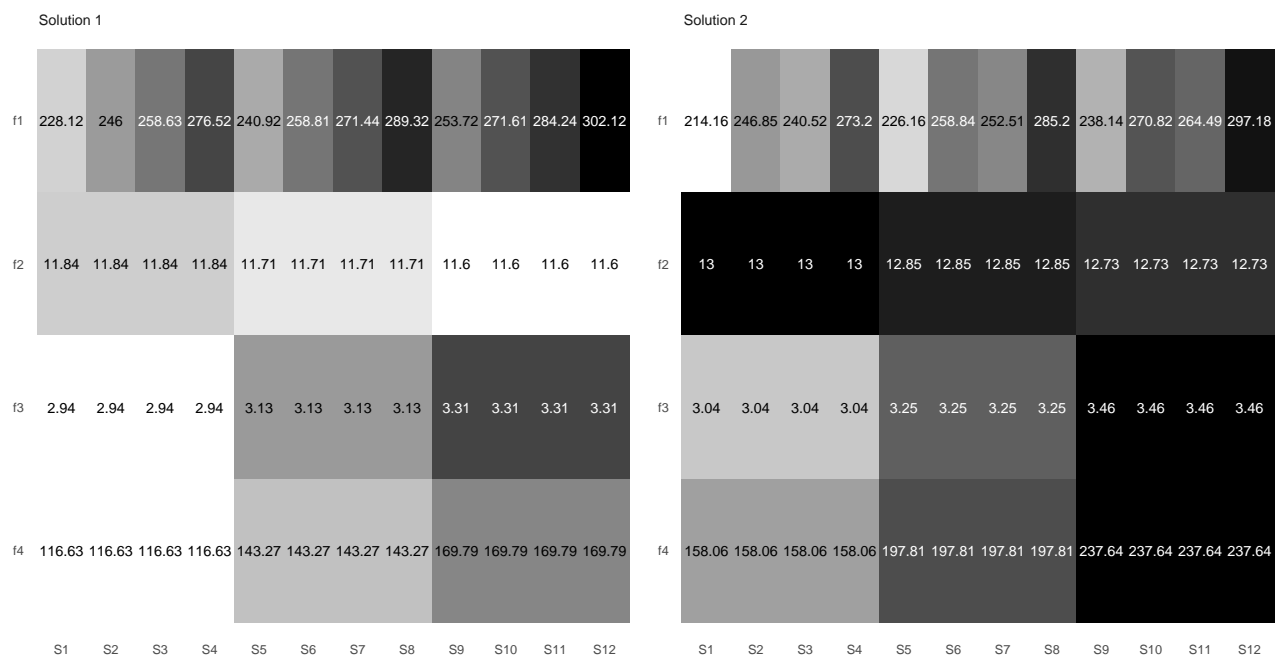


Figure 6: Comparing two Pareto optimal solutions in twelve scenarios via Heatmaps. Darker values are better (all objectives are to be maximized). $f1$: Revenues (million EUR), $f2$: Habitat availability (thousand), $f3$: Carbon storage (million MgC), $f4$: Deadwood volume (thousand m^3).

465 5 Discussion

466 In our experiment, the DM found the option of simulating the preferences reasonable and
 467 helpful in reducing the cognitive burden of setting preferences in all scenarios. Indeed,
 468 although the consideration of all generated scenarios is crucial in finding a robust solution,
 469 not all the scenarios may be highly interesting for the DM, or the DM may lack confidence
 470 regarding the importance of some scenarios at the beginning of the solution process. Indeed,
 471 as a human, the DM may have some expectations and imagination based on their experiences

472 and judgments. For example, the DM might (truly or mistakenly) foresee the likelihood of
473 some scenarios as low (even though one cannot calculate the likelihood of the scenarios in
474 deep uncertainty) or be less concerned about the effect of some sources of uncertainty on
475 planning outcomes (e.g., not expecting significant loss or potential noteworthy gains). On
476 the other hand, interesting scenarios can be interpreted as ones that the DM is expected
477 to be realized more likely or to significantly affect planning outcomes in a good (best-case
478 scenario) or harmful (worst-case scenario) way.

479 Indeed, it is vital to identify vulnerability/fragility in a system (as critical scenarios) and
480 investigate the consequences of candidate solution(s) on those scenarios. For instance, in our
481 case study, the worst-case financial scenario is when neither compensations for landscape
482 conservation nor thinning forest subsidies could be gained. Therefore, it might be neces-
483 sary for the DM to track the revenue values in that scenario and ensure it does not lead
484 to a financial crisis. Alternatively, assuring enough environmental benefits (e.g., based on
485 some agreement) in high-emission (A2) climate scenarios might make these scenarios im-
486 portant/interesting for a DM, so that their changes should be tracked more closely. These
487 kinds of scenarios are sometimes called vulnerable scenarios (i.e., scenarios that cause poor
488 performance in some objectives). If so many scenarios are generated for a problem, identi-
489 fying vulnerable scenarios requires more systematic approaches, such as scenario discovery
490 approaches (see, e.g., Bryant and Lempert (2010); Shavazipour et al. (2021a)). Considering
491 such vulnerable scenarios and the performance of the solutions in terms of various objectives
492 is essential in finding robust solutions. Besides, the DMs may have preferences/feelings on
493 considering some particular scenarios and comparing the objective values and trade-offs with
494 other scenarios (e.g., the current, average, the most probable, or the best-case scenarios).

495 Furthermore, observing and comparing the ranges of different objective functions across
496 the scenarios and analyzing their interdependencies and trade-offs helped the DM get a
497 deeper insight into the problem and decision-making process. For Our DM, it was more
498 convenient to update the aspiration levels when studying the trade-offs between objectives
499 in various scenarios. Moreover, although the DM was quite satisfied with the solution, he
500 wanted to compare the solutions and trade-offs under different scenarios in more detail. The
501 visualization approaches proposed recently proved to be useful in trade-offs and scenario
502 analysis and find the most preferred robust solution.

503 We acknowledge the importance of generating the set of scenarios, but it is outside
504 the scope of this paper. Generally, two approaches are most often used in the literature:
505 1) using experts' judgment, as was done in our case study, and 2) random generation of
506 the scenarios (e.g., when only possible ranges of some uncertain parameters are known).
507 However, in either case, generated scenarios should reflect the significant vulnerabilities of

6 CONCLUSIONS

508 the system/phenomena as well as the DM's preferences (Giudici et al., 2020). Nevertheless,
 509 considering too many scenarios is inefficient. On the one hand, the problem may become
 510 computationally expensive, and on the other hand, the performances of solutions may be
 511 very similar in an ample portion of the scenario space. Utilizing the DM's preferences in
 512 reducing the number of scenarios is in line with the philosophy of scenario planning (Ram
 513 et al., 2011; Shavazipour et al., 2020).

514 The calculations were performed on a laptop computer with Intel CORE i7 CPU and 16
 515 GB RAM. All calculation times were short, and the preference simulations took only a few
 516 seconds. Solving the resulting mixed-integer problem (2) took 1 – 2 minutes each time. This
 517 is a surprising result taking into account that the problem has 31 continuous and 152 281
 518 integer variables. The most time-consuming part was creating the multiobjective optimiza-
 519 tion problem within the Gurobi solver (due to a large amount of data), which took 13 – 14
 520 minutes. However, this had to be done only once before the solution process started, and did
 521 not cause any waiting time for the DM. Nonetheless, one should be aware of possible longer
 522 solution times in case of larger problems (e.g., when more scenarios, objectives, management
 523 regimes, and stands are involved).

524 **6 Conclusions**

525 In this study, we proposed a novel interactive approach to handle several important chal-
 526 lenges of real decision-making situations in forest management. The challenges are: dealing
 527 with multiple sources of deep uncertainty, dealing with incomplete preferences, and treating
 528 conflicts between various sustainability objectives such as timber revenue, carbon storage,
 529 and biodiversity (including habitat availability and deadwood indicators). In contrast to pre-
 530 vious approaches to decision support in forest management, the proposed approach supports
 531 the DM in investigating a large variety of characteristics of forest planning and studying
 532 conflicts between objectives in various future scenarios. In this way, the DM can get deeper
 533 insight through various possibilities reflecting the unknown future and avoid extreme losses.
 534 Moreover, the interactive nature of the preference elicitation and solution processes reduces
 535 the problem's complexity and the cognitive load of the DM. It provides a more peaceful
 536 environment for the DM to learn about the attainability of one's preferences as well as the
 537 limitations of the problem in different realization of future scenarios. This helps to find the
 538 most preferred solution to such a complex decision problem confidently.

539 The benefit of investigating possible outcomes in different plausible future scenarios is
 540 that the DM can gain more profound and more realistic insights into the problem, the
 541 consequences of alternative management strategies in various plausible scenarios, and their
 542 overall robustness. It is vital for the DM to analyze the consequences of potential strategies

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543 in the various realization of the future and not be fooled by a simple average or a most
544 probable scenario (what is usually done in regular probabilistic methods), which may lead to
545 failures in the case of a different realization of uncertainty. Indeed, the proposed approach
546 helps the DM ensure that the chosen management strategy is robust enough and works
547 relatively well in a wide range of scenarios.

548 The proposed approach can also be applied in other decision-making problems for differ-
549 ent objective functions and sources of uncertainty. For instance, in this study, for simplicity,
550 we only considered three scenarios for climate change. As a future direction of research,
551 it is interesting to consider more climate change scenarios (e.g., among 40 SRES (Special
552 Report on Emissions Scenarios) emissions scenarios developed by IPCC (Nakicenovic et al.,
553 2000)). It would also be beneficial to consider combinations with other sources of uncer-
554 tainty to analyze how robust the current strategies are. Some work needs to be done for
555 more advanced estimation of the objective function coefficients under different scenarios, for
556 example, augmenting predictions with expert judgments.

557 As discussed, the current study was the first attempt to address some challenges of
558 extending interactive multiobjective optimization methods for considering multiple sources
559 of deep uncertainty, providing better support for robust decision-making in environmental
560 planning. The next step is extending the proposed approach to dynamic multi-stage decision-
561 making problems, allowing for the consideration of adaptive decisions and contingency plans
562 (Haasnoot et al., 2013) for each scenario. This way, we can better handle deep uncertainty
563 by monitoring and adapting the plan in our continuously changing future, further improving
564 the resistance of forests to climate change and other sources of deep uncertainty.

565 **Software availability**

566 All code used for this research can be found at [https://github.com/industrial-optimization-group/
567 Interactive-decision-support-and-trade-off-analysis-for-sustainable-forest-landscape-
568 planning-under-](https://github.com/industrial-optimization-group/Interactive-decision-support-and-trade-off-analysis-for-sustainable-forest-landscape-planning-under-).

569 **Declaration of competing interest**

570 The authors declare that they have no known competing financial interests or personal
571 relationships that could have appeared to influence the work reported in this paper.

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574 This research is related to the thematic research area Decision Analytics utilizing Causal

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A MODIFICATION OF COEFFICIENT MATRICES FOR MULTIPLE SCENARIOS

732 Appendix

733 A Modification of coefficient matrices for multiple scenarios

734 As described in subsection 3.2, each scenario is a combination of partial scenarios of three
 735 types. The rules of modification are introduced separately for each type of partial scenarios.
 736 The climate change scenarios result in multiplying of coefficients by certain ratios, while
 737 both types of monetary-related scenarios result in adding subsidy values to the coefficients
 738 of the timber revenue objective function. The combined modification is obtained by first
 739 applying the climate change modification and then the other two modifications. Below we
 740 describe the modification rules for each of these three scenario types.

741 A.1 Modification for climate change scenarios

Due to the complexity of forest ecosystems, the effects of climate change likely differ for individual forest stands. In the absence of exact models, we simulate this complex nature by introducing randomness in the modification rules. Namely, for each objective function and management regime, we introduce two values: $r^{\min} < r^{\max}$, and multiply each coefficient by the random number generated in the interval $[r^{\min}, r^{\max}]$:

$$r^{\min} + g(r^{\max} - r^{\min}),$$

742 where g is the geometric mean of two independent, uniformly distributed random numbers
 743 between 0 and 1. The shape of the obtained distribution is similar to the normal distribution
 744 (Wilson and Martin, 2006). Thus, creating realistic modification rules is reduced to defining
 745 values r^{\min} and r^{\max} for all objective functions under the two additional climate change
 746 scenarios.

747 In order to define the realistic values for *the timber revenues and carbon storage objectives*,
 748 we use the study of the effects of climate change on timber production and carbon storage
 749 published by Garcia-Gonzalo et al. (2017). The paper contains estimations of the two men-
 750 tioned indicators under the current climate and the climate change scenario HadCM2 for
 751 four different management regimes and four types of tree age distributions. We calculated
 752 the ratios of change of the indicators caused by climate change. For each selected man-
 753 agement regime, we defined r^{\min} and r^{\max} as the minimum and maximum ratios obtained,
 754 respectively, across the four distributions of tree age.

755 For management regimes without thinning (SA, NTLR and NTSR), we used ratios cor-
 756 responding to the regime without thinning studied in the paper, which results in the val-
 757 ues $r^{\min} = 1.0699$, $r^{\max} = 1.1350$ for the timber revenues objective and $r^{\min} = 1.1304$,

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758 $r^{\max} = 1.1408$ for the carbon storage objective. For the rest of our management regimes, we
 759 used the ratios calculated from the paper for the BAU management regime: $r^{\min} = 1.0851$,
 760 $r^{\max} = 1.1701$ for the timber revenues objective and $r^{\min} = 1.0500$, $r^{\max} = 1.1053$ for the
 761 carbon storage objective.

762 Note that the above values are defined based on data for the climate change scenario
 763 HadCM2. As follows from the description of the scenarios, HadCM2 can be considered as an
 764 intermediate between B1 and A2. As a rule of thumb, we defined the values of r^{\min} and r^{\max}
 765 for scenarios B1 and A2 by multiplying the corresponding values obtained based on scenario
 766 HadCM2 by 0.75 and 1.5, respectively.

767 In order to define ratios for the *deadwood objective*, we used results published in Mazziotta
 768 et al. (2014). The deadwood volume in boreal forests was estimated separately for three wood
 769 species under two climate scenarios (current climate and A2) for BAU and SA management
 770 regimes. Same as above, for both management regimes, we calculated ratios of change of
 771 deadwood volume caused by the climate change, and defined r^{\min} and r^{\max} values as the
 772 minimum and maximum ratios, respectively, across tree species. As a result, we obtained
 773 $r^{\min} = 1.19$, $r^{\max} = 1.51$ for the BAU management regime and $r^{\min} = 1.33$, $r^{\max} = 1.74$ for
 774 the SA management regime. For the rest of the regimes, we used the same values as for BAU
 775 since they represent modifications of the latter. In order to obtain r^{\min} and r^{\max} values for
 776 B1 climate change scenarios, we divided the corresponding values for A2 scenarios by two
 777 as a rule of thumb.

778 Unlike the other three objectives considered above, in the case of the *habitat availability*
 779 *objective*, we did not find any published data that could be directly used for defining values
 780 of r^{\min} and r^{\max} . There are papers that can provide some general hints about the effects
 781 of climate change on species habitat. For example, in the paper Mazziotta et al. (2016),
 782 the effects of three climate change scenarios (B1, A1B and A2) were studied for habitat
 783 suitability of species of beetles and fungi associated with boreal forests. The results are in
 784 a way contradictory: in terms of the habitat quality aggregated across species, more forest
 785 stands are predicted to improve than deteriorate. However, for individual species, more
 786 species would have deteriorated habitat suitability than improved. Another paper (Cadieux
 787 et al., 2020) describes the effects of two climate change scenarios (RCP 4.5 and RCP 8.5)
 788 on 72 bird species in Canadian boreal forests. The authors predict the average growth of
 789 habitat quality by 13% under RCP 8.5; however, the changes across species range from -
 790 47% to +262%. Finally, it is worth mentioning the report by the Finnish Ministry of the
 791 Environment and Statistics (Niinistö et al., 2017) that states: "Climate change is expected
 792 to increase the total number of species in the Finnish flora and fauna and will cause a
 793 turnover of species. Furthermore, considerable changes are likely to occur in the distribution

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794 patterns of species and habitats.” Without a clear indication of the direction of change in
 795 habitat quality, we assume the possibility of changes in both directions and set $r^{\min} = 0.9$,
 796 $r^{\max} = 1.1$ in the case of B1 and $r^{\min} = 0.8$, $r^{\max} = 1.2$ in the case of A2 climate change
 797 scenarios independently on the management regime.

798 A.2 Modification for monetary scenarios

799 The amounts of subsidies for thinning as well as compensation for landscape conservation are
 800 calculated proportionally to the areas of individual forest stands. The publication Triviño
 801 et al. (2017) does not contain this information (only the total area of the landscape). Keeping
 802 in mind that our purpose is merely generating a problem that looks realistic to a forestry
 803 expert, we used estimations of forest stand areas based on the coefficient matrices. For each
 804 objective function and each management regime (represented by a column of a coefficient
 805 matrix), we calculated the shares of coefficients for all stands in the sum of coefficients,
 806 ignoring missing and negative coefficient values. Then for each stand, we calculated the
 807 average of shares across all objective functions and regimes. This average share multiplied
 808 by the total landscape area serves as the estimation of the stand area.

809 According to the Finnish Forest Center¹, forest owners can apply for *subsidies covering*
 810 *forest thinning activities*, up to 430 EUR/ha. In the scenario of obtaining the subsidies, we
 811 increase the coefficients of the timber revenue objective by 430 multiplied by stand area for
 812 all management regimes involving thinning (BAU, EXT10, EXT30, GTR30).

813 Moreover, in Finland, there are programs providing compensation to forest owners for
 814 excluding forest areas from timber production or delaying the cutting process (Mäntymaa
 815 et al., 2018). As an example, we assume that there is 30 EUR compensation for delaying
 816 harvest per one year, per one ha of forest. Then in the scenario where the forest owner gets
 817 compensation, the coefficients of the timber revenues objective are increased as follows: 300
 818 EUR/ha for management regime EXT10 (delaying harvest by 10 years), 900 EUR/ha for
 819 EXT30 (delaying harvest by 30 years), and 1500 EUR/ha for SA (setting aside forest, taking
 820 into account 50 years planning horizon).

821 B Proof of model's feasibility

822 **Theorem B.1.** *Optimization problem (4) is always feasible and bounded.*

823 *Clearly, $\tilde{z}_{it} = \max_{1 \leq u \leq q} g_{it}^u$ (for all i) would be a feasible solution for model (4). Moreover,*
 824 *all the preferences might not be worse than the nadir point (z_{it}^{nadir}) nor be infinitely better*
 825 *than the ideal point (z_{it}^{ideal}) (which none of them has any infinite component); then, the*
 826 *maximum value for the objective functions is bounded below by $\sum_{i=1}^k |z_{it}^{nadir} - (z_{it}^{ideal} \pm \epsilon)|$*

¹<https://www.metsakeskus.fi/tuki-nuoren-metsan-hoitoon>

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827 *which is a finite number and ϵ ($0 \leq \epsilon \ll \infty$) is a difference between the DM preferences*
828 *and the ideal point). ■*