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Data-Driven Interactive Multiobjective Optimization using a Cluster-Based Surrogate in a Discrete Decision Space

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Abstract. In this paper, a clustering based surrogate is proposed to be used in offline data-driven multiobjective optimization to reduce the size of the optimization problem in the decision space. The surrogate is combined with an interactive multiobjective optimization approach and it is applied to forest management planning with promising results.

Keywords: Data-driven optimization, surrogates, clustering, preference information, decision maker, boreal forest management

1 Introduction

Recently, emphasis on optimization has been shifting from model-based to data-driven optimization where the optimization problem is formulated based on available data. The size of the data can sometimes be large which means that the optimization problem(s) to be solved become large as well increasing their solution times. This is especially challenging in multiobjective optimization having a large number of objective functions. In more details, this is because interaction with a human decision maker (DM) is required to find satisfactory solutions to such problems and long solution times can make the interaction less efficient.

Surrogate-assisted optimization approaches are often used to solve computationally expensive optimization problems both for single and multiobjective problems (see, e.g., [2,4]). Typically, computational expensiveness is considered as the time taken to evaluate objective and/or constraint functions since that can take a long time for e.g. simulation or experiment-based models. In data-driven optimization, the expensiveness is typically not in evaluating the objective function values, but in the size of the problems solved (in the decision and/or objective space). The main idea in surrogate-assisted optimization is to use a relatively small sample of expensive function evaluations to train surrogate functions that approximate the expensive functions but are faster to evaluate [2,4].

In this paper, we introduce a surrogate-assisted approach for data-driven multiobjective optimization problems that are based on large data sets motivated by a case study in forest management described later. We assume that all data is available at the beginning of optimization and no new data can be obtained (often referred to as offline data-driven optimization [15]). Further, we consider linear problems with discrete decision space. The method uses clustering in the decision space as a surrogate to decrease the size of the optimization problem by reducing the number of similar variables. The resulting optimization problems are not as accurate as the original problem but are faster to solve. The proposed surrogate is combined with an interactive multiobjective optimization approach that iteratively utilizes preferences of a DM in finding a most preferred solution for the multiobjective problem considered.

In the literature, one approach has been presented that is somewhat similar to what we present, in [15] where the design of a trauma system was optimized. Due to the large amount of data available, the data was first clustered and the cluster centers were then used as data in evolutionary optimization of finding non-dominated solutions for a bi-objective problem. In our approach, we use mathematical programming together with interaction with a DM to find the most preferred PO solution. Furthermore, hierarchical clustering was used in [15] to represent the real hierarchy of the data which is not necessary in our case study. Further, functional analysis of variance decomposition was used in [12] to decompose a multiobjective optimization problem both in objective and decision spaces. Then, solution of the original problem was constructed by solutions of the decomposed problems. A different approach from ours was presented in [1] where clustering was used to find versatile solutions after finding a set of non-dominated solutions by multiobjective optimization. To summarize, there does not exist similar approach in the literature as far as we know.

As a case study to demonstrate the developed approach, we consider a boreal forest management problem where both the economical and biodiversity related objectives are considered. The underlying data gathered from around 30 000 forest stands simulated 50 years into future (with seven management options) was used to formulate a four objective combinatorial optimization problem which was then solved by interacting with an expert DM. Previous considerations of similar problems have included directly using the combinatorial optimization problem together with the epsilon constraint method which optimizes only one of the objectives while considering others as constraints [9,13,14]. When using our proposed approach, it is possible to 1) consider larger problems (i.e., more stands and/or management options) with comparable results in fewer time, and 2) more conveniently handle the conflicting objectives and inherent trade-offs while interacting with an expert DM.

The rest of the paper is organized as follows. First some background information is given in Section 2, while the proposed clustering based optimization approach is described in Section 3. Our case study and the obtained results are described in Sections 4 and 5, respectively. Finally, conclusions and future research ideas are given in Section 6.

2 Background

2.1 Multiobjective optimization

When multiple conflicting objectives are concerned, the optimal solutions are often called Pareto optimal (PO) which means none of the objective values can be improved without impairing some other ones [6]. In this paper, we consider multiobjective integer linear programming problems of the form

$$
\begin{aligned}
\text{maximize} \quad & \left\{ f_1(\mathbf{x}) = \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij}^1 x_{ij}, \ldots, f_k(\mathbf{x}) = \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij}^k x_{ij} \right\} \\
\text{s.t.} \quad & \sum_{j=1}^{m} x_{ij} = 1, \; \forall i = 1, \ldots, n, \\
& x_{ij} \in \{0, 1\}.
\end{aligned} \tag{1}
$$

The problem includes k objective functions to be maximized. Further, $i \in \{1, 2, \ldots, n\}$ denotes index for the ith decision variable while $j \in \{1, 2, \ldots, m\}$ denotes index for different values for the decision variables. Note that categorical variables having several possible values in the original problem have been converted into binary variables, i.e., $x_{ij} \in \{0, 1\}$. Coefficients c_{ij}^l denote the objective values for the decision variable values x_{ij} for the lth objective function and they are attained from data.

A feasible solution $\mathbf{x}^*$ for problem (1) is called PO if there does not exist another feasible solution $\mathbf{x}$ such that $f_i(x) \geq f_i(x^*)$ for all $i = 1, \ldots, k$ and $f_j(x) > f_j(x^*)$ for at least one j. Note that there can exist infinitely many PO solutions that are mathematically equally good, i.e., none of them is better than others without any additional preference information.

Many different approaches have been developed over the years for solving multiobjective optimization problems (see, e.g. [3,6]). In this paper, we will concentrate on interactive approaches [7], where a DM provides preference information in order to find the most preferred solution for the problem considered. The general idea of interactive approaches is that first some PO solution is computed and shown to the DM for evaluation. The DM indicates how that solution should be improved if she is not satisfied with it by providing preference information. The type of preference information depends on the interactive method used. Then, the preference information is taken into account and new PO solution(s) is computed and again shown to the DM for evaluation. This iterative process continues until the DM is satisfied.

To solve problem (1) with the help of a DM, we will use a surrogate approach based on clustering (described in more details in Section 3) combined with the synchronous NIMBUS method. Synchronous NIMBUS [8] is an interactive method based on classification where preference information is indicated by classifying objective functions into different classes at the current PO solution. More precisely, an objective function can be classified either 1) to be improved as much as possible, 2) to be improved until a given aspiration level z^{asp}, 3) to retain its current value, 4) to be allowed to impair until a given bound z^{bnd}, or 5) to change freely (i.e., not interesting at this iteration). A feasible classification is such that there should be at least one objective function in the first two classes and in the last two classes since if any improvements are required, some impairments have to be allowed. Then, the original multiobjective problem together with the preference information are used to formulate up to four different single objective scalarized subproblems that are then solved by using a suitable single objective optimizer. The resulting solutions are proven to be PO [8].

2.2 Forest management

In Fennoscandia, much of the countries are dominated by Boreal forests, which provide a wide range of ecological, economic, and social values. Most of these forests can be considered to be semi-natural, where limited silvicultural and management actions are done infrequently throughout the development of each forest stand (a relatively homogeneous parcel of forest). A forested stand in Fennoscandia follows rather similar development following a clear felling (the removal of the trees in a specific area). Depending on the site, trees are either planted, seeded, or allowed to grow through natural regeneration (where seeds provided from the forests surrounding the stand, and specific trees left within the stand for this specific purpose). Following this, within 5 to 10 years, tending of the stand may be required to remove grasses and shrubs. Once the forest stand is established it is left to grow. Throughout the forest stands development the forest stand can be thinned (the selected removal of specific trees) several times prior to clear felling, where the process is repeated.

From a forest management perspective, the specific actions conducted in a forest stand can vary according to intensity and timing. For instance, thinnings may or may not be performed, and final felling can be delayed, done years prior to the expected maturity or delayed indefinitely. Each management decision will impact the quantity of timber provided, and ecosystem services provided from the forest stand. At a landscape (500-5000 ha) or regional scale (500-20000 km^2) managing forests becomes a combinatorial optimization problem where the decision variables describe the number of stands and the number of options allowed to for managing each forest stand. Managing the use of forests involves significant conflicts between different objectives. Economic objectives conflict with ecological objectives, and conflicts can arise between different ecological objectives. The quantification of the economic and ecological objectives is done through forecasting future forest growth through forest simulators. In Fennoscandia, there are multiple varieties of forest simulators available, and each software package utilize over four hundred empirically based models to predict forest development and growth.

3 Clustering based interactive multiobjective optimization approach

The main idea of the developed surrogate is to cluster the decision variables in such a way that similar variables are represented in the optimization problem through a representative one within the cluster, thus, reducing the size of the optimization problem. In this paper, we consider only discrete decision variables, but our approach can also be extended to mixed variables. To solve the resulting multiobjective optimization problem, we utilize here the synchronous NIMBUS method as already mentioned, which leads us to solve a series of single objective subproblems. By reducing the number of decision variables, the resulting subproblems are easier/faster to solve which reduces the time that the DM needs to wait between interactions.

3.1 Clustering as a surrogate

The core of forming the surrogate is clustering the discrete decision variables using some hard clustering method: original n variables are assigned to $K \leq n$ clusters according to their similarity in values. To guide how the clustering is performed, it is important to define a similarity measure, i.e., how the similarity of variables is defined. Even though clustering using expert knowledge is possible, the numerical similarities of the variables in each cluster are more important. As the method is used to reduce the computational burden, manual clustering would require extreme human effort due to large number of decision variables.

The clustering based surrogate is built on a large number of round clusters used to approximate the decision space. In the traditional clustering, the number of clusters K is supposed to match the real number of different classes in the data, and it is one of the most important elements of clustering. However, in the clustering based surrogate this aspect is not as important but the focus of designing clusters should be the ability to compress and represent the data accurately and to be sufficient for its purpose. On occasions, it could be profitable to use more clusters than compared to what would be otherwise optimal to improve accuracy.

In traditional clustering, the shapes of the clusters are supposed to capture and separate different classes from the data. In the clustering based surrogate, this does not need to be the case as the focus could be on appropriately approximating and compressing the data. Especially when the number of clusters is "too large", the most suitable shape for clusters is rounded. This enables that all the clusters can be handled similarly as local approximations.

When the n variables have been assigned into K clusters, the most "representative" variable x_i is selected from each cluster $i \in \{1, 2, ..., K\}$ as a proxy variable. As the clusters are rounded, the most representative should be the center of each cluster. If the chosen clustering method is not using existing variables as centers, then the variable closest to the center can be used as proxy. The proxy variables that are representing all the variables of individual clusters are then already existing variables. Note that if variables in the same cluster have different numbers of discrete value alternatives, the proxy variable's ability to represent all the variables in the cluster is greatly impaired.

The chosen proxy variable x_i is denoted by y_i and it is assigned a weight w_i according to the proportion of the variables in the given cluster i. For example, if there are 356 variables in a single cluster i, its corresponding weight is $w_i = \frac{356}{n}$.

In addition, the coefficients c_{ij}^l are renamed to d_{ij}^l, and the previously presented multiobjective integer linear programming problem (1) is transformed to

$$
\begin{aligned}
\text{maximize} \quad & \left\{ n \sum_{i=1}^{K} \sum_{j=1}^{m} w_i d_{ij}^1 y_{ij}, \ldots, n \sum_{i=1}^{K} \sum_{j=1}^{m} w_i d_{ij}^k y_{ij} \right\} \\
\text{s.t.} \quad & \sum_{j=1}^{m} y_{ij} = 1, \; \forall i = 1, \ldots, n, \\
& y_{ij} \in \{0, 1\},
\end{aligned}
\tag{2}
$$

where $i \in \{1, 2, ..., K\}$, denotes index for proxy variable, $j \in \{1, 2, ..., m\}$ index for discrete value alternatives for each proxy variable i, and w_i the weighting coefficient for the proxy variable. Value d_{ij}^l denotes the lth objective value of the proxy i when the jth discrete value alternative is chosen. For ith proxy variable, y_{ij} has value 1 if jth value is chosen for proxy variable i, and otherwise 0. The parameter n is the number of original variables. As can be seen, if $K = n$, then $w_i = \frac{1}{n}$ for all $i \in \{1, 2, ..., K\}$ and this formulation is identical with problem (1). Thus, this guarantees the validity of this approach of combining the described surrogate and optimization.

Building the cluster-based surrogate is summarized as follows:

1. Cluster n decision variables into K clusters by using some clustering method.
2. For each K clusters, choose the center of the cluster as the proxy variable if the center is an existing variable. Otherwise, choose the variable closest to the center as the proxy variable.
3. Solve multiobjective optimization problem (2) by using the values of the ith proxy variable for all the variables in the ith cluster.

The proposed surrogate is based only on local approximations of the decision space, so the results of the clustering based multiobjective optimization problem naturally include some approximation error. Due to the structure of the surrogate, the larger the number of the clusters used the more accurate is the surrogate and, thus, the result of optimization. On the other hand, since the idea of clustering is to reduce the number of decision variables, the amount of reduction is dependent on the number of clusters, so that the less clusters there are, the lighter the computational burden. It is thus evident, that the accuracy and the ability to compress the decision space are contradicting features.

In multiobjective optimization, the different objectives are typically contradicting with each other and this is likely to show in the clustering also. In practice, this means that depending on the chosen clustering paradigm, approximation errors for different objectives may be different. When using the clustering based surrogate in multiobjective optimization, this problem becomes more evident as different objectives may reach their real optima to different degrees.

As the scalarized subproblems of problem (1) used here are linear [8] with integer variables, the resulting values in the objective space may be discontinuous in its original state. When using the clustering based surrogate and combining several decision variables, this trait will be emphasized and there will be “bigger holes” in the PO front (i.e. the set of all PO solutions in the objective space).

Finding the most preferred PO solution from this kind of PO front can be quite challenging depending on the multiobjective method used. Therefore, we have decided to use the synchronous NIMBUS method, which uses up to four scalarizing functions [8] that can be used for any kind of PO fronts, even discontinuous, to find different PO solutions using the same preference information. To summarize, we are much more likely to find an acceptable solution even from such a challenging PO front.

For the scalarizing functions used in the synchronous NIMBUS method it is important to attain ranges for all the objectives within the PO front, i.e., to calculate ideal and nadir vectors. This is usually done by computing the optimal solutions for all the single objective optimization problems (forming the ideal objective vector) and then estimating the nadir values by using a so-called pay-off table [6]. When using the clustering based surrogate, these values can be calculated with optimization using the surrogate, but if possible, the optima based on the original variables and problem should be used instead. Even though the scalarizing functions in synchronous NIMBUS were used with the clustering based surrogate, it would still be better to use the original ideal and nadir values in their formulations. The reason is that the surrogate based ideal and nadir values are more averaged because of the approximations used in the surrogate.

The interactive solution process itself remains the same even when using the clustering based surrogate in optimizations. The DM gives her/his preferences, explores different PO solutions, and finally chooses the most preferred PO solution as usual with interactive approaches. The main effect of using the surrogate is that it reduces the computational burden significantly and so enables more seamless and less delayed interaction during the iterative solution process.

When the preferred PO solution is found using the clustering based surrogate, it would be good to know how far it is from the real PO front, i.e., what is the approximation error introduced by using the proposed surrogate. This is required as the usage of any surrogate always introduces some error, which may misguide optimization and, thus, also the selection of the most preferred solution. To overcome this problem, the values of the chosen surrogate based optimal solution can be used as a reference point for the achievement scalarizing function (see, e.g., [8]) and optimize it with the original objective functions. As this would require using the original uncompressed decision space and be potentially computationally very expensive, it may not always be possible to solve the optimization problem in a reasonable time.

3.2 Implementation

The clustering based surrogate approach is not dependent on a specific clustering algorithm, a similarity metric, or a way of choosing the most representative variable, as these are always case specific. As an example, in the following case study the clustering based surrogate is constructed using commonly known K-means algorithm with cosine distance and the variable closest to the Euclidean center of each cluster is chosen as the representative one.

The actual clustering was implemented and verified using Python libraries and Jupyter Notebooks[3]. To solve the resulting multiobjective problem, IND-NIMBUS [10], an implementation of the synchronous NIMBUS method, was used. The single objective subproblems produced were solved with the CPLEX optimizer. Note that all solutions produced by synchronous NIMBUS are PO if the single optimal subproblems are solved to optimality [8].

A screenshot of the graphical user interface of IND-NIMBUS is shown in Figure 1. On the left hand side, the current PO solution is shown in the *Classification* panel as a bar chart. Each horizontal bar represents an objective function and the end points denote the nadir and ideal values, respectively. For maximized objective functions the colored part starts from right and, thus, the less color the better the value. In this case, all objectives are to be maximized. The DM can indicate preferences by clicking different parts of the bars. If one clicks on the colored part, it means that the objective needs to be improved. On the other hand, if one clicks on the non-colored part, it means that the objective is allowed to impair. All the PO solutions computed during the solution process are shown in the top right panel called *Alternatives* while the most interesting ones found so far can be dragged to the *Best candidates* panel in bottom right.

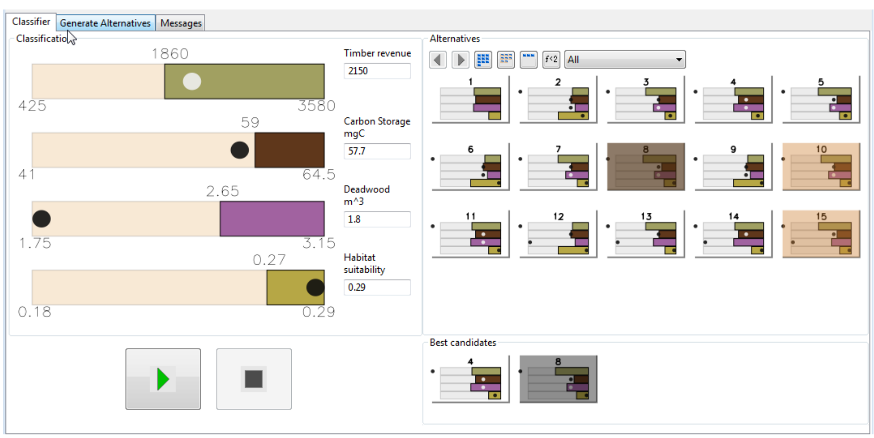

Fig. 1. A screenshot of IND-NIMBUS showing interaction with the DM.

4 Case study: Multiobjective forest management

A forest landscape from Central Finland is used as a demonstrative example of the clustering approach. Information on the current state of the forest was collected by the Finnish Forest Center through field measurements. The forest information represents 68700 ha, organized as 29666 stands. To predict the future forest resources, a forest simulator (MOTTI [11]) was used. The forest simulator predicted forest growth for a 50-year period, according to a pre-determined set of management alternatives. Depending on the initial

[3] Code available in `https://github.com/josejuhani/gradu-code`

stand characteristics, a range of seven management alternatives were generated. These alternatives ranged from setting the forest aside (doing nothing), conducting the typical management (business as usual), with a variety of extending / shortening the final harvest and including or excluding the option to thin the forest prior to final harvesting. The simulated data is openly available at `https://dvn.jyu.fi/dvn/dv/Boreal_forest`, and more detailed descriptions of the data and simulations can be found in [9,13,14].

Following the simulation of the set of different management alternatives, indicators representing a range of values were extracted. This set of indicators represented economic and ecological interests, and the set was selected to represent potential interests of specific stakeholders. The set of indicators (i.e., objective functions) was: timber revenue, carbon storage, deadwood volume, and a species habitat availability. The timber revenue was measured as the net present value revenue using a 3% discount rate. Carbon storage was measured as the tonnes of carbon contained within the forest (including the carbon in the soil, in the deadwood and in the standing trees). The deadwood volume was evaluated as a diversity weighted index: this is ecologically justifiable proxy for deadwood-inhabiting biodiversity [5]. The species habitat availability is evaluated as done in [9] which aggregates high quality habitat for six indicator species.

The multiobjective optimization problem was formulated as follows:

$$
\begin{aligned}
\text{maximize} \quad & \left\{ \sum_{i=1}^{n} \sum_{j=1}^{7} T_{ij} x_{ij}, \sum_{i=1}^{n} \sum_{j=1}^{7} C_{ij} x_{ij}, \sum_{i=1}^{n} \sum_{j=1}^{7} D_{ij} x_{ij}, \sum_{i=1}^{n} \sum_{j=1}^{7} S_{ij} x_{ij} \right\} \\
\text{s.t.} \quad & \sum_{j=1}^{7} x_{ij} = 1, \; \forall i = 1, \ldots, n, \\
& x_{ij} \in \{0, 1\},
\end{aligned} \tag{3}
$$

where T_{ij} is the timber revenue, C_{ij} is the amount of carbon in storage, D_{ij} is the volume of deadwood, S_{ij} is the habitat availability, each provided by stand i from management alternative j. Note that all the objective values are presented as per hectare. The decision variable values x_{ij} denote the jth management alternative selected for stand i. The total number of stands $n = 29666$.

This forest management problem has been solved earlier, focusing on various conservation related issues. In [9] the focus was on understanding the impacts conservation has on the profitability of forest management. The range of compromise solutions and the conflicts between various solutions has been explored in [13] and [14]. The common feature between these earlier solutions is the lack of integration with the DM.

For solving this forest management problem, the implementation of the clustering based surrogate presented in Section 3.2 was used. When empirically tested, the accuracy of the surrogate increased linearly with the increase of the number of clusters. Based on this, it was decided to choose 600 clusters for the surrogate as that amount kept the time between interactions in about 10 seconds. For the case study, the ideal and nadir values were obtained by using the original functions as previously suggested. These were verified with the previous research in [14]. For the chosen clustering, the optimal solutions for the four individual objective functions differed from the known real optima by 0.15%, 0.47%, 2.67% and 1.38%. Further, the usefulness of clustering was verified by comparing the approach against random clustering. The accuracy with random clustering in optimizing each objective individually varied between 3.2%–17.8% indicating poor performance of random clustering (results based on 10 independent runs).

5 Results and discussion

The interactive solution process was performed by using the implementation described in Section 3.2. The DM involved has significant experience in both research and implementation of forest management solutions. To start the solution process, a neutral compromise solution with values $(2710, 58.3, 2.76, 0.26)$ (obtained by using the midpoint between ideal and nadir values as a reference point), i.e., a solution where all the objectives were balanced, was shown to the DM. Starting from that solution, the DM wanted in the second iteration to improve carbon storage and habitat suitability while allowing timber revenue and deadwood volume impair. Based on those preferences, four fairly similar new alternative solutions were produced as shown in Table 1. From the new solutions obtained, the DM deduced that he would like to improve timber revenue.

Iter	Issue	Timber Revenue [€]	Carbon Storage [mgC]	Deadwood Volume [m^3]	Habitat Suitability
	Ideal	3640.0	64.8	3.18	0.29
	Nadir	450.0	41.2	1.16	0.17
1	Init. Sol.	2710.0	58.3	2.76	0.26
2	Cur. Sol.	2710.0	58.3	2.76	0.26
	Classif	$z_1^{bnd} = 2070.0$	$z_2^{asp} = 59.2$	$z_3^{bnd} = 2.19$	$z_4^{asp} = 0.28$
		2070.0	60.4	3.02	0.28
		2180.0	60.0	2.92	0.28
		2250.0	59.9	2.92	0.28
		2150.0	60.1	2.91	0.28
3	Cur. Sol.	2070.0	60.4	3.02	0.28
	Classif	$z_1^{asp} = 2500.0$	$z_2^{bnd} = 59.9$	$z_3^{bnd} = 2.19$	$z_4^{bnd} = 0.28$
		2280.0	59.9	2.99	0.28
		2420.0	59.3	2.83	0.27
4	Cur. Sol.	2420.0	59.3	2.83	0.27
	Classif	$z_1^{bnd} = 2400.0$	$z_2^{asp} = 59.5$	$z_3^{bnd} = 2.81$	$z_4^{asp} = 0.28$
		2380.0	59.4	2.87	0.28
5	Cur. Sol.	2380.0	59.4	2.87	0.28
	Classif	$z_1^{asp} = 3640.0$	$z_2^{bnd} = 41.2$	$z_3^{bnd} = 1.16$	$z_4^{bnd} = 0.17$
		3630.0	41.2	1.16	0.17
		3630.0	41.8	1.53	0.19
	Final Sol.	**2380.0**	**59.4**	**2.87**	**0.28**

Table 1. Results of iterations in solving the multiobjective problem.

As the current solution for the third iteration, the DM chose the first solution $(2070, 60.4, 3.02, 0.28)$. He wanted to see how solution changes if timber revenue is desired to improve until 2500 and the others left to reach for the values set already in the previous iteration except for small increase for carbon storage. Now, the DM wanted to see two new solutions (i.e. use only two scalarizations) and optimization produced two new alternative solutions shown in Table 1.

The DM was quite happy with both the solutions, slightly preferring the second one which had higher timber revenue (2420) when compared to the first one (2280). He also realized that deadwood volume was not changing much. However, he wanted to see how would a solution in between these too look like and, thus, gave preferences as $(2400, 59.5, 2.81, 0.28)$. After optimization, the solution $(2380, 59.4, 2.87, 0.28)$ was obtained which the DM was happy with. It had a moderate amount of timber revenue and quite high carbon storage and overall it was focusing more on the ecological aspects of forest management.

Finally, the DM wanted to still see what happens to ecological objectives if the timber revenue is maximized while letting the other values change freely. That should produce an alternative solution focusing on the monetary aspect and enable comparison with the preferred solution already found. As expected, the two solutions found maximizing the timber revenue had poor values for all the ecological objectives and, thus, supports the selection of the balanced solution having objective values $(2400, 59.5, 2.81, 0.28)$. The DM was now satisfied and the solution process was finished.

6 Conclusions

Using the developed cluster-based surrogate approach to find nearly optimal solutions, a quick interactive decision process was enabled. Although the DM only went through a small number of iterations, the process was quick enough to maintain interest in the decision making process until a final acceptable solution was found. By using the implemented decision support tool, the DM was able to conveniently steer the solution process towards a final solution emphasizing ecological values while still having moderate amount of timber revenue. In addition, the nature of the conflicts between different objectives considered became more clear to him.

While this forest management problem has been solved in the extensive form earlier, it can be made more realistic. In this case, only a limited number of predefined management alternatives were used, which prevented the problem from being too large. Additionally, we did not explore the temporal sequence of planning outcomes, nor were spatial relationships maintained. As future research is concerned, the proposed cluster-based approach will be extended to mixed variables. In addition, it will be tested with larger and more realistic data sets in forest management as well as applied to different types of applications.

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