# Enhanced Multi Criteria Decision Analysis for Planning Power Transmission Lines

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## Abstract

The energy transition towards alternative energy sources requires new power transmission lines to connect these additional energy production plants with electricity distribution centers. For this reason, Multi Criteria Decision Analysis (MCDA) offers a useful approach to determine the optimal path of future transmission lines with minimum impact on the environment, on the landscape, and on affected citizens. As objections could deteriorate such a project and in turn increase costs, transparent communication regarding the planning procedure is required that fosters citizens' acceptance. In this context, GIS-based information on the criteria taken into account and for modeling possible power transmission lines is essential. However, planners often forget that the underlying multi criteria decision model and the used data might lead to biased results. Therefore, this study empirically investigates the effect of various MCDA parameters by applying a sensitivity analysis on a multi criteria decision model. The output of this analysis is evaluated combining a *Cluster Analysis*, a *Principal Component Analysis*, and a *Multivariate Analysis of Variance*. Our results indicate that the variability of different corridor alternatives can be increased by using different MCDA parameter combinations. In particular, we found that applying continuous boundary models on areas leads to more distinct corridor alternatives than using a sharp-edged model, and better reflects actual planning practice for protecting areas against transmission lines. Comparing the results of two study areas, we conclude that our decision model behaved similarly across both sites and, hence, that the proposed procedure for enhancing the decision model is applicable to other study areas with comparable topographies. These results can help decision-makers and transmission line planners in simplifying and improving their decision models in order to increase credibility, legitimacy, and thus practical applicability.

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# 1 Introduction

Multi Criteria Decision Analysis (MCDA) has been successfully applied in a large number of research projects to identify the optimal solution across a variety of conflicting criteria [12]. Regardless whether the underlying problem is spatial or not, the principle is the same, as different alternatives are compared by their utility to solve the given problem. Therefore, a decision-maker assigns each factor that contributes to the decision a value describing the utility to solve the underlying problem. Each factor is then weighted according to the decision-maker's preferences and summed up to the total utility by applying a set of decision rules [11]. Ideally, these decision rules should be based on consensus among all decision-makers to minimize the potential for post-decision regret [2].

When applying prescriptive MCDA on spatial problems, Geographic Information Systems (GIS) can be used as Decision Support Systems (DSS) to support decision-makers in identifying the best decision to take [19]. In particular, a large variety of visualization techniques has been successfully applied to support decision-making either when comparing sensitivities on maps or charts [15], or when determining pareto-optimal solutions [5, 20, 25]. Spatial decisions are taken, for example, for allocating an object to the optimal location, for evaluating the land use suitability, or for assessing a phenomenon's impact on the environment [19]. One field that strongly considers location-based factors is the planning of energy systems. The ongoing energy transition towards alternative energy sources incites national governments and companies to build new renewable energy power plants for various reasons, i.e., reliability of supply, providing cheap energy, reducing dependency, and reducing environmental impacts [24]. Consequently, the grid must be extended to connect a growing number of electricity producers with the consumers [16].

However, public acceptance of grid expansion projects is generally low [16], as transmission lines evoke opposition particularly when they are sited in rural landscapes [17]. Furthermore, land owners fear depreciation of their land value [4]. This low acceptance leads to high social resistance, which in turn raises objections, causes delays, and increases costs – all of them barriers against necessary grid expansions [1]. In order to increase acceptance, various methods have been applied or proposed so far. First, involving citizens in the decision-making process is known to foster acceptance [7]. Second, a transparent dialogue between grid operators and affected citizens can be enhanced by supporting communication with immersive virtual reality [21]. Both approaches move in the same direction, as acceptance might be increased through greater degrees of transparency in communicating the planning process to citizens. Moreover, the use of realistic virtual reality environments can support decision-makers in imagining how a transmission line could be blended into the landscape.

In this context GIS can support transparent communication and there are various examples of GIS-based DSS for determining the optimal path for transmission lines [3, 14]. The approach mostly used hereby is explained in section 2.3, which uses *spatial costs* to determine how feasible an area is for building a power line on its surface. However, the suggested corridors and paths resulting from such a DSS might be biased, as the underlying data or decision model limits the number of possible solutions and what the solutions actually reflect. With regard to transmission line planning particularly the spatial resistance against the construction of transmission lines (according to the law, etc.) and distances to spatially protected areas (e.g., nature protected areas or certain settlement zones) need to be reflected adequately. Therefore, we developed a 3D DSS and modified a standard MCDA model in a way that these aspects are taken into account. Moreover, a sensitivity analysis was conducted to proof the quality of our MCDA model.

As the effects of raster-based MCDA have been explored in prior work, we specifically investigated if a sensitivity analysis shows whether our modified MCDA model causes a systematic trend in computing the resulting suitability maps. By identifying such a trend, the corresponding parameters or parameter levels could be considered to be grouped to simplify the decision model. We further focused on the extent to which the single parameter levels contribute to the typical characteristics of a suitability map. In this respect, we assumed that in an initial procedural step decision-makers might appreciate to compare route alternatives that are clearly distinguishable. Therefore, we wanted to determine the most influential parameter levels that contribute to a wide variability of the resulting suitability maps. By doing so, stakeholders can focus their discussions on factors that essentially contribute to a specific alternative. To this end, we explore the utility of a *Cluster Analysis* in combination with a *Principal Component Analysis* and a *Multivariate Analysis of Variance* (MANOVA) for improving a decision model.

In this paper, we present the results of the sensitivity analysis and discuss how this approach supports simplifying and improving the MCDA model. Overall, we contribute to calibrating MCDA models so that they can actually assist in real world spatial planning processes to make transmission line planning faster, more reliable, and more accepted by affected citizens.

## 2 Method

### 2.1 Study areas

In accordance with our project partners *Swissgrid* and *Austrian Power Grid* we focused on the two study areas *Innertkirchen – Mettlen* in central Switzerland and *Kärnten* in southern Austria. Both areas have a similar topography, as the main settlement areas are located on a flatland on approx. 500 meters above sea level, each partially surrounded by Alpine foothills and crossed by rivers and lakes. In these areas, the legal requirements outlined in [9] oblige to successively reduce the area of interest for transmission lines. Therefore, we decided to use a general decision modeling approach similar to [14], which narrows down the area of interest in four steps: 1) from a large-scale planning area to 2) a corridor with a width of a few hundreds of meters to 3) a path and finally, to 4) the exact pylons' positions. The geodata were then represented in an interactive, online 3D Decision Support System (3D DSS).

### 2.2 Data preparation

In order to build a decision model, we analyzed the criteria that must be considered by law [9] and identified 33 spatially explicit factors with a legal influence against the construction of a transmission line (see tab. 1). These factors were grouped into the three categories *environmental protection*, *urban planning*, and *technical implementability*. Each of the 33 factors used in our decision model was assigned a *main objective* [11] based on the importance of the underlying legal source [8] (see tab. 1).

Based on this decision model, we collected the appropriate data from publicly accessible data portals and stored them in a database. In case a dataset was represented by point or line features, a buffer distance was assigned according to the legal requirements or expert's opinion. We further integrated two factors that foster building of new paths in areas already characterized by transmission lines, highways, or railway lines. These factors allow a decision-maker to assess bundling with existing linear infrastructure as more or less important.

**Table 1** Factors used in the decision model, sorted by category and main objective.

| **Category** | **Influencing factor** | **Main objective with code Ω** | |
|---|---|---|---|
| Environmental protection | Biosphere reserve<br>Dry grassland<br>Flood plains: high importance<br>Inventory of protected landscapes<br>Mire landscapes<br>Mires<br>Bird protection area | Preserve ecosystems: primary | $\Omega_5$ |
| | Flood plains: low importance<br>Forest<br>Natural reserves<br>Protection areas according to hunting laws | Preserve ecosystems: secondary | $\Omega_6$ |
| | National parks<br>UNESCO World Heritage Site | Preserve landscape: primary | $\Omega_1$ |
| | Geotopes | Preserve landscape: secondary | $\Omega_2$ |
| Technical implementability | Natural hazard areas | Decrease risks | $\Omega_{10}$ |
| | Groundwater zone<br>Inappropriate relief<br>Water bodies | Ensure implementability | $\Omega_8$ |
| Urban planning | Infrastructure facilities | Avoid infrastructure facilities | $\Omega_7$ |
| | Airports | Decrease risks | $\Omega_{10}$ |
| | Urban sprawl caused due to the grid<br>Urban sprawl caused due to traffic routes | Increase bundling | $\Omega_9$ |
| | Arable land | Preserve landscape: secondary | $\Omega_2$ |
| | Areas within noise threshold of 40 dBA<br>Residential / work / mixed areas<br>Residential areas<br>Cultural heritage: high importance | Preserve living space: primary | $\Omega_3$ |
| | Cultural heritage: low importance<br>Historic areas<br>Historic traffic routes<br>Public areas<br>Recreational areas<br>Tourism areas | Preserve living space: secondary | $\Omega_4$ |

Moreover, we extended our decision model with a factor that includes all areas unsuitable for constructing a transmission line. In particular, the results of a preliminary study showed that construction costs for a transmission line strongly increase for areas over 1300 meters and for areas with a slope greater than 55°.

## 2.3 Representing spatial resistances adequately

In collaboration with our project partners, we defined an MCDA model to compute the cost surface. In general, the corridor suitability maps and the transmission line paths were computed by combining MCDA with a *Least Cost Path* (LCP) analysis [10]. First, MCDA was applied on overlapping raster lattices with the same direction, origin, and cell size of 100 meters to obtain a *cost surface* [19]. Based on this cost surface, the LCP algorithm determined suitable corridors and the optimal transmission line path.

Further, decision-makers were deemed capable of making decisions about **resistances** and **weights** to distinguish between an interest-based assessment and the relative importance of a decision. Whereas the former represents a factor's friction against constructing a transmission line on top of the corresponding area, the latter represents the subjective importance the decision-maker assigns to this decision. Decision-makers used the direct rating method [11] to define a resistance on a Likert 5-point acceptability scale and a weight on a Likert 3-point priority scale [23]. In collaboration with the legal departments of various federal authorities we then restricted the resistance range of all factors that must comply with the hierarchy of laws [8]. For example, as wetlands are protected by the Swiss constitution, the range of possible resistances was restricted to 'unacceptable' and 'totally unacceptable'. By this, we expected to comply with factual premises in order to obtain realistic results.

In general, the total resistance $t_x$ can be calculated for each location $x$ by multiplying the resistance with the weight, as shown in the following equation:

$$t_x = \sum_{i=1}^{n} r_{i,x} \cdot w_i \tag{1}$$

where $r_{i,x}$ represents the resistance of factor $i$ at location $x$ and $w_i$ the weight of factor $i$. However, this equation required modification for lack of consideration of special characteristics concerning the meaning of the resistance, the weight's effect on the total resistance, the behavior of overlapping pixels, and the influence of the boundary model. As such, these four modifications are explained subsequently.

**Modification 1: utility function** First, decision-makers might not perceive the differences between the levels of a given Likert scale equally. Strictly speaking, 'totally unacceptable' does not necessarily translate to 'twice as bad as unacceptable', even though the relative difference between the levels on the Likert scale are equal. In practice, the utility function is determined by applying different techniques when interviewing a decision-maker [11]. Therefore, we empirically defined four distinct utility functions for stretching or narrowing the relative distances between the levels on the Likert scale. By doing so, we expected the highest probability to determine whether different curve shapes, thus, utility functions have a significant effect on the result or not. Therefore, the modified resistance $u_{c,i,x}$ resulting from applying the subsequent utility functions replaces $r_{i,x}$ of eq. 1 and is defined as follows for the range from 1 to 5:

$$\forall\, [5 \geq r \geq 1] \rightarrow u_{1,i,x}\,(r_{i,x}) = r_{i,x} \tag{2}$$

$$\forall\, [5 \geq r \geq 1] \rightarrow u_{2,i,x}\,(r_{i,x}) = \frac{0.575}{\sqrt{|r_{i,x} - 3| + 1}} \cdot 3(r_{i,x} - 3) + 3 \tag{3}$$

$$\forall\, [5 \geq r \geq 1] \rightarrow u_{3,i,x}\,(r_{i,x}) = \sqrt{6 \cdot r_{i,x} - 5} \tag{4}$$

$$\forall\, [5 \geq r \geq 1] \rightarrow u_{4,i,x}\,(r_{i,x}) = \frac{{r_{i,x}}^2}{6} - \frac{5}{6} \tag{5}$$

The utility function described by eq. 2 is linear and does not apply any corrections on the chosen resistance. In contrast, eq. 3 enhances the effect of the resistances the more they differ from the mid neutral value. Finally, eq. 4 applies a logarithmic correction whereas eq. 5 uses an exponential correction for increasing aversion against constructing a transmission line. All utility functions are shown in fig. 1.

**Modification 2: weighting model** Due to its unipolar character, the application of eq. 1 leads to higher total resistances the higher the weights are. As decision-makers assessed the suitability of a factor on a bipolar range from 'totally acceptable' to 'totally unacceptable', they would expect lower total costs when applying a high weight on a low resistance instead of a low weight. Consequently, three weighting models were defined that enhance the effect of the chosen resistance $r$ the higher the weight is. Additionally, we defined that our models must not overlap that is, a weight of 1 on the most extreme resistance (either 1 or 5) always leads to a more pronounced total value than applying a higher weight on a less pronounced resistance. Furthermore, we specified that the effect of the weighting model should, on the one hand, not be too extreme and, on the other hand, balanced between accepting and dismissing resistances. Thus, the modified weight $h_{b,i}$ resulting from applying the subsequent empirically defined weighting models, replaces $w_i$ of eq. 1:

$$\forall\left[5 \geq r \geq 3\right] \rightarrow h_{1,i}\left(w_i\right) = \sqrt[7]{w_i} \quad \text{and} \quad \forall\left[3 > r \geq 1\right] \rightarrow h_{1,i}\left(w_i\right) = \sqrt{\frac{1}{w_i}} \tag{6}$$

$$\forall\left[5 \geq r \geq 3\right] \rightarrow h_{2,i}\left(w_i\right) = \sqrt[10]{w_i} \quad \text{and} \quad \forall\left[3 > r \geq 1\right] \rightarrow h_{2,i}\left(w_i\right) = \sqrt{\frac{1}{w_i}} \tag{7}$$

$$\forall\left[5 \geq r \geq 1\right] \rightarrow h_{3,i}\left(r_{i,x}, w_i\right) = r + \frac{sgn\left(r\right) \cdot \left(w_i - 1\right)}{4} \tag{8}$$

The weighting models of eq. 6 and eq. 7 are similar because they only differ in the chosen order of the root. Since the chosen weights must equally affect the decision of supporting or avoiding the construction of a transmission line, it follows that they had to be defined differently for negative and for positive resistances. In contrast, eq. 8 simply adds or subtracts 0.25 or 0.5 to or from the resistance, depending on the resistance's sign and on the weight.

**Modification 3: MCDA method** The situation may arise that an area $A$ defined in one dataset partially or completely overlaps with an area $B$ of another dataset. A reason for this could be that $A$ or parts of it may be listed in different protection inventories. As inventories are often based on different laws, it becomes more difficult to construct a transmission line in an area that is part of different inventories, as it is protected by various laws. From this perspective, the question arises whether the increase in difficulty should be considered to be linear and depend on the number of according protection inventories or not. Hence, the modified resistance $u_{c,i,x}$ and the modified weight $h_{b,i}$ were included in eq. 1 and therefore defined the three MCDA methods $t_{a,x}$ in terms of the way overlapping pixels should be treated by using the following equations:

$$t_{1,x} = \sum_{i=1}^{n} u_{c,i,x} \cdot h_{b,i} \tag{9}$$

$$t_{2,x} = \frac{\sum_{i=1}^{n} u_{c,i,x} \cdot h_{b,i}}{\ln p_x + 1} \quad \forall p_x \geq 1 \tag{10}$$

$$t_{3,x} = \max_{i \in \{1,\ldots,n\}} \left(u_{c,i,x} \cdot h_{b,i}\right) \tag{11}$$

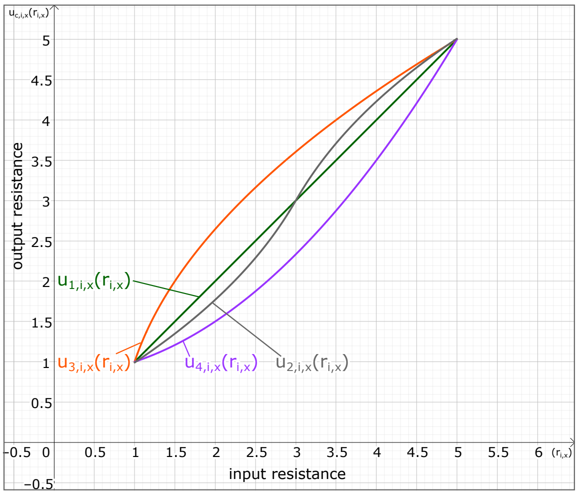


**Figure 1** The four utility functions used to modify the resistances.

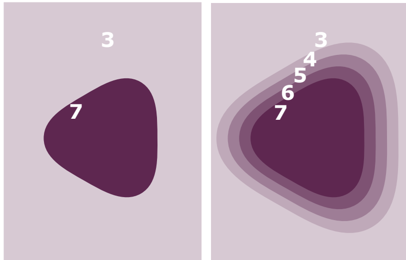


**Figure 2** The sharp-edged (left) and the continuous (right) boundary model.

where $p_x$ is the number of overlapping pixels at location $x$. The approach used in eq. 9 is defined as *Simple Additive Weighting* [6] as it simply weights the factors and sums them up to a total resistance. In contrast, eq. 10 is an adaption of eq. 9 as it diminishes the effect of overlapping pixels by applying a logarithmic correction, aiming at reducing a potential overrating of overlapping pixels. Last, the *Maximum Value Method* described by eq. 11 chooses the maximum value of all overlapping pixels, as it is supposed to represent the strictest protection law.

**Modification 4: boundary model** Malczewski's theory of fuzzy sets [19] states that fuzzy values define the grade of membership to a specific factor, leading to fuzzy boundaries. If we take Tobler's First Law of Geography [22] into account and assume that the effect of a factor is not uniquely defined over distance, we recognize a similarity to the fuzzy sets explained above. Because protective effects do not often end at a protection area's border, we used an approach that protects an area beyond its borders by continuously decreasing the cell resistance with increasing distance from the cell center (see the right panel of fig. 2). As an effect, the borders become fuzzy and adjacent borders may overlap (which might be corrected for instance by applying eq. 10). Consequently, protective effects are increased because the extended protection area presses – figuratively speaking – the transmission line away from the protection area. This approach complies with the current legal understanding, as greater levels of protection should be afforded to valuable locations. Furthermore, it is directly applicable to human perception, as [13] demonstrated that the visual impact of a transmission tower mainly depends on distance.

Consequently, we wanted to identify the distances that experts assign to each factor for protecting the corresponding areas according to the continuous boundary model. For this, we conducted three preliminary studies with a total of 28 participants, consisting of transmission line planning experts (n=18), representatives of federal authorities (n=7), and NGO representatives (n=3). For each of the decision model's 33 influencing factors, experts defined the distance over which protective effects should influence the result. Furthermore, they could decide if the decreased shape should be defined linearly, logarithmically, or exponentially. This was followed by a statistical evaluation of the results and setting of the median as additional protective distance for the continuous boundary model. For each factor, we chose the linear decreasing curve, as it was always the most frequently chosen.

## 2.4 Sensitivity analysis

Contrary to the common approach to sensitivity analysis, in which the input factors' uncertainties are used to model the output variability, we set up a full factorial design to analyze the effect of all possible combinations between the different factor levels. Thus, the overall model consists of the **2 boundary models** (fig. 2), **3 MCDA methods** (eq. 9-11), **4 utility functions** (eq. 2-5), and **3 weighting models** (eq. 6-8), which results in 72 possible combinations. For computational reasons, the subsequent simplifications had to be applied. First, we aggregated the geometries of the decision model's 33 influencing factors according to their main objective set in the decision model. By doing this, we reduced the model's complexity to 10 factors, each representing areas with the same main objective. Moreover, we decreased complexity by limiting the number of Likert scale levels to 1 (low) and 3 (high) – for resistances as well as for weights.

According to the main objectives set in the decision model (see tab. 1), we only chose reasonable combinations by omitting combinations in which the resistance of the secondary protection objective was higher than the primary protection objective. If the resistances were equal, we only chose combinations in which the primary objective's weight was at least as high as those of the secondary objective. Similar to the approach chosen by [18], we then computed the following output files for every possible remaining combination for further analysis:

- corridor suitability maps, including the optimal path (see fig. 3)
- length over which a specific objective is violated (see tab. 4)

To compute the data, we used 48 CPUs on an Intel® Xeon® CPU E5-2680 v4 @ 2.40GHz server with 132 GB RAM by using Python's multiprocessing library. Generating the maps of all possible and reasonable settings took between 1 to 3 seconds for each map. This equated to approx. 8 days of computing time with a storage volume of approx. 4.0 TB per study area. Running the simulation for the study area in Innertkirchen − Mettlen generated n=3'871'389 records, while n=3'190'344 valid results could be generated for the study area Kärnten.

## 2.5 How the results were evaluated

The output parameters listed in section 2.4 including the rasters emerging from the simulation process were then sorted and statistically evaluated according to one of the 72 MCDA parameter combinations. Next, a moving average algorithm computed the mean of all rasters with the same parametrization. These 72 averaged maps were then compared to each other by determining Pearson's correlation coefficient $R$. The resulting correlation matrix was used to categorize the 72 parameter combinations into clusters of similar maps. For this, the *Partitioning Around Medoids* (PAM) method was applied because it defines differences by real Euclidean distances. This is similar to the model used to compute the maps, as location-based differences are represented by distances.

In order to support the evaluation, we determined the effect and the significance of the MCDA parameters' decomposed factor levels by conducting a *Multivariate Analysis of Variance* (MANOVA). For this, we first decomposed the 72 compound parameter combinations into 22 basic factor levels (see regressors in tab. 2). Since these represent explanatory variables, we used them as regressors for building the MANOVA regression model. As the variation in the suitability maps results from different parameter settings, we determined the model's principal components by applying *Principal Component Analysis* (PCA) on 3 items with orthogonal rotation. Although we determined that in both study areas eight components had eigenvalues over Kaiser's criterion of 1, we decided to use 3 principal components

**Table 2** Regressors used in MANOVA that represent the decomposed parameter settings in order to determine the influence of the underlying factor levels.

| Regressor | Refers to | What the decomposed parameter might affect |
|---|---|---|
| $\beta_1$ | fig. 2 | Does the MCDA model have an influence? |
| $\beta_2$ | fig. 2 left | Does the sharp-edged boundary model have an influence? |
| $\beta_3$ | fig. 2 right | Does the continuous boundary model have an influence? |
| $\beta_4$ | eq. 9-11 | Does the MCDA method have an influence in general? |
| $\beta_5/\beta_6/\beta_7$ | eq. 9/10/11 | Does the MCDA method 1/2/3 have an influence? |
| $\beta_8$ | eq. 2-5 | Does the utility function have an influence in general? |
| $\beta_9/\beta_{10}/\beta_{11}/\beta_{12}$ | eq. 2/3/4/5 | Does the utility function 1/2/3/4 have an influence? |
| $\beta_{13}$ | eq. 6-8 | Does the weighting model have an influence in general? |
| $\beta_{14}/\beta_{15}/\beta_{16}$ | eq. 6/7/8 | Does the weighting model 1/2/3 have an influence? |
| $\beta_{17}$ | interaction | Do the boundary model and the MCDA method interact? |
| $\beta_{18}$ | interaction | Do the boundary model and the utility function interact? |
| $\beta_{19}$ | interaction | Do the boundary model and the weighting model interact? |
| $\beta_{20}$ | interaction | Do the MCDA method and the utility function interact? |
| $\beta_{21}$ | interaction | Do the MCDA method and the weighting model interact? |
| $\beta_{22}$ | interaction | Do the utility function and the weighting model interact? |

in our multivariate model because inflexions on the scree plot indicated that the highest decrease of the principal components' eigenvalues occur at the $4^{\text{th}}$ component. The 3 principal components explained 93.8% (Innertkirchen – Mettlen) and 88.9% (Kärnten) of the variance. Furthermore, Bartlett's test of sphericity, $\chi^2$ (2556, N = 72) = 35341.61, p < .001 (Innertkirchen – Mettlen) and $\chi^2$ (2556, N = 72) = 31764.79, p < .001 (Kärnten), indicated that correlations between items were sufficiently large for PCA. We therefore defined the factor loadings of the principal components as dependent variables, which should be predicted by the regressors. After conducting the MANOVA, we used the resulting *Pillai's trace* as a metric for evaluating the parameters' effect on the suitability maps.

## 3 Results

Surpisingly, the cluster analysis revealed a similar decision pattern in both study areas, as shown in the dendrograms in fig. 4. However, the dendrogram of the study area Innertkirchen – Mettlen was higher than the one of Kärnten, thus, the used parametrization model leads to more distinct patterns when used in Innertkirchen – Mettlen. This is also supported by analyzing the results of the PCA, as the two primary components explain 90.3% of the factor loading variability in Innertkirchen – Mettlen, whereas only 77.8% of the factor loading variability could be explained in Kärnten. By applying PAM, the k-medoids algorithm proposed as a means of grouping the suitability maps of Innertkirchen – Mettlen into 3 clusters, whereas 8 clusters were proposed for grouping the suitability maps of Kärnten (see fig. 3).

Our results reveal that the relative importance of the underlying parameters used for computing the corridor suitability maps is structured hierarchically. By ranking the regressors based on the averaged Pillai's traces among both study areas – as listed in tab. 3 – we could determine that the selection of the boundary model is most important, followed by the MCDA method, the weighting model, and last, the utility function. We will therefore detail the results using the same order.

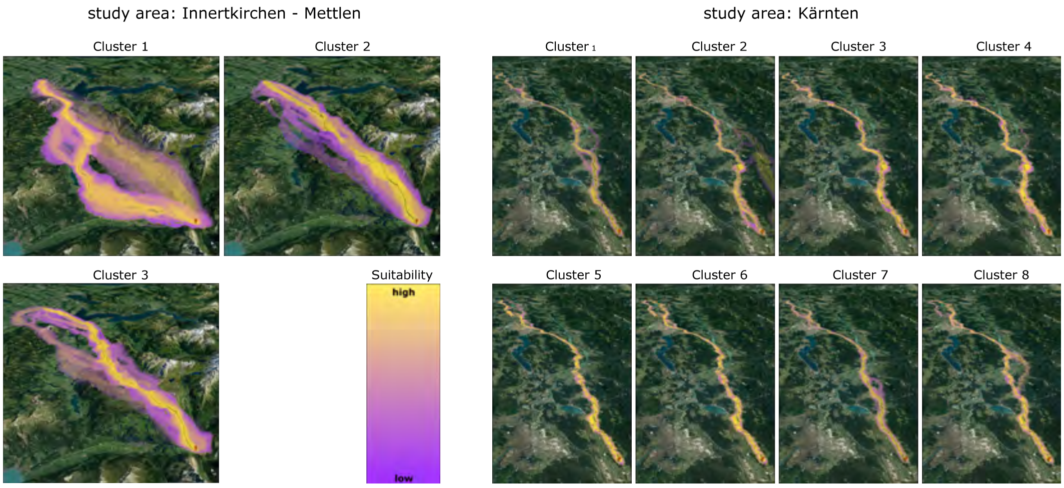


**Figure 3** Suitability maps (opacity: 20%) of both study areas showing the optimal corridors for a new transmission line. According to the dendrograms of fig. 4 and read from left to right, the results are grouped into the clusters proposed by the k-medoids algorithm. Visualized with Google Earth. Yellow areas are suitable for constructing a transmission line, whereas purple areas are less suitable.

In general, the suitability maps in the study area Kärnten demonstrate higher average Pillai's traces and one significant regressor more than in Innertkirchen – Mettlen. This is because the effect of contributing to a diversification of the resulting maps must be higher the more clusters are suggested for this study area. Factors entailing the boundary model contribute most to the explanation of the model's principal components, as Pillai's traces lie between 67.6% and 99.3% with p<.001. Indeed, the application of different boundary models affects different solutions on a large scale. Furthermore, the dendrograms demonstrate that the choice between the sharp-edged and the continuous boundary model is most important, as this decision branched the dendrogram at the maximum height of approx. 37 for Innertkirchen – Mettlen and 17 for Kärnten.

Second, the MCDA methods contribute to the explanation of the principal components with a Pillai's trace between 47.0% and 96.2%. However, methods 1 ($\beta_5$) and 2 ($\beta_6$) explain the outcome of the resulting corridor alternatives better than method 3 ($\beta_7$). A reason for this might be that method 3 does not account for overlapping resistances, which in turn, results in less diversified corridor alternatives as the cost surface is flattened out. Moreover, the dendrograms illustrate a branching of MCDA method 3 between a relatively large height of 7 to 16. They also reveal that distinct clusters can be created when MCDA method 3 is applied on a continuous shape model. In contrast, the use of MCDA method 3 on a sharp-edged model branches the dendrogram at height 6, which does not necessarily affect separate clusters. Branching between MCDA methods 1 and 2 occurs at a very low height around 1 to 2 and is thus not relevant.

Third, the distinction between the different weighting models explains the model's principal components with a Pillai's trace between 22.0% and 98.5%. Certainly, the general distinction between the models ($\beta_{13}$) seems to be important as the corresponding Pillai's trace is very high. However, the variance among the weighting models is large, as $\beta_{14}$ has a Pillai's trace of 49.4% to 82.5%, whereas $\beta_{15}$ has 22.0% and $\beta_{16}$ was insignificant. Generally, if MCDA methods 1 (eq. 9) or 2 (eq. 10) are used, the weighting model leads to a clear branching, although on a low height around 2. In contrast, the weighting model had no branching effect when it was applied on the *Maximum Value Method* (eq. 11), as it neglects the influence of overlapping factors.

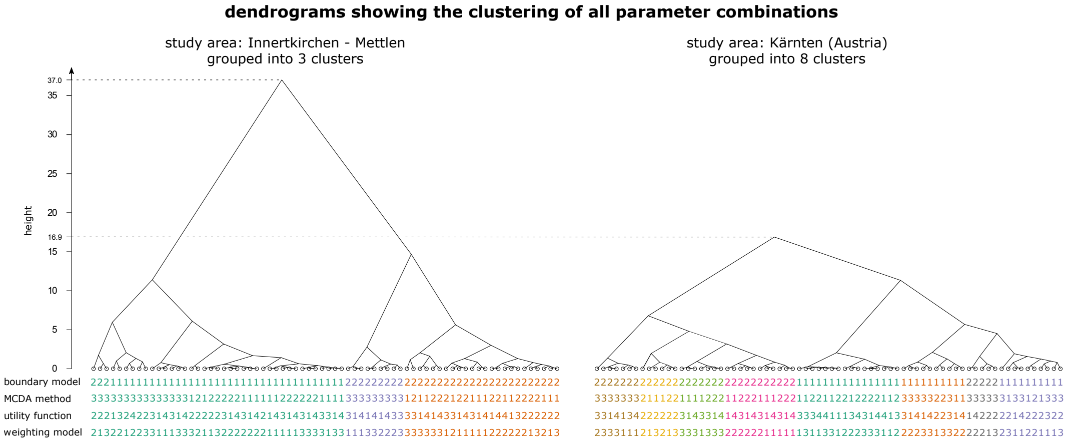


**Figure 4** Clustering dendrogram of the study areas Innertkirchen – Mettlen (left) and Kärnten (right), normalized to the same absolute height. The numbers 1-4 represent the factor levels listed in tab. 2.

Fourth, the variation of the utility functions had the weakest effect with a Pillai's trace between 18.2% and 90.4%. $\beta_{10}$ and $\beta_{12}$ modeled the principal components best with average Pillai's traces of 81.0% and 79.5%. However, $\beta_9$ and $\beta_{11}$ ranked lower and could explain the underlying principal components only to 49.7% and 28.2%. A distinct branching could only be determined for $\beta_{10}$, however, on a very low dendrogram height of approximately 1.

However, the corresponding regressor $\beta_9$ and even $\beta_{10}$ were not determined to be significant by applying the MANOVA. In contrast, utility functions $u_{1,i,x}(r_{i,x})$ ($\beta_8$) and $u_{4,i,x}(r_{i,x})$ ($\beta_{11}$) were significant with a Pillai's trace of 56.3% and 44.2% (both $p<.001$). The general result of distinguishing between the utility functions used, as shown by $\beta_8$, had an effect on explaining the model by 22.3%. However, we could not determine any significant interaction between the boundary model, the MCDA method, the utility function, and the weighting model, as $\beta_{17}$ to $\beta_{22}$ were insignificant.

Another method to compare the goodness of the data model is to calculate to what extent the main objectives of the decision model have been violated. As shown in tab. 4, the primary objectives ($\Omega_1$, $\Omega_3$, and $\Omega_5$) have been respected, which resulted in a low violation whereas areas corresponding to a secondary objective have been crossed more often.

## 4 Discussion

We set out to investigate the utility of a cluster analysis for improving a decision model. We therefore discuss in the following subsections, how our results are applicable in practice in order to simplify and improve a given decision model.

### 4.1 How the results help to simplify the decision model

Given that the considered principal components explain the variance of a defined model sufficiently, a MANOVA yields the strength of underlying factors that contribute to the explanation of the principal components. Thus, insignificant results indicate factors that can be excluded from the decision model. If the decision model aims at being universally applicable to different study areas, only factors significant across all study areas should be considered. In this study, only weighting model 1 (eq. 6, represented by $\beta_{14}$), could be used

**Table 3** Effect of all significant regressors used in the MANOVA, split by study area. The right panel lists the averaged Pillai's traces and the according ranks of each regressor (see tab. 2).

| **Innertkirchen – Mettlen** | | | **Kärnten** | | | **Averaged Results** | | |
|---|---|---|---|---|---|---|---|---|
| Regressor | Pillai | Sig. | Regressor | Pillai | Sig. | Rank | Regressor | Pillai |
| $\beta_2$ | .967 | p <.001 | $\beta_2$ | .993 | p <.001 | 1 | $\beta_2$ | .980 |
| $\beta_{13}$ | .925 | p <.001 | $\beta_{13}$ | .985 | p <.001 | 2 | $\beta_{13}$ | .955 |
| $\beta_3$ | .915 | p <.001 | $\beta_3$ | .977 | p <.001 | 3 | $\beta_3$ | .946 |
| $\beta_5$ | .825 | p <.001 | $\beta_5$ | .962 | p <.001 | 4 | $\beta_5$ | .894 |
| $\beta_{10}$ | .716 | p <.001 | $\beta_{12}$ | .929 | p <.001 | 5 | $\beta_6$ | .817 |
| $\beta_6$ | .712 | p <.001 | $\beta_1$ | .924 | p <.001 | 6 | $\beta_{10}$ | .810 |
| $\beta_1$ | .676 | p <.001 | $\beta_6$ | .921 | p <.001 | 7 | $\beta_1$ | .800 |
| $\beta_{12}$ | .662 | p <.001 | $\beta_{10}$ | .904 | p <.001 | 8 | $\beta_{12}$ | .795 |
| $\beta_{14}$ | .494 | p <.001 | $\beta_{14}$ | .825 | p <.001 | 9 | $\beta_{14}$ | .660 |
| $\beta_7$ | .484 | p <.001 | $\beta_9$ | .746 | p <.001 | 10 | $\beta_9$ | .497 |
| $\beta_8$ | .263 | p <.001 | $\beta_7$ | .470 | p <.001 | 11 | $\beta_7$ | .477 |
| $\beta_9$ | .247 | p <.01 | $\beta_{11}$ | .425 | p <.001 | 12 | $\beta_{11}$ | .282 |
| $\beta_{11}$ | .140 | p <.05 | $\beta_{15}$ | .220 | p <.01 | 13 | $\beta_8$ | .223 |
| | | | $\beta_8$ | .182 | p <.05 | 14 | $\beta_{15}$ | .220 |

as $\beta_{15}$ and $\beta_{16}$ were insignificant across both study areas. It is further questionable whether factors with a small Pillai's trace should be considered in the decision model. However, this would beg the question, from which value on a contribution should be specified to be sufficient. Thus, this question could be a line of interesting future research.

Although decision-makers might expect different outcomes based on every chosen parameterization, our results indicate that the solution space is limited. Even if solutions may differ slightly, it is still desirable for transmission line planners to obtain corridor alternatives that are clearly different from each other. For this, the applied procedure could help to determine the factors with the highest effect on the resulting corridor. The importance of these factors can be discussed within a group of decision-makers in order to improve the decision model based on a conjoint solution. Being able to explain which factors contribute most and adapting them in a participatory approach might lead to a fostering of transparency, which in turn will increase the acceptance of the model.

Especially when considering the MCDA methods used, the results concerning the weighting model would probably have been more distinct if we refused using MCDA model 3, as its results were categorized into a separate cluster. In addition, even though MCDA model 3 leads to more direct connections between start and end point, it intersects more protected areas when compared to the application of the remaining MCDA methods. As the branching between MCDA methods 1 and 2 occurs at a low height of around 1 to 2, we conclude that this distinction is not of high importance. Thus, *Simple Additive Weighting* as described in eq. 9 would be the easiest and most accessible solution to conduct an MCDA.

## 4.2 How the results help to improve the decision model

The statistical evaluation performed indicates that the factors contained by the decision model are structured hierarchically. Thus, factors contribute differently to the variability of the suitability maps. By knowing the Pillai's trace, the decision model could be improved by multiplying each factor with a value that inverts its effect on explaining the model. In this

**Table 4** Percent of the average path length over which the according objective ($\Omega_i$ that correspond to tab. 1) does not comply with. The values were averaged across both study areas.

| Parameter | Level | $\Omega_1$ | $\Omega_2$ | $\Omega_3$ | $\Omega_4$ | $\Omega_5$ | $\Omega_6$ | $\Omega_7$ | $\Omega_8$ | $\Omega_9$ | $\Omega_{10}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Boundary model | 1 | .00 | .46 | .11 | .16 | .08 | .37 | .01 | .09 | .50 | .00 |
| | 2 | .00 | .37 | .08 | .13 | .09 | .42 | .00 | .17 | .61 | .00 |
| MCDA method | 1 | .00 | .41 | .09 | .14 | .08 | .40 | .01 | .13 | .56 | .00 |
| | 2 | .00 | .41 | .09 | .13 | .08 | .40 | .01 | .13 | .56 | .00 |
| | 3 | .00 | .43 | .11 | .18 | .10 | .41 | .00 | .15 | .59 | .00 |
| Utility function | 1 | .00 | .42 | .10 | .15 | .09 | .40 | .01 | .13 | .56 | .00 |
| | 2 | .00 | .40 | .11 | .14 | .10 | .39 | .01 | .15 | .57 | .00 |
| | 3 | .00 | .43 | .09 | .16 | .08 | .40 | .01 | .12 | .56 | .00 |
| | 4 | .00 | .42 | .10 | .15 | .09 | .40 | .01 | .13 | .56 | .00 |
| Weighting model | 1 | .00 | .41 | .10 | .15 | .09 | .40 | .01 | .13 | .57 | .00 |
| | 2 | .00 | .41 | .10 | .14 | .09 | .39 | .01 | .14 | .56 | .00 |
| | 3 | .00 | .43 | .09 | .15 | .08 | .40 | .01 | .12 | .57 | .00 |

way, the weight of factors with a low contribution could be increased and vice versa. If we took the only significant weighting model eq. 6 and aimed at standardizing the effect of all factors, the weighting model might be extended by the subsequent equation, where $i$ is the total number of factors and $p_i$ the factor's Pillai's trace, which is used as a *swing weight* [2]:

$$\forall\, x \geq 0 \rightarrow h_{1,i}\,(w_i, p_i) = \frac{\sqrt[7]{w_i}}{i \cdot p_i} \quad \text{and} \quad \forall\, x < 0 \rightarrow h_{1,i}\,(w_i, p_i) = \frac{1}{\sqrt{w_i} \cdot i \cdot p_i} \tag{12}$$

Furthermore, we could not detect any significant interactions between the factor levels used; neither by increasing the number of considered principal components to 8, as considered by using Kaiser's criterion. Thus, we conclude that the factor levels used are independent, which emphasizes the unbiased nature of the decision model. In turn, this unbiased decision model may support decision-making, as decision-makers can independently choose a parametrization without accounting for the effect that a factor might have on another.

Another point that helps to improve the model can be deduced from the dendrograms. As large branching heights result in distinct clusters, the ideal choice of distinct factors might improve outcome variability. However, as the rules applied to generate the maps remained unchanged across both study areas, we assume that the underlying data model influences the amount of variability. Thus, decision-makers should pay attention when carefully deciding, which data model represents the reality best. The results listed in tab. 4 point in the same direction, as large and continuous areas were crossed more often than small and dispersed areas. We therefore propose that both the size and the spatial distribution of the underlying geodata should also be considered when defining the data model. A reflected setting of the data model might thus help to improve the quality of the subsequent analysis.

## 5 Conclusion

This study investigated to what extent a multi criteria decision model leads to biased results when determining the suitability for constructing new transmission lines at a specific place. We first defined a decision model consisting of 33 spatially explicit factors, each representing an area that emits a resistance against constructing a transmission line on it. Besides these factors, we modified a standard MCDA model by defining four modeling parameters that might alter the location and the course of the resulting transmission line corridor and path. We then followed this by conducting a sensitivity analysis by computing all suitability maps resulting from combining all parameter levels with each other. Then, we averaged the resulting corridors by the 72 possible parameter settings. A cluster analysis was subsequently conducted to determine mutual corridor courses, thus, the decision model's bias. Finally, we applied a MANOVA to identify the parameters' influence for explaining the decision model based on its principal components.

Our results demonstrate that the decision, whether a sharp-edged or a continuous boundary model should be applied, is of highest importance, as the resulting corridors significantly differ from each other. Concerning the MCDA method chosen, *Simple Additive Weighting* and the *Maxium Value Model* led to the highest diversity, whereas the latter should be handled with caution, as the model considered the spatial structure of the given data worst. Our analysis further revealed that a logarithmic weighting model and a utility function enhancing the effects of low and high resistances led to more distinct corridor alternatives than using linear models. Moreover, our proposed procedure for enhancing the decision model led to similar results across both investigated study areas. Consequently, it also might be applicable to other study areas to simplify and to improve other MCDA models.

Contrary to prior work that commonly used AHP/ANP, MAUT/MAVT, or PROMETHEE for determining the factors' weights, we propose to adapt them based on the results obtained by statistically evaluating the results of a sensitivity analysis using the described analysis method. The proposed method aims at adjusting the subjectively assigned weight by including an additional swing weight for each factor. As the swing weights represent the statistically determined influence of the corresponding factors, the bias given by the data and decision model can be diminished, thus, enlarging the solution space for other corridor alternatives. We assume that acceptance can be increased by first knowing the DSS's behavior in generating alternative suitability maps and then improving it based on the results obtained by the proposed approach. Future work could, for example, explore whether the proposed weighting adaption effectively results in a higher diversity of generated alternatives, also by performing a sensitivity analysis with continuous, normally distributed weights around an expected value. Moreover, settings of resistances and weights pursuing the same objective could be combined to scenarios, which in turn could be integrated into an analysis approach to determine the combined effect of the geodata, the scenarios, and the MCDA parameters. It remains to be further investigated how planning experts assess the goodness, usability, and practicability of the proposed approach.

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