Automatic selection of weights for GIS-based multicriteria decision analysis applied to transmission line siting

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Abstract

Transmission line (TL) siting consists of finding suitable land to build transmission towers. This is a complex geographical problem often solved using GIS-based multicriteria decision analysis (MCDA), which is a set of techniques that weight several geographical features to identify suitable locations. This technique is often employed using expert knowledge to identify the correct set of weights; thus adding a certain amount of subjectivity to the analysis, meaning that for the same problem if we change the experts involved, we may reach different results.

In this research we employ a statistical analysis to quantitatively calculate these weights. We compare the distances between each geographical feature and the location of transmission towers with the distance between the same feature and random points. If transmission towers present an average distance from geographical features significantly different compared to the random points, this feature is important for planning TLs. High-voltage transmission towers, which are the focus of this research, are, for example, purposely built as far away as possible from urban areas. Random points are on the contrary by definition sampled without any constraint. Therefore, when comparing the two datasets, we should find that transmission towers have a larger average distance from urban areas than random points. This allows us to determine that this criterion (i.e. distance from urban centers) is important for planning new TL.

The results indicate that this method can successfully weight and rank the most important criteria to be considered for an MCDA analysis, in line with weights proposed in the literature. The advantage of the proposed technique is that it completely excludes human factors, thus potentially increasing the social acceptance of the MCDA results.

Keywords

Multicriteria decision analysis; transmission line siting; statistical analysis; Geographic Information System

1. Introduction

The need to integrate a growing percentage of renewable energy systems (RES) into the electric network has created the need to reshape the power grid. In fact, RES do not rely on large power plants, but on a more distributed and intermittent production. To successfully implement them into the network a new concept of transmission lines, namely smart grids, needs to be implemented.

The construction of new transmission lines is an issue that needs to be tackled from various conflicting perspectives (Borlase, 2012). For example, distribution operators seek the minimization of the construction costs of the project, while other stakeholders may want to minimize different factors, such as the environmental impact of the line or its visual impact on the landscape. This creates serious conflicts of interest, which need to be solved with a technique capable of planning new infrastructures in a way that is acceptable by all parties involved. In particular, transmission line (TL) siting consists of finding suitable land to build transmission towers, using a process that excludes areas that cannot be developed (Grassi et al., 2014), while aiming at minimizing the total economic cost of the project.

GIS-based multicriteria decision analysis (MCDA, Malczewski, 1999) is a set of techniques for solving spatial problems by considering and weighting different criteria in the decision making process (Dedemen, 2013). For transmission line siting, MCDA is used to weight several geographical parameters into a single cost surface (here cost is not referred to economic cost; it is a broad term that indicates the suitability of an area to be crossed by a TL), which determines the geographical cost of building a TL, i.e. its impact on the landscape. Once this cost surface has been created, the least cost path is used to connect two points (e.g. two transmission towers or two transformation points) by the line that minimizes this cost (Grassi et al., 2014). For example, TL cannot be built on nature reserves, hence in these areas and their surroundings (a buffer around protected areas is often included) the geographical cost of building additional lines would be very high so that the least cost path algorithm is less likely to choose them.

These techniques have been extensively used in the past for solving complex geographical problems. According to Malczewski (2006a) the majority of the literature on GIS-based MCDA deals with land suitability problems. One of the earliest tests was performed by Carver (1991), who employed MCDA to find suitable sites for nuclear waste disposal in the UK. Few other examples of land suitability assessments include Malczewski (2006b), Ligmann-Zielinska and Jankowski (2014), Bojorquez-Tapia et al. (2001), Kwaku Kyem (2001), Mendoza and Martins (Mendoza and Martins, 2006), and Pereira and Duckstein (1993). GIS-based MCDA was also utilized in other fields: hydrology and water management (Tkach and Simonovic, 1997; Kwaku Kyem, 2001; Mendoza and Martins, 2006), waste management (MacDonald, 1996; Charnpratheep et al., 1997), and agriculture (Ceballos-Silva and Lopez-Blanco, 2003; Mendas and Delali, 2012; Akıncı et al., 2013). Many examples are related to research in the energy sector. For example, in Van Haaren and Fthenakis (2011) and Höfer et al. (2014) MCDA was used to identify optimal locations to build wind farms; Omitaomu et al. (2012) adapted a GIS-based MCDA method for assessing the land suitability requirements to build additional power plants in the US. Moreover, Voropai and Ivanova (2002) used MCDA for power systems expansion planning, Charabi and Gastli (2011) used it for identifying sites suitable for large photovoltaic plants, and in Vučijak et al. (2013) MCDA was employed for locating best basins for additional hydropower.

According to Malczewski and Rinner (2010) MCDA algorithms can be divided into two main categories: multi attributes decision analysis (MADA) and multiobjective decision analysis (MODA). Generally speaking, for environmental studies, where several geographical features need to be evaluated at once, the former is used. However, MADA is a general term that identifies a wide collection of algorithms. These may again be divided into four classes: weighted summation, aggregation, ideal point and outranking. Below we will provide an overview of the most common methods in each of these classes.

The first class is occupied by the simplest methods of which the most commonly used is the simple additive weighting (SAW, Churchman and Ackoff, 1954). As the name suggests, this method is a very simple weighted sum of all the geographical features multiplied by their weights, which are derived from expert judgment. This method is widely used because it is simple to understand and apply, particularly in a GIS application with a simple map algebra operation (Tomlin, 1990). Moreover, it is easy to understand and interpret, thus inherently appealing for decision makers (Malczewski and Rinner, 2010). It is therefore not surprising that this method is implemented in the software IDRISI (Eastman, 1995) and still in use for solving GIS related decision problems, such as land allocation (Jankowski, 1995; Eastman et al., 1998), road siting (Geneletti, 2005), or land fill location identification (Gbanie et al., 2013).

The second class of algorithms, i.e. aggregation, is occupied by AHP (Analytic Hierarchy Process; Saaty, 1990), which is again based on the additive weighting model (Argyriou et al., 2016). The main difference here is in the weights calculation, which is achieved using a preference matrix where each criterion is compared to all others in a pairwise comparison. This technique is more robust than SAW, since it allows for checking the weights (again derived by expert judgment) assigned to the criteria in terms of consistency using the pairwise comparison, and calculating the consistency index (Dedemen, 2013). This technique is widely used in the literature to solve many different problems: for example, Argyriou et al. (2016) used AHP to map neotectonic landscape deformations in Crete. In Şener et al. (2006) AHP was used to identify suitable location for landfills, Zhu and Dale (2001) developed a web AHP tool to solve complex multicriteria environmental problems, and Akash et al. (1999) used it to identify suitable locations for power plants.

Another technique belonging to the aggregation class is the ordered weighted averaging (OWA), developed by Malczewski (2003). This technique is similar in formulation to SAW, the main difference is in the treatment of each criterion. Basically, each weight is ordered based on the relative importance of each criterion. For doing so OWA uses an index of dispersion that tries to order the criteria between worst case and best case scenarios. This method assumes that decision makers, who need to provide the weights, may be tempted to overweight or underweight certain criteria based on their own perception of risk. By including this dispersion index, this method can decrease the impact of the personal judgment of decision makers on the analysis. This method is also included in IDRISI (Eastman, 1995), thus it was used for various environmental studies, such as watershed management strategies (Malczewski et al., 2003), or landslide susceptibility mapping (Feizizadeh and Blaschke, 2012).

Ideal points methods evaluate criteria based on their distance to some ideal or reference point (Malczewski et al., 2003). The most famous is TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), developed by Hwang and Yoon (1981). This technique chooses criteria that simultaneously have the shortest distance from the ideal solution and the largest distance from the worst solution. It is again based on a decision matrix, which is the starting point of a complex iterative approach that includes several phases in which each criterion is compared to the other based on its distance to the goal or solution. This method is also popular in the literature and has been used for problems ranging from personnel selection (Kelemenis and Askounis, 2010), to water resource systems (Afshar et al., 2011), to the selection of ideal turbine manufacturers (Adhikary et al., 2013), and land-suitability analysis (Ligmann-Zielinska and Jankowski, 2014).

The final class is occupied by outranking methods, which are based on pairwise comparison between criteria (Malczewski et al., 2003). The most famous methods in this class are ELECTRE (ELimination Et Choix TRaduisant la REalité), developed by Benayoun et al. (1966), and PROMETHEE, developed by Brans (1982). Here again the weights are compared in pairs, similarly to the previously described algorithms. The difference lies in the assumption that criteria selected by experts can be represented by outranking relations (Malczewski and Rinner, 2010), meaning that the method can quantitatively define that one set of weights that is clearly preferred compared to another. These methods are widely employed in the literature for various studies, among which energy related tasks: for example, Atici et al. (2015) used ELECTRE to select sites for wind farms, while Kabir and Sumi (2014) used PROMETHEE to locate power substations.

By definition these techniques require several criteria that must be considered carefully in order to provide a solution to the problem at hand. For example, the distance between the planned line and urban centers is of major interest and can be considered an important criterion, since in some cases the population is opposed to high-voltage lines passing directly above their heads, and in general high-voltage lines cannot be built close to settlements for issues related to electromagnetic pollution. Other interesting geographical features to consider may include the bedrock composition or the presence of major aquifers. These factors are carefully considered and weighted by experts, based on their own experience. However, this way of decision making is highly subjective (Klosterman, 1997; Feizizadeh et al., 2014a) and therefore, depending on the weights selection, the results may change significantly. In fact, all the techniques described above, from the simplest to the most complex, are all dependent upon weights suggested by decision makers or experts in the field. Clearly, while SAW takes these weights and simply uses them without any modifications, the other methods were specifically developed to decrease the impact of these subjective decisions on the algorithms' outcome. For example, AHP works with a complex pairwise heuristic approach that is based on a preliminary development of a general ranking of the criteria. This ranking has to be suggested by decision makers, and that is where the uncertainty of this method may originate (Feizizadeh et al., 2014b). The same is true for all the other methods, in which the starting point is always provided subjectively by decision makers.

This is a major weak point of these methods. Even though they have a long history of successful application in various fields of research, the fact that they all depend upon subjective decisions may decrease their social acceptance, particularly when dealing with hotly debated topics or ideological decisions. If a project is highly opposed by the local community, having experts from the industry decide which parameters are the most important ones will certainly add fuel to the debate. On the contrary, involving environmental groups may not be the best solution, since their interests are often very different from the industry and they are sometimes unwilling to make concessions. In our opinion, the only plausible way to start solving these issues is developing techniques to quantitatively select the weights to apply for MCDA analyses. Only a weights selection based on robust mathematical and statistical analysis can increase the acceptance of these techniques, minimizing any intervention of parties (i.e. industry experts or environmental groups) that may create conflicts in the community.

This research is a first attempt to address this issue. We focus on the quantitative selection of weights for MCDA, developing a technique based on statistical analysis to define the weights for the criteria. In particular, we compare the distance between transmission towers already built and several important geographical features; in parallel we also compute the distance between the same features and randomly selected points. The idea is that random points will have distances to the geographical features that by definition are independent of anything in particular, while transmission towers will have distances that depend on the importance of the selected feature during the planning phase. For this reason, when comparing the two datasets we will find differences that are proportional to the importance of each geographical feature for the planning of new transmission lines.

2. Materials and Methods

2.1 Datasets

For this research we worked at the national scale, considering the entire country of Switzerland. The most important dataset we used are the locations of the 220 kV transmission towers (n = 5 044) built by Swissgrid (Swisstopo, 2015), which is the national high-voltage power grid operator (these are presented in Figure 1 as red dots). This dataset is provided digitized from the 1:25 000 scale topographic map. Most of the data regarding infrastructures were collected from the VECTOR25 dataset (Swisstopo, 2015), which is a collection of GIS data of natural and man-made features, also digitized from the 1:25 000 topographic map. From the VECTOR25 collection we used data regarding the following parameters: rivers, lakes, rock outcrops, screes, woods, buildings, highways and other types of roads, railways and tram lines. An updated version of this dataset is also available, digitized from orthophotos (Swisstopo, 2013), where additional features are present. From this we used the location of landfills, historic sites, mines, quarries, and wastewater treatment plants. Finally, we gathered data from the geological map of Switzerland (Swisstopo, 2005), scale 1:50 000, that covers the entire country, and the ESA land-cover map (Bontemps et al., 2011).

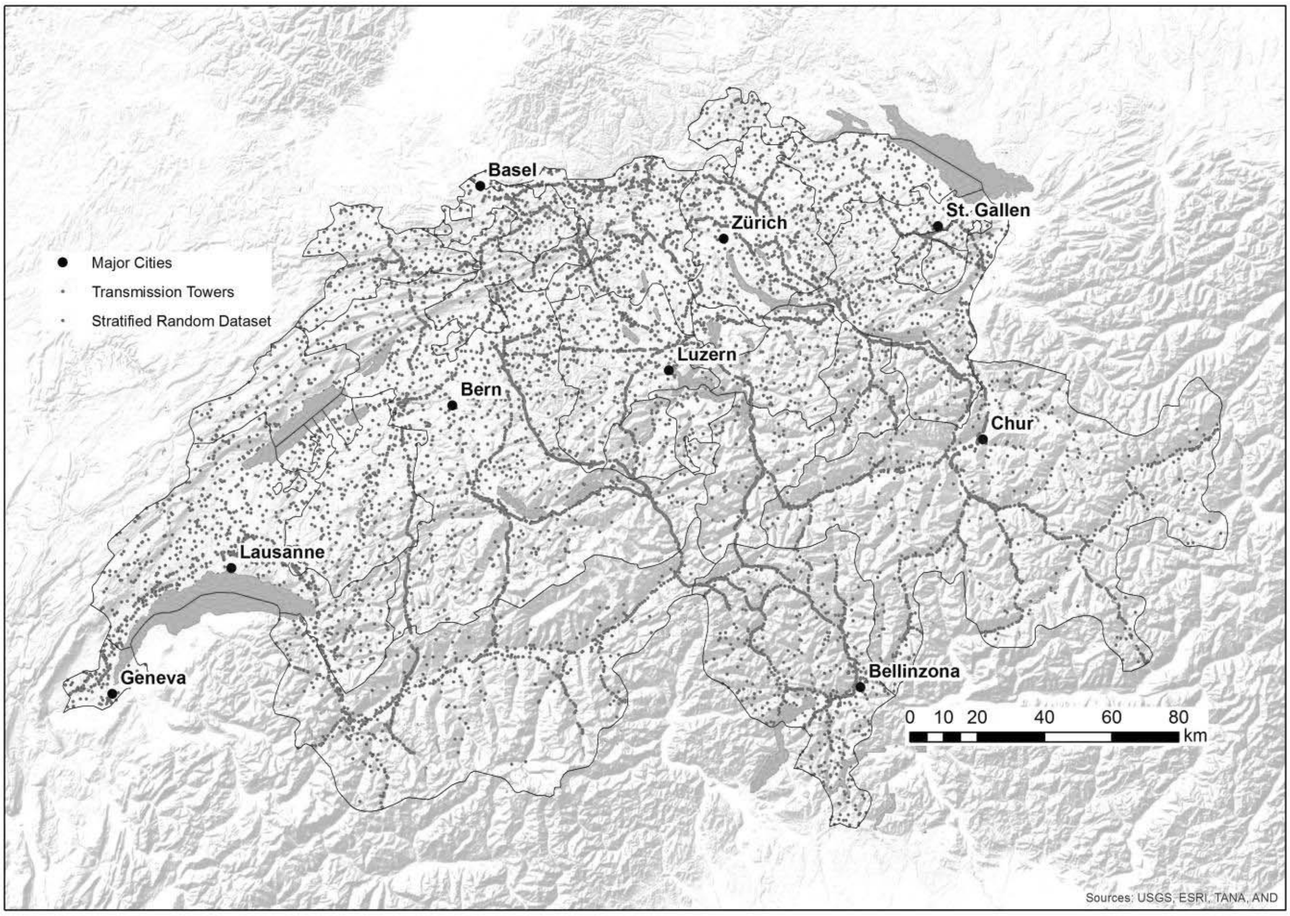

Figure 1: Map of Switzerland with the location of the transmission towers (red) and the stratified random points used for comparison. These two datasets have the same distribution in elevation, meaning that the high peaks in the alpine regions of Switzerland are not covered by the analysis.

2.2 Random Control Points

The statistical analysis is based upon the comparison of locations of transmission towers with the location of points randomly selected across the country. By comparing transmission towers already built with random points we can determine which parameters were the most important ones in determining their locations. Whereas random points have equal probabilities of being close or far away from important geographical features, such as urban areas or natural reserves, transmission towers are located at distances from these features determined during the planning phase. However, we may not be aware of the rules used during planning (since they may change over time and depends on regional/local law and regulation), therefore by comparing random points with the locations of the towers we may determine these rules experimentally. If the two datasets are statistically different when investigating a particular criterion, it means that this criterion was considered important during the planning process.

2.3 Statistical Analysis

To determine whether the distance differences between the two datasets and various important features are significant we employed a basic two-sample *t*-test (Urdan, 2010). In essence, we calculated the distances between transmission towers and all the features described in section 2.1, and then repeated the process for the random points. Subsequently, we used the *t*-test to determine if the two distance distributions presented significantly different mean values. If the two means were not significantly different we concluded that the transmission towers had the same probability of being at a certain distance from a particular feature as random points, therefore this feature was not accounted for in the decision-making process. Alternatively, a significant difference means that planners purposely placed towers closer or farther away from this feature, and for this reason this needs to be taken into account as an important criterion for the MCDA.

The *t*-test is based on the *t* statistic, which can be easily computed as follows (Urdan, 2010):

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \qquad 1$$

where $\bar{x}_1$ and $\bar{x}_2$ are the mean values of the distances of the two datasets, s_1^2 and s_2^2 are the standard deviations of the two distance distributions, and n_1 and n_2 are the numbers of points in each dataset. The two terms in the denominator, namely the ratios between the standard deviations and the number of points, are the standard errors of the two datasets. After calculating the *t* statistic we can calculate the probability that the two means are equal by computing the *p* value. If this is lower than 0.05, the two means are significantly different.

A problem with this work flow is that the *t* statistic relies on the standard error, which in turn is calculated as the ratio between the standard deviation and the number of samples in the dataset (in this case the number of points). This implies that for large samples the standard error is very low, and the *t*-test would return significant values even if the two means are very similar. This is referred to as effect size (Urdan, 2010) and can be simply taken into account by calculating the Cohen's *d* (Cohen, 1977):

$$d = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 - n_2 - 2}}} \qquad 2$$

Equation 2 represents the difference between the two means, divided by what Cohen refers to as the pooled standard deviation, which is the weighted sum of the number of values of each sample, minus 1, multiplied by the variance of each sample, divided by the sum of the number of samples, minus 2. This value is generally between 0 and 1 and can be interpreted in different ways: typically, a *d* value of around 0.2 indicates a weak difference, 0.5 a moderate difference and a 0.8, or more, a strong difference. This index indicates quantitatively how important each feature was considered during the planning phase, since it allows us to determine how strong the differences in distance are; thus we can use its value as a weight for the MCDA analysis.

3. Results and Discussion

3.1 Random Dataset

We started this experiment by comparing the towers' locations with the locations of completely random points. However, the statistical tests performed on this dataset offered some results that seemed erroneous. For example, the random dataset had an average distance from urban areas higher than the towers. This would suggest that transmission towers are purposely placed closer to urban areas, and this is not what happens in reality. For this reason, we realized that we were comparing datasets that were not comparable, since the random points were distributed all across the country even in high elevation areas, which are unsuitable for transmission line siting.

As a consequence, we decided to use a stratified random dataset instead, with elevation as a constraining parameter. We divided the digital terrain model (DTM) of Switzerland into discrete elevation intervals, and randomly sampled the same number of points as the towers in each interval. For example, if between an elevation of 100 and 200 m there are 40 towers, 40 points were randomly sampled only in areas within this range of elevation. The results are presented in Figure 1. Even though the two datasets seem very different they have the same distribution in elevation, and in fact the highest peaks in the alpine region of Switzerland are not sampled, since transmission towers are located at a maximum elevation of around 2 700 m.

3.2 Statistical Analysis

We compared the average distance of transmission towers and the stratified random dataset to a series of 41 features (the categories are listed in section 2.1). In some cases, the distance between the two datasets resulted in a non-significant difference, meaning that the p value was above 0.05. This happened, for example, for minor highways without guardrails (Autostrasse). This result means that in the planning phase this feature was not considered important for transmission line siting. In other words, a tract of a transmission line can either be close, cut through, or be far away from the feature “Autostrasse” and it would not make any difference. For other features the differences in distance resulted to be statistically significant, meaning with a p value below 0.05, but the d value, which takes into account the effect size, was extremely low. This happened for highways (Autobahn), which presented a p value of 3×10^{-5} but a d value of 0.01. For this feature the same reasoning applies, meaning they were simply not considered during planning.

The most important feature appeared to be the geological nature of the bedrock, in particular the presence of magmatic or metamorphic terrains resulted to be extremely important. These two features presented d values of 0.57 and 0.59 respectively, with the distance of the transmission towers that is on average 10 km lower than random data. This means that these two features are important for TL siting. This makes sense since in Switzerland there are areas with shallow soils and in which foundations need to be built directly on rock, for which magmatic and metamorphic are good choices. For similar reasons the presence of rock outcrops resulted to be important. A complete list of all important features is presented in Table 1.

Table 1. List of the most important features for transmission lines siting and their corresponding *d* values.

Features	***d* value**	***d* Value 50%**	***d* Value 25%**
Metamorphic rocks	0.59	0.57	0.54
Magmatic rocks	0.57	0.57	0.53
Permanent Ice	0.5	0.49	0.47
Glaciers	0.49	0.48	0.46
Aquifers	0.42	0.43	0.39
Buildings	0.38	0.39	0.39
Screes	0.35	0.32	0.37
Urban areas	0.35	0.33	0.34
Minor roads	0.34	0.33	0.34
Rock outcrops	0.31	0.29	0.34

In order to provide context to our results, we compared our ranking to other studies on TL siting from the literature. Despite the fact that many articles are dedicated to TL siting using MCDA algorithms, only a small fraction of these present the weights that were used in the research. This may be caused by the fact that sometimes these projects are considered strategically important and thus utility companies are not willing to share detailed data. However, we found two articles in which the weights are presented and therefore allow a comparison of our results. The first is the paper by Monteiro et al. (2005), who used MCDA for TL siting in Spain. In this article the authors suggest that distance to urban areas is one of the crucial geographical features to consider when placing TL, and also that TL are often built along roads to "concentrate the impact of roads and power lines in the same geographical areas" (Monteiro et al., 2005). This article however did not consider the other factors we included in our analysis so these two conclusions are the only ones that we can use for comparison. A more thorough research in terms of weights description is the one carried out by Eroglu and Aydin (2015). Here the authors used several features to help with TL siting in the Black Sea region of Turkey. Their results suggest once again that distance from urban areas is a major factor in TL siting, which stands in line with our findings. However, as in this research, the results from Eroglu and Aydin (2015) do not rank urban areas as the most important factor. By looking at the tables of weights they present, it is clear that the most influential factors are magmatic and metamorphic rocks, major roads (two or more lanes roads), historic places and ice zones. These results are partially in line with what we found in this research. The type of bedrock is clearly of primary importance for building solid foundations for the towers, hence its high ranking. We also found a significant correlation between transmission towers and distance to roads, in line with the results from Eroglu and Aydin (2015), even though in our case not with major roads, therefore not with highways, but only with minor roads. This may be related to differences in the road network between Switzerland and Turkey, but also to the fact that we focused on the entire country, while Eroglu and Aydin (2015) focused on a single region. Historic places were also considered in our research but not found of significant importance for TL siting. Finally, areas under permanent ice were found important in both studies and this makes sense, since it is very difficult to build new infrastructures on these terrains.

3.3 Cross Validation

The *d* values in the second column of Table 1 were calculated using the full dataset of transmission towers, comprising 5 044 locations. The problem is that in certain areas access to this amount of data may not be possible. For this reason, we created a validation experiment to verify what would be the changes if we had a much smaller starting dataset. We randomly divided the dataset into subsets keeping 50% of the towers (n = 2 522) for the first experiment, and 25% (n = 1 350) for the second. For each of these two subsets we resampled the random points according to the new elevation distributions. Subsequently we repeated the statistical analysis for comparison.

The results of the statistical analysis indicate close similarities between the features considered important using the subsets, compared to the important features in the complete experiment. All the features that resulted as unimportant in the complete experiment resulted unimportant also when considering subsets. These results are presented again in Table 1 in columns three and four.

This validation allowed us to determine that such a method is very robust against the number of locations we have in our starting dataset. Clearly this method can be used only if users have the location of at least some of the transmission towers already built. However, with this validation we demonstrated that the number of these locations can be limited in size so that the method can be used also for small countries or in locations where accessing power data is difficult.

4. Conclusion

In this paper we proposed a method to quantitatively and robustly calculate the weights for a multi criteria decision analysis. This method requires a relatively small number of locations with transmission towers and from them it can calculate the most important criteria to consider in the planning phase. The weights calculated from the effect size (i.e. parameter *d*) can readily be used for relatively simple algorithms such as SAW, and their ranking can also provide the basis for more complex methods such as AHP, which still relies on expert judgments in their first step.

Since this method is based on a statistical analysis it is not affected by the same amount of subjectivity typical of traditional MCDA analyses. By relying on statistics and not on expert knowledge we can identify important criteria for transmission line siting in a reproducible and consistent way. This may well decrease the conflict between proponents and opponents of projects that are politically sensitive. Avoiding expert judgment from the industry side, a controversial project may be better digested by the local community, because its results are reproducible and based on a strong statistical background.

As mentioned, the criteria selected for building transmission towers may change over time, with updates in the national policies, or in line with regional/local laws and regulation. In this experiment we considered the full dataset of transmission towers, without taking into account possible changes in policies, since this is not possible with our data. The available dataset consists of transmission lines older than 40 years. Then not only the regulations but also the spatial distribution of the settlements and infrastructures was clearly different compared to today. This may lead to erroneous estimations of important criteria, but in no way affects the validity of the methodology. In fact, as demonstrated with the cross-validation, this method is only slightly affected by changes in the starting dataset, including a decrease in the number of towers used for comparison. This means that to take into account local laws or changes in policies over time, one should only subset the initial dataset to maintain a consistency in the criteria used during the planning phase, and the method should work just as well.

A major limitation of this work is that we considered only level 1 transmission lines, meaning high-voltage. We only had access to these data because lower voltage lines are managed by cantonal energy distributors, who are not willing to share their data. For this reason, the results we obtained can only be used to plan high-voltage lines. More data are needed to identify which features are important for medium to low-voltage line siting. Moreover, this first test focused on estimating weights considering all of Switzerland. However, local or regional conditions may highly affect the way in which infrastructures were built in the past, hence may impact the results of the statistical analysis.

Acknowledgments

The authors acknowledge the CTI - Commission for Technology and Innovation (CH), and the SCCER-FURIES - Swiss Competence Center for Energy Research - Future Swiss Electrical Infrastructure, for their financial and technical support to the research activity presented in this paper. The authors would also like to thank Swissgrid for providing the GIS dataset used in this study, and the Atlas of Switzerland for make them available in a GIS format.

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