ELECTRE TRI is a well-known approach to decision aid when there is a discrete set of actions $a_1, \ldots, a_m$ (e.g. investment projects) to be assigned to a set of ordered categories (e.g. “reject,” “accept if ...”, “accept as is”), according to multiple criteria. This method builds a fuzzy outranking relation (Roy, 1991) and then exploits it for decision aid (see description in Section 3). Decision Makers (DMs) have to set the performance of each action on each criterion, the thresholds that characterize pseudo-criteria, the importance and veto power of each criterion plus a cut threshold that is used to transform the resulting fuzzy relation into a crisp one, all of which constitute the model’s parameters. We refer to parameters in a broad sense, including input usually referred to as “data”, input concerning the DMs’ values and beliefs, etc.

Given a numerical value for each parameter, the pessimistic or optimistic ELECTRE TRI assigns each action to a well-determined category. However, it is unrealistic to expect that DMs are able to agree on the values for the parameters, since (see also on this subject Roy and Bouyssou, 1989; French, 1995):

- the performance of each action on each criterion may be unknown at the time of the analysis (uncertainty concerning the future), it may result from aggregating several

...
aspects with impact on the criterion (arbitrariness in constructing parts of the model), and it may result from a measuring instrument or a statistic measure (which usually involve imprecision);

- parameters such as the importance coefficients and veto thresholds have no objective existence (independent from the method): they reflect the DMs’ subjective values, which they may find difficult to express and that may change over time;

- in either case, the DMs may not entirely agree on the values that each parameter should take, due to different opinions (perceptions) and values (preferences).

We consider a group decision setting where multiple instances of a model (each one corresponding to an admissible combination of values for the parameters) are accepted. The multiple instances are expressed as a set of constraints, rather than a discrete set of values. The constraints may be explicitly provided by the DMs or inferred from holistic comparisons (as in Mousseau, 1993). Although constraints are not always easy to provide, requiring precise values for the parameters is obviously more demanding. We consider the use of our approach to be an interactive learning process, where the results of the analysis may stimulate the DMs to discuss and revise their inputs.

The information leading to the set of constraints is often called “imprecise” (e.g. Athanassopoulos and Podinovski, 1997), “incomplete” (e.g. Kim and Ahn, 1997), “partial” (e.g. Hazen, 1986) or “poor” (e.g. Bana e Costa and Vincke, 1995). We will use the expression “imprecise information”, meaning that it does not impose a precise combination of values for the parameters, which also allows coping with insufficient or contradictory information.

Let T represent the set of all acceptable combinations of parameter values. This set could be either the intersection or the union of the combinations of values accepted by each individual DM, as discussed in the next section. The first possibility implies accepting a conclusion as possible if it is compatible with the input of all the DMs. The second possibility amounts to accept a conclusion as possible if any DM, individually, could reach that conclusion. In general, DMs may begin with little information (starting with a set T not too constrained) and then progressively enrich that information (reducing T) as they form their convictions and as consensus emerges regarding the input values. Our aim is to identify conclusions that can be accepted by all the DMs, even in the situations where they might not have agreed on precise values for the input parameters.

Robustness analysis considers all the results compatible with all the acceptable combinations of values for the parameters. Roy (1998) presented a framework defining the concept of robust conclusion as a formalized premise that is true for all these combinations. This contrasts with traditional sensitivity analysis, conducted after obtaining a result, which determines how much may each parameter vary without leading to a different result. Although useful in many circumstances (e.g. Henggeler Antunes and Clímaco, 1992) sensitivity analysis requires an initial value for each parameter (where some consensus would be needed) and focuses on the first result found, hence ignoring other interesting conclusions that might have been reached otherwise. For instance, in the context of ELECTRE TRI, it is interesting to know the range of categories where an action may be assigned. Sensitivity analysis is often performed changing a single parameter at a time, thus ignoring possible interdependencies among the parameters.