Chapter 14
Decision-Making Tools: Deleting Criteria Using Sensitivity Analysis

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Abstract Research has shown that as the attractiveness of alternatives rises with more choices, individuals experience conflict between the alternatives, which causes them to defer their decision, search for new alternatives, or choose the default option. Having lesser attributes simplifies complex problems and the decision-making process. This chapter uses the sensitivity analysis in hierarchical decision model, developed by Hongyi Chen, to prove that we can reduce the size of a problem and make the decision easier with the future change of values of attributes, without affecting the final decision.

14.1 Introduction

As the world has become more complex and information flows from every direction with an easy access, decision problems must contend with increasingly complex relationships and interactions among the decision elements. Among a variety of decision-making fundamentals, models, and tools, the ability of individuals to estimate their needs and generate personal and organizational objectives for a given decision is critical to succeed. Management science and decision making research use different words like objectives, goals, criteria, or attributes to represent what the decision maker wants to achieve by making the decision [1]. In this research we choose "attributes" as a decision criteria or cue decision makers want to achieve in their decision.

Decision makers usually are attracted to choice, and sometimes they get disappointed when they do not have many alternative solutions [2, 3]. However, having more choices does not make the selection process easier [4] and often tends to yield to less confident about the choice [3]. Research shows that the percentage of

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positive judgments decreased with increasing complexity. When facing many choices, individuals experience conflict between the alternatives, which causes them to defer their decision, search for new alternatives, choose the default option, or simply not to choose [2], because goals shifted from maximizing benefits to minimizing the decision complexity and reaching a justifiable decision [3]. Malhotra [5] found that people experienced information overload when both the number of attributes and the number of options were increased. Research participants reported having too much information when the number of attributes was increased not when the number of options was increased [2]. When choosing among products described by more attributes, people reported feeling more confused and unsure of having made the right choice than when faced with fewer attributes [2].

Increasing number of attributes to be evaluated in making decision usually increases the cognitive costs associated with processing this information (Gigerenzer). The problems with having large assortments of data have been rooted in the ability of human cognitive system to compare and make a decision between several alternatives (psychology book). Cognitive system can process, remember, compare, and recognize up to seven variables—plus or minus two—at the same time. When people have more variance, they become ignorant about what is going to happen [6]. Process tracing studies have repeatedly shown that individuals employ simple strategies that minimize the amount of considered information and mental effort invested in the decision [7, 8].

To eliminate the effort decision makers might consider fewer choices, apply fewer attributes in the evaluation, and process a smaller fraction of the overall information available regarding their choices. Smith [9] found that smaller number of attributes were used to reach the desired decision in prescribing medication. Dhami [10] suggests that physicians use fewer attributes to make decision. Proctor & Gamble reduced the number of versions of Head and Shoulders shampoo from 26 to 15, and as a result sales increased by 10 % [2]. Bond et al. [1] found that the participants consistently omitted nearly half of their objectives even though they were perceived to be almost as important as the remaining ones. Despite omitting these objectives, decision makers were satisfied with their decisions.

Are all attributes important to the decision maker or important to the quality of the decision? Not always. The usefulness of the available attribute information is to help a decision maker in making decision; when the number of attributes increased, it does not always lead to increase in the quality of information. There is a point where more is not better, but harmful because the relation between level of accuracy and amount of information, computation, or time takes an inverse U shape. These facts raised many questions like the following: Should we reduce the number of attributes in strategic decisions? How can the number of attributes be reduced without affecting the quality of the decisions? This study uses sensitivity analysis of the attributes founded by Chen [11] to eliminate attributes without affecting the final decision in strategic planning decision making.

Sensitivity analysis (SA) is a fundamental concept that has been used and implemented in quantitative decision models. It provides information more significant and useful than simply knowing the model solution, and serves different purposes in the decision-making process.

Chen classified several benefits of applying sensitivity analysis to hierarchical decision models (HDM) including the following: (1) help visualize the impact of changes at the policy and strategy levels on decisions at the operational level; (2) test the robustness of the recommended decision; (3) identify the critical elements of the decision; (4) generate scenarios of possible rankings of decision alternatives under different conditions; (5) help judgment providers (the experts) reach consensus; and (6) offer answers to "what-if" questions. This research is adding another value of applying the sensitivity analysis, which is eliminating the ineffective decision criteria to reduce the complexity.

14.2 Eliminating Attributes in Literature

Many researches study the effect of eliminating information in the decision-making process on the quality of the decisions. The impact of using an incomplete set of the nine attributes on choice inaccuracy was measured in terms of the proportion of value lost (PVL) [12]. PVL is obtained by comparing the value of the option chosen using partial attribute information to the value of the option chosen using full attribute information. PVL ranges from 0, when the option chosen using partial information coincides with the best option determined by full information, to 1, when the option chosen coincides with the worst option determined by full information. Option values were computed using multi-attribute utility theory.

When attributes are negatively correlated, the results depend on the relative attributes' importance; given that attributes are negatively correlated and equally important, choosing fewer attributes can lead to substantial increases in PVL, and it is necessary to use at least 80 % of attributes to make a choice at the 10 % PVL level [4, 12].

When weights are unequal, then it remains sufficient to know and use the most important attribute to make a choice within 10 % of the highest value possible [4].

When all attributes are considered, in the negative correlation, there are on average 95 % non-dominated options (s.d. = 5 %); earning that, with full information, the choice gets very complicated because about 20 of 21 options are most attractive regarding at least one attribute. Thus, considering fewer attributes has the benefit of making the choice less conflicted and less complicated.

Using unequal weight attributes—with positive correlation—Barbara [4] found that PVL was very low even when choice was based on a single attribute if attributes were positively correlated. Only one or two attributes are enough to make a choice at an acceptable 10 % PVL level. If attributes are unequally important to the decision maker, it is sufficient to use the most important one. We can still find the same relationship between the number of attributes and non-dominated options. In this case, about one-third of non-dominated options can be eliminated.

Gigerenzer and his research group tried to discover the power of one-reason decision making through applying the Take the Best algorithm [13–15]. Take the Best algorithm depends on the rule of thumb "take the best and ignore the rest."

Results [14] show that Take the Best performs as well as the regression model and has performed better than the linear models under lack of information. On average, the algorithm tested three attributes before it stopped searching and picked a choice, which it found to be acceptable.

14.3 Research Objective and Methodology

In this highly competitive and fast-changing environment, managers have to keep track of the changes in values of the criteria, which would cost money and effort.

This research used the sensitivity analysis to test the effect of deleting one or more attributes on the first (top) rank alternative decision in hierarchical decision model. In order to understand the impact of changes in the attribute value on the alternatives rank, we studied and analyzed the sensitivity of the attributes and tolerance values using Chen's doctoral dissertation and publications [11]. Tolerance is defined as "the allowable range in which a contribution value can vary without changing the rank order of the decision alternatives" [11]. To determine the tolerance of each attribute weight, the allowable range of perturbations on the contribution is used [11]. The allowable range of perturbations corresponds to "allowable increase and decrease," as used in the sensitivity analysis of linear programming.

14.3.1 Notations and Formulas

The classical notion of attributes implies on the [16] preference structure.

"*P*" denotes preference while "*I*" denotes indifference.

$a\ P\ b$ *iff* $C_a > C_b$.

$a\ I\ b$ *iff* $C_a = C_b$.

C_k represents the value given to criterion.

K is the number of attributes, then

A is the alternative technology.

$C_k(A)$ is the weight given to alternative A under criteria k.

$$\sum\nolimits_{k=1}^{K} C_k = 1.00 \tag{14.1}$$

$$\sum\nolimits_{k=1}^{K} C_k(A) = 1.00 \tag{14.2}$$

The total weight of alternative A is $R(A)$:

$$\begin{aligned} R(A) &= \sum_{k=1}^{K} \left(C_k \times C_{k(A)} \right) \\ A_1 P A_2 &\text{ if } R(A_1) > R(A_2) \\ A_1 I A_2 &\text{ if } R(A_1) = R(A_2) \end{aligned} \tag{14.3}$$

$R(A_1)I$, if no change happens to the A's rank even with changing the criteria weight.

14.3.2 Experiments and Results

To understand when the deletion of an attribute will not affect the decision, we studied simulated data where we randomly assigned four attributes different values keeping the condition that the sum of all attribute values equals one, Eq. (14.1).

We had two sets of alternatives: one had three different alternatives and a decision has to be done to choose one of them, and the other contained five different alternatives.

The weight of the alternatives regarding each attribute was randomly selected with keeping the total value of weights of each attribute equal to one, Eq. (14.2).

Then, alternatives were ranked depending on the rate value which was calculated using Eq. (14.3).

In order to find out when (at what point) deleting the attribute will not affect the first rank, we tried to change the value of each attribute C_k one at a time, keeping the weight of alternative's attributes C_k (A) without any change.

From studying many simulated values of four attributes with three and five alternatives and concerning only changes happened to the first rank alternative, we can classify our findings as follows:

Some attributes have C_k value that could go to 0.99 without changing the first rank. Others can go down to zero without changing the first rank.

When we change the C_k value of an attribute, in most of the cases, this change caused changing of the top rank at a certain point (we called it the break point), and then changing the C_a value will not cause changes to the decision until it reaches another break point; see Fig. 14.1.

Some attributes have one or two break points; others do not have any break points.

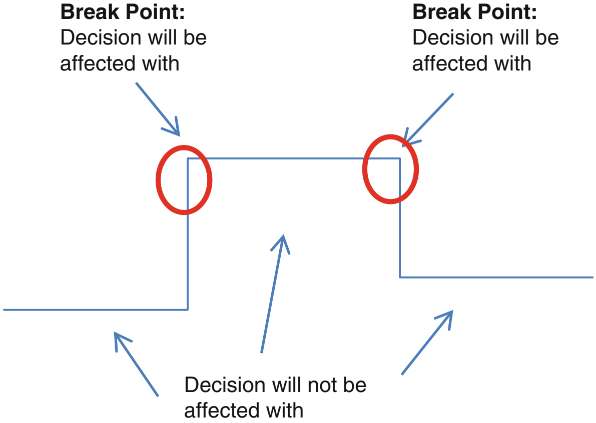


Fig. 14.1 When change of criterion's weight changes the top decision

We studied the sensitivity of each attribute and used the tolerance value to identify when we can delete the attribute without affecting the decision.

To calculate the tolerance of each attribute while keeping the first rank with no change, we need to calculate the perturbation value for criteria k^* (p_{k^*}), Eq. (14.4) [11].

Since we only care about the first rank we will set r in the following equations with value 1.

n is the variable which will take the value of criteria we want to test.

If $r = 1.\ n = 1, 2, \ldots K$, where K is the total number of all attributes, criteria are ranked from more important to less important, and technologies are ordered from the more important to less important. T_1 is the technology with higher $R(T)$ value.

$C_{r,k}$ is the weight value of technology that gains rank r under criterion k.

C_k is the weight of criterion k.

Equation (14.4) [11]:

$$p_{k^*} = \frac{y}{w} \tag{14.4}$$

$y = R(T_r - RT_{r+n})$ is the difference between the values of first rank and other rank values:

$$w = C_{r+n,k^*} - C_{r,k^*} - \sum_{k=1,\,k\neq K^*}^{K} C_{r+n,k} \times \frac{C_k}{\sum_{k=1,k\neq K^*}^{K} C_k} + \sum_{k=1}^{K} C_{r,k} \times \frac{C_k}{\sum_{k=1,k\neq K^*}^{K} C_k}$$

where

$$\sum_{k=1,\,k\neq K*}^{K} C_k = C_2 + C_3 + \ldots.. + C_k$$

After calculating p_{k*} $for\ all\ values\ of\ n$ $(from\ n = 1,\ \ldots n = K)$

p_{l-} is the lower perturbation value of p_{k*}.

p_{l+} is the higher perturbation value of p_{k*}.

Equation (14.5) [11]:

$$Tolerance = \ p_{l-} + C_l, p_{l+} + C_l \tag{14.5}$$

From studying sensitivity analysis we can summarize our finding as follows:

- Top choice will remain at the first rank (the decision will not change) if for all criteria C_a has changed within the tolerance limit for each criterion:

$$R(A_1)\ \ I \text{ iff } \forall\, k\, C_k\ \ = C_k \pm p_k$$

- Once the value of a criterion goes beyond the tolerance range, the first rank will change and A_x will preference A_1, where x represents any alternative, and A_1 represents the first rank:

$$R(A_x)PR(A_1) \text{ iff } \exists\ k\boldsymbol{,}\ C_k\ < Tolerance(a)$$

- If the value of the criteria goes lower than the lower tolerance value, the value of the first rank will change and if it continues to go down until zero, this change will not affect the new change:

$$R(A_x)\ PR\ (A_1) \text{ iff } \exists\ k\boldsymbol{,}\ C_K\ < Tolerance(k)$$
$$R(A_x)\, I \text{ if } 0 \leq C_k\ < Tolerance(k)$$

- If the value of the criteria goes higher than the highest tolerance value, the value of the first rank will change and if it continues to go up until one, this change will not affect the new change:

$$R\ (A_x)PR(A_1) \text{ iff k}, C_K\ > Tolerance(k)$$
$$R(A_x)\, I\ \text{ if } Tolerance(k) < C_K \leq 1$$

14.4 Case Study

We are going to use a hierarchal decision model for the semiconductor foundry industry in Taiwan developed by Ho [17], and used by Chen [11], where the main goal is increasing the return on investment (ROI) rate for the company. Experts from the industry, research organizations, and the government identified four different criteria to reach the goal by choosing a technology among five different technology alternatives.

The four criteria with their weights of importance are displayed in the following Table 14.1.

The five different alternative technologies with their attributes weights are displayed in Table 14.2.

With current weight of criteria and alternatives, the rank of the alternatives is shown in Table 14.3 with *R* (*A*) values.

The tolerance value of all attributes to preserve the ranking of the top choice is calculated and summarized in Table 14.4.

Table 14.1 The four criteria and their weights

Criteria	Weight
Cost leadership1	0.36
Product leadership	0.25
Customer leadership	0.21
Market leadership	0.18

Table 14.2 Weight of different alternative technology criteria

	Alternatives				
Criteria	Increasing wafer size	Reducing line width	Hi K	Lo K	Factory integration
Cost leadership1	0.19	0.24	0.13	0.19	0.24
Product leadership	0.27	0.22	0.13	0.18	0.20
Customer leadership	0.21	0.24	0.13	0.19	0.22
Market leadership	0.22	0.24	0.13	0.19	0.21

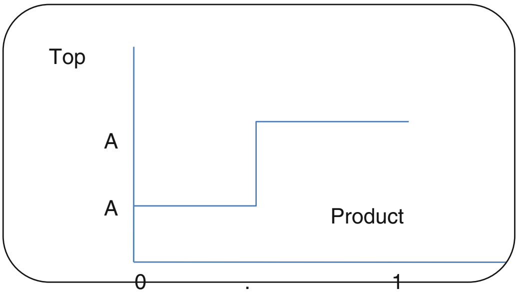
Table 14.3 Alternative technologies in ranked orders with the contribution values

Technology	*R*(*A*)
Reducing line width	0.235
Factory integration	0.2204
Increasing wafer size	0.2196
Lo K	0.193
Hi K	0.132

Table 14.4 Tolerance of attributes for keeping the top-ranked alternative unchanged

Criteria	Tolerance range
Cost leadership1	0.75–1
Product leadership	0–0.427
Customer leadership	0–1
Market leadership	0–1

Fig. 14.2 Changing the decision depends on changing product attribute's weight



If the value of attribute changed within the tolerance ranges, this change will not affect the first rank (and our decision) but when it breaks this tolerance boundary, the first rank will change.

For example, if the value of production increases to 0.43, the first rank will change from *reducing line width* alternative to *increasing wafer size*. Moreover, we found that if the value of production increased more than that this increasing will not affect the new rank and *increasing wafer size* will stay as the top rank even if the production value reaches 100 %.

In this case, decision makers and strategic planners in companies don't need to forecast and track the increase of the production once it goes higher than the upper limit of tolerance (which is 0.43 for production attribute) (Fig. 14.2 and Table 14.5).

It is interesting to see that customer and market leadership has a wide tolerance range which tells us that if we do not consider the changes that will happen to these two criteria, we will still have the same top rank and the decision will not be affected with these changes. See Table 14.6.

Therefore, decision makers may delete these attributes from their considerations to simplify the problem.

14.5 Conclusion

Having fewer attributes simplifies complex problems and the decision-making process. This chapter shows that not including all the available information in the decision-making process can still lead to good decisions. Decision makers can reduce the number of criteria and simplify the problem without reducing the quality of the decision in many cases. This process should start with outlining the primary goals and important criteria needed to achieve the objective and eliminating the unnecessary ones. Depending on the problem and type of criteria, decision makers can apply fast and frugal algorithms if they need to make quick decisions. Or they can use sensitivity analyses when there is enough time to study and forecast the changing that could happen to criteria.

Table 14.5 Rate of technologies with different weights of product

Criteria		Increasing wafer size	Producing line width	Hi K	Lo K	Factory integration
Cost leadership1	0.443	0.19	0.24	0.13	0.19	0.24
Product leadership	0	0.27	0.22	0.13	0.18	0.2
Customer leadership	0.293	0.21	0.24	0.13	0.19	0.22
Market leadership	0.263	0.22	0.24	0.13	0.19	0.21
		0.204	0.240	0.130	0.190	0.226
Cost leadership1	0.3	0.19	0.24	0.13	0.19	0.24
Product leadership	0.43	0.27	0.22	0.13	0.18	0.2
Customer leadership	0.15	0.21	0.24	0.13	0.19	0.22
Market leadership	0.12	0.22	0.24	0.13	0.19	0.21
		0.231	0.231	0.130	0.186	0.216
Cost leadership1	0.29	0.19	0.24	0.13	0.19	0.24
Product leadership	0.46	0.27	0.22	0.13	0.18	0.2
Customer leadership	0.14	0.21	0.24	0.13	0.19	0.22
Market leadership	0.11	0.22	0.24	0.13	0.19	0.21
		0.233	0.231	0.130	0.185	0.216
Cost leadership1	0	0.19	0.24	0.13	0.19	0.24
Product leadership	1	0.27	0.22	0.13	0.18	0.2
Customer leadership	0	0.21	0.24	0.13	0.19	0.22
Market leadership	0	0.22	0.24	0.13	0.19	0.21
		0.270	0.220	0.130	0.180	0.200
Cost leadership1	0.43	0.19	0.24	0.13	0.19	0.24
Product leadership	0.32	0.27	0.22	0.13	0.18	0.2
Customer leadership	0	0.21	0.24	0.13	0.19	0.22
Market leadership	0.25	0.22	0.24	0.13	0.19	0.21
		0.223	0.234	0.130	0.187	0.220

(continued)

Table 14.5 (continued)

Criteria		Increasing wafer size	Producing line width	Hi K	Lo K	Factory integration
Cost leadership1	0	0.19	0.24	0.13	0.19	0.24
Product leadership	0	0.27	0.22	0.13	0.18	0.2
Customer leadership	1	0.21	0.24	0.13	0.19	0.22
Market leadership	0	0.22	0.24	0.13	0.19	0.21
		0.210	0.240	0.130	0.190	0.220

Table 14.6 Including or deleting the customer and market criteria does not affect the top rank

Criteria		Increasing wafer size	Producing line width	Hi K	Lo K	Factory integration
Cost leadership1	0.5	0.19	0.24	0.13	0.19	0.24
Product leadership	0.5	0.27	0.22	0.13	0.18	0.2
Customer leadership	0	0.21	0.24	0.13	0.19	0.22
Market leadership	0	0.22	0.24	0.13	0.19	0.21
		0.230	0.230	0.130	0.185	0.220

14.5.1 Limitations and Future Studies

This research considered reducing the number of criteria in one level of the hierarchal decision model and did not go through change in multiple levels. In addition, this study focused on changes to top rank and ignored changes that happened to the rest of the ranks. Future research could be done to study how to reduce the number of criteria in multiple levels of the hierarchical decision model without affecting the rank of all alternatives.

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