Engineering Economy

Chapter 14: Decision Making Considering Multiattributes

The objective of Chapter 14 is to present situations in which a decision maker must recognize and address multiple problem attributes.

Few decisions are based strictly on dollars and cents.

- We will address how diverse, nonmonetary considerations (*attributes*), that arise from *multiple objectives* can be explicitly considered.
- *Nonmonetary* means there is no formal mechanism to establish *value*.

Value is difficult to define.

- Seven classes of value: economic, moral, aesthetic, social, political, religious, judicial
- Only *economic value* is measured in monetary units.
- Economic value can be established through *use value* (properties that provide a unit of work) and *esteem value* (properties that make something desirable).
- Use and esteem value defy precise quantification in monetary terms.

Buying a car is a multiattribute decision.

What are some of the things you consider when purchasing a car? A car enthusiast may care about the following.

Attribute	Car A	Car B	Car C
Horsepower	195	320	230
Transmission	automatic	automatic	manual
Color	red	blue	gray
Body style	sedan	coupe	sedan
Brand	import	domestic	import
Gas mileage	26 mpg	18 mpg	21 mpg
Dealer Reputation	Excellent	Fair	Poor

The same data may bring different values to different decision makers.

- While one may be able to assign a dollar amount to gasoline mileage, the other attributes are not nearly as clean.
- Some drivers would rate an automatic transmission as "good," while others would rate it as "bad," or at least less desirable.
- Do you have a favorite color? Do you "buy American"?
- Many decision problems in industry are similar.

Choosing the "right" attributes is critical.

- Each attribute should distinguish at least two alternatives.
- Each attribute should capture a unique dimension of the decision problem (i.e., attributes are independent and nonredundant).
- All attributes, collectively, are assumed sufficient for selecting the "best" alternative.
- Differences in values for each attribute are meaningful in distinguishing among alternatives.

Choosing attributes is a subjective process.

- It is usually the result of group consensus.
- The final list is heavily influenced by the decision problem and by an intuitive feel for which attributes will discriminate among alternatives.
- Too many attributes is unwieldy, too few limits discrimination.
- Attributes must have sufficient specificity to be measured and therefore useful.

Measurement scales must be selected for each attribute.

- The measurement scale for monetary attributes is easy to define, less so perhaps for other attributes.
- Some attributes may be measurable, such as horsepower or mileage, but that may not directly translate into value.
- Sometimes gradation measures such as "good," "fair," or "poor" are used.

The dimensionality of the problem dictates solution methods.

- All attributes can be collapsed into a single dimension (*single-dimension analysis*) such as dollar equivalents, or a *utility equivalent* perhaps ranging from 0 to 100. It might be difficult to assign such to a color.
- This is popular in practice because a complex problem can be made computationally tractable.
- Single-dimension models are termed *compensatory* models (allowing trade-offs among attributes).

Full-dimension analysis retains the individuality of all attributes.

- No attempt is made to create a common scale.
- This approach is especially good for eliminating inferior alternatives from further analysis.
- Models for full-dimension analysis are termed *noncompensatory* (no trade-offs among attributes).

Noncompensatory models attempt to select the best alternative considering the full-dimensionality of the problem

- Dominance: screening to eliminate inferior alternatives.
- Satisficing: when all attributes meets a minimum threshold.
- Disjunctive resolution: when at least one attribute meets a minimum threshold.
- Lexicography: Choose the alternative with the "best" value for a particular attribute. If there is a tie, consider scores for the next most-valuable attribute, etc. So, the attributes must be ranked in order of preference.

Revisiting the car problem.

Attribute	Car A	Car B	Car C	Preference	Minimum
Horsepower	195	320	230	Higher	200
Transmission	Automatic	Automatic	Manual	Automatic	Manual
Color	Red	Blue	Gray	B, G, R	R
Body style	Sedan	Coupe	Sedan	Sedan	Coupe
Brand	Import	Domestic	Import	Domestic	Import
Gas mileage	26 mpg	18 mpg	21 mpg	Higher	20 mpg
Dealer reputation	Excellent	Fair	Poor	Better rep.	Fair

Pairwise comparison to determine dominance.

Attribute	Car A vs. Car B	Car A vs. Car C	Car B vs. Car C
Horsepower	Worse	Worse	Better
Transmission	Same	Better	Better
Color	Worse	Worse	Better
Body style	Better	Same	Worse
Brand	Worse	Same	Better
Gas mileage	Better	Better	Worse
Dealer reputation	Better	Better	Better
Dominance?	No	No	No

Assessing the alternatives using noncompensatory methods.

- Dominance: None of the alternatives is dominated (each is a "winner" for at least one attribute).
- Satisficing: None meet the minimum threshold in all categories. Car A does not meet horsepower, Car B does not meet mpg, and Car C does not meet dealer reputation.

Assessing the alternatives using noncompensatory methods.

- Disjunctive resolution: All of the alternatives meet at least one minimum threshold.
- Lexicography: If we rank horsepower as most important, Car B is selected. If we select mileage, then Car A is selected. If body style, then color, Car C is selected.

Compensatory models require attributes to be converted to a common measurement scale.

- The scale may be, for example, *dollars* or *utiles* (a dimensionless unit of worth).
- This conversion allows one to construct an overall index value for each alternative, which can then be directly compared.
- The construction of the overall index can take many forms depending on the decision situation.
- Good performance in one attribute can *compensate* for poor performance in another.

Converting attribute values to nondimensional form.

- *Nondimensional* scaling converts all attribute values to a scale with a common range (e.g., 0 to 1, 0 to 100). Otherwise, attributes will contain implicit weights.
- All attributes should follow the same trend with respect to desirability; most preferred values should be either all small, or all large.
- Assessing each alternative can be as simple as adding the individual scaled attribute values.

Converting original data to nondimensional ratings

When original data are numerical values, the following conversions can be used. First, when larger numerical values are *undesirable*,

$$Rating = \frac{\text{worst outcome - outcome being made dimensionless}}{\text{worst outcome - best outcome}}$$

Then, when larger numerical values are *desirable*.

$$Rating = \frac{\text{outcome being made dimensionless - worst outcome}}{\text{best outcome - worst outcome}}$$

Rating horsepower and mileage in the car example.

In each case, more is considered better. For example, the rating for 230 horsepower would be

$$Rating = \frac{230 - 195}{320 - 195} = 0.28$$

The ratings for these attributes for each car are below.

Attribute	Car A	Car B	Car C
Horsepower	0.0	1.0	0.28
Gas mileage	1.0	0.0	0.38

For non-numerical attribute values, a ranking process can be used.

Attributes can be ranked from 1 to n, where there are n possible values of the attribute, and 1 is considered best. Then the following formula can be used for rating.

$$Rating = \frac{\text{Relative rank } - 1}{n - 1}$$

The next slide provides ratings for the five non-numerical attributes in the car example.

Attribute	Value	Relative Rank	Nondimensional Value
Transmission	Manual	1	0.00
	Automatic	2	1.00
Color	Red	1	0.00
	Gray	2	0.50
	Blue	3	1.00
Body style	Coupe	1	0.00
	Sedan	2	1.00
Brand	Import	1	0.00
	Domestic	2	1.00
Dealer reputation	Poor	1	0.00
	Fair	2	0.33
	Good	3	0.67
	Excellent	4	1.00

Nondimensional data for the car buying decision. Car B is the "best" choice!

Attribute	Car A	Car B	Car C
Horsepower	0.00	1.00	0.28
Transmission	1.00	1.00	0.00
Color	0.00	1.00	0.50
Body style	1.00	0.00	1.00
Brand	0.00	1.00	0.00
Gas mileage	1.00	0.00	0.38
Dealer Reputation	1.00	0.33	0.00
Sum of ratings	4.00	4.33	2.16

The *additive weighting* technique allows some attributes to be more “important” than others.

- An ordinal ranking of the problem attributes yields attribute weights that can be multiplied by the nondimensional attribute values to produce a *partial contribution* to the overall score, for a particular alternative.
- Summing the partial contributions results in a total score for each alternative, which are then compared to select the “best” one.

Establishing and using attribute weights.

1. Rank attributes from 1 to n based on position, with higher numbers indicating greater importance. n may be the number of attributes, indicating constant and difference (importance) between attributes, or it may be larger allowing for uneven spacing between attributes.
2. Normalize the relative ranking numbers by dividing each by the sum of all rankings.
3. Multiply an attribute's weight by the alternative's rating for that attribute to get the partial contribution.
4. Sum the partial contributions to obtain an alternative's total score to be used for comparison.

Weighting factors for the car example.

Attributes	Relative Rank	Normalized Rank
Horsepower	7	0.16
Transmission	11	0.24
Color	1	0.02
Body style	10	0.22
Brand	8	0.18
Gas mileage	6	0.13
Dealer reputation	2	0.05
	45	1.00

Combining weights with nondimensional data for the car buying decision. Car A is now the best choice!

		Car A		Car B		Car C	
Attribute	Weight	Rate	Score	Rate	Score	Rate	Score
Horsepower	0.16	0.00	0.00	1.00	0.16	0.28	0.04
Transmission	0.24	1.00	0.24	1.00	0.24	0.00	0.00
Color	0.02	0.00	0.00	1.00	0.02	0.50	0.01
Body style	0.22	1.00	0.22	0.00	0.00	1.00	0.22
Brand	0.18	0.00	0.00	1.00	0.18	0.00	0.00
Gas mileage	0.13	1.00	0.13	0.00	0.00	0.38	0.05
Dealer rep.	0.05	1.00	0.05	0.33	0.02	0.00	0.00
Sum of score			0.64		0.62		0.32