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Abstract

Comparison of information systems by evaluation of several specified criteria is a critical and often arduous process in organizational IT. The process is often done by compilation and consolidation of utility values using weights for the criteria. There is ample room for manipulation and misrepresentation of system aspects via the use of utility values and weights. In this work simulation results are presented which show that preference aggregation methods used in Social Choice can be applied to this problem, avoiding the use of utility values and weights altogether. Instead, only ordinally scaled expert judgment along the criteria is necessary, greatly facilitating the process, while in a large majority of simulated cases arriving at the same results.

Keywords

multiple attribute decision making, information systems, social choice, voting rules, preference aggregation.

1. Introduction

Multiple attribute decision making (MADM) techniques can be observed in all major business branches, including IT (Renkema & Berghout, 1997), but also construction (Kaklauskas, Zavadskas, & Trinkunas, 2007) or healthcare (Hanmer, 1999). In such a decision making approach the decision makers seek the best alternative to maximize the achievements of a number of goals reflected by the attributes of the decision process. In general the model requires that all relevant alternatives are evaluated along all specified criteria. In the case of information systems, typical criteria are system attributes such as reliability or user friendliness; another scenario is the aggregation of expert evaluations from different departments, such as accounting, sales, and logistics.

Among other things, it is increasingly important for the evaluation process to be accountable and to allow for the recognition of all consequences of an information system selection, since the complexity and interconnectedness of such systems is steadily rising. Therefore, methods that are simple and easily explained have a distinct advantage over more complex approaches. The weighted sum method is such a simple method that is widely used for supporting decision making, especially when it comes to information systems selection (Zangemeister, 1976). For each alter-native and attribute a single value is derived, usually from expert judgements, and these values are summed up to represent the overall utility of an alternative. A weighting scheme is employed to reflect to relative importance of attributes.

The weighted sum method is deceptively simple, as the mathematics are easily implemented in a spreadsheet, and the whole process seems objective and rational. However, the method not only exposes ample opportunity for manipulation, but also puts rather high demands on experts and decision makers. In addition, important preconditions are often violated. Regularly, scale types are misused, and ordinally scaled values are used as if they were cardinally scaled. The definition of attribute weights is a major challenge for decision makers. The practicality problems can still be explained by the early works of Simon (Simon, 1977) with the concept of "bounded rationality" or the work of Lindblom who saw the decision-making as incremental, "muddling through" (Lindblom, 1959).

This article describes a social choice preference aggregation approach to the MADM problem that demands less rigorous information from the experts and decision makers, and therefore should appeal to business practitioners. Neither single-attribute value functions nor weighting of attributes are needed. The preference aggregation methods discussed here were originally developed for social choice applications, but there is a close analogy between voting and multiple criteria decision support: voters are replaced by attributes, and candidates by alternatives. Therefore, the move from voter preferences over candidates or political parties to attributes and alternatives is easily explained to business users, even if they tend to think in terms of preferences gained along a single dimension or attribute in MADM (Bouyssou et al., 2000).

In the following sections, a small number of preference aggregation methods are presented, and then applied in a simulation based on a case study with a large enterprise IT decision process. The results of weighted sum and preference aggregation are compared, and shown to be to a large extend identical where winners are concerned, while at the same time demanding much less information from experts and decision makers.

2. Rank aggregation

In the following we will formulate the decision problem in terms of preference aggregation. A set of alternatives is defined as the candidates for the IT system to be implemented. The number of alternatives m is typically small in this context; a recent study has shown it to be around three for typical system selection tasks in enterprise IT (Bernroider & Mitlöhner, 2005).

For each attribute the alternatives are put into a ranking by the experts and decision makers. In social choice this ranking is usually not allowed to contain indifferences, i.e. all preferences must be strict. In this work, as we will apply the method to data derived ex post from weighted sum values, therefore indifferences are allowed; however, there must not be any cycles in the preferences specified by the experts. A complete set of preferences for all attributes over all alternatives is called a "profile". The preference aggregation problem consists in finding an aggregate ranking that represents the individual preferences in some meaningful way, while at the same time ensuring some properties for the result, such as being free of cycles.

We state the problem in the form of a set of n attributes providing n rankings for m alternatives, resulting in a profile p, e.g., alternatives {a, b, c} and rankings {a > b > c, b > c > a, c > a > b, b > c > a}. Rank aggregation aims to find an aggregate ranking x > y > z such that the preferences stated by the attributes are somehow expressed in the aggregate ranking; e.g., a suitable aggregation from the example above is b > c > a, where alternative b is the (only) winner. In general, an aggregate ranking may contain indifferences, e.g. b > (c = a), and the winner set may contain more than one alternative, e.g. (b = c) > a. However, neither the individual input preferences nor the aggregate result may contain cycles such as a > b > c > a.

Several other demands are usually placed on aggregation rules, such as the Condorcet criterion:

if an alternative x exists that beats all other alternatives in pairwise comparisons, x is the Condorcet winner (Fishburn, 1977). An obvious demand on an aggregation rule is that it select x as a winner. Different voting rules fulfill this and other demands to differing degrees. At this point the classical theorem by Arrow (Arrow, 1963) should be mentioned which has shown that no aggregation method exists for m 3 and n 2 that always implements all of a small number of seemingly benign assumptions. However, in the context of this work we are primarily interested in comparing the results of the social choice aggregation rules to the weighted sum method, accepting that those rules fulfill certain requirements only to some degree.
Not all social choice aggregation rules can be applied to preference sets including indifferences. The following methods of rank aggregation are based on “margins”; These methods allow for resolving indifferences in a simple way. The margin of x versus y is |x > y| -| y > x| i.e. the number of rankings where x is preferred to y minus the number of rankings where y is preferred to x. We extend this definition for profiles with indifferences by excluding the indifferent voters from the count: rankings with indifference of x and y do not contribute to the margin of x versus y.

Maximin (MM): The Maximin rule scores the alternatives with the worst margin they each achieve and ranks them according to those scores.

Copeland (CO): The Copeland rule scores the alternatives with the sum over the signs of the margins they achieve and ranks them according to those scores.

Kemeny (KE): The Kemeny rule chooses the strict ordering with minimal distance to all rankings in the profile, where distance is defined as the number of different pairwise relations.

Borda (BO): The Borda rule scores the alternatives with their sums over the margins and ranks them according to those sums.

Note that all these methods can be applied to margin data alone, including Borda and Kemeny; the Borda rule is usually described by assigning decreasing points to consecutive positions, such as 2 points for first place, 1 point for second and zero for third. The alternatives are then ranked according to their total scores. It turns out that the resulting ranking is identical to the ranking based on the sums of the margins; see, e.g., (Klamler, 2005) for details.
The Kemeny rule is computationally very expensive for high numbers of alternatives; however, this is rarely a problem in MADM applications where the number of alternatives is usually small. More information on these and other commonly used voting rules and their properties can be found, e.g., in (Fishburn, 1977) and (Saari, 2001). Some observations on the proximity of the results the rules mentioned deliver can be found in (Eckert, Klamler, Mitlöhner & Schlötterer, 2006).
The simple majority rule should be mentioned as well in this context, as it is a very well-known procedure based on margins: a positive margin means that x wins against y in pairwise comparison and results in x > y in the aggregate relation, a negative margins leads to y > x, and a zero margin means indifference x = y. Unfortunately, this rule can easily result in cycles, such as x > y, y > z, z > x (drop the fourth voter from the example given at the begin of this section to arrive at a cycle). This limits the use of the simple majority rule in practical applications, and it is not applied in this work.
As the aggregation rules have been introduced, in the next section we will describe the data used

for their comparison with the weighted sum approach.

3. Case Study

This case analysis is based on a decision problem faced by an international wholesaler of liquid and gaseous fuels. For more detailed description about the company and the Enterprise Resource Planning (ERP) adoption process see (Bernroider & Stix, 2004).

The ERP decision method was a simple weighted sum approach, complemented with a separate financial analysis. The company wanted the desired system to achieve a high ERP utility score through simple additive weighting based on a number of pre-selected attributes: (1) controlling and reporting, (2) accounting, (3) logistics, (4) purchasing, (5) needs of local divisions, (6) services and engineering, (7) sales, and (8) business management. To simplify the following analysis we set all weights to one and arrive at the sums given in Table 1. Alternative B outranks its opponents whereas A and C seem to have a tie, i.e. they can be considered as almost equally good. This situation demonstrates shortcomings of the weighted sum method: the resulting utility scores are hardly interpretable and do not provide a clear-cut ranking.

For the application of social choice aggregation methods the demands placed on the data are considerably lower. No rationally scaled values are needed. Instead, only preference information must be gathered, which for our ex-post analysis were derived from the case study data. The derived rankings for the individual attributes are shown in the last column of Table 1. Then, the aggregation rules described above were applied to the derived rankings. The result for each aggregation rule is shown in Table 2.

In terms of alternative B, the application of all methods validates B as the winner i.e. as the best alternative. In terms of the remaining alternatives, C is preferable to A, except for the Maximin rule stating indifference which corresponds well to the almost identical utility values of the weighted sum method. Therefore, the social choice aggregation methods reproduce the results of the weighted sum method almost identically, while at the same time requiring much less information from the experts and decision makers, i.e. only rankings instead of rationally scaled utility values.

This case study provides us with some data for the comparison of the two approaches in a specific decision problem. However, for more general observations on the properties of social choice aggregation rules versus the weighted sum method we need more data. As large amounts of case study data from actual enterprise decision problems are hard to come by, this article explores a simulation approach: based on the case study we generate more data and simulate a much larger number of cases in the following section.

4. Simulation

With the encouraging results from the previous section we now analyse the properties of the aggregation rules over a wide array of situations by using the case study data to generate further cases.

The simplest approach is to generate random attribute values uniformly distributed over the range of minimum and maximum attribute values in the case study. This was done for a sample size of $s = 100000$; for each generated case the sum of the attribute values for each alternative was calculated, and the winner determined. In addition, from the generated attribute values the corresponding rankings were derived, and the aggregation methods were applied to arrive at aggregate rankings, as in the case study in the previous section.

In the simulation the number of attributes was set to 8 as in the case study, and the number of alternatives was set to 3. Both values fall within the typical range found in ERP selection problems in an empirical study of medium and large scale enterprises (Bernroider & Mitlöhner, 2005).

The obvious question to ask is how often the winning alternatives differ for the individual methods. Table 3 shows the fraction of simulation cases where the two respective methods return different winning alternatives, e.g., the Borda rule winner and the weighted sum (WS) winner are different in only about 27% of the cases. In other words, in about 73% of the cases the Borda rule arrived at the same winner as the weighted sum method, while only requiring ordinally scaled data, i.e. rankings of alternatives, instead of utility values.

The Kemeny method fares almost as well; however, the algorithm is harder to explain to business users than the Borda count, and it is significantly more difficult to implement; prohibitively so with typical user tools such as spreadsheets, while the Borda count can be implemented easily with a spreadsheet. The Copeland and Maximin rules deliver different results from the weighted sum method much more often than Borda and Kemeny.

For those cases where the weighted sum method and the respective aggregation rule did not produce the same winner it is interesting to note by how much the results differ. Table 4 shows the distance of the results produced by the two respective methods. The distance is measured by the number of switches necessary to make the winner of one ranking into a winner in the other ranking. The distances in the last column of Table 4 are very close to one, meaning that very few social choice rule results are more than one switch apart from the weighted sum results.

Note that distances below one occur when there is more than one winner, e.g. when rule i produces the ranking (A = B) > C and rule j produces A > B > C. In these cases, moving B out of the winner set counts as 0.5 switches. With the exception of the Kemeny rule all aggregation rules described in this work can produce indifferences, and of course they may also occur in the result of the weighted sum method. Rankings with indifferences are by definition never produced by the Kemeny rule, which corresponds to the fact that its result distance is higher than the rest. Further data on result distances in various simulation settings and for an additional number of well-known social choice aggregation rules can be found in (Eckert et al., 2006).

5. Conclusion

The main point of the approach presented in this work is the lower amount of information necessary to be compiled from the experts and decision makers when using social choice aggregation rules, compared to the weighted sum method. Ranking alternatives is much easier than specifying rationally scaled utility values. The fact that no weighting scheme has to be defined further facilitates the process. The many mistakes caused by the bounded rationality and muddling through phenomena observed in complex human decision making, more specifically for the MADM setting, e.g., misused scales, invalid scale transformations, or even manipulated attribute weights, can be avoided by the application of simple social choice approaches to IS decisions while providing results that are transparent and similar to the MADM approach. The case study and the simulation results show that the margin-based social choice aggregation rules correspond well to the results of the weighted sum method. In the case study the distinctive winner of the weighted sum method was ranked first in all social choice rules, and a tie between the two other alternatives was identified with one rule. The simulation data further showed that in about 73% of the simulated cases the winners of the social choice rules and the weighted sum method were identical, and in the remaining cases the distance of the results measured by the number of switches was near to one, i.e. the winner of one method was rarely ever more than one place down in the ranking of the respective other method.

Attribute	A	B	C	Ranking
Controlling and Reporting	13	15	14	B > C > A
Accounting	14	21	16	B > C > A
Logistics	9	6	6	A > B = C
Purchasing	8	7	5	A > B > C
Local Divisions	12	13	9	B > A > C
Services and Engineering	15	18	18	B = C > A
Sales	24	25	27	C > B > A
Management	13	16	14	B > C > A
Total	108	**121**	109	

Table 1: Utility values for the three investment alternatives in the case study and rankings corresponding to individual attributes. The total scores correspond to the ranking B>C>A.

Rule	Ranking
SM	B > C > A
BO	B > C > A
CO	B > C > A
MM	B > C = A
KE	B > C > A

Table 2: Results of different aggregation methods to case study data.

	BO	CO	MM	KE	WS
BO	0.000	0.157	0.254	0.204	0.272
CO	0.157	0.000	0.113	0.219	0.332
MM	0.254	0.113	0.000	0.264	0.391
KE	0.204	0.219	0.264	0.000	0.278
WS	0.272	0.332	0.391	0.278	0.000

Table 3: Fraction of cases with different winning alternatives

	BO	CO	MM	KE	WS
BO	0.000	0.602	0.524	0.860	1.003
CO	0.602	0.000	0.555	0.732	0.914
MM	0.524	0.555	0.000	0.623	0.842
KE	0.860	0.732	0.623	0.000	1.144
WS	1.003	0.914	0.842	1.144	0.000

Table 4: Distance of results for cases with different winners

Comparing various social choice aggregation rules in terms of the proximity of their results to the weighted sum method in the setting described, the Borda rule emerges as delivering the closest results; in terms of method usability it is also easily explained and can be implemented with little effort in commonly used decision support tools. Future work will concentrate on the acquisition of more case study data and subsequent simulation, as well as practical application and user feedback for the social choice aggregation methods in enterprise decision processes.

References

Arrow, K. (1963). *Social Choice and Individual Values, 2nd ed*., New York: Wiley.

Bernroider, E. and J. Mitlöhner (2005). "Characteristics of the Multiple Attribute Decision Making Methodology in Enterprise Resource Planning Software Decisions", *Communications of the International Information Management Association (CIIMA),* 5, pp. 49-58.

Bernroider, E. and V. Stix (2004). "Enrichment of a Utility Ranking Method using Data Envelopment Analysis – a Case Study of an ERP selection problem", in *Proceedings of IRMA 2004,* pp. 292–295.

Bouyssou, D., Marchant, T., Pirlot, M., Perny, P., Tsoukias, A. and P. Vincke (2000). *Evaluation and Decision Models – a critical Perspective,* Boston: Kluwer Academic Publishers.

Eckert, D., Klamler, C., Mitlöhner, J. and C. Schlötterer (2006). "A Distance-based Comparison of Basic Voting Rules", *Central European Journal of Operations Research,* 14(4), pp. 377-386.

Fishburn, P. C. (1977). "Condorcet Social Choice Functions", *SIAM Journal of Applied Mathematics,* 33, pp. 469-489.

Hanmer, L. (1999). "Criteria for the Evaluation of District Health Information Systems", *International Journal of Medical Informatics,* 56, pp. 161–168.

Kaklauskas, A., Zavadskas, E. and V. Trinkunas (2007). "A Multiple Criteria Decision Support On-line System for Construction", *Engineering Applications of Artificial Intelligence,* 20(2), pp. 163–175.

Klamler, C. (2005). "Borda and Condorcet: Some Distance Results", *Theory and Decision,* 59(2), pp. 97-109.

Lindblom, C. (1959). "The Science of Muddling Through", *Public Administration Review,* 19, pp. 79-88.

Renkema, T. and E. Berghout (1997). "Methodologies for Information Systems Investment Evaluation at the Proposal Stage: a Comparative Review", *Information and Software Technology,* 39, pp. 1–13.

Saari, D. (2001). *Decisions and elections - Explaining the Unexpected,* Cambridge, UK: Cambridge University Press.

Simon, H. (1977). *The new Science of Management Decision,* Englewood Cliffs, NJ: Prentice-Hall.

Zangemeister, C. (1976). *Nutzwertanalyse in der Systemtechnik,* Munich: Wittemann.