A decision aid for finding performance groups.

1. Introduction

Performance improvement requires the identification of groups of organisations with which comparisons may be made and from which lessons may be learned. The focus may be strategic or tactical. For the first, strategic group analysis proposes that similarly structured organizations will have similar levels of performance and so identifying which strategic group we belong to and which it may be profitable to join helps in deciding business strategy. For tactical improvements it is useful to consider performance directly and, again, identify those organizations with similar performance and those others which may be useful comparators. At a more detailed level, particular business functions may be identified in quite different organizations and those working practices imported.

This article is concerned with identifying *performance groups* (Wiggins and Ruefli, 1995), groups of organizations with similar levels of performance. This apparently simple task is made difficult because it is usually not easy to say what is meant either by "similar" or by "group". Managers may have firmly held beliefs about groups of organizations which characterise their business sector, but how reliable are these necessarily subjective views? On the other hand, strategy analysts use quantitative models in an attempt both at objectivity and comprehensiveness, but does the abstraction of the model aid or impede interpretation of the results? Neither extreme – reliance just on quantitative analysis or just on judgement – seems satisfactory. Combining both in a way which supports a decision about group membership is more helpful.

For this to work the measures of similarity and definitions of group need to be expressed as simply as possible: it is unreasonable to expect judgements to be made using results which are imperfectly understood. Finding the right balance between data, model and judgement is an important part of any analytical task (Phillips, 1984). This article describes a model which balances what is judged and what is calculated in a way different to that usual in performance analysis. It requires careful thought about definitions but offers a corresponding gain in clarity of interpretation.

The airport business is an area in which comparative performance assessment is particularly useful. Changes in ownership from government and municipality to the private sector have meant that both airport owners and regulators have an interest in finding performance groups of airports for benchmarking. In this article the proposed method is used to identify performance groups among a sample of international airports.

In the rest of this article a method will be described which supports judgements which airport managers may make about performance group structure. As illustration the method is applied to a set of international airports.

2. Airport performance

The ownership and management of airports has undergone significant changes with privatisation and deregulation leading to a more commercial orientation (Jarach, 2001; Starkie, 2002; Graham, 2003) and the consolidation of ownership. Rather than being seen as facilities run by and for a community airports are increasingly privately owned utilities, the expectation being that this new form leads to increased efficiency, though evidence as to whether this has happened is equivocal (Oum *et al*., 2006). In this new environment there has been a move from measuring just operational performance to considering financial and commercial performance and, in some cases, environmental factors too (Humphreys and Francis, 2002).

These performance comparisons are needed for one or more of three reasons: in an airport group it is natural to wish to compare the performance of the airports in the group; in a regulated system

(which most are) the regulator will wish to assess the performance of airports when making decisions about pricing regimes; airports may, in any case, wish to benchmark as part of their performance management as do the FLAP airports (Frankfurt, London, Amsterdam, Paris) who cooperate to exchange information for their mutual benefit.

It may not always be clear just which other airports should be included in a comparator set and so some method of finding appropriate reference groups is needed. There are two broad approaches to organizational grouping: strategic groups and performance groups. Both have as their purpose the definition of groups of organizations either so that an organization may compare itself with its peers or so that an organization may identify a different organizational form which it wishes to emulate.

Strategic groups are based on the proposition that "within an industry firms with similar asset configurations will pursue similar competitive strategies with similar performance results" (Thomas and Pollock, 1999). The motivation is to find groups of similar structure with the expectation that they also have similar performance, although the evidence for this is not always clear (Cool and Schendel, 1988). Strategic groups may act as reference groups so that "a particular firm benchmarks those firms within the same strategic group, as well as targeting positions in competitive space occupied by other strategic groups…" (Feigenbaum and Thomas, 1995). A more direct approach is to find *performance groups* (Wiggins and Ruefli, 1995) whose members have similar performance levels. In both cases cluster analysis is the most often used methodology.

In airport performance analysis current practice (Francis *et* al., 2002; Graham, 2005; Mackenzie-Williams, 2005) uses a number of methods of which Data Envelopment Analysis (DEA) is popular (Gillen and Lall, 1997; Pels *et al*., 2003). DEA finds for each airport an efficiency measure which is the ratio of the weighted sum of outputs to the weighted sum of inputs. DEA outputs and inputs are defined by the analyst or manager. Weights are found for each airport which maximise its own efficiency. Each airport has its own set of weights.

Airports may be compared not just by a league table of efficiencies but also by identifying airports with similar profiles but different efficiencies so that the less efficient may learn from the more efficient (though it has to be said that in much published work it is the league table which is predominant). Sarkis and Talluri (2004) use a cluster analysis based on cross-efficiencies (Doyle and Green, 1994) as a way of finding groups for benchmarking.

Because efficiency maximising weights are found unique to each airport, the frequent result is that a large number of the airports studied have perfect or very high efficiencies. Table 1 shows distributions of DEA efficiencies found in some published papers. This is in no sense a systematically chosen set but serves to illustrate the point. A quarter of airports are less than 50% efficient. The median efficiency is 78%. About one third are perfectly efficient, which seems implausibly high. This is unhelpful for any sort of benchmarking but is always likely to occur if no restrictions are put on weights.

Since there is no need exogenously to specify values for DEA weights there is no opportunity to take a view of the relative importance of the different inputs and outputs. This is seen as beneficial in that the results can be presented as objective. On the other hand, it may well be that for the analyst or manager it is entirely reasonable to describe the purpose of the analysis *from their point of view* by expressing their judgements through specified weights, or weight restrictions.

So, although the apparent objectivity and the use of a single performance measure, the DEA efficiency, have an appeal they may also limit the usefulness of the method by producing results which may be hard to interpret and apply (Schefczyk, 1993).

It is likely that in characterising performance and in implementing and monitoring improvements managers will more naturally favour a number of performance ratios (as with key performance indicators) rather than one overall efficiency. This multiattribute approach is the basis for both

aggregation into an overall measure and for the cluster analyses used in strategic and performance group analyses. The differences between DEA and multiattribute approaches may, in any case, not be as great as at first appears (Thanasoulis *et al*., 1996; Stewart, 2010).

Both to allow the articulation of a point of view and because managers are likely to find performance ratios more useful than a single efficiency, a multiattribute clustering approach is preferred. The method has two important characteristics. First, the specification of similar groups is made using simple ideas which are easily understood. Second, a number of equally good sets of performance groups are found so that final selection is left with the manager or analyst. This second point is in recognition that alternative groupings may be possible but that conventional clustering methods do not allow their identification. The purpose of the method is to provide an aid for decision rather than to produce a single best result.

3. Performance measures

Measures are chosen which reflect the point of view of the analyst or manager (provided the data are available). These measures are not necessarily the key performance indicators used by each airport to monitor its performance against its own strategic and operational objectives, for these objectives are not necessarily the same for each airport and they may not, in any case, be made public. In using readily available measures for inputs and outputs there is always the well-known possibility that what is achieved is not what was intended (Mintzberg, 1978) so that a spurious attribution of efficiency in performance may be made. This difficulty does not depend on the method of analysis.

For this illustrative analysis five measures are used.

Airport revenues are mainly from two sources; charges for the use of the airport by aircraft (landing and passenger fees) and commercial revenues, mainly from concessions and rents. The first is a result of air traffic movements (atms) and the latter of passenger volumes and so two obvious measures of income generation are aeronautical revenue/atms and commercial revenue/passengers.

The proportion of revenues from each source is a measure of how successful the airport has been in diversifying its income streams (Oum *et al*., 2006). The percentage of revenue derived from aeronautical charges is a third measure.

Aggregate output is a combination of the number of passengers and the amount of freight using the airport. The work load unit (wlu, equivalent to one passenger or 100kg of freight) describes this aggregate. The efficiency with which resources are used is measured by the ratios wlu/employees and wlu/assets.

For this analysis, then, the five performance measures are

aeronautical revenue/atms
commercial revenue/passengers
percentage of revenue derived from aeronautical charges
wlu/employees
wlu/assets

Data are taken from a study by Transport Research Laboratory (Mackenzie-Williams, 2006) which examined the performance of thirty five airports (Table 2) and fourteen airport groups. The data are adjusted to account for different operational and accounting practices in ways described in the report and by Mackenzie-Williams (2005). For this article single airports only are considered.

4. Similarity

Each airport is described by the five performance measures. There are two ways to describe the difference between two airports. The most usual is to scale each measure to a common base (so that all values are between 0 and 1, for instance) and then, for any pair, to find some measure which combines in one value the difference or distance between the two. For instance, in the same way that we measure the distance between pairs of points on a map and find the same distance between points even though the orientation of the difference may be quite different for each pair, so we may decide that different pairs of airports are about equally similar even though the constituent differences on the five measures are quite different. Using weights for each attribute modifies this effect, the weights expressing a view about the relative importance of each measure from the viewpoint of the analyst or manager. But just what does this overall dissimilarity mean? While it permits a ranking it is hard to interpret in any other way.

The alternative approach is to disaggregate the idea of similarity so that at each stage it is possible to say in a very straightforward way just what we mean. This simple idea is more commonly found in rule-based methods for interrogating databases (e.g. Kolodner, 1993, Ch. 9) but is used here to describe differences between pairs rather than similarity to an archetype.

And so, airports may be judged to be similar or not at three levels:

attribute similarity	for any two airports and any one measure are the values for the two airports similar (close) or not?
item similarity	are two airports (items) similar overall, taking account of all attributes?
group similarity	how may we decide that a number of airports are sufficiently similar that they may constitute a group?

Attribute similarity

Take a view for each measure in turn about just what is meant by similar. For example, we may wish to take as similar only airports of roughly the same size and so decide that for two airports to be similar the total passenger throughput should not differ by more than ten percent. The tightness of these critical differences plays a role analogous to weights in expressing just how critical a measure is in deciding similarity — if size were less important critical differences could be set at, say, twenty percent.

Item similarity

The simplest rule is to say that only those airports similar on all attributes are similar overall. This rule is strictly non-compensatory: airports must be similar on all counts, a large difference in one cannot be compensated by a small difference in another, as with a simple summation.

Rules may be less strict, allowing some flexibility of definition. An easy variation is to say that airports are similar if they are similar on at least, say, three of the five measures.

Group similarity

It is intuitively appealing to say that all airports in a group must be similar to each other and that an airport may appear in only one group. Such independent groups are called *cliques*. Cliques in which all airports are similar are maximally connected cliques, an idea familiar from social network analysis (e.g. Wasserman and Faust, 1997, Ch. 10) and elsewhere. The motivation for this strict requirement is the same as that for using complete linkage groups in cluster analysis.

Again, alternative rules are possible which relax the maximum density constraint. They are not used here.

5. Finding groups

In strategic and performance group analyses, the most frequently used model for finding groups is hierarchical cluster analysis. A measure of inter-group dissimilarity is chosen and then organisations are grouped, starting with each organisation as its own group of size one, then amalgamating the most similar pair and continuing in this way until there is just one group containing all organisations. The number of subjective judgements needed when making a cluster analysis is well known (McKelvey, 1982; Ulrich and McKelvey, 1990) and a number of recommendations have been made to help ensure a reliable result (Ketchen and Shook, 1996).

A tree diagram shows the inter-group dissimilarity at each amalgamation. By examining this pattern of group formation it is hoped to find some discontinuity, a natural break, beyond which the dissimilarity of amalgamated groups noticeably increases. This break simultaneously determines the number of groups and the threshold dissimilarity (Figure 1(a)). The judgement is made on the basis of a pattern of agglomerations rather than explicitly on the degree of similarity within and between groups. In this way it is unnecessary to think just what similarity means, just that it is the basis of some ranking or patterning (Li, 2006). This leads to the criticism that by this method groups will always be found and are just tautological artefacts of the analysis (Barney and Hoskisson, 1990). One reaction to this discomfort is to form groups on the basis of management judgement alone (Reger and Huff, 1993), a strategy which seems to be about as popular as quantitative modelling (Day *et al*., 1995), though with its own difficulties of making well-founded judgements.

Setting a threshold similarity in advance of group formation, rather than as a reaction to the pattern of agglomeration, answers the criticism of tautology. Depending on the threshold there may be many small groups or a few large groups. But it may be harder to set a threshold the more abstract the measure of similarity. This argues in favour of simple rules for attribute and item similarity rather than, for instance, distance measures common in cluster analysis. These simpler rules are used here.

Finding groups is greatly simplified if the number of groups can be specified in advance (the *k* means method). Each organization is then allocated to one of the *k* groups so that some error term is minimised. The number of groups, *k*, may be specified by appeal to some theory, such as that of Porter (Dess and Davis, 1980), or by rules of thumb (Chang *et al*., 2003), or by simply trying a number of values for *k* and choosing what looks to be the best, according either to some statistical measure or theoretical construct or by a narrative discussion involving both (Buysse and Verbeke, 2003). While finding *k* by invoking some theoretical argument is attractive it may be hard to sustain. In the absence of any other criterion, economy of description favours minimising *k*, given rules for group membership.

There are likely to be many sets of *k* feasible groups (partitions). To list them all may not be possible but, even if it is, there may be just too many to be considered, in which case it makes sense to pick those partitions which favour large groups, since this most clearly reveals the structure inherent in the data: if there are large groups of similar airports we want to identify them. We do this by maximising the sum of squared group sizes, *S*, (Simpson, 1949), a measure also used for the Herfindahl-Hirschman index of industrial concentration (Hirschman, 1964).

The model (Figure 1(b)) is a four-stage optimisation (Jessop, 2009; Jessop *et al*, 2007):

step 1	enumerate all feasible cliques
step 2	find the minimum number of cliques
step 3	find a partition for which *S* is a maximum
step 4	list all other partitions with this maximum *S*

The result is a number of partitions, solutions to the grouping problem, which are known to be equivalently optimal. One of these candidates may be chosen or some modification made using those judgemental considerations not part of the formal model.

6. Mathematical model

Candidate cliques can in principle be found by enumeration. In general, the full enumeration of all combinations is practicable only for small problems. Fortunately, by applying criteria for group membership the number of possible combinations is much reduced and enumeration is feasible for a usefully large class of problems. The results of the enumeration are stored as a matrix with elements $x_{ij} = 1$ if airport j is in clique i and 0 otherwise. The value of the squared clique size, s_i, is also stored.

An integer linear program (ILP) selects which of the enumerated cliques are chosen. The indicator $\lambda_i = 1$ if clique i is chosen and 0 if not. The number of groups, n, is $\sum_i \lambda_i$ and so the ILP to find the minimum number of groups is

$$\begin{aligned} \min \quad & \textstyle\sum_i \lambda_i = n_{min} \\ \text{s.t.} \quad & \textstyle\sum_i x_{ij}\lambda_i = 1 \quad ; \forall j \end{aligned}$$

The constraint ensures that each airport appears in only one clique. Candidate cliques are then found by solving a second ILP:

$$\begin{aligned} \max \quad & S = \textstyle\sum_i \lambda_i s_i \\ \text{s.t.} \quad & \textstyle\sum_i x_{ij}\lambda^k_i = 1 \quad ; \forall j \\ & \textstyle\sum_i \lambda^k_i = n_{min} \\ & \textstyle\sum_i \lambda^k_i \lambda^a_i < n_{min} \; ; \; a = 1 \ldots k\text{-}1 \; ; \; k > 1 \end{aligned}$$

Here the membership vector is modified to describe a series of solutions, so that $\lambda^k_i = 1$ if group i is part of the kth solution. The first solution found is k=1, the second k=2 and so on. The third constraint ensures that new solutions are different from previous solutions. Solving this model gives, initially, alternative optimal partitions (the same value for S) and then, if required, increasingly suboptimal solutions.

7. Application

To see how the method works decide, first, the similarities:

attribute similarity	similar if different by no more than ten percent of the range of the variable
item similarity	similar on three or more of the five attributes
group similarity	maximum density cliques

The attribute similarity is defined in terms of the range of values in the data. This sort of rule may be useful when the units of measurement – ratios in this case – are not that easy to interpret in an absolute sense.

Of all airport pairs, 28% are similar.

Using the optimisations, there is a minimum of twelve groups (k = 12) and sixteen optimal partitions which are presented as the base for a final decision about groups.

The purpose of the model is to recognise ambiguity by requiring explicit consideration of all sixteen candidate solutions. This would be difficult if all were completely different, but they are not: 23 of the 35 airports appear in exactly the same five groups (the largest) in all sixteen optimal solutions:

Group 1.	MIA,SFO,MAN,OSL,ZRH,MUN,LGW,ATH
Group 2.	CPH,BHX,VIE,CPT,JNB
Group 3.	STO,VAN,CHI,CAL
Group 4.	IAD,DCA,ONT
Group 5.	GVA,FRA,PEK

These are the core of the result.

Of the remaining twelve airports, nine are either Australian or North American. Figure 2 shows the resulting combinations, shown in square brackets. So, for example, the group of three airports [AKL,PER,SYD] is common to eight of the candidates. The first partition (the top line of the diagram) has the following groups, as well as the core:

Group 6.	AKL,PER,SYD
Group 7.	BNE,MEL
Group 8.	LAX
Group 9.	DFW,ATL
Group 10.	TOR
Group 11.	HKG,SIN
Group 12.	LHR

In this configuration the Australian, American and Canadian airports are distinct; a reasonable interpretation indicating similar regulatory and operational regimes. Candidate solution 2 does this too.

In the same way, it makes sense to group the two Far East airports and leave Heathrow as a singleton. And so candidate solution 1 is chosen.

Other interpretations may be possible which argue for a different configuration, or which retain some ambiguity in the conclusion of the analysis.

The number of groups is fixed at twelve. This follows from two decisions. First, no minimum group size is specified and so singletons and pairs are acceptable, which is reasonable enough: some organisations may just be different from all or most others. Second, the requirement that groups must be cliques necessarily restricts group size and correspondingly increases their number. Some amalgamation of groups may be justifiable and to help this decision Figure 3 shows the partition described above (the first line of Figure 2). Off-diagonal similarities give an indication of where an airport, or airports, might plausibly be linked in a different grouping. The inter-group densities show the degree to which groups overlap. For example, there is a 58% overlap between the first two groups; perhaps they may be considered together in a narrative based on these results.

8. Discussion

A decision aid has been used which gives groups of similarly performing airports. The purpose of this analysis is not to produce a single solution but rather a number of candidate solutions with known optimal properties, to be interpreted by the analyst or manager. The motivation for this approach is to recognise the ambiguity of analysis and the necessary interplay between calculation and judgement.

The criteria which determine groups are expressed in the language of performance measures which are in common use. This retains a clear meaning so as to help the interpretation of the results. The necessary price of intelligible results is paid in the extra effort of definition of the various aspects of similarity.

In the application sixteen alternative partitions were found. Each contained twelve groups. Two thirds of the airports, in five core groups, appeared in all solutions and so it can be fairly said that these groups are a robust result of the analysis. The remaining airports were plausibly assigned on the basis of country of jurisdiction and so were defensible on these interpretative grounds. Different judgements — different points of view — may have led to a preference for a different grouping to be defended and debated. This illustrates how the model respects the possibility of ambiguous recommendation by providing space for interpretation by the users of the analysis.

It is the role of the model reliably to provide this short list. For the same input data the same list will be produced. As with any analysis, if different data are provided – different performance indicators, say – then differeent results will be obtained. This is one aspect of user choice and will reflect the strategic purpose of the organisation making the analysis (as well as the availability of data). The second aspect of choice comes in the interpretation and selection from the short list. The argument in this article is that this is rightly left for the user who can be sure that the model has provided a set of alternatives all of which have the same optimal properties. In the illustration a final selection was made plausibly based on geographic jurisdictions but there may be other criteria (though none were obvious here). All this is as it should be and the differences would be the basis for debate. The benefit of the the method is that it is makes explicit that which is reliably computed and that which remains open to interpretation.

It may be, of course, that different definitions of the various aspects of similarity might give different results. Recalculating the model is straightforward. The criteria of optimality are unchanged so that altered results are entirely the result of altered ideas of similarity.

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9. References

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source of analysis	n	percentage DEA efficiency								
		0-30	30-40	40-50	50-60	60-70	70-80	80-90	90-99	99-100
Pels, Nijkamp and Rietveld (2003)	34		3	3	12	12	12	9	3	47
Yoshida and Fujimoto (2004)	67	6	19	13	16	12	3	3	3	24
Sarkis and Talluri (2004)	43		7	23	16	9	7	12	7	19
Pacheo and Fernandes (2003)	30	20	7	7	3	10	3	10	3	37
Pels, Nijkamp and Rietveld (2001)	34	9	12	18	6	12	24	15	3	3
Barros and Dieke (2007)	34	3			3		6		9	79
Curi, Gitto and Mancuso (2010)	31			3			3	16	26	52
Martin and Román (2001)	37	11	16	14	11	8	14	5		22
Yu (2004)	14	21			29		7	14	14	14
all	324	6	9	10	10	8	8	8	6	32

Table 1. Distribution of DEA efficiencies from 9 analyses of n airports.
For each paper, the first listed results are taken as a sample.
Figures in the table are percentage distribution of DEA values.

Location	Airport	Code
United States	Atlanta	ATL
	Dallas Fort Worth	DFW
	Chicago O'Hare	CHI
	Washington National	DCA
	Washington Dulles	IAD
	Los Angeles	LAX
	Miami	MIA
	San Francisco	SFO
Canada	Calgary	CAL
	Ontario	ONT
	Toronto	TOR
	Vancouver	VAN
UK	Birmingham	BHX
	London-Gatwick	LGW
	London-Heathrow	LHR
	Manchester	MAN
Europe	Athens	ATH
	Copenhagen	CPH
	Frankfurt	FRA
	Geneva	GVA
	Munich	MUN
	Oslo	OSL
	Stockholm	STO
	Vienna	VIE
	Zurich	ZRH
Australia	Auckland	AKL
	Brisbane	BNE
	Melbourne	MEL
	Perth	PER
	Sydney	SYD
South Africa	Cape Town	CPT
	Johannesburg	JNB
Far East	Beijing	PEK
	Hong Kong	HKG
	Singapore	SIN

Table 2. Airports used in the analysis.

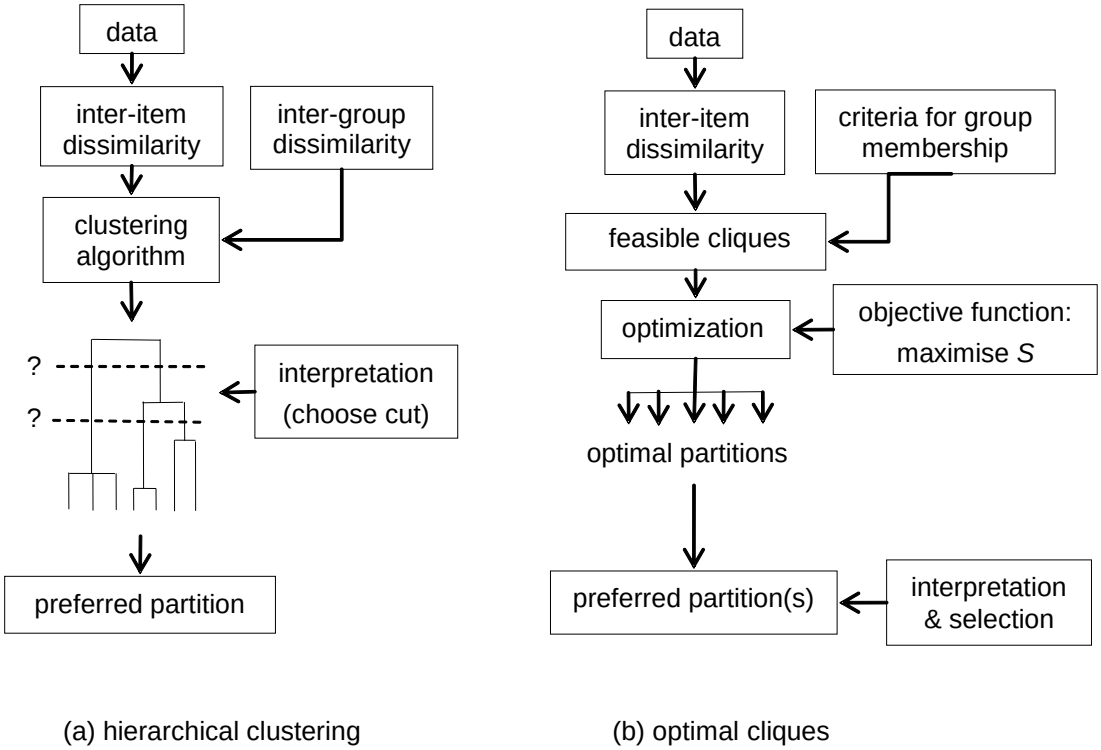

Figure 1. Comparison of hierarchical cluster analysis and the optimization method.

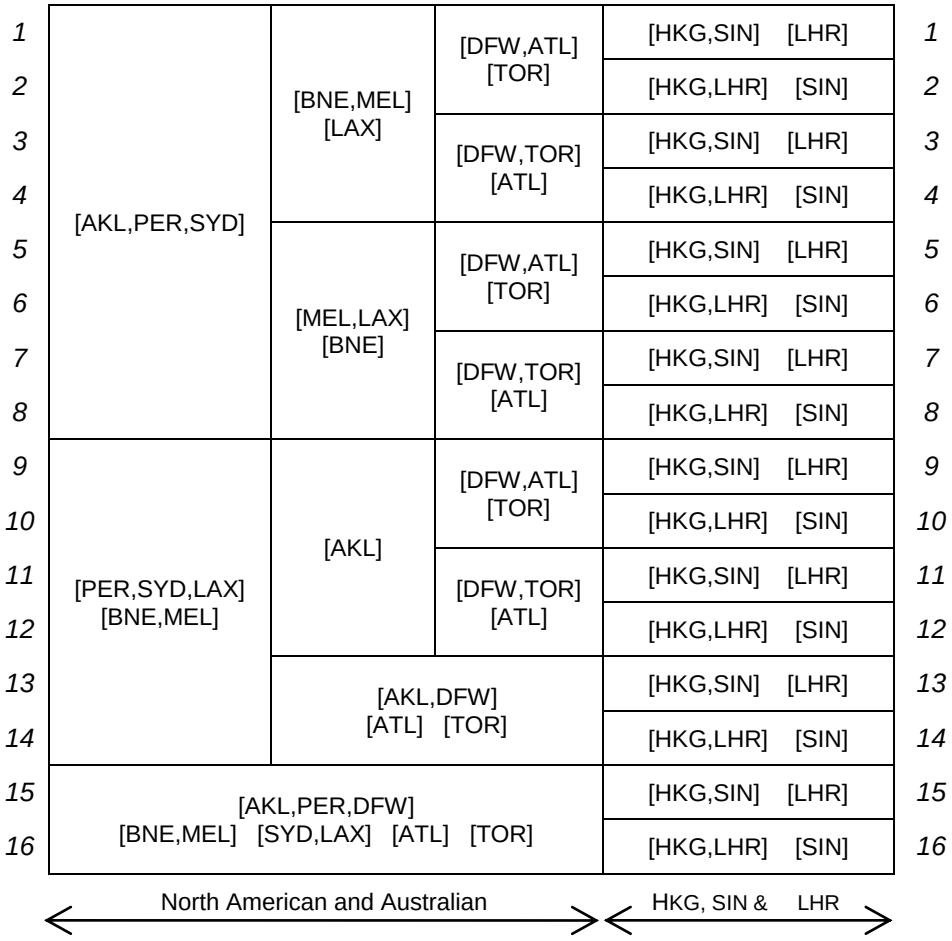

Figure 2. 16 optimal groupings for twelve airports

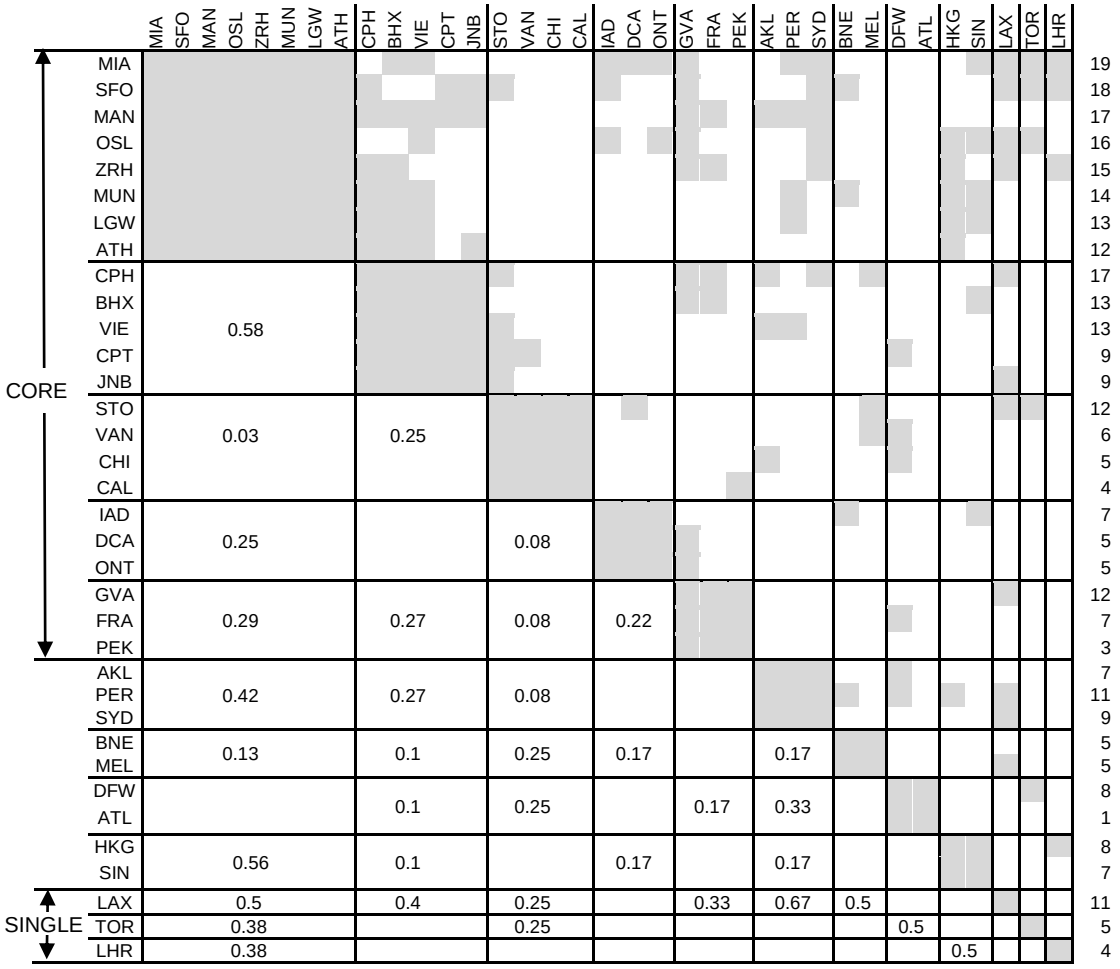

Figure 3. Shaded squares show pairs of similar airports.
Those on the diagonal show the groups in the partition.
Those above the diagonal show inter-group interactions.
Values in cells below the diagonal show inter-group densities greater than zero.
Figures at right show, for each airport, the number of other airports with similar performance.