"Garbage in – Garbage out"

(A word of wisdom or a bad excuse)

Logistic Support and Spares Analysis with Rough Data

M.Sc. Tor G. Isdal   Systecon AB
Prof.   Olof Wååk   Systecon AB/Swedish National Defence College

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0. SUMMARY

The world of logistics is changing. We see changes in customer behaviour in such a way that outsourcing of maintenance and logistics support put new requirements on contractors. We see changes put forward by the exploding availability of computer power thus permitting new analysis and optimisation possibilities as well as new more advanced support systems.

This put even stronger requirements on early analysis - Front End Analysis (FEA) – both of the Technical System as well as the Logistics Support System. It is well known that in order to have impact on the results of the analysis, the corresponding demand for changes must come very early in the process. This in turn puts forward requirements on the ability to work with uncertain, approximate data for two reasons. One reason is that organisations that previously not have been used to deliver various data necessary for Logistics related analysis now have to chase this information. Another reason is the constantly ongoing struggle within organisations used to FEA to be even quicker out of the starting blocks.

This paper studies various methods to handle such approximate data and the magnitude of the inaccuracy in doing so.

The conclusion – supported by cases and computer simulations – is that the inaccuracy generated by inaccurate or approximated data is surprisingly small, in particular when viewed in relation to other uncertainties. The value of achieving the results early, by far outweighs the drawbacks of minor inaccuracies and hence - "Garbage in – Garbage out" is indeed a very poor excuse for delaying various forms of Logistics oriented analyses.

1. BACKGROUND

1.1 Changes in customer behaviour

Within the world of Maintenance and Logistics Support we are witnessing a change in the customer behaviour. There is a strong trend to outsource Maintenance and Logistics Support. The customers wish to concentrate on their core business, airlines concentrate on the traffic, not on maintaining and supporting aircraft. So are the military. The phenomena is known under various names like "Power by the hour", "Gasoline Station in the Sky" etc.
This will put new requirements on the contractors.

1.2 Changes in requirements on and incentives for the contractors

In this new environment the contractors faces new challenges.
They have to be:

a) Skilled in the art of designing for low Life Cycle Cost
b) Skilled in organising the overall Maintenance and Logistics Support
c) Skilled in the detailed Maintenance and Logistics Support

Normally contractors are good in performance under c). This of course is not surprising – after all the designed and built the equipment. Many contractors however are not skilled in activities under a) and b). This has been shown in many case – see for example in Ref. [PaW 82]; [Wal92]; [Waa98] – This sad fact has been recognised by many contractors and they are rapidly improving their skills.

When doing so they are faced with a well-known dilemma:

- In order to have effective influence on the equipment design the analysis must be made early in the development process
- But - Good (or precise) data are not available until late in the process

This dilemma has shown itself to frequently be an effective block against doing analysis. The phrase "Garbage in – Garbage out" is used as an excuse for delaying the analysis – and consequently the opportunities for design improvements are lost.

1.3 Data accuracy

When talking about "data" the focus in this paper mainly is on failure rates or rather demand rates but also on other data, like unit prices of LRUs (LRU = Line Replaceable Unit) and other items. As will be illustrated in the next chapter the spares optimisation is a key activity the combines Systems Analysis and Logistics Support Analysis. In order to perform a Spares Optimisation a System Baseline as well as a Logistics Support Organisation baseline is necessary (see also Ref. [Waa99]. A key element here – probably the element that most analysts regard as the most uncertain – is the demand rate of LRU and other primary spare items.

When understanding the accuracy of demand rates we have to look at various phases of the system development. First a clarification – the term "predicted failure rates" or "predicted demand rates" refer to prediction in accordance with some standard method e.g. MIL-Std 217 etc. When performing such prediction the design of the item to be predicted must be known in some detail.

Early analysis:
The design is not known to such a degree that the predicted data are available. Consequently some other methods must be used (see ref. [Waa99].

Later analysis:
Predicted data are available.

Operational phase:
Field data become available and can complement/replace the predicted data.

Some comments should be made with respect to the accuracy of predicted data. The accuracy actually is rather poor.

To illustrate we can look at the following example taken from [Cho96]. It concerns 9 items (LRUs) in a manpack radio and the estimation of mean time between failure/demand.

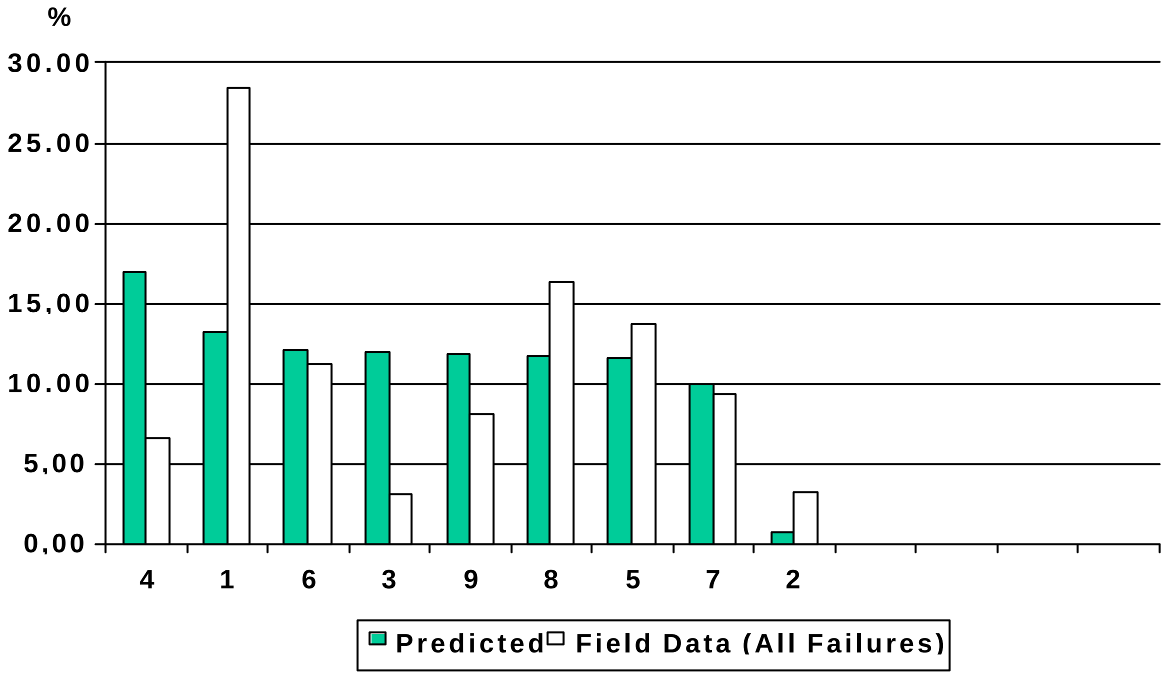


Figure 1: Relative contribution to MTBF – predicted values and field data

Figure 1 shows the relative contribution to system MTBF from the different items. As indicated, the relative contribution changed drastically once actual field data could be collected. Furthermore, the absolute value of system MTBF changed by almost a factor 2. A predicted MTBF of 2114 hours was given, while field data showed a mean of 2402 hours. However, as much as 38 percent of all reported demand could be assigned to the "no fault found" (NFF) category; that is, items were reported as faulty but when thoroughly scrutinised no fault could be found. Hence, the intrinsic system MTBF was 3876 hours according to field data.
The above example illustrates the difficulty to correctly estimate the mean demand. The predictions were made by a major, capable electronics company using state-of-the-art methods. It simply (and unfortunately) reflects the status of accuracy of failure rate predictions.

What can be stated about the accuracy of the field data? Aside from all the well known problems of missing reports, misinterpreted reports we also have the problem of changes in the environment, operational scenario, system modifications – in fact, nothing is constant (see ref. [Isd99]).

Conclusion: Failure rate/demand rates data will never be really accurate or precise.

2. LAY-OUT OF THE STUDY

2.1 Scope Of The Study

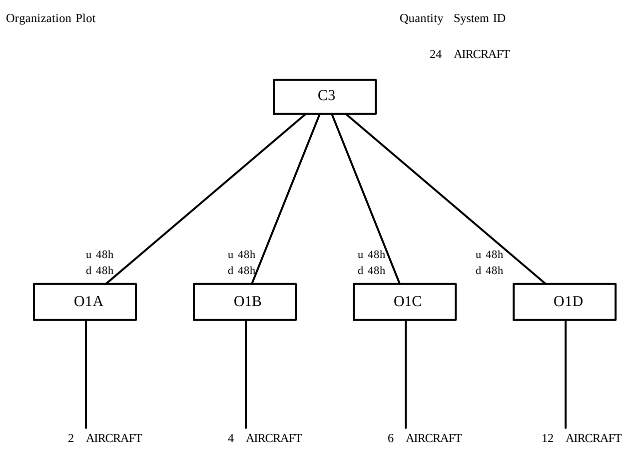
The scope of the study is to compare the results from spares calculations with accurate data vs rough approximate data. The calculations are performed both with spares optimising methods as well as with a slightly modified Item-by-Item method. The calculations are performed with two different support organisations.

2.2 Logistics Support Organisation

Two different organisations are used in the study:

1 echelon or storage level
3 non-symmetrical echelons or storage levels

The LSO:s are shown below



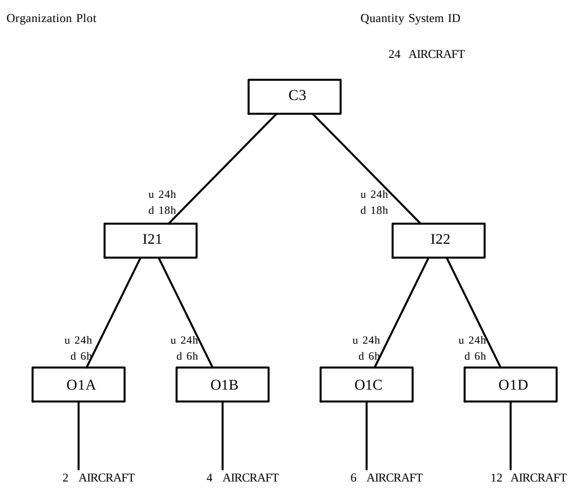


Figure 2: Spares only stocked a C3

Figure 3: Spares stocked at all 7 positions

The 1-echelon organisation correspond to the 3-echelon organisation's transportation and turn-around-times.

2.3 System data

The "precise" LRU data are generated by the OPSA program[1]

The system is assumed to have an MTBF during operation of 50 hrs (giving 20 demands/ 1000 op.hrs) and a "sum of LRU" prices of 40 MEUR. The MTTR is assumed to be 2 hrs. It consists of 100 LRUs (no SRU at this stage). The data generated are based on a standard deviation factor (STD) of 2 both for the demand rates and the prices. The correlation between demand rate and prices is 0.3. Both the STD and the correlation factor are in reasonable agreement with values achieved during tests on actual systems.
The utilisation rate is assumed to be 5% equivalent to 438 op.hrs per year.

2.4 Calculation methods

The OPUS10 software for Logistics Support and Spares Optimisation (Ref. [Sys98])

[1] The OPSA program – OPUS10 System Analyser – is a part of the OPUS10 package and consequently a member of the OP-suite of programs. OPSA has 3 main functions.

- Generate approximate data sets
- Graphical display of data sets
- Calculation and ranking of various system data like cost driver index etc.

The Varimetric calculation algorithm developed by Graves (Ref. [Gra85]) and Sherbrooke (Ref. [She86]) is used. The theory of Spares Optimisation is described in Ref. [She68].

The Item-by-Item method is a rather crude and non optimal method. It is intended for a 1-store situation and each item is dimensioned towards a certain confidence against shortage. In a 1 echelon situation OPUS10 can simulate the item-by-item method by setting all LRU unit prices equal.

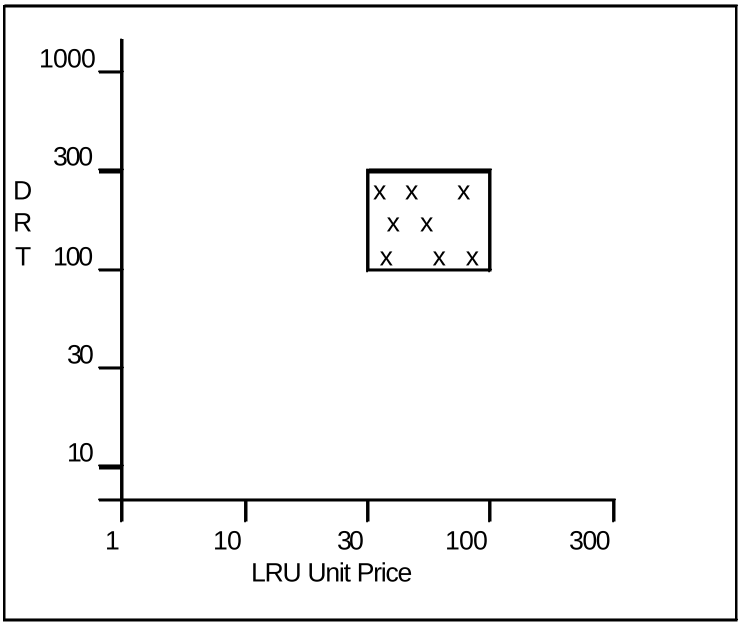
When plotting in the Cost/Effectiveness -diagrams the correct prices then are included by using the multianalysis function in the OPUS10.

In the case of the 3-echelon organisations the OPUS10 simulation of the item-by-Item method becomes slightly favourable for the calculated results since OPUS10 correctly reflects the interrelation between the various stores on different levels. This deviation however is accepted as it will not disfavour the Item-by-Item method and cumbersome manual calculations are avoided.

2.5 Group the data

The rational behind the way of grouping the data described below is to assist in the real world data estimation.
It is difficult to have the designer to make estimates on direct figures but it is much more easy to have the designer to place their estimates in an interval e.g. a failure rate between 30 and 100 failures per 10^6 hours. The same applies to item prices. In most cases it is much easier to indicate whether the LRU price is in the interval 3000 - 10000 EUR or in the interval 10000 - 30000 EUR than to give a real price indication. This way of giving data is also more stable to different kind of rapid changes, e.g. currency rates.

The original data set is split into groups in accordance with how the values fall into squares in a demand rate – price diagram. This is illustrated in the diagram below.



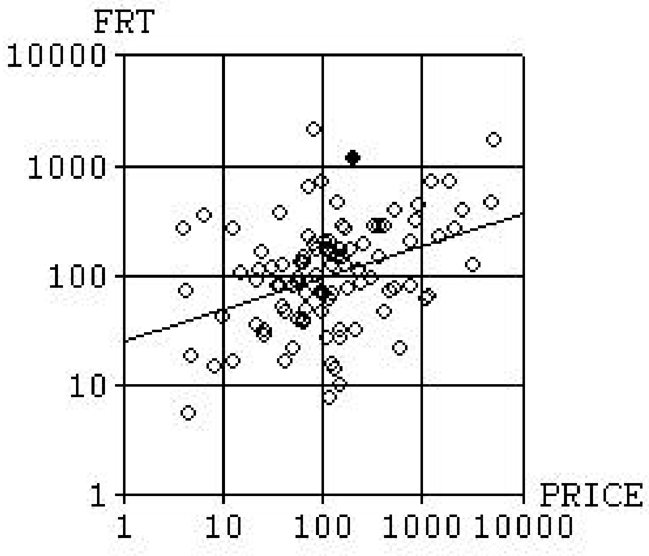
The 8 crosses in the square represents the “real” values for 8 LRUs in the set.

In the grouped calculations all those 8 LRUs are given the DRT corresponding to the geometrical (logarithmic) mean value = (log(100)+log(300))/2 = 173.21.

In analogy the LRUs units price will be set to (log(30)+log(100))/2=54.77.

Figure 4: Examples of grouped information

This is hopefully clarified by the figures given below:



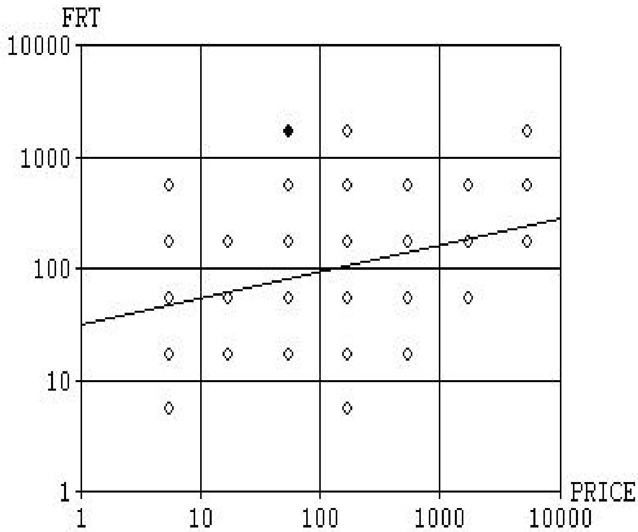


Figure 5: Original data set

Figure 6: Approximate data set

Also a more course split is made by 10-factor squares.

2.6 Summary of data runs

We have 2 organisations – 1 and 3 echelons. We also have 3 different data sets:

1. Original data,
2. Data grouped in 1-3-10-30 intervals (fine grouping),
3. Data grouped in 1-10-100 intervals (course grouping).

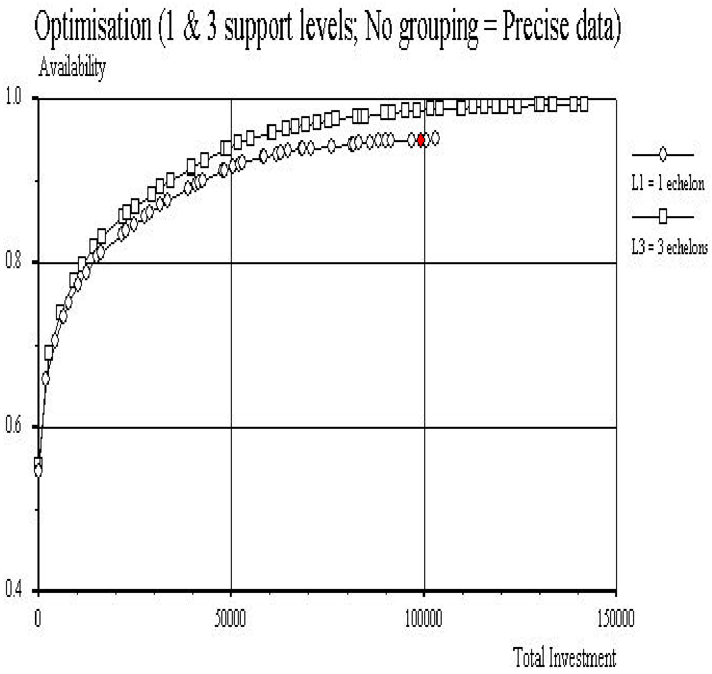
Finally we have 2 different calculation methods – system Oriented Optimisation and Item-by-Item.

Since the aim is to compare the results achieved with the original data set with what is achieved with different grouping the runs are made accordingly. Furthermore some more comparison were made.

3. RESULTS

3.1 Original data set/Optimisation

The figures below shows the Availability as a function of the spares investment with precise (original) data



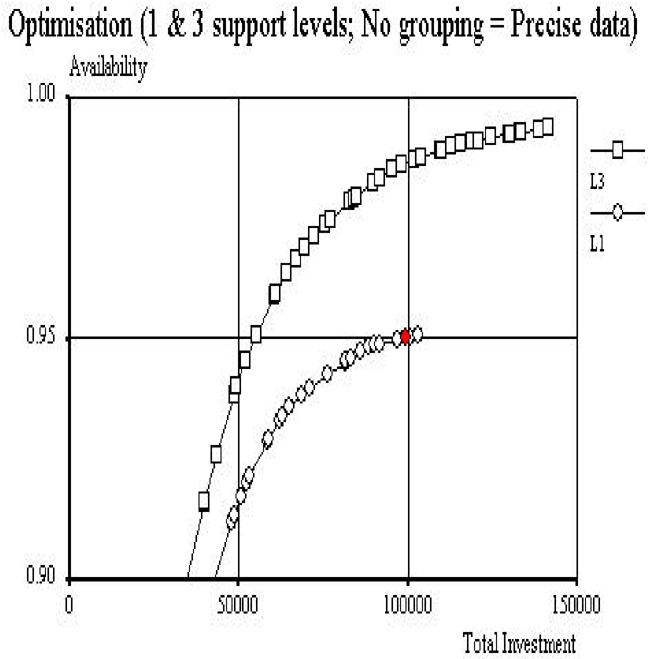


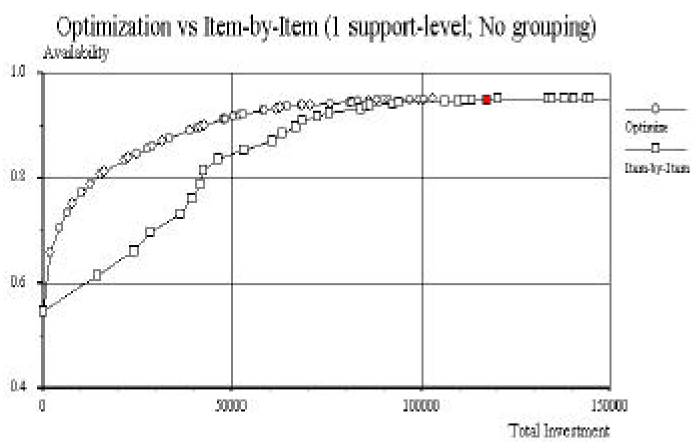
Figure 7: Availability vs Spares Investment

Figure 8: Enlarged display

The results are fairly typical and the effect of the long transportation to the equipment in the 1-echelon organisation limits the availability.

3.2 Optimisation Vs item-by-item

This comparison is interesting since it clearly displays the effectiveness of the optimisation.



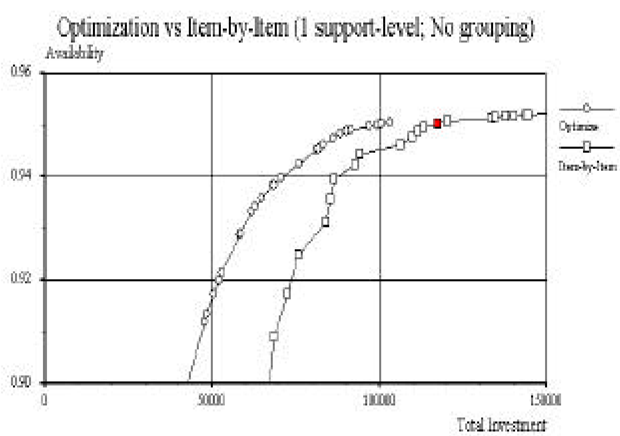


Figure 9: Cost/Effectiveness comparison

Figure 10: Enlarged display

To reach the availability A=0.95 the Item-by-Item method is 18% more costly compared to the system oriented optimisation method.
A similar comparison for the 3-echelon organisation shows an increased cost of about 44%. These values are fairly typical.

3.3 Impact of grouping

3.3.1 Fine grouping

The figures below show the results for a comparison between the original data set and the fine grouping (grouping factor 3) 3 echelon and a 1 echelon organisation

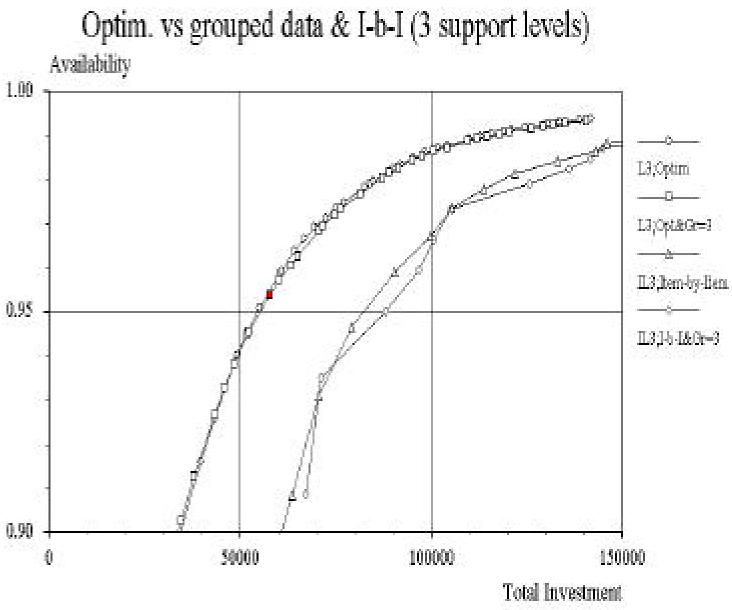


Figure 11: Effect of inaccurate data - 3-echelons

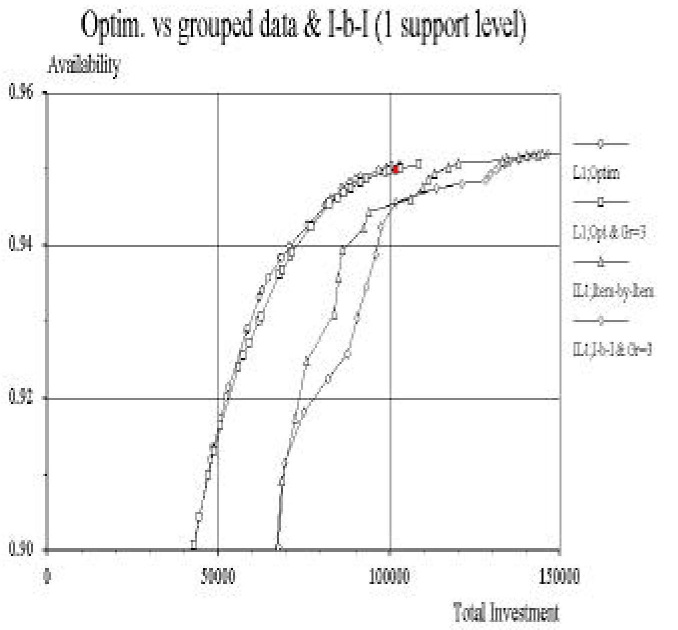


Figure 12: Effect of inaccurate data - 1 echelon

It can be noted that the results agree reasonable well. It should be observed however that the grouping has a tendency to give a slightly less favourable result for a single support level support organisation due to the lower number of choices (degree of freedom) that the optimising algorithm has.

3.3.2 Impact of Course grouping

Doing the same analysis as above with a grouping factor of 10 (course grouping) and compering the needed investment in spare to achieve 95% availability the following results were achieved.

	Needed investment 95% Availability		
Corresponding Uncertainty Factor	0	1.73	3.16
Group size	Precise	Grouped 3	Grouped 10
Optimisation 1-Level	98 458	101 966	98 147
Item-by-Item 1-Level	116 146	131 397	140 982
Optimisation 3-Level	54 412	55 159	53 034
Item-by-Item 3-Level	82 347	87 640	74 408

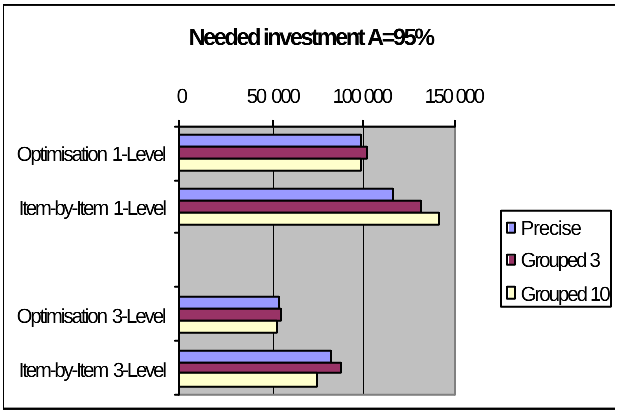


Figure 13: Impact of different levels of inaccuracy

Figure 14: Graphical view

Two things can be observed

a) The optimisation technique is much less sensitive to uncertainties in LRU prices and failure rates than the Item-by-Item method

b) The deviation from the calculation with precise data can be both positive and negative. This is due to the fact that some cost driving LRU might get too optimistic or too pessimistic value when using rough - grouped - data

3.4 Impact on the spares assortments

So far we have studied the impact of inaccurate or rough data on the Cost/effectiveness analysis.
In some cases we even have to base our real spares purchase, position by position, on rough data.
The results will by definition not be optimal, but the natural question is - how far from optimal?
We also presumes that it is not possible to do any corrections in the spares mix when more correct data becomes available. See further [Isd99].
Using OPUS10 multianalysis facility we can study the effectiveness of the spares recommendation based upon group data in the scenario with precise - exact- data. The result for the 3-echelon organisation can be seen in figure 15:

The resulting diagram shows that the agreement – as expected is not as good as the in 3.3.1 but still acceptable at least for grouping interval 3.

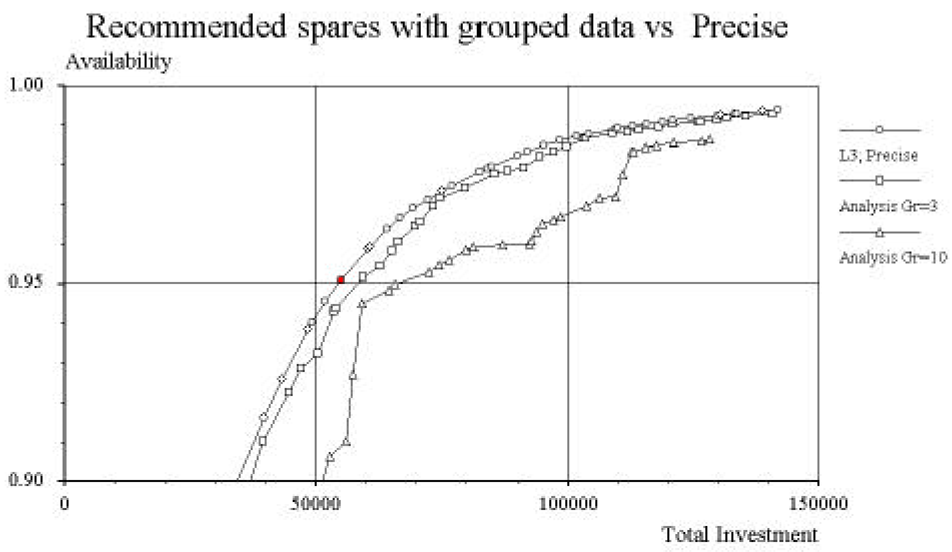


Figure 15 Effect of inaccurate data on spares recommendation

By comparing the investment needed to reach a certain availability (in our case 95%) with exact data we will have a picture of the cost of imperfect information:

Alternative	*Investment*	*Increased Inv.*
3 Support Levels		
Precise	55 000 kEUR	
Grouped 3	59 000 kEUR	+ 7,2%
Grouped 10	65 700 kEUR	+19,5%
1 Support Level		
Precise	99 000 kEUR	
Grouped 3	107 500 kEUR	+ 8,6%
Grouped 10	125 000 kEUR	+26,2%

Figure 16: Increased investment in spares due to grouped - rough - data

The conclusion is clear: The cost of having inaccurate data is in all studied cases much less then the cost of selecting non-optimising methods or selecting wrong logistic support organisation.

4. CONCLUSIONS

The results achieved are based upon a number of numerical examples and computer runs. Even if we believe these results are of general nature - a more thoroughly theoretical examination is needed to finally confirm the following conclusions:

1. The inaccuracy generated by approximated - grouped - data is surprisingly small, in particular when viewed in relation to other uncertainties
2. Optimising methods will generally give better results with "rough" data than non-optimising methods like item-by-item method with "exact" data
3. The value of achieving the results early, by far outweighs the drawbacks of normal inaccuracies in the input data
4. "Garbage in – Garbage out" is indeed a very poor excuse for delaying various forms of Logistics oriented analyses
5. Using these results may save money, not only in the effort of collecting data, but basically through better logistics decisions through real front end analysis instead of guessing and “a-finger-in-the air” estimates due to claimed shortage of data.

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