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Both Pareto and EOQ have limitations combining them delivers a powerful management tool for MRP and beyond

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ABSTRACT

It has been understood for a long time that parameter maintenance is one of the key factors in the successful operation of MRP systems. The author's research in to effective management of MRP has shown that 50% of ERP systems MRP modules do not provide parameter setting tools for optimizing the cycle stock settings, mostly offering Fixed Order Quantity and Fixed Period which require the User (Planner) to determine and manage the settings. It also identified that where the tools, like EOQ, were provided that the User does not use them preferring to use their judgment instead.

Pareto and EOQ are the most readily available tools used for the setting of cycle stock and management of inventory in the majority of MRP systems. The paper critically examines these two techniques and identifies their strengths and weaknesses. EOQ is often challenged and many alternatives have been developed in an attempt to overcome the weaknesses. Whereas Pareto is not so widely challenged and is extensively used as a rough guide for inventory planning

Firstly a closer look at Pareto, through the evaluation of MRP data from manufacturing businesses the paper shows how Pareto can produce a less than optimum result and identifies the root cause of the weaknesses. Thus it can be shown that Pareto's strength only applies when a whole group of parts are evaluated; any division into a sub-set and the risk of a sub-optimal answer increases.

Secondly a critical examination of EOQ and its more popular derivatives summarises the arguments that are well documented. The paper debates the issues specifically related to the key elements of the cost of inventory and the cost of ordering as used within the EOQ formula. The key weakness is that often the data required for accurate evaluation of the elements of the EOQ are not typically available in most businesses.

Finally the paper examines an alternative technique; the *K*-curve, first identified in the 1990s, which is derived by combining the two techniques of Pareto and EOQ and shows how it successfully eliminates the weaknesses and enhances the strengths of both Pareto and EOQ. There is an increasing body of academic evidence that demonstrates the robustness of *K*-curve as a solution to the weaknesses of Pareto and EOQ.

The paper uses material gathered from manufacturing businesses in recent years and shows how the *K* curve methodology has been successfully applied as a business management tool and can then be used to determine the optimum parameters settings for individual items within an MRP environment.

The paper concludes by demonstrating that the use of *K*-curve as a MRP management tool is a significant advance since the effective management of MRP parameters is simplified to an easily made business judgement. Application of the technique within business has enabled inventory reductions of 25% and significant improvements in the effectiveness of MRP operations.

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1. Introduction

The paper will first review the results of a survey in the use of inventory management tools in MRP systems (Relph, 2006). Second it explains the limitations of Pareto and EOQ, two of the most popular inventory management tools when applied in a business context, through case examples. Third the paper then

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outlines the basis of the *K*-curve theory as described by (Shah, 1992), and how it was further developed by (Dupernex, 1993) and (Relph, 2006) into a business tool. Finally the paper will conclude with case examples of the application of the tool in a business setting.

2. Background—The use of inventory tools in MRP

The author's research (Relph, 2006 p. 125) has shown that 50% of ERP system MRP modules do not provide parameter setting tools for optimizing the cycle stock settings as seen in Table 1. They mostly offer Fixed Order Quantity and Fixed Period which require the User (Planner) to determine and manage the settings. It also identified that where the tools, like EOQ, were provided that the User does not use them preferring to use their judgment instead. The case research identified that one case study site's MRP had EOQ but it was not used by the manager or planner, a second case study site had used statistical safety in the past but due to staff changes it fell into disuse.

The same research conducted from 2004 to 2006 also shows that there are gaps between the skill levels (measured by education and experience) of the software salesman, company manager and the planner using the MRP on a day to day basis. The distinguishing difference was the education level rather than the experience level. This can be seen in Fig. 1.

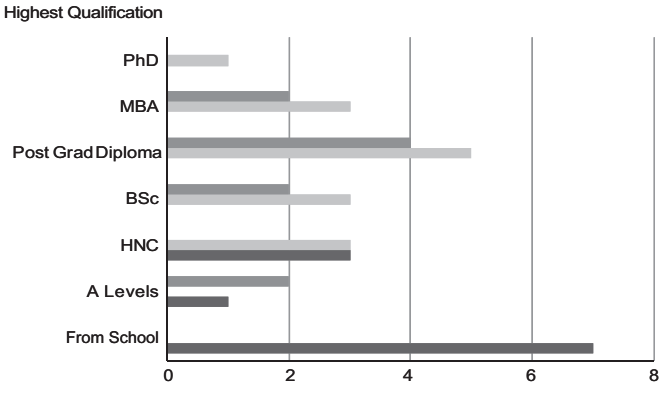
A possible interpretation is that the Managers are peers of the MRP sales staff and will conceptually understand some of the difficulties and nuances of MRP management. However it is also possible that the Planners many not share this understanding unless attention has been given to this during training when new systems are implemented. Often planners will rationalise by preferring their own judgement/experience over a system and claim that the system is too generic to appreciate the fine detail available to a planner.

Thus we can argue that as systems evolve it is possible that the Managers who buy the system will have a different understanding of the capabilities to the Planners who are responsible for the day to day analysis. Very recent research (Liao, 2012) shows a correlation between non-compliance, that is planner adjustments to MRP, and the skill levels of the planner. This in some part corroborates the earlier findings that skill level is key to better effective use of MRP.

In summary the gap between the skill level of the Manager (Purchaser of the ERP system) and the Planner (the day to day user of the system) possibly has a detrimental effect on the effective operation of MRP.

Table 1
Percentage split between manual and automatic parameters, Relph (2006 p. 125).

Parameter area	Manual User judgement (%)	Automatic Mathematical model (%)
Cycle stock	50	50
Safety stock	50	50
Customer service levels	63	38
Forecasting	50	50
Inventory control	38	63
Lead-time	63	38
WIP parameters	88	13
Non-compliance	88	13



	From School	A Levels	HNC	BSc	Post Grad Diploma	MBA	PhD
Supplier Consultants	0	2	0	2	4	2	0
Managers	0	0	3	3	5	3	1
Planners	7	1	3	0	0	0	0

Fig. 1. Case Comparative analysis, Comparison of highest qualification of Managers, Supplier Consultants and Planners, Relph (2006 p. 119 and p. 255).

3. Review of Pareto and EOQ

Both Pareto and EOQ have long been sighted as tools for the management of inventory and the use of Production and Planning and Control Systems (Vollmann, et al., 1998), (Wild, 2002) and other authors. Closer examination shows that both have practical limitations when applied to certain common business scenarios.

3.1. Pareto—Grouping strategies

If we consider a scenario where a business has a number of groups of parts which have different characteristics, for example in house manufacture and long lead-time overseas purchased parts. These two groups will need to be managed in entirely different ways in respect to order size and safety stock parameters. To illustrate this example we have taken data from a SME company that has these characteristics (Company A). Company A had chosen to separate the two groups and then perform the Pareto class allocation, this results in a sub-optimal result, shown in Table 2, which compares the traditional ABC Pareto group, based on 80%/20% and 95%/50% splits, when the whole range of parts is considered to where the sub-group "Far East is considered" separately.

Table 2 shows parts from a company manufacturing in the UK and sourcing parts from the Far East. The traditional approach is to calculate a Pareto for all the parts being managed. In Table 2a the parts Far East parts are show as they would have been classified as part of the whole population of SKU's; in Table 2b the parts are shown as they would be classified when the "Far East" are considered separately. Table 2c shows the difference i.e. there are 13 fewer parts that are classed as A Class when considered as part of the whole population and B Class when considered within the Far East Class Group. This shows that the sub group can distort the original intent of the classification process re-classifying parts in to lower classes. The net result will be to imply that the

Table 2
Pareto Sub-optimisation example.

Far East Parts Class when part of total population		Far East Parts Class when considered separately		Movement
Class	SKU count	Class	SKU count	
A	45	A	32	13 Fewer A class
B	32	B	28	13 From Class A, 17 to Class C, Net of 4 fewer
C	18	C	35	17 More C Class
Table 2a		Table 2b		Table 2c

inventory controls can be relaxed for these parts as they are less important. The result would be larger batch and safety policies, which in turn will result in larger inventories. When considered as part of the whole the majority of the Far East parts are truly Class A parts, 45 of 95, however when considered in a unique sub-group, the number is reduced to 32 of 95, this is because Pareto is based on proportions. If you reduce the size of the total group, you automatically reduce the size of each of the classes, this means that the more groups used the greater the risk that sub-optimisation may occur. The simple solution is to perform the Pareto on all the SKU's first then de-compose the SKU's into their respective sub groups.

3.2. Pareto—Annualized demand.

The second Pareto issue is the primary assumption that the grouping is based on the annual demand. Here in order to perform the ranking in Pareto the annual demand for each part is calculated first and then the parts are ranked. This is fine where the demand is evenly spread over the whole year, however if the demand varies over the year then there is a risk that there will be anomalies in the ranking. This can be seen in Table 3 which shows how based on the annual demand all four examples would be ranked the same, however if you examine the differing demand patterns by quarter then the ranking, and possible Pareto class, can be dramatically different. For example the seasonal product varies from low to high to low ranking, and the end of life and new product move from highest to lowest and vice-versa. Again the obvious solution will be to re-calculate the ranking each quarter. If this nuance is not properly understood in the business environment then the significance of the approximation will not be understood. Typically the Pareto ranking is part of an annual business planning cycle, implying that both these issues are either not understood, ignored as irrelevant or that in the past the pace of change was not that high.

Table 3
Comparison of Pareto Classification for different demand patterns during the annual period.

Groups	Q1	Q2	Q3	Q4	Annual demand
Flat	100	100	100	100	400
Seasonal	50	125	150	75	400
End of life	175	100	75	50	400
New product	25	75	100	200	400
Pareto rank					
Demand	Q1	Q2	Q3	Q4	
Flat	B	B	B	B	
Seasonal	B/C	A	A	B/C	
End of life	A	B	C	C	
New product	C	C	B	A	

Table 4
Typical Pareto Order policy (Wild, 2002).

Pareto class	(%) Of parts	Order policy	Resulting average inventory	Estimate numbers of orders placed in a year
A	20	Weekly	1/2 Week	52
B	30	Monthly	1/2 Month (2 1/2 weeks)	12
C	50	Bi-Annually	3 Months (13 weeks)	2

3.3. Pareto as an inventory planning tool

Many authors (Wild, 2002; Vollmann, et al., 1998; Silver, et al., 1998; Waters, 2003) identify the usefulness of Pareto when identifying the planned level of inventory for a business. Some of the authors even recommend possible order policies, as shown in Table 4.

This type of ABC analysis provides a simple and effective planning tool. The analysis in Table 5 shows how the policy would work when applied to a sample dataset. The sample data of 614 parts shows an inventory of £112k, applying the simple Pareto policy rules for Table 4 results in just under 10k batches per annum delivering a stock turn of about 9 if this policy was put into effect. However when this inventory level is achieved, there is a strong likelihood that senior management would request a further inventory reduction. To achieve an inventory reduction there are two options, either reduce the Order Policy from Weekly (every 5 days) to every 4 days that is reducing what is received on all parts in the class. Alternatively move the A Class boundary from 20% to 22%, which will increase the number of parts that are considered as Class A parts, that is changing two percent of parts from monthly to weekly ordering. The benefit of the later approach is that it would only affect the two percent of parts that are moved from Class B to Class A, whilst the former requires all parts to change their order policy and requires an order pattern that may cause issues with a supplier. Whilst the change from Monthly ordering to weekly ordering may be more difficult it is spread over a smaller number of parts. Thus an approach that moves the boundaries is seen to be the most pragmatic.

The table below shows the results of varying the Class A Pareto % from 17% to 21% of parts and the Class B Pareto % from 39% to 43% of parts for the data shown in Table 5.

The other consequence of moving the boundaries is to increase the numbers of orders that will be placed, this is because two percent of the parts move from monthly ordering to weekly ordering, which reduces inventory in exchange for processing more orders, this relationship has been identified by (Murdoch, 1965) and others as an inventory exchange curve.

3.4. EOQ—The classic optimizing formula

The classical EOQ formula (Harris, 1913) is, shown in Fig. 2, based on the premise that the costs for holding inventory and the costs for ordering or setting up intersect at the minimum cost point, it is further based on the assumption that the, cost of ordering (C) and the cost of holding inventory (i) are known and constant. There has been continued debate about the ease with

Table 5
Typical Pareto Analysis based on policy in Table 4 when applied to sample data.

Pareto Class	Cumulative No of parts	(%)	Cumulative annual usage	(%)	Class usage	Order policy	Estimated no of batches	Estimated cycle stock
A	113	18	£797,010	80	£797,010	5	5650	£31,880
B	242	39	£934,073	94	£137,062	20	3025	£21,930
C	614	100	£993,234	100	£59,160	125	1228	£59,160
					£993,234		9903	£112,971

D = Demand C = Cost of Ordering / Setup P = Unit Cost I = inventory holding rate as%			1000 £4.50 £75.00 30%	
Economic Order Quantity	$Q=\sqrt{\frac{2*D*C}{P*i}}$		$Q=\sqrt{\frac{2*1000*4.50}{£75.00*30\%}}$	20
Common Factor (k)	2C/i		2 * £4.50/ 30%	30
Simplified EOQ	$\sqrt{kD/P}$		$\sqrt{30}$ * 1000/ £75.00	20
Economic Order Period (EOP)	EOQ / D		20/ 1000	0.02 years If 250 days = 5 days
Economic Order Period (EOP)	$\sqrt{\frac{2*D*C}{P*i}}$ / D	$\sqrt{k/Dp}$	$\sqrt{30}$/ 1000*£75.00	0.02 years or 5 days

Fig. 2. Classical EOQ (Harris, 1913) and simplification (Brown, 1982 p. 131) with examples.

which these two elements are identifiable and constant. Variations also seek to suggest that the Unit Cost, P can also be varied as the quantity ordered increases, often incentivised by the supplier as a price break, leading to the price break model illustrated by (Chase, 2001 p. 525). Whilst not challenging the evaluation of the elements of the EOQ formula (Brown, 1982 p. 131) identified that for ease of calculation the expressions could be simplified by expressing the common elements as a constant *K* as shown in Fig. 2. Brown (1982) also showed how the expression could be manipulated to provide an 'Economic Order Period' arguing that business tended to work in/round up to weeks and months.

There is also the same issue as identified with Pareto in that the approach is based on the assumption that the annual demand is constant, which will mean in certain scenarios the evaluation will be either under or overstated. There are thus two weaknesses in EOQ; the inability to easily evaluate the costs and the risk that the demand is not even across the year. The later can be solved by more frequent evaluations, whilst the former remains a more persistent weakness.

3.5. Summary of strengths and weaknesses

In summary there is some evidence that MRP modules within ERP systems still only provide simple tools, which even when provided can be largely ignored in favour of 'user' knowledge. This can possibly be explained and is supported by the finding of (Relph, 2006) and (Liao, 2012). When we critically apprise two of the primary cornerstones of inventory management, Pareto and EOQ we find that whilst both are simple and effective and can provide valuable insights, they can also give quite misleading results. Whilst some of the weaknesses can be addressed by more frequent calculation and a careful understanding of the demand profile, the issue of the holding and ordering cost is not so simply resolved. The extension of Pareto as a planning tool and the existence of the inventory exchange curve (Murdoch, 1965) provide very simple and useful tools for the inventory manager. However the fact that Pareto only has 3 Classes whilst ensuring simplicity, means that it is a fairly crude instrument particularly if the range of SKU's (parts to be managed) is large and the desire to split into sub-groups is increased.

3.6. Building a bridge between Pareto and EOQ

Typically business will favour an Order Period Policy rather than discrete order quantities, (Brown, 1982 p. 132) identifies this and suggests a likely sequence, is based on a logarithmic

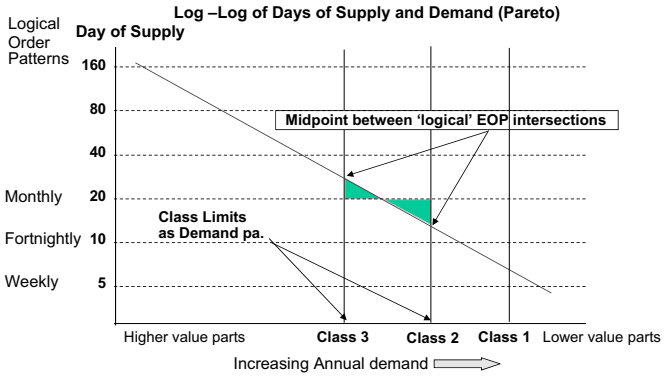


Fig. 3. Log–log of "Logical Days of Supply and Demand" with midpoint class limits RG Brown (1982 p. 131), Shah (1992 p. 100).

relationship, and fits weekly, fortnightly, monthly ordering cycles, which is commonly used by businesses. Further (Brown, 1982) identifies that if the range of parts annual demand as a value and resulting EOP (Economic Order Period) as derived using the EOP derived in Fig. 2 were plotted on a log/log scale they would result is a straight line as shown in Fig. 3. If the logical periods of weekly, fortnightly, monthly etc are then used as horizontal grid lines, their vertical intersections represent the annual demand (D) as value that would result in the EOP value on the *y* axis. If the midpoint between two subsequent EOPs is selected then the vertical line represents the logical point where it is best to switch from one EOP to the next. Thus these EOP switching points become the class boundaries in the same way as 20% indicates the transition from Pareto class A to class B.

The use of this log-log plot was extended by (Shah, 1992) who used it to EOP class boundaries which divided groups of parts into classes and used these defined class boundaries, in the same way as the class groups were used in Tables 4 and 5, to estimate the cycle stock the results are shown in Table 7.

This provides a handy rules table for a planner to use to classify parts into groups based on demand and delivering an order size related to the principles of EOQ/EOP. It is logical and offers a simple way to improve on the 3 Class Pareto ABC systems with more classes, typically organisations using Pareto eventually create a 'super A Class' or split Class C in to low and very low usage parts. The drawing these extra boundaries are typically judgemental. The log–log technique provides a practical order period rule which is in line with the Pareto rank. The order frequency is thus based on the EOQ logic and used to divide Pareto in to more than 3 classes.

3.7. K-curve approach

The use of the class limits allows the planner to divide all the parts into classes, according to the rules shown in Table 7, and thus estimate the number of batches and cycle stock in the same way as for Pareto as discussed in Section 3.3. What can be seen is that the resulting *K* curve inventory estimate in Table 7 is lower than the estimate from Table 5 i.e. £93.6k vs. £112.9k as well as the number of batch to be processed reducing from 9903 to just over 3130. Thus it clear that *K* curve delivers a more efficient relationship between inventory and the number of batches to be processed. The simplification of EOQ by defining *K* avoids the need to evaluate the cost of ordering (C) and the cost of holding inventory (i). (Shah, 1992 p. 108) showed that through the variation of this common factor k (2C/i) from say 500 to 10 an inventory exchange curve as shown in Fig. 4 can be created. Fig. 4 also shows a plot of the Pareto Exchange curve derived in Table 6. The two curves show the difference between *K* curve and Pareto approaches. It is clear that *K* curve is significantly more efficient than the 3 Class Pareto approach.

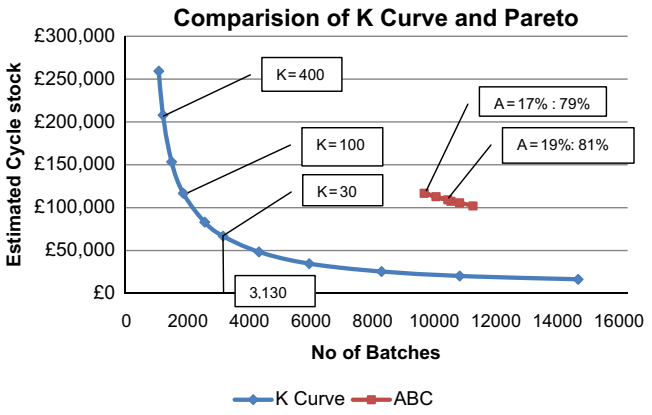


Fig. 4. Comparison of *K* curve and Pareto exchange curves adapted from *K* curve, Shah (1992 p. 108).

Table 6
Effect of variation of the Pareto Class Percentages in inventory and batches.

Percentage of parts in Class A (%)	Percentage of parts in Class B (%)	Estimated no of batches	Estimated cycle stock
17	39	9,528	116,891
18	40	9,903	112,971
19	41	10,278	109,305
20	42	10,653	105,780
21	43	11,078	102,140

Thus it can be seen that the *K* curve represents the EOQ relationship for an entire group of parts, showing the relationship between inventory and the number of batches. The *K* curve describes an envelope which represents all the possible solutions to the *K* factor (2*C*/*i*). This avoids the issue of determining 2*C*/*i*, however this still leaves the problem of determining where on the curve the business should be. We know that to determine the EOQ we need to know, to a good degree of accuracy the values of *C* (Cost of ordering/set up) and i (inventory carrying rate), we know from experience that these are very difficult to evaluate. However, to identify the correct position on the curve we now need to know either the number of batches processed or the desired cycle inventory. This is a simpler issue to resolve as both are typically measured by a business. For example the question could be asked of a goods inwards department supervisor—"how many receipts are you processing" or "how many receipts can you process". Similarly a machine or mould shop supervisor could be asked "how many set ups are you making" or "how many set-ups can you make". Both these questions are practical to answer.

This then provides a fix for the *x* axis and the vertical line would intersect the *K* curve and thus identify the entitlement or 'optimum' inventory level for that number of batches being processed indicated as initial position in Fig. 4. This modification to the evaluation of EOQ fundamentally changes the business metrics that needs to be determined. For traditional EOQ the business needs to determine two indeterminate variables, where as the *K* curve method (KCM) of using EOQ requires the evaluation of easily measured variables.

3.8. Grouping of parts and alternate policies

In Section 3.1 the issues relating to sub-optimisation of Pareto were identified when a group of parts is split and the sub-groups are then evaluated individually. If we now consider the same case using the *K* curve we see that the issue is resolved. If we consider two groups of parts to be managed, first Far East purchased parts and second manufactured parts from a moulding shop. It is obvious that the number of *C* (cost of ordering/set up) for these two groups is significantly different. However, if the parts were divided and then plotted as separate *K* curves, each would have its own unique inventory batch relationship. If we consider batches, purchased parts receipts, are related to the ability to manage receipts in good inwards and for the mould shop the batches, which relate to change-over's, are controlled by the ability to change tools on the moulding machines. We can identify for each group the ideal *K* value using the same mechanism described in Section 3.7. This evaluation is based on easily measured variables in the case of the purchased parts it is the number of receipts and for the mould shop it is the number of tool changeovers, the *K* curve easily manages this sun-group situation where the two

Table 7
Typical Class Limit table based on Simplified EOQ Adapted from Shah (1992 p. 103).

Work Days	250	($K=2C/i$ $C=$£4.5 and $i=30\%$ from Fig. 2				
K value	30					
Class	Class limit £	No in class	Annual demand in class	Order policy days	Estimated no of batches	Estimated cycle stock
1	£37,500	3	£150,128	5	150	£2,699
2	£9,375	19	£342,612	10	475	£14,003
3	£2,344	56	£233,685	20	700	£18,823
4	£586	149	£199,560	40	931	£32,164
5	£146	172	£53,750	80	538	£17,483
6	£–	215	£13,499	160	336	£8,507
Totals		614	£993,234		3130	£93,678

capabilities are quite different. By selecting different values of *K* for each group the resulting optimal inventory will be adjusted to the capability of the related process i.e. receiving goods or mould change-overs, this approach is better than Pareto which simply defines the first 20% as A Class. This means that *K* curve is not sub-optimised by dividing into sub-groups on the contrary it provides an easy mechanism to adjust to the differing process capabilities in any manufacturing business.

The assumption by Brown (1982), Shah (1992) was that six classes based on a weekly, fortnightly, monthly to annual sequence was optimal. Dupernex (1993), Schwarz (2000), Relph (2006) examined this issue of how many classes and which order period sequence was optimal. Dupernex's (1993) conclusions, based on examining different numbers of classes and order policy sequences for a range of companies were:-

- The variation in Pareto profile and thus inventory does not affect the optimum periodic order cycle solution
- The more advanced (higher annual usage value) a business enterprise the greater the advantage in moving from traditional ABC to 6 or 8 Class divisions (Duperneux, 1993).

Schwarz (2000) found after applying heuristic optimisation techniques to the size of the individual class order policies states:-

> We conclude that although the KCM [*K* curve] does not represent the optimal inventory policy for the objective function that usually has been treated, our investigation reveal why it nevertheless may be considered to work well. (Schwarz, 2000)

Relph (2006) found after a case research on the application of a business process that could be used for selecting the optimal class and order sequence:-

> In all case studies, the *K* curve approach was able to deliver a plan that met the management's general objective.

3.9. Business case analysis

Another typical action in business is to require an inventory reduction. The *K* curve analysis provides a useful analysis insight and numerical expression to the "low hanging fruit" comment. Fig. 5 *K* curve method used as a business case evaluation shows two cases. In case 1 the *K* value is reduced from 400 to 100 this delivers an inventory benefit of £91k (or 43%) which can be achieved by increasing the number of batches processed by 645 (or 53%). If however we look at Case 2 the *K* value is reduced from 50 to 30 this only delivers £32k (or 48%) but in this case the increase in number of batch processed has increased to 2739 (or 88%). From these examples it is easy to see the inventory benefit.

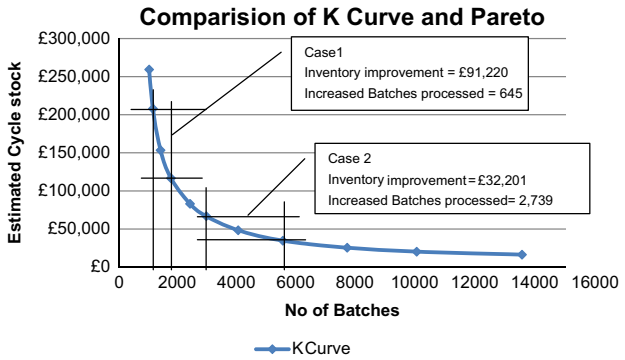


Fig. 5. *K* curve method used as a business case evaluation.

However, understanding the cost can now be achieved by asking "can you increase the number of receipts from 1200 per year to 1800 per year. If for example to increase from 1200 to 1800 receipts per day will cost £30,000 pounds in overtime/staff increases and the inventory benefit is £91k then the business case holds. If however the investment required is bar code equipment and training costing £1.5m then it is clear that the cost outweighs the benefit. Thus it is possible to evaluate different inventory reduction schemes with a robust business case analysis. Typically business seek year on year benefits, so we can see that in Case 2 the effort to deliver the same % improvement in inventory is significantly increased. It thus follow that there will be a point where further improvements are not cost effective.

3.10. The aggregate inventory curve combining K curve, safety stock and over-stock

Once the practicality of the exchange curve is accepted it is logical to consider the effect of the inclusion of safety stock. The possibility of a composite curve which considered the inventory resulting from a specific ordering policy and safety stock policy or algorithm was first examined by (Gardener, 1979 p. 711) and extended by Silver et al. (1998, p. 294) and (Relph, 2006 p. 104) who showed that it is, with the increase of computational power, possible to creating a complex curve which includes both cycle stock and safety stock policies.

Relph and Barrar (2001p. 171) identified the importance of considering over stock when planning inventory levels.

> The paper concludes that from understanding the possible causes of over-stock, we can see that it is both possible and desirable to collect the relevant data to enable an evaluation of overage to be made during the business planning process.

Relph (2006 p. 108–112) then extended the *K* curve to include both safety stock and over stock to create an aggregate curve and demonstrated the practicality of including both in an aggregate inventory curve and evaluated a process for the determination of the optimal policies. Fig. 6 shows a typical set of four aggregate curves where (1) indicates that the 4 class policy which becomes sub optimal at higher batch rates, (2), indicates that ultimately the two 6 class policies coincide and finally (3) indicates the case site's current inventory level and no of batches processed giving its current position in relation to the aggregate curves that would suggest that a using a 4 class system would return a lower inventory for the number of batch they are currently processing, however if they were to increase their ability to process batches

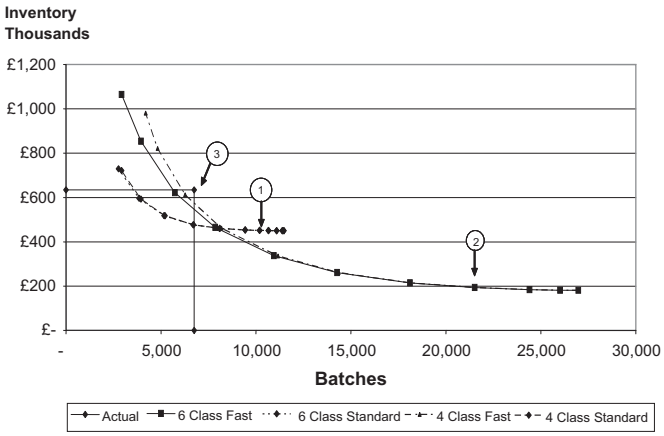


Fig. 6. Typical aggregate curve from case study research by Relph (2006 p. 209).

Table 8
Typical planner rules table for the implementation of an aggregate curve.

Work days	250	**Proposed time based modifiers based on $K=40$**					
***K* value**	40						
	UK £	Order values			**Safety days**	**MOQ**	**Multi**
Value class	**Cycle days**	**Class limit**	**Max**	**Min**			
1	**5**	50,000.00	£–	£1000.00	**5**	**1**	**1**
2	**10**	12,500.00	£2000.00	£500.00	**5**	**1**	**1**
3	**20**	3,125.00	£1000.00	£250.00	**10**	**1**	**1**
4	**40**	781.25	£500.00	£125.00	**15**	**1**	**1**
5	**80**	195.31	£250.00	£62.50	**20**	**10**	**10**
6	**160**	–	£125.00	£–	**25**	**10**	**10**

above 7000 then they should re-consider this decision and move to a six class policy.

Table 8 shows how the implementation of an aggregate curve can be achieved, by using a simple rules table which can be used by a planner at his desk.

The case study conducted by Relph demonstrated the benefits in a practical setting, (Relph, 2006 p. 291) concludes the case research by stating that:

> The case studies have shown that it is possible to incorporate an aggregate inventory planning model into the business management process to assist in the management of inventory and the definition of cycle and safety parameters. The case studies have shown that it is feasible to implement an aggregate inventory planning approach in SMEs. The case studies show that the implementation of such a process would still be subject to support from management; adequate training; implementation support and the maintenance of an effective plan. This was most clearly demonstrated by the [Weston] case study where there was strong management support and a motivated planning team.

4. Conclusion

Parameter management continues to be an issue in small and medium enterprise (SME) companies using MRP systems, the UK government statistics for 2010 show that there are approximately 230,000 SME businesses in the UK. Thus a simple and pragmatic solution for these small businesses is important.

The issues within an SME are in part related to the technical capabilities of the Planners and the provision of complex tools that still require part number level decisions by planners are not sustainable in the long term. The provision of a simple and effective tool that enable the business managers to examine complex policies and then implement by providing simple rules table is of significant benefit to the SME community. However the process must be able to demonstrate that it is based on sound theory and tested by academic rigour.

In summary, the *K* curve approach addresses the issue of sub-optimisation of Pareto when sub dividing in to groups and it overcomes the issues related to the determination of $2C/i$ in EOQ. The business manager can evaluate his current position based on readily available data. The *K* curve approach provides a simple approach which is pragmatic and implementable within most manufacturing enterprises. Thus it is possible to determine for a variety of groups the most effective number of classes and order period sequences. It is also capable of examining a business case to test whether investment in additional resource will bring a realistic improvement in inventory.

The use of aggregate curves based on *K* curve delivers a strategic, tactical and operational tool that is effective and simple to apply.

K curve is a logical extension of both theories and addresses the weaknesses and builds on the strengths of both techniques.

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