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RISK BASED OPTIMISATION OF SPARES INVENTORY MANAGEMENT

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Abstract:
Spare parts inventories assist maintenance staff to keep equipment in operating condition. Thus the level of spares stocked has a direct bearing on machine availability. This paper presents an innovative risk based approach for spare parts inventory optimisation.

Research presented here is in response to a real-life problem of developing a methodology for optimising the stocking of spare parts in the shipping sector. The trade-off involved here is the cost of stocking spare parts on the one hand and the cost of not meeting a demand for a part (stockout) on the other. The research has benefitted from access to some databases used in spares management, and discussions with Shell International Trading and Shipping Company Limited (STASCO) and Lloyd's Register (LR) regarding practical issues involved in the management of an inventory of spare parts.

Research presented in this paper is of value to industry where spares need to be stocked or supplies need to be ordered. In many of these situations, there is a requirement to prioritise the ordering within user specified constraints and, at times, with limited data to forecast demand. The model presented here provides an innovative and a practical risk based methodology to address such issues.

Key Words: Spares, Inventory, Risk, Operations, Optimisation

1. INTRODUCTION

The level of spares in an inventory has a direct bearing on machine availability. The availability of a machine is a function of the mean time to correct a failure, which in turn often depends upon, among other factors, the time to obtain a spare (to conduct repairs) or a replacement. The level of spares in a spares inventory is constrained by the cost of having stock and the penalty of being out of stock. In a competitive climate companies strive to keep their spares inventory at an optimum level to minimize the costs involved.

Decisions within asset integrity management that include decisions regarding inspection, repair, maintenance, replacement, and the stocking of spares have traditionally been based on a range of practices including the prescriptive time-based (rule-based) approach, the condition-based approach, Reliability Centred Maintenance (RCM) and Reactive Maintenance (RM).

Whilst there will remain the need for traditional approaches to asset integrity management, it is increasingly felt that more advanced approaches are required to reflect the complexity and innovation involved in the assets, and to operate at an optimal level within the competitive pressures faced by asset managers. Risk based approaches, as opposed to many other approaches, give operators some flexibility in the management of their assets whilst meeting the same objectives. The flexibility is as a result of undertaking actions not on a fixed schedule or rule, but on some identified measures of risk. The risk based approach uses risk based criteria to prioritize efforts and make the optimum use of this flexibility.

The uptake of risk based practices is growing as increased operational experience and a greater understanding of failures (and its consequences) lead some parts of industry to adopt a more informed approach to planning, targeting resources to reduce risk to as low as reasonably practicable. Risk based approaches are used in many sectors of industry and for prioritizing different types of actions; for example, there are risk based approaches in the process industry to manage maintenance and inspection and there are standards or guidance documents to implement these approaches [1,2,3 and 4].

As opposed to other approaches, in a risk based approach, actions are based on the risk estimate of various options. In the current context, this means maintaining an inventory at an optimal level depending on the risk profile of the spares in which the likelihood of a failure to meet the demand for a spare is considered in conjunction with the consequences of the failure to meet that demand. The optimal level is such that financial benefits are optimised, given risk-associated constraints. As opposed to a more prescriptive approach that is adopted by many inventory management methodologies, for example, to hold a stipulated level of stock bearing in mind the lead times involved, the risk based approach shown here presents a flexible and an efficient way to maintain a spares inventory.

In the discussion below, some of the unique features of spares inventories vis-à-vis other types of inventories are mentioned at the outset. Then there is a section on typical costs associated with inventories followed by a brief note on the main principles underlying various current approaches to spares inventory management. The main body of the paper then presents the risk based methodology and the basic model that has been created to implement that methodology. This is followed by possible areas of further research and conclusions. *(In this paper, for convenience, this often repeated term is used without the hyphen as in 'risk-based'.)*

2. SPARE PARTS INVENTORIES

2.1 Main types of inventories and their attributes

Spare parts inventories are maintenance inventories; they are used by maintenance personnel to keep machines available and exist to meet an internal (in-house) demand for spares. They perform a different function compared to other inventories such as Work-in-progress (WIP) inventories and Finished Product Inventories. WIP inventories smooth out irregularities in production flow. Finished Product Inventories provide a buffer stock to protect against lead time demand, differences in quality levels, differences in machine production rates, labour troubles, scheduling problems, gap between capacity and demand and other well established production problems [5].

Some characteristics of spare parts inventories: Spares Inventories are hugely influenced by maintenance policies rather than customer usages that dictate WIP or Finished Product Inventories. For scheduled maintenance, the demand for spares is relatively more predictable and it may be possible to order parts to arrive just in time for use and indeed not stock such parts at all. For unplanned maintenance, a lack of some stock often means that the consequences of not keeping some stock include production loss and the extra cost incurred in procuring parts at short notice.

There are other factors such as the amount of redundancy within a system, the availability of information from condition monitoring equipment, the inter-dependency of failure events, the possibility of demands being met by cannibalism and the effect of parts or machine obsolescence on the level of stock holding. There has also been research illustrating how other factors such as the organizational context of inventories, especially the responsibilities and authorities of the persons concerned, have a bearing on inventory management [6].

2.2 Typical costs associated with inventories

Businesses like to avoid excess inventory as there are costs incurred in keeping stock. Some of these are:

(a) Ordering and setting up costs: These are fixed costs that do not depend on the size of the order. For example, ordering costs would include paperwork and billing associated with the order.

(b) Unit purchasing cost: This is the variable unit cost of a part or a component.

(c) Holding or carrying cost: These are essentially the inventory costs expressed in monetary value per unit part per year. It includes storage cost, insurance cost, taxes on inventory, and cost due to the possibility of spoilage, theft, or obsolescence. However, usually the most significant of the holding cost is the opportunity cost incurred by tying up capital in inventory.

(d) Stockout costs: When a demand for a product or a part is not met on time, a stockout is said to have occurred. If it is acceptable for demands to be met at a later date, no matter how much later, it is said that demands may be back-ordered. If it is necessary for demands to be met on time, and if this is not achieved, then the scenario is a lost case one.

In the current context, risk is the combination of the probability of a stockout event and its consequential cost, where a stockout is a lost case scenario. Such a stockout may result in production loss, having to procure spares at an additional cost (‘distress cost’), knock-on failures requiring more parts and/or resulting in more production loss, regulatory penalty and other consequences such as loss of goodwill. Usually it is more difficult to measure the cost of a stockout rather than the cost of ordering, purchasing or holding.

2.3 Approaches to inventory management

There are different approaches to Inventory Management. Prasad categorizes inventory models into two: Economic Order Quantity (EOQ) and Materials Requirement Planning (MRP) [7]. Under these, he classifies about ninety inventory models. The basic model in an EOR method determines, subject to a number of assumptions, an ordering policy that minimizes the yearly sum of ordering cost, purchasing cost, and the holding cost of a part in the inventory. The basic model in an MRP based method considers the relationship between a component that is demanded and other associated (sub) components that also need to be available in order to fulfil that demand.

Winston classifies models as Deterministic EOQ Models, Probabilistic Models and other recent models such as MRP, Just-in-time (JIT) and Exchange Curves [8]. Of particular interest, within probabilistic models, is the ABC classification system devised by General Electric during the 1950s. Within this system, in its very basic form, items are stocked according to empirical studies that show that 5%-20% of all items stocked account for 55%-65% of sales; these items are classified as Type A. Similarly Type B and Type C are items that account for a decreasing percentage of sales and are accordingly allocated lower priority in stocking.

Nahmias looks specifically at repairable inventory systems and classifies existing models into three general classes: continuous review, periodic review and models based on cyclic queuing systems [9].

The risk based approach presented here is unique in that it does not completely fall in any of these categories although it might have some elements of the approaches listed above.

2.4 Risk based approach to inventory management

In the current context, the following terms have a special meaning: Risk is the combination of the probability of a stockout event and its consequence, where a stockout is an event when a spare is not available on demand. Qualitative risk analysis broadly covers methods that use engineering judgment and experience as the basis for the analysis of probabilities and consequences. Failure Modes, Effects, and Criticality Analysis (FMECA) and Hazard and Operability Studies (HAZOPs) are examples of qualitative risk analysis. These techniques become quantitative when consequences and failure probability values are estimated in numerical terms. Quantitative risk analysis usually involves a) identifying the combinations of events that, if they occur lead to an undesired event, b) calculating the frequency of occurrence for each combination, and c) calculating the consequences.

The approach shown here is a semi-quantitative approach that captures best estimates from experts as well as raw historical data. The risk of a stockout referred here is relative risk, i.e. the risk of a stockout of a component or equipment in relation to each other.

In the method described below, a risk profile of the spares is obtained by considering the likelihood of a failure to meet the demand for a spare in conjunction with the consequences of the failure to meet that demand. This risk profile is then used to find the optimal level of inventory such that financial benefit is maximized given an identified acceptable risk level.

3. RISK OPTIMISATION MODEL

3.1 Underlying concepts and assumptions

The model presented here was developed to address a situation as follows. There is an inventory of spares to service a fleet of ships. There is demand for parts of different kinds to keep these ships available for service. There is cost involved in purchasing and holding these parts in the inventory, and a penalty (risk) in not meeting demands for spares (stockouts).

There is some historical data available - in the form of the previous demands for each part within the timeframe considered. The question then is, what is the optimum numbers of the different parts the inventory should stock under the constraints of budget and/or acceptable risk of stockout? The risk model was developed using the principles of linear programming.

The model has two parts: Part 1 establishes some baseline values, and Part 2 optimises values. The implementation of the approach is shown by way of an example shown in Figure 1.

3.2 Part 1: Obtaining baseline values

This part of the model aims at establishing baseline values for certain parameters for the purpose of optimising in the second part of the model. The model is shown in Figure 1. In the inventory considered, there are 10 types of parts. The parameters with their descriptions are as follows:

$i =$ unique number representing type of part;

$n_{i(ideal)} =$ the number of parts that a company would ideally like to hold if it had no financial constraints to meet any possible demand that might reasonably be considered.

Part 1: Establishing baseline values								
Part no.	**Demand**	**Units in stock**	**Stock ratio**	**Unit cost**	**Stock cost**	**Stockout consequence**	**Stockout probability**	**Stockout risk value**
		0.9						
i	*ni(ideal)*	*ni(ref)*	*αi*	*Ci*	*ni(ref)*Ci*	*CoSi*	*P(ni(ref))*	*RVi*
1	20	18	0.90	1000	18000	M	0.10	6
2	20	18	0.90	4500	81000	M	0.10	6
3	10	9	0.90	8000	72000	VL	0.10	2
4	5	4	0.80	6000	24000	VH	0.20	20
5	8	7	0.88	10000	70000	VH	0.13	13
6	17	15	0.88	2000	30000	L	0.12	5
7	14	12	0.86	1000	12000	M	0.14	9
8	11	9	0.82	3000	27000	H	0.18	15
9	4	3	0.75	3500	10500	VL	0.25	5
10	15	13	0.87	6000	78000	M	0.13	8
					(TSCb) **422500**			(TRVb) **87**
Part 2: Optimising values								
i	*ni(ideal)*	*nio*	*αio*	*Ci*	*nio*Ci*	*CoSi*	*P(xio)*	*RVio*
1	20	20	1.00	1000	20000	M	0.00	0
2	20	20	1.00	4500	90000	M	0.00	0
3	10	2	0.20	8000	16000	VL	0.80	16
4	5	5	1.00	6000	30000	VH	0.00	0
5	8	8	1.00	10000	80000	VH	0.00	0
6	17	17	1.00	2000	34000	L	0.00	0
7	14	14	1.00	1000	14000	M	0.00	0
8	11	11	1.00	3000	33000	H	0.00	0
9	4	4	1.00	3500	14000	VL	0.00	0
10	15	15	1.00	6000	90000	M	0.00	0
					(TSCo) **421000**			TRVo) **16**
Max stockout prob P(xio*(max)*)			1.00		Condition : P(xio(max) > or =[1-αi(ref)]			
Minimize TRV within budget constraint					Minimize Risk			
Minimize TSC subject to acceptable RV					Minimize Cost			

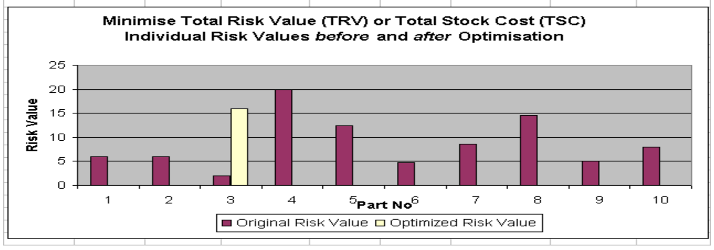

Figure 1: Minimise Total Risk Value (TRV) subject to given Total Stock Cost (TSC) constraint.

(Other factors that influence managing stock, such as warehouse space requirements, spoilage, obsolescence can be factored in the model as shown later); the number is based on any or a combination of historical demand data, expert opinion and manufacturer's recommendations. There are guidelines/ procedures for combining data from various sources using, for example, Bayesian inference [10, 11].

= the maximum demand within the timeframe the company expects to meet if it held stock without financial constraints.

$\alpha_i =$ ratio of the number of part i stocked, say, n_i, to the number the company would ideally like,

$$= \frac{n_i}{n_{i\,(ideal)}}$$

$\alpha_{i(ref)} =$ baseline value of α_i for planning purpose

$n_{i(ref)} = \alpha_{i(ref)} * n_{i(ideal)}$ = baseline number of part i, rounded to the nearest integer

$C_i =$ unit cost of part i

$CoS_i =$ consequence of a stockout for part i (weighted value)

$P(x_i) =$ probability of a stockout for part i,

$$= 1 - \frac{n_{i(ref)}}{n_{i(ideal)}} \tag{1}$$

where $P(x_i) = P(n_{i(ref)} < x_i \le n_{i(ideal)})$ given that,

a) $n_{i(ref)}$ is the quantity in stock,

b) x_i is the number of that part demanded during the timeframe such that $x_i > n_{i(ref)}$,

c) $n_{i(ideal)}$ is the ideal number of part i in stock to meet maximum demand, and
d) the number of parts demanded follow a discrete uniform distribution.

The nature of distribution depends on what sort of data one has and what confidence one has in the available data. The uniform distribution is usually used when little is known about the parameters, apart from the minimum and maximum value within the dataset [12]. A uniform distribution assigns equal probability to all values between its maximum and minimum. Other distributions can also be used in the model created here.
$RV_i =$ Risk value associated with stockout of part

$$i = CoS_i * P(x_i) \tag{2}$$

TSC = Total cost of stock for all parts

$$\text{ni(ref)} = \sum n_{i(ref)} * C_i \tag{3}$$

TRV = Total risk value associated with stockouts for all parts

$$\text{ni (ref)} = \sum RV_i \tag{4}$$

(In the figures showing snapshots of the model, TSC_b and TRV_b are used in Part 1 of the model; the suffix 'b' is used to indicate baseline values.)

In the model, qualitative estimates of CoS_i, Very High, High, Medium, Low, Very Low have been assigned values of 100, 80, 60, 40 and 20 respectively. In a more advanced model, these values would be a weighted average of values obtained by considering a number of consequence or impact factors. One such possible scheme is described later and shown in the Figure 5.

3.3 Part 2: Obtaining optimised values

Part 2 of the model optimises the number of each part held in stock from the reference values selected in Part 1 subject to specified constraints using a linear programming tool. The optimised values contain the subscript 'o'. For example, n_{io} is the optimised value of units of part i to be held in the inventory.

3.4 Working of the model

At the outset, in Part 1 of the model, a suitable value for $\alpha_{i(ref)}$ is assumed; in Figure 1, this is 0.90. $\alpha_{i(ref)}$ (shown in the highlighted box with a small circle towards its top right corner) is a fraction of the ideal number of parts (a wish list) that a manager of an inventory would like to hold given that there will be demands necessitated by failures requiring these parts. This starting assumption is necessary to find baseline values for Total Stock Cost (TSC) and the Total Risk Value (TRV) of the inventory, say, TSC_b and TRV_b respectively where,

$$TSC_b = \sum n_{i(ref)} * C_i \tag{5}$$

$$TRV_b = \sum RV_i \tag{6}$$

This part of the model establishes the correspondence between three critical values (1) the reference stock level as denoted by the ratio $\alpha_{i(ref)}$, (2) the total cost of the stock as denoted by TSC_b (in monetary units) and (3) the unitless TRV_b denoting a measure of risk associated with the inventory.

The initial value of $\alpha_{i(ref)}$, 0.9, can be changed at any stage to bring the TSC_b to a feasible level, if not so already.

The values above are, in essence, baseline values that establish what is an acceptable level of overall risk and the associated cost of stock holding at that level. Part 1 of the model determines these baseline values as a starting point, and part 2 of the model carries out the linear optimisation. In the model demonstrated here, the Linear Programming (LP) is through the Solver add-in to Microsoft Excel.

3.5 Modes of operation of the model

The model has three modes of operation performing three distinct functions. These are:

(A) Minimize Total Risk
Figure 1 shows the results when Total Risk Value (TRV) is minimized subject to a given budget for the purchase of stock, i.e. (TSC). As seen, TRV reduces from 87 before optimisation to 16 after optimisation. Note that the portfolio of parts in the inventory has changed from the baseline or reference case. For example, for part 8 the initial reference holding of 9 has increased to 11, and instead of 9 of part 3, the optimised holding is only 2. Correspondingly, the RV of these parts has also changed.

(B) Minimize Total Cost
Figure 2 shows the results when budget for the purchase of stock (TSC) is minimized subject to maintaining the reference level of (assumed tolerable) Total Risk (TRV). As shown in the figure, the TSC comes down to £304,500 from £422,500, given a Total Risk Value tolerance of 87. Again, the portfolio of parts in the inventory has changed from the baseline or reference case, but in a different way to that for minimising Total Risk above. Individual changes in the number of each part stocked and its contribution to Total Risk can be observed.

Part 1: Establishing baseline values								
Part no.	Demand	Units in stock	Stock ratio	Unit cost	Stock cost	Stockout consequence	Stockout probability	Stockout risk value
		0.9						
i	*ni(ideal)*	*ni(ref)*	*αi*	*Ci*	*ni(ref)*Ci*	*CoSi*	*P(ni(ref))*	*RVi*
1	20	18	0.90	1000	18000	M	0.10	6
2	20	18	0.90	4500	81000	M	0.10	6
3	10	9	0.90	8000	72000	VL	0.10	2
4	5	4	0.80	6000	24000	VH	0.20	20
5	8	7	0.88	10000	70000	VH	0.13	13
6	17	15	0.88	2000	30000	L	0.12	5
7	14	12	0.86	1000	12000	M	0.14	9
8	11	9	0.82	3000	27000	H	0.18	15
9	4	3	0.75	3500	10500	VL	0.25	5
10	15	13	0.87	6000	78000	M	0.13	8
					(TSCb) **422500**			(TRVb) **87**
Part 2: Optimising values								
i	*ni(ideal)*	*nio*	*αio*	*Ci*	*nio*Ci*	*CoSi*	*P(xio)*	*RVio*
1	20	20	1.00	1000	20000	M	0.00	0
2	20	7	0.35	4500	31500	M	0.65	39
3	10	0	0.00	8000	0	VL	1.00	20
4	5	5	1.00	6000	30000	VH	0.00	0
5	8	8	1.00	10000	80000	VH	0.00	0
6	17	17	1.00	2000	34000	L	0.00	0
7	14	14	1.00	1000	14000	M	0.00	0
8	11	11	1.00	3000	33000	H	0.00	0
9	4	4	1.00	3500	14000	VL	0.00	0
10	15	8	0.53	6000	48000	M	0.47	28
					(TSCo) **304500**			TRVo) **87**
Max stockout prob P(xio*(max)*)			1.00		Condition : P(xio(max) > or =[1-αi(ref)]			
Minimize TRV within budget constraint					Minimize Risk			
Minimize TSC subject to acceptable RV					Minimize Cost			

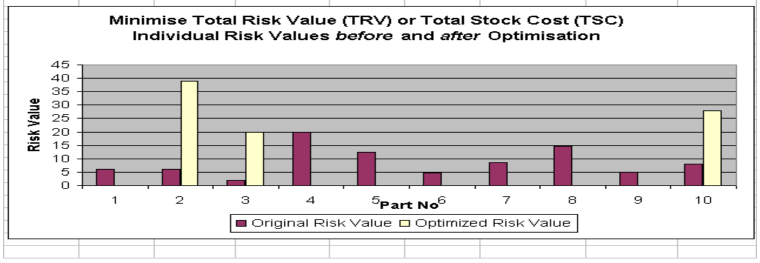

Figure 2: Minimise Total Stock Cost (TSC) subject to a tolerable level of Total Risk Value (TRV).

(C) Minimize Total Risk Value (TRV) or Total Stock Cost (TSC) subject to maximum individual risk constraints

Although optimisation has been carried out as described above, there may be some components for which the risk associated with a particular part may be considered too high to be acceptable to the decision maker. For example, as shown in Figure 1, the optimised RV for part 3 i.e. RV_{3o} is 16; this is an expensive part of VL stockout consequence, but the likelihood value of a stockout relative to other parts is high at $\beta_{3o} = 0.8$. Similarly, in Figure 2, Part 3 has a stockout likelihood of 1.00 (100%).

Such high probabilities of stockout may be deemed too high by the decision maker especially when they are substantially different to that implied by $\alpha_{i(ref)}$ that was assumed in part 1 of the model that established baseline values. It may be noted here that $\alpha_{i(ref)} = 0.9$ implies a reference stock level that plans to meet 90% of the maximum considered demand, i.e., 10% of maximum demand is expected not to be met resulting in a stockout probability of 10%. In these cases the decision maker would be likely to want to hold a greater number of these parts than the optimisation in modes A or B would suggest, even though the consequence of a stockout may be low.

To address the issue of having types of parts with a relatively very high probability of stockout, one more constraint is added to the above optimisation process. This is by way of adding a maximum acceptable stockout probability, $P(n_{io})_{\max}$ for each of the optimised number of parts, n_{io}. This constraint is shown in the highlighted box with two concentric circles towards its top right corner in Figure 3.

Part 1: Establishing baseline values								
Part no.	**Demand**	**Units in stock**	**Stock ratio**	**Unit cost**	**Stock cost**	**Stockout consequence**	**Stockout probability**	**Stockout risk value**
		0.9						
i	*ni(ideal)*	*ni(ref)*	*αi*	*Ci*	*ni(ref)*Ci*	*CoSi*	*P(ni(ref))*	*RVi*
1	20	18	0.90	1000	18000	M	0.10	6
2	20	18	0.90	4500	81000	M	0.10	6
3	10	9	0.90	8000	72000	VL	0.10	2
4	5	4	0.80	6000	24000	VH	0.20	20
5	8	7	0.88	10000	70000	VH	0.13	13
6	17	15	0.88	2000	30000	L	0.12	5
7	14	12	0.86	1000	12000	M	0.14	9
8	11	9	0.82	3000	27000	H	0.18	15
9	4	3	0.75	3500	10500	VL	0.25	5
10	15	13	0.87	6000	78000	M	0.13	8
					(TSCb) **422500**			(TRVb) **87**
Part 2: Optimising values								
i	*ni(ideal)*	*nio*	*αio*	*Ci*	*nio*Ci*	*CoSi*	*P(xio)*	*RVio*
1	20	20	1.00	1000	20000	M	0.00	0
2	20	14	0.70	4500	63000	M	0.30	18
3	10	7	0.70	8000	56000	VL	0.30	6
4	5	5	1.00	6000	30000	VH	0.00	0
5	8	8	1.00	10000	80000	VH	0.00	0
6	17	17	1.00	2000	34000	L	0.00	0
7	14	14	1.00	1000	14000	M	0.00	0
8	11	11	1.00	3000	33000	H	0.00	0
9	4	4	1.00	3500	14000	VL	0.00	0
10	15	13	0.87	6000	78000	M	0.13	8
					(TSCo) **422000**			TRVo) **32**
Max stockout prob P(xio*(max)*)			0.30		Condition : P(xio(max) > or =[1-αi(ref)]			
Minimize TRV within budget constraint					Minimize Risk			
Minimize TSC subject to acceptable RV					Minimize Cost			

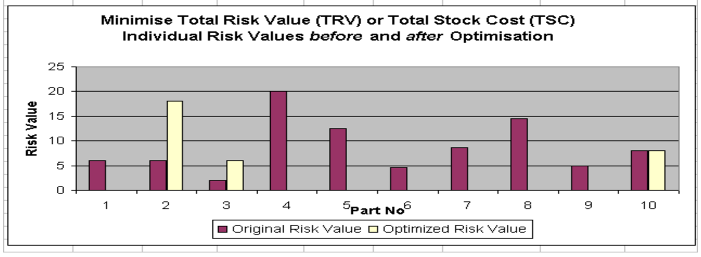

Figure 3: Minimise Total Risk Value TRV) subject to i) a maximum Total Stock Cost (TSC) and ii) a maximum probability of stockout.

In Figure 1 and Figure 2, $P(x_{io})_{\max}$ is mentioned but the value is 1.0. This means that a stockout probability of 100% (a certainty) is acceptable so, in effect, it is not a constraint. Imposing a constraint on the probability of stockout of any type of part when holding an optimised number, $P(x_{io})_{\max}$ (shown in Figure 3 and Figure 4), means that however low impact a failure to meet a demand for a part is, a minimum stock level will be maintained.

Figures 3 and 4 repeat the optimisation with the same values as in fig. 1 and 2 with the added constraint of. $P(x_{io})_{\max} = 0.3$ As seen in figure 3 and 4, the additional constraint ensures that however 'Low' consequence a part maybe and however expensive it may be, it will be stocked within the stipulated level (0.7 or 70% of expected maximum demand, in this case) of tolerable risk both at a system level (as indicated by Total Risk Value) and at the individual or component level (as indicated by various $P(x_{io})$ values). However, as shown in the figures, this extra risk mitigation effected by the constraint $P(x_{io})_{\max} = 0.3$ comes at a price. Figures 3 and 4 show that the Optimised Total Risk Value TRV_o is now 32 up from 16, and the Optimised Total Stock Cost TSC_o is £375,500 up from £304,500.

Part 1: Establishing baseline values

Part no.	Demand	Units in stock	Stock ratio	Unit cost	Stock cost	Stockout consequence	Stockout probability	Stockout risk value
		0.9						
i	*ni(ideal)*	*ni(ref)*	*αi*	*Ci*	*ni(ref)*Ci*	*CoSi*	*P(ni(ref))*	*RVi*
1	20	18	0.90	1000	18000	M	0.10	6
2	20	18	0.90	4500	81000	M	0.10	6
3	10	9	0.90	8000	72000	VL	0.10	2
4	5	4	0.80	6000	24000	VH	0.20	20
5	8	7	0.88	10000	70000	VH	0.13	13
6	17	15	0.88	2000	30000	L	0.12	5
7	14	12	0.86	1000	12000	M	0.14	9
8	11	9	0.82	3000	27000	H	0.18	15
9	4	3	0.75	3500	10500	VL	0.25	5
10	15	13	0.87	6000	78000	M	0.13	8
					(TSCb) **422500**			(TRVb) **87**

Part 2: Optimising values

i	*ni(ideal)*	*nio*	*αio*	*Ci*	*nio*Ci*	*CoSi*	*P(xio)*	*RVio*
1	20	20	1.00	1000	20000	M	0.00	0
2	20	14	0.70	4500	63000	M	0.30	18
3	10	7	0.70	8000	56000	VL	0.30	6
4	5	5	1.00	6000	30000	VH	0.00	0
5	8	6	0.75	10000	60000	VH	0.25	25
6	17	12	0.71	2000	24000	L	0.29	12
7	14	13	0.93	1000	13000	M	0.07	4
8	11	11	1.00	3000	33000	H	0.00	0
9	4	3	0.75	3500	10500	VL	0.25	5
10	15	11	0.73	6000	66000	M	0.27	16
					(TSCo) **375500**			TRVo) **86**

Max stockout prob P(xio(*max*)) 0.30 Condition : P(xio(max) > or =[1-αi(ref)]

Minimize TRV within budget constraint — Minimize Risk

Minimize TSC subject to acceptable RV — Minimize Cost

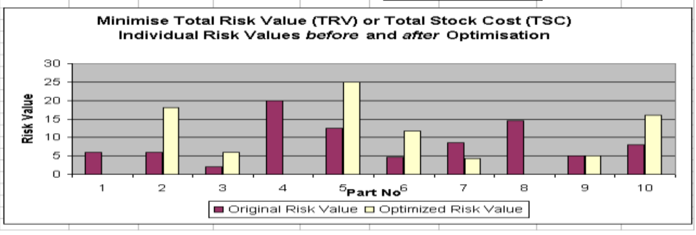

Figure 4: Minimise Total Stock Cost (TSC) subject to i) a maximum Total Risk Value (TRV) and ii) a maximum probability of stockout.

	Impact Factors	IF1	IF2	IF3	IF4	IF5	Total
	Description	Lead time	Technical staff availability	Knock-on failures	Redundancy	Obsolescence	
	Weights	10	10	60	15	5	100
Part 1	Assessment	H	M	VH	L	H	
	Total	8	6	60	6	4	84 CoS
	Values						
VH	100						
H	80						
M	60						
L	40						
VL	20						

Figure 5: Deriving CoS for a type of part from a number of factors.

4. DISCUSSION OF THE SPARES MODEL

4.1 Assessment of the impact of not meeting a demand for a part

It is at times difficult to quantify the full implications of not meeting a demand for a part when required (stockout). Therefore, qualitative assessments of consequences or impact of stockout, despite the subjectivity involved, are often the best way to factor in certain intangibles, such as loss of orders or reputation. It is worth noting that the same model will work by directly putting in the likely impact cost (in monetary terms) of a failure to meet a demand for a particular spare.

One can make such qualitative estimates more precise by fine-tuning the consequence part of the risk estimate. For example, CoS can be a weighted sum of various consequences factor values such as: extra cost of procuring a part on an urgent basis and the lead time under such circumstances, availability of technical personnel to effect repairs, knock-on effect of failure to meet a part on the general availability of the system and the risk of obsolescence of a part or the machine itself. Fig. 5 shows how such an approach can be developed.

The approach consists of the following main steps: (1)Identify factors (termed as Impact Factors (IF) in Figure 5) that impinge on failure to meet a demand for a type of spare. In the figure, these are lead time, availability of technical staff, knock-on failures and associated demands, potential for machine or spare redundancy and obsolescence.

(1) Ascribe weights to each of these impact factors to reflect their relative importance. These are 10, 10, 60, 15, and 5 for IF1 through to IF5 respectively.
(2) Determine relative importance values for VH, H, M, L or VL representing Very High, High, Medium, Low and Very Low. In the approach shown in the figure, these are 100, 80, 60, 40 and 20 respectively.
(3) The spare type is then assessed qualitatively- VH, H, M, L or VL - under each of the impact factors identified in step (1). The net result of this exercise is a total Impact Value or the CoS for the type of part under consideration.
(4) In Fig. 5, the value '8' in the first column is (10*80)/100. Weights need to total 100 as this is a relative assessment; the weighted total '84' is the CoS value for that part. This process is repeated for each type of spare part that is under consideration in an inventory. The relative weights or values in step (2) and step (3) may or may not be the same for all parts. Indeed, impact factors also may differ with parts.

The impact or criticality of a stockout can also be calculated by using other techniques that may have some advantages over qualitative or strictly numerical methods. One such technique involves the use of fuzzy logic, the application of which is shown in prioritization of failures in [13].

4.2 The initial assumption about 'ideal' stock level to meet a maximum demand

The starting assumption is necessary to set a baseline. A distinction must be noted: 'ideal' values here mean the hypothetical scenario in which the decision maker has no constraints; this is in contrast to optimal values or optimised values that are values that represent optimum trade-offs, given the constraints that apply. The starting assumption is more in the nature of a carefully thought of scenario considering historical data, expert opinion or guesstimates. For example, if one has no incidence of a propeller failing in a particular fleet of ships, one might consider a bigger sample or use expert engineering judgement to assess demand. If one was charged with the responsibility of stocking grit for next year's winter, one reasonable way to start assessing the demand would be to look at what has been the maximum demand in the past, say, five years and use this as a benchmark.

4.3 Changes to the rate of demand

In the calculations carried out, this model uses a demand trend for each type of part in the period under consideration. The trend is considered fixed in this snapshot in time. The model in its current form is thus based on periodic reviews of the stockholding using prior experience.

The assessment of the demand can be made continuous by using a moving average method for the demand trend. This would represent a continuous review model that may be more advantageous in some circumstances [14]. The model can also be configured to take in statistical distributions other than the discrete uniform distribution in describing the demand for parts.

The rate of demand for parts may well increase as structures or equipment get older. This change in the rate of demand is another factor that could be built into a spares inventory model. It would require a more sophisticated treatment of time dependent effects that is beyond the scope of this work.

5. DISCUSSION

Research described here applies risk based principles to spares inventory management. It extends the risk based approach that is well established in other areas of industry.

The approach outlined here has the potential to increase plant or system availability and manage business as well as operational risks. It is thus of wider interest to a number of other stakeholders including operators, maintenance personnel, regulators and insurance companies, and other industries. The methodology can also be extended for use in other areas that impinge on asset management such as inspection and maintenance where competing risks (of failure) need to be managed within finite resources.

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