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SERVICE PARTS FOR PERSONAL COMPUTERS:
A CASE STUDY

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Inventory Management of Repairable Service Parts for Personal Computers: A Case Study

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1. Introduction

In many consumer manufacturing organizations the production process has changed drastically in the recent years. Attention has shifted from increasing efficiency by means of economics of scale and internal specialization to meeting market conditions in terms of flexibility, delivery performance and quality. Ideally, this trend towards JIT production implies working with absolute minimum work-in-process and finished good inventories. However, not enough attention has been paid to the management of after sales activities. One of the important aspects is the management of (repairable) service parts inventory. Competition has forced consumer products industries to provide very short call service contracts in order to boost sales and this has resulted in large inventory of service parts in the after sales logistics chain.

Recent years have seen an increase of interest in the field of service parts inventory particularly in computer industry. This increase can be attributed to the wide use of micro-computers. When a computer or a system fails, it is not always easy to trace the reason for its failure. It is frequently due to either a quality problem or the wrong way of using the computer or its component parts, or a combination of both. Whatever the reason for the failure is, the computer availability or generally system availability and the time needed for maintenance or repair are important to most users. For example, in a financial institute like a bank, any short interruption may cost thousands of dollars. Here the goal is to reach 100 % system availability, or to come as close to it as possible. Without any doubt good service parts inventories can contribute to this goal. Computer industry as a whole is a highly competitive industry, products have to be repaired as quickly as possible, since a slow repair can lead to loss of future business to competitors with better service reputations. Therefore, a good reputation is closely linked to the availability of spares on the market. For companies that operate worldwide the problem becomes even more complex and important.

Although in the design of computer systems, attention is already paid to reliability through careful selection of components, design sophistication, incorporating of various types of redundancy and provision of back-ups, there is no doubt that a good management of service parts inventory is of prime importance to many consumer companies, particularly computer industry. Given this fact and

a real-life case study, we first elaborate the management and control of service parts inventory in section 2 using the case as vehicle. In section 3 we present a brief overview of the contemporary literature on the subject. The solution approach adopted and results of study are presented in section 4. Finally in section 5 the overall conclusions are drawn.

2. Management & Control of Service Parts Inventory: The Olivetti Case

Olivetti is an Italian company that produces and distributes computers, monitors, printers etc. The sales of complete units in the Netherlands is coordinated by the Olivetti office in Leiden. Customer service calls are arriving at Olivetti Service in Nieuwegein, where the service activities are coordinated for the whole country. This department plays an important role in the management of service parts for the after sales activity of Olivetti in the Netherlands.

The structure of inventories with repairable service parts for the case under study is comparable with the structure of a two-level distribution inventory problem. The major difference here is that there exists repair facilities in the system. The repair facilities are located in different countries, namely in the Netherlands and in France. Usually repair is performed locally in an electronic lab (e-lab) except for more complex or large repair batch that is performed in Paris (see figure 5 for an overview of service parts logistics flow at Olivetti in the Netherlands). The non-Olivetti parts are sent to external repair facilities. The Olivetti service parts are divided into repairable modules and non-repairable components. These parts are separately stocked in the inventory in Nieuwegein.

There are over 10.000 different components stored in Nieuwegein. Almost 50% of the components have a positive inventory status. The components on hand occupy about 20% of inventory space and are worth about fl. 900.000. The inventory management system for components is developed by Olivetti and is called SigerC. The system forecasts the demand for the components using "double exponential smoothing". Based on this forecast and using the classical Economic Order Quantity (EOQ), the orders are generated for different components. The current inventory control system of components has proved to be reliable enough. However, it does not control the flow of repairable modules. The repairable modules consists of 2300 different types from which 1600 types are frequently demanded. The stock of modules utilizes the 80% rest of inventory space and worth about fl. 12.000.000. Comparing the value of stock of components with those of modules, one can see that a good management and control of modules is a necessity. Therefore, the study concentrated on the development of a solution approach for management of the modules. In order to understand the methodology adopted and discussed in section 4, below the logistics flow of repairable modules is elaborated.
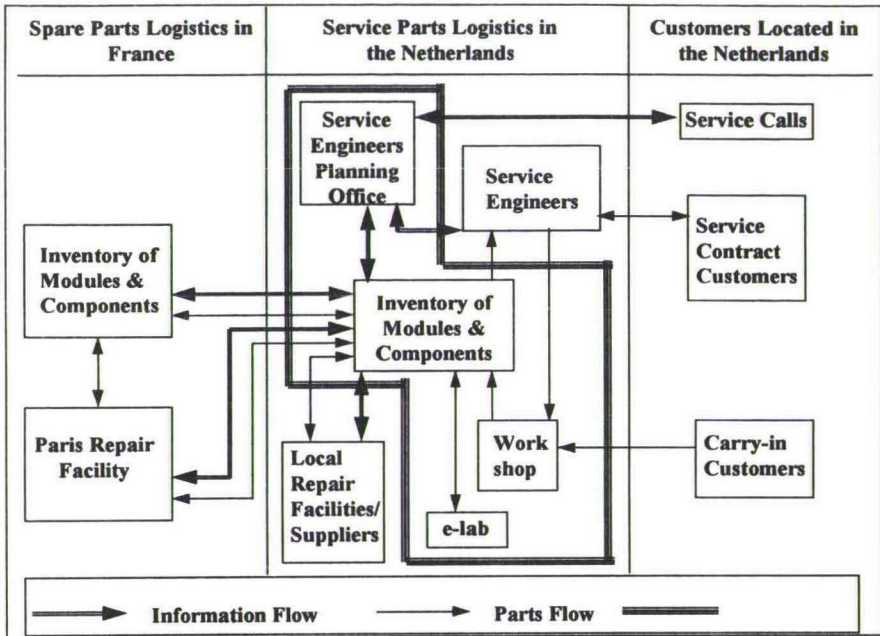
Spare Parts Logistics in France	Service Parts Logistics in the Netherlands	Customers Located in the Netherlands

Service Engineers Planning Office

Service Calls

Service Engineers

Service Contract Customers

Inventory of Modules & Components

Inventory of Modules & Components

Paris Repair Facility

Local Repair Facilities/ Suppliers

Work shop

Carry-in Customers

e-lab

Information Flow — Parts Flow ══

Figure 1. The logistics flow of service parts inventory

Demand for repairable modules are of two types, those generated by the customers who have no service contract (carry-in) arriving directly at Olivetti and those with a service contract. The latter constitutes a major portion of the demand for repairable modules (90%). As illustrated in figure 1, telephone calls reporting a particular defect are all arriving at a central office in Nieuwegein where a rough diagnose of the potential problem is made. Depending on the problem a field engineer is assigned to look after the service. The service contracts usually fall in one of the following categories of 2, 4, and 8 hours service delivery after receipt of phone calls. The service is provided from 8:30 to 17:00 (weekend is not included). Therefore, when a customer with a 4-hour service contract reports a defect at 16:00 on Monday, he should be serviced before 11:30 on Tuesday. As mentioned earlier respecting this "response-time" is crucial. In order to meet the obligations and to reduce costs as far as possible the stock of modules are centralized in Nieuwegein. However, a small portion of the inventory lays maximum for one day with the service engineers to meet the short service contracts and then is returned to Nieuwegein.

The logistics process between Olivetti and service engineers and the repair facilities is as follows. When for example a number of modules are delivered on Monday evening to a service engineer for a prognosed defect, on Tuesday the modules are taken by the engineer to the customer. Then a good module or more is swapped with the defect one(s). The good modules which are unused will stay with the service engineer until Wednesday evening and if not required for the day after, they are returned back together with defect modules to Nieuwegein on Thursday. Thus it takes all together three days to re-book the good modules in inventory in Nieuwegein. The defect modules are then either repaired locally or are shipped to Paris for repairing. The repair facility in Paris

usually deliveries a repaired module in one day when enough inventory exists (*Inventory in Circulation*) or repairs the same module and returns that when there is enough time (*Pure Repair*). In the latter case the "Turn Around Time" is about 10 days. Exclusive repaired modules (more customer specific) are also available in very limited number in inventory and are lend temporary until the original module is repaired (*Lend Inventory*). From the three possible options, lending is the most expensive and pure repair is the cheapest. Given the three days delay in re-booking a good module sent by service engineers and the possible delay caused by the repair facility in Paris, currently a safety stock of 4 days is kept in Nieuwegein.

The current logistics flow of modules is managed by a simple information data base developed by Olivetti called OLBORD (OLivetti BOard Repair Decentral). However, all decisions concerning the modules are made manually. One of the important decisions made is batching, that is how many modules should be sent together to the repair facilities and when. A hurdle on the way of this decision making process is the fact that the real defect is not known, only the customer complain is noted. Therefore, a specialist given his experience and the back-order list, decides which modules should be sent to which repair facility for further examination. It is then that an estimation of repair time can be made. At this stage a fraction of defect modules is considered as scrap and therefore from time to time new modules should be procured. Thus the repair batch sizing decision and the decision concerning the number of new modules to be ordered and the timing of such an order is a complex task.

In order to develop a solution approach for the above decision making process, first an ABC analysis of different types of modules was performed (see figure 2). The analysis revealed that about 20% of the total number of module codes represent about 80% of the demand. Therefore, the attention was focused on only these modules. These modules roughly speaking are demanded from two times per month up to three times a day.
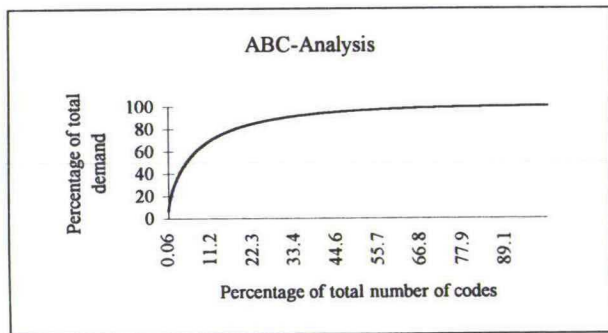

Figure 2: ABC Analysis of all modules

3. Literature Overview & Modeling Aspects of Olivetti Case

The history of the subject of (multi-level) inventory systems with repairables is not a long one since it is hardly more than three decades ago that the first works devoted to the subject appeared. This period has however seen the publication of a large number of papers covering a limited aspect of real-life problems of the design and control of complex inventory systems with repairables. It is worthwhile to mention a few here.

About three decades ago, the mid sixties have witnessed the publication of a number of papers treating, essentially, single-level inventory systems, but with more centrally controlled stocking points and possible redistribution of stocks. Of the well-known publications is the work of Schrady (1967). Early applications of this work can be found in expensive slow-moving items with relatively low demand. Most of the papers applied (S-1, S) ordering. They usually assumed that the delivery and repair times are deterministic and the demand distribution is either deterministic or follows a Poisson process. The literature is not limited to the single-level inventory system, several papers treated the two- and multi-level inventory problems with repairables. Among the latter papers we can refer to the work of Sherbrooke (1968) which presented METRIC model (Multi-echelon Technique for Recoverable Item Control). Originally, in this model a two-level system was considered in which the peripheral subinventories (bases with repair facility) follow continuous review (S-1, S) policies and second-level subinventory (depot with repair facility) performs no reordering since all failed units are always repairable. Sherbrooke assumed that the external demand at each base obeys a Poisson process, while repair and shipping times are random. Performance measure of the system is the sum of backorders at peripheral subinventories. Inspired by Sherbrooke's paper many authors proposed a modified version of METRIC. The most commonly cited among them is MOD-METRIC model by Muckstadt (1973).

As mentioned earlier many contributions have been made by different authors. Among the models with deterministic demand besides the work of Schrady, we can refer to Nahmias and Rivera (1979), Muckstadt & Isaac (1981), and Mabini (1991). Many stochastic models have been reported among which we can refer to the works of Simon and D'Espose (1971), Richards (1976), and Porteus and Landsdowne (1974). Interested reader may refer to Nahmias (1981) for a detailed study of the written history and Mabini and Gelders (1991) for an overview distinguishing single-level and multi-level models. Both papers have divided the inventory system with repairables into the following modeling approaches:

a) Continuous systems: (S-1,S) or batch
b) Periodic systems
c) Systems using queuing models
d) Heuristics & Simulation

The environment for the first three categories of approaches are well-known. In these categories the demand is assumed to be constant or stationary following a Poisson process. The last category usually deals with situations where the number of repairable items is fixed or the demand does not follow a Poisson process. From the interesting works related to our case we can refer to work of Matta (1985) who has discussed a simulation program for a dynamic demand pattern and to the work of Little et al. (1992). They actually present a simulation study of a comparable environment, i.e. a computer industry.

The situation of inventory of repairable modules in Nieuwegein can be formulated in different ways; as single-echelon or a multi-echelon system. The inventory laying with the service

engineers can be neglected since with a short delay it is registered back in the stock in Nieuwegein. The inventory of modules in Paris can also be overlooked since what counts is the repair time delay and that indirectly represents the inventory level in Paris. Thus the situation can be considered as a single-echelon inventory with repairables. Then the question is which modeling class is most suitable for the Olivetti case. Given the extensive information capacity of the company, and the fact that transactions are directly and continuously updated, a continuous system looks more promising. Thus a periodic system is not a solution. Solutions based on queuing are not applicable as the demand is not truly a Poisson process and the repair time is variable. Figure 3-a and 3-b show respectively the observation of gross and net demand over a period of 3 months for one type of A-class module. As can be seen the gross demand is stationary and non-negative, independent with finite expectations but the net demand is surely not a Poisson distribution, as the the definition region is $(-\infty, +\infty)$. Moreover, in 90% of the investigated modules the variance of the gross demand is at least 25% larger than its average, meaning that a Poisson process is doubtful.

Given the above observations, the study approach is somehow limited to the last category which is simulation. Before describing the solution methodology adopted (i.e. combination of batches and simulation), here we elaborate the deterministic model of Schrady (1967) as this model is extended and used in our solution approach discussed in section 4.
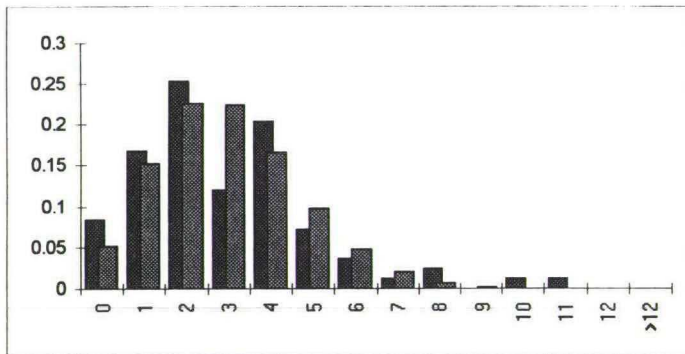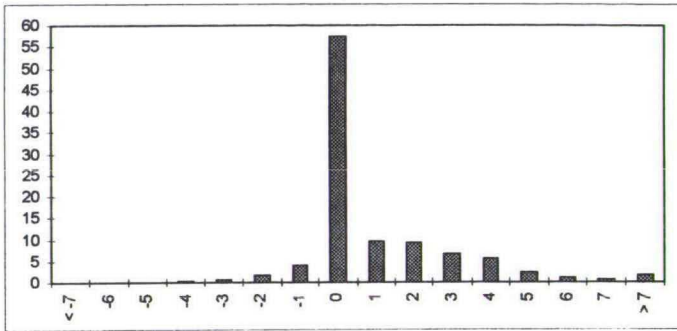

Figure 3-a: Gross Demand Pattern for an A-class Module per Day
Note that the dark shaded bars represent the empirical distribution and gray bars represent a Poisson distribution with the average of the empirical observations

In order to discuss the Schrady's model, first we list the major input data required. These are:
- Demand for each module (deterministic)
- repair time (deterministic)
- Ordering lead time (deterministic)
- Ordering cost
- Cost of repairing a batch
- Inventory holding cost per module
- Scrap percentage
- repair capacity
- Price of modules

Figure 3-b: Net Empirical Demand Pattern for an A-class Module per Day
Note that observations for a net demand lower than -4 have a probability < 0.05

Performance measures used are the average inventory of defects and Ready-For-Service (RFS) modules, and the total costs of ordering, repairing, and inventory. The generated outputs of the models are the quantity and frequency of ordering new modules and the quantity and timing of repair batches.

The Schrady model is a deterministic inventory model for single service module. He distinguishes two types of inventory in his model, namely defect inventory and RFS inventory. When a module fails, the module is replaced by an RFS one out of inventory. A fraction of defect modules (r) can be repaired and the rest ($1-r$) are discarded as scrap. The modules which can be repaired are returned to inventory as RFS after being fixed. Given the fact that there is a scrap fraction, new modules must be procured from time to time to replace those which were scrapd. Thus the RFS inventory has two input sources - procurement and repair. Schrady's model determines the optimal procurement and repair quantities. In order to find these quantities he suggested two policies. The first policy calls for a repair batch when the defect inventory level reaches a certain level, the repair trigger. This policy is supplemented with new procurement. The second policy is suggested by noting that there is a trade-off between stock held in RFS condition and stock held in defect condition. This is to say that the cost of defect modules held is less than the cost of RFS modules by at least the cost of repair labor and replacement components. Thus, if inventory is to be held in the system it would be better held in defect condition than in RFS condition.

The second policy, called "Substitution Policy" supplies 100 percent of demand from repaired modules until the return of defect modules decreases to a point where there are insufficient modules on hand to trigger another repair batch. At this time, a procurement quantity is received, and the repair triggering is suspended. Then during the period that procurement quantity is used, defect modules are accumulated for repair and then the repair batch can be triggered. Figure 4 illustrates this process.
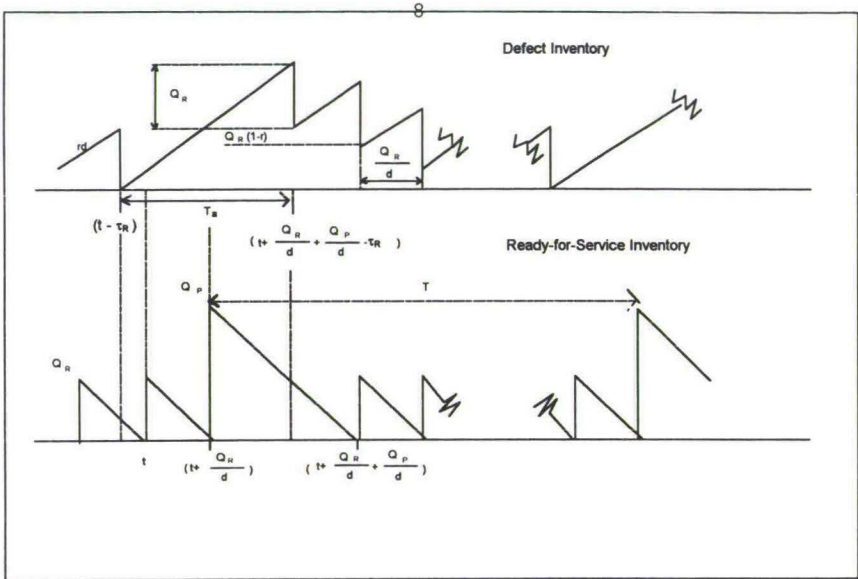
Figure 4: The "Substitution" Policy

The model proposed for the second policy is presented is detail in the appendix A. The basic notations used in the model are:

Q_P - Procurement batch
Q_R - Repair batch
d - Demand rate, unit per unit time
$1-r$ - Scrap-rate, r is repairable rate
τ_P, τ_R - Procurement and repair leadtimes including transportation time
A_P - Fixed procurement cost
A_R - Fixed cost for triggering a repair batch
h_1 - RFS inventory holding cost per unit per time unit
h_2 - Defect inventory holding cost per unit per time unit
T - System cycle time, time between successive procurement quantity arrivals to RFS
         inventory
T_a - Time period during triggering repair batch is suspended

The optimal quantities for repair and procurement that minimizes the total cost per unit time are:

$$Q_P^* = \sqrt{\frac{2 A_P d(1-r)}{h_1(1-r) + h_2 r}}$$

and

$$Q_R^* = \sqrt{\frac{2 A_R d}{h_1 + h_2}}$$

The situation at Olivetti is similar to the one described by Schrady with some differences. The first difference here is that once a defect module is brought to the workshop, it would take some time to check the type of problem and make a decision whether the module should be considered as scrap or repairable one. Thus in our case we can distinguish two types of defect inventory, those which can be repaired and those which are scrap. To overcome this problem, we can use historical data and estimate the percentage of scrap.

The second difference is that repair time and the leadtime to get new modules and demand are not constant. The ordering leadtime of new modules can be determined as the average of historical leadtimes and considered to be constant. The repair time usually depends on the repair batch which is not fixed. This time can be estimated as the average of repair times per batch and assumed to be constant. Using the repair batch, one of the outputs of the Schrady model, a new repair time can be estimated. When this time is close to the earlier estimation, the solution is accepted. Otherwise, the the repair batch release time can be adjusted by either triggering the batch earlier if the new time is longer or later when the new time is lower.

Finally, the third problem is that repair capacity is not unlimited. The latter is not a serious restriction and can be considered as unlimited. Given all the foregoing assumptions made, the Schrady model has potential use. This model is further explored in the next section.

4. The solution approach & results

4.1 Basic model adapted

The deterministic basic model as described earlier does not represent the real situation perfectly. For example, this model does not take into account the returning modules, which are unused. However, this aspect can be easily put into the basic model by reformulating the input in the following way.

Gross demand (d):	=	demand per time unit by the registration system
Net demand (x):	=	gross demand minus the number of modules per time unit which is returning unused.

Assume further that there is a fixed percentage (e) of the gross demand (d) per time unit which is returning unused, that is ed units per time unit. This increases the inventory of modules ready for service.

Let's now assume that the following input is given:

- demand rate d in units per time unit;
- a fraction $(1-r_g)$ of the gross demand d which is rejected;
- a fraction e of the gross demand d which is returning unused.

On the average there are returning ed_g units unused per time unit, so the net demand is

$d - ed = d(1-e)$ and on the average there are $(1-r_g)d$ units rejected per time unit, such that the growth rate of the inventory level of the defects is $(1-e-(1-r_g))d = (r_g-e)d$ units per unit time.

Based upon the above reasoning the following input for the basic model is chosen to determine the optimal repair and order batch:

- the net demand $x = d(1-e)$
- a fraction $(1-r_n) = (1-r_g)/(1-e)$ of the net demand which is rejected.

So it is confirmed that the growth rate of the inventory level of the number of defects is indeed $r_n x = \{1 - (1-r_g)/(1-e)\} * d(1-e) = (r_g-e)d$. It should be noted that the net demand level $x = d(1-e)$ is significantly lower than when unused returnings are not taken into account (In our case the percentage e is on the average 40%). The rest of the input for the model remains unchanged.

In reality the demand process is of course stochastic and its characteristics will be analyzed now. Let d_i be the gross demand on day i. This demand process can have an arbitrary empirical distribution with expectation $E(d_i)$ and variance $V(d_i)$. We further assume that these demands are identically distributed and independent of other demand days. Assume also that a fraction e of the gross demand of day i, d_i, is returned unused. So every module which is demanded will be returned unused with probability e. Let's define for this purpose a help variable:

h_j: =   dummy variable representing if demand j of a certain day is returned unused (1) or that a defect is return (o).

The variable h_j has a binomial distribution with parameters $(n, p) = (1, e)$ and $j = 1, ---, d_i$. The expectation of h_j is $np = e$ and the variance is $np(1-p) = e(1-e)$.

Further define

x_i = net demand on day i

On a certain day, x_i is determined by what is demanded on that day minus what is returning unused on that day of what was demanded three days ago. Assume that on day i-3 there are d_{i-3} total demands. Then for every demand it is decided whether the module is returned unused or not. This is done by taking d_{i-3} times a realisation of h_j. The sum of these realisations of h_j are the total number of modules that on day i is returned unused from day (i-3).

This gives

$$x_i = d_i - \sum_{j=1}^{d_{i-3}} h_j$$

Hereby it is realistic to assume that the variables d_i and h_j are independent and identically distributed and independent of each other. The expectation and variance of the net demand x_i for a fixed returning time (3 days) and stochastic demand, can be determined as follows:

$$E\{x_i\} = E\{d_i - \sum_{j=1}^{d_{i-3}} h_j\} = E\{d_i\} - E\{\sum_{j=1}^{d_{i-3}} h_j\} =$$

$$E\{d_i\} - E\{d_{i-3}\}\, E\{h_j\} = E\{d_i\} - E\{d_i\}e = (1-e)E\{d_i\}$$

$$Var\{x_i\} = Var\{d_i - \sum_{j=1}^{d_{i-3}} h_j\} = Var\{d_i\} + Var\{\sum_{j=1}^{d_{i-3}} h_j\} =$$

$$Var\{d_i\} + E\{d_{i-3}\}\, Var\{h_j\} + E^2\{h_j\}\, Var\{d_{i-3}\} =$$

$$Var\{d_i\} + E\{d_i\}e(1 - e) + e^2\, Var\{d_i\}$$

The variance of the net demand x_i is larger than the variance of the gross demand d_i, which is intuitively clear, as x_i has a realisation region which is larger than that of d_i. It should further be noted that for the variance expression of x_i it does not matter if the returning time of the unused modules lasts three days or another fixed number of days (greater than zero). When

the gross demand has a Poisson distribution (with parameter m), then it can be shown that the net demand has expectation $m(1-e)$ and variance $m(1+e)$.

However, for our case it was doubtful to use the Poisson distribution, as for 10 important modules 9 of them had a variance which was more than 25% larger than its mean. The above can be extended to the case of variable returning times for unused modules. Assume that a module is returned unused with probability s after one day, ..., with probability w after 5 days. Note that: $s + t + u + v + w = 1$. The expectation of the net demand in case of variable return times is the same as for fixed return time (see appendix B). The variance is (see appendix B)

$$V(x_i) = V(d_i) + E(d_i)e(1 - e) + e^2 V(d_i) +$$
$$2e^2 * (st + su ... + uw + vw) (E(d_i) - Var(d_i))$$

Comparison of this variance with that of a fixed return time, leads to a difference which is formed by the last term in the above expression.

For this last term the following holds

$2e^2 (st + su + ... + uw + vw) (E\{d_i\} - Var\{d_i\})$

> 0 *when* $E\{d_i\} > Var\{d_i\}$

< 0 *when* $E\{d_i\} < Var\{d_i\}$

Note that when d_i follows a Poisson distribution there is no difference between the two situations. When the expectation of d_i is smaller than the variance, then the variance of x_i in the case of variable returning times is smaller than in the case of fixed returning times. In the reverse case the conclusion is contrary. However, in our case for all modules analyzed, we found that $V(d) > E(d)$, but the difference in the resulting variance of the net demand was very small between the two situations. Therefore, we used a fixed returning time of three days in the simulation study.

4.2 Simulation study to validate

The deterministic basic model can not be used right away for the real case situation. As a mathematical analysis of the real situation is very complex (the real situation does not fit to the traditional model assumption in the literature), we have chosen to use simulation.

The modifications and extensions of the basic model of Schrady are:

- net demand is assumed stochastic, and has non-Poisson characteristics which will be taken into account;
- repair and order lead times are assumed stochastic, and their empirical distributions are used;
- modules which are returned unused are explicitly taken into account using a fixed return time of 3 days.

The simulation model now describes the real situation pretty accurately. In comparison with the basic model, the stochastics introduced will increase safety stocks to reach a certain high service level. This can be done by repairing and ordering earlier than in the basic model was the case. The repair and order batch size are those taken from the basic model. This idea is based on classical inventory theory where the EOQ-order quantity under high service levels gives good results in a situation with stochastic demand. Using simulation one can search for a

relation between the level of stochastics and the level of safety stock. The approach runs as follows.

With help of the analysis in section 4.1 the expectation and variance of the net demand (x_i) can be determined. Given the expectation and variance of the repair lead time (τ_R), the net demand during the repair lead time (y) can be determined:

$$y = \sum_{i=1}^{\tau_R} x_i$$

We assume that the x_i are independent for all i with expectation μ_x and variance σ_x^2 and identically distributed and independent of τ_R. The stochastic variable τ_R has expectation μ_{τ_R} and variance $\sigma_{\tau_R}^2$. It is now well-known that:

$$E\{y\} = \mu_{\tau_R}\,\mu_x$$

$$\sigma_y^2 = \mu_{\tau_R}\,\sigma_x^2 + \sigma_{\tau_R}^2\,\mu_x^2$$

The repair point can now be determined as follows

$$\text{repair point} = E\{y\} + k\sigma_y$$

In the above expression the factor $k\sigma_y$ can be seen as safety stock. The order point is determined as follows:

$$\text{order point} = \text{expected net demand during order lead time} + \text{factor}.$$

The factor is determined by adding 1 unit each time when the repair point is increased by 1. The analysis is concentrated on the repair point as in a cycle of 72 working days, 9 repairs take place and only 1 ordering in the deterministic case for an important module which is worked out in the next section. A similar structure holds for the other modules.

The factor k stands for the safety factor, which can be varied and then by simulation the realised service can be measured and k can be increased when the realised service is not enough.

With help of the simulation package GPSS-PC the basic model is extended such that it resembles the real situation very much. In general the extensions with regard to stochastics, increase the safety stock to reach a desired high service level. Neverthless, the results when compared with the basic model do not change drastically. Generally speaking it appears that the variance in the demand and repair lead times can best be taken care of by repairing earlier than in the basic model, the variance in the order lead time can best be taken care of by ordering earlier.

The fixed return time of three days has little influence and the unused returning process in fact only increases the variance of the net demand and makes it to have a positive and negative definition region.

The new approach can be broken down into the following steps:

step 1: Determine the input data (d, r_g, e).
step 2: Determine expectation and variance of net demand during repair time and during order dead time.
step 3: Determine $Q_R^{\ast}$, $Q_P^{\ast}$ and the repair and order point for the deterministic case.

step 4: Using simulation adjust the repair and order point from step 3 until a certain realised service is reached.

step 5: On a daily base inventory levels should be checked and compared with the calculated repair plus order points and possible action should be taken.

For an important module, things will be demonstrated through a numerical example.

Practical example

Empirical data information of an important module:

Average gross demand	= 2.96
variance gross demand	= 4.718
Fraction of gross demand returning unused (e)	= 0.336
scrap rate $(1 - r_g)$	= 0.05665
average net demand	= 1.967
variance net demand	= 5.913
Fraction of net demand which is rejected $(1 - r_n)$	= 0.085

μ_{r_R} = 5 days (50% 4 days, 50% 6 days), $\sigma^2_{r_R}$ = 1

μ_{r_l} = 7.5 days (50% 5 days, 50% 10 days), $\sigma^2_{r_l}$ = 6.25

μ_y = 9.84, σ^2_y = 33.435

$A_P = fl\ 150.0$, $A_R = fl\ 50.0$, $h_1 = fl\ 0.66$ per unit per day (operational unit)

$h_2 = fl\ 0.33$ p. unit per day (defect unit)

deterministic model solution

$Q_P^* = 12$, $Q_R^* = 14$

repair point = 10

order point = 2

T = 71.47 working days

n = 9

Adaptation because of uncertainties:

repair point = 9.84 + 5.782 k

order point = 7.5 * 1.967 + factor

Factor is increased with one unit each time the repair point is increased with one unit. In the table hereafter the simulated effect can be seen.

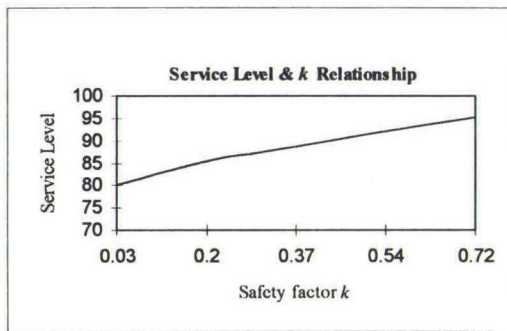| k	repair point	order point	average inventory operational	average inventory defects	service level
0.03	10	2	9	17	80.20 %
0.20	11	3	10	18	85.52 %
0.37	12	4	10	19	88.49 %
0.54	13	5	11	20	92.21 %
0.72	14	6	12	21	95.24 %

Figure 5: Service level versus safety factor

In figure 5 it is remarkable that there is a nearly linear relationship between service level and safety factor, which we obtained via simulation. If we had assumed that y is normally distributed with expectation m_y and variance s_y^2, then $P\{y > m_y + ks_y\} = P\{u > k\}$, where u is a standard normal variate. Given a certain service and m_y and s_y, then k can be looked up in a table, for example for the above module for a service level of 95.25 % the k factor is 1.67. As can be seen in the above table the simulated k factor was for this situation 0.72, which is quite a large difference. The resulting repair point is now: $9.84 + 1.67 * 5.782 = 19.496$, instead of 14; and the order point is 12 instead of 6.

Had we used the normal approximation for y for the above action points, then the average inventory of operational modules would have been 17 instead of 12 (an increase of 42%).

When demand is assumed to be normally distributed then k would have grown exponentially with increasing service instead of linearly as in the simulation study. For this module we can conclude that the normal approximation is not at all suitable.

Via simulation the safety factor k can also be obtained for other modules rather efficiently (approximately 5 CPU seconds per module on a Commodore 486DX-33C machine).

4.3 Simulation study to measure the benefits

The optimal repair and order quantity can be determined via the basic model of Schrady and the safety factor is determined via simulation. This safety factor is nearly the same for a number of modules in a certain class. The proposed system will every day <u>automatically</u> select these codes to be repaired or ordered. This is done by comparing the present inventory positions with the calculated repair and ordering points.

This appears to be a great advantage with regard to the present situation: inventory management for a large number of codes (1600) can be done automatically which is now done manually. A good comparison between present inventory management and the proposed method is difficult, as the average inventory levels of the modules during a longer period is not known for the present system.

However, the impression exists that for some codes too much is held in inventory, while for others too less is there to reach a certain service. The new method would reallocate the total inventory, which would improve the total system performance.

For the module which we analyzed in the previous section we try to compare as far as possible the present situation with the proposed one. As the average inventory level for the present situation is not known, we looked at the average number of back orders per day, given a certain service.

For the code in question we get: service level: 81.3%; average number of back orders: 1.01. The service level is determined at the end of a day. However, the percentage of the daily demand which can be delivered directly is much lower, approximately 50%. This means that there are a lot of emergency repairs. In fact this should also be taken into account. Further note that we are considering an average service level and an average number of back orders. In practice the present realised service level and number of back orders appear to be quite lumpy in time. For the simulation model the following table illustrates the relationship between safety factor and average number of back orders per day (see also figure 6).

k	0.03	0.20	0.37	0.54	0.72
Service-level	80.20 %	85.52 %	88.49 %	92.21 %	95.24 %
Average * back-orders	1.09	0.81	0.96	0.29	0.18

See the remarks below

* Remarks:

- For a service level of approximately 80% the average number of back orders in the simulation model is approximately equal to that in the present situation (However, with emergency repairs in the present case!).

- In the present situation there also exists large deviations of the average service level, which are significantly smaller in the simulation model. One of the major reasons is the sort of panic reaction towards modules whose inventory levels are low. The other reason is the fact that large clients request preventive repair once they observe a certain number of defects in a given time period (see the right tail in figure 3-a). Therefore, through the simulation model we can reach the desired service which is far more reliable, and important to clients nowadays.

- In the simulation model the safety factor k can be increased until a certain service level and average number of back orders or average inventory level is reached. When costs are available its cost consequences given a certain service can be evaluated.
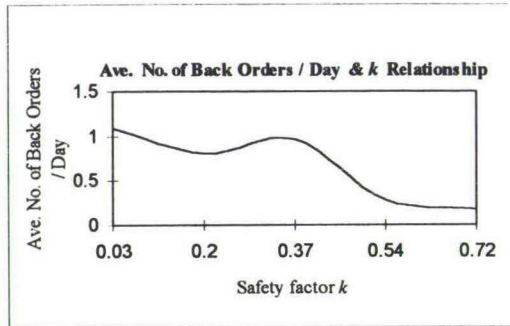

Figure 6: Average number of back orders versus safety factor.

5. Conclusions

In this paper we discussed a combined normative and simulation approach to the problem of service parts inventory with repairable items of a large computer company. The study showed that despite of the literature richness on the subject, in practice no attention has been paid to properly manage and control service parts inventory. Two reasons can be raised. First assumptions made in many of the models developed do not fit the reality, second there is a lack of awareness. We showed significant benefits can be gained from the extensive literature and from the experience in the management and control of general inventory systems which have accumulated so far by proper adapting the existing models to the real-life situation. The models then serve as a potential base tool to determine the value of major decision variables and when combined with simulation will allow the management to examine more precisely the effect of factors that have not been fully incorporated in the normative models.

Such an approach has great benefits. The first benefit is cost-savings and service improvement. The second benefit is a more structured and quantitative decision-making process. This means that management changes values of influential factors, for example by coordinating preventive repair of several large users, foresees the change in the solution, runs the simulation, and then checks whether the new strategy meets his expectation and results in any improvement. This makes the decision-making process more challenging, and more improvement can be realized. Furthermore, we believe that for service parts, inventory improvement by reallocation is essential.

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Appendix A: Schrady's Model

Referring to figure 4, T_a was defined as the time period during which triggering repair batches are suspended and the inventory of defect modules is simply accumulating. Assume that at time t a *repaired* batch Q_R arrives in the RFS inventory. This batch should have been released for repair at time $t-\tau_R$ when the inventory of defect modules is equal to zero (see figure 4). The batch Q_R will be used as the RFS stock over period of Q_R/d. Then at $t+Q_R/d$ a new procurement order Q_P arrives which is used over a period Q_P/d. When the procurement quantity is fully depleted, i.e. $t+Q_R/d+Q_P/d$, a new repaired batch arrives, the batch which was released $t+Q_R/d+Q_P/d-\tau_R$. Thus T_a, the time between release of two successive repair batches is:

$$T_a = [(t+Q_R/d+Q_P/d-\tau_R)-(t-\tau_R)]$$
$$= (Q_P + Q_R)/d$$

Next, let n be the number of repair batches per cycle. In general, it will not be possible to insure that the last repair batch triggered before T_a begins, will reduce the defect inventory to zero. The residual defect stock when T_a begins will be some fraction of the net loss in defect modules per repair cycle, i.e. Q_R/d. The net loss of defect inventory over the period between two successive repair batches is given by the released batch quantity (Q_R) minus rate of accumulation (rd) times the accumulation time (Q_R/d), i.e.:

$$Q_R - rd(Q_R/d) = Q_R(1-r)$$

Thus, the residue when T_a begins will be some fraction of $Q_R(1-r)$, call it $\beta Q_R(1-r)$, where $0<\beta<1$. While the β factor is unavoidable due to the requirement that there be an integral number of repair batches in each cycle, β is considered to be equal to zero in subsequent developments. The inaccuracies introduced are negligible as scrap rates, $(1-r)$, are on the order of 5% to 10%, and the term $\beta Q_R(1-r)$ is correspondingly small. Now, the first batch after triggers are resumed takes the amount Q_R from the defect inventory. Subsequent triggers cause a net reduction of only $Q_R(1-r)$ modules. Thus, the amount of defect modules available for (n-1) triggers is rdT_a-Q_R, assuming that n is the number of repair batches per cycle. This after replacing T_a gives, $Q_R(r-1) + rQ_P$. Dividing the last expression by $Q_R(1-r)$, we obtain:

$$(n-1) = \frac{Q_R(r-1)+rQ_P}{Q_R(1-r)} =$$

$$-1 + \left(\frac{r}{1-r}\right)\frac{Q_P}{Q_R}$$

or

$$n = \left(\frac{r}{1-r}\right)\frac{Q_P}{Q_R}$$

The system cycle time, T is then $nQ_R/d + Q_P/d = (nQ_R + Q_P)/d$, or

$$T = Q_P/(1-r)d.$$

Thus the total costs per cycle is: the fixed ordering cost time the number of orders, plus the fixed repair cost time the number of repair batches triggered, plus the inventory cost of RFS modules, plus inventory costs of defect modules.

From figure 4 it can be seen that area under the RFS inventory curve is sum of n triangles with height of Q_R and base of Q_R/d plus the triangle with height of Q_P and base of Q_P/d. The area under

$$A_l = n\frac{1}{2}Q_RQ_R/d + \frac{1}{2}Q_PQ_P/d$$

$$\left(\frac{r}{1-r}\right)\frac{Q_P}{Q_R}\frac{1}{2}Q_RQ_R/d + \frac{1}{2}Q_PQ_P/d$$

$$= \frac{1}{2d}\left(\frac{r}{1-r}\right)\left[Q_PQ_R + \left(\frac{1-r}{r}\right)Q_P^2\right]$$

the curve of RFS is thus:

From figure 4 and the following figure it can be seen that the area under the defect inventory curve during the system cycle can be determined as the sum of one single triangle (gray shaded area) and (n-1) trapezoids (dark shaded area). The first triangle area is calculated as follows:
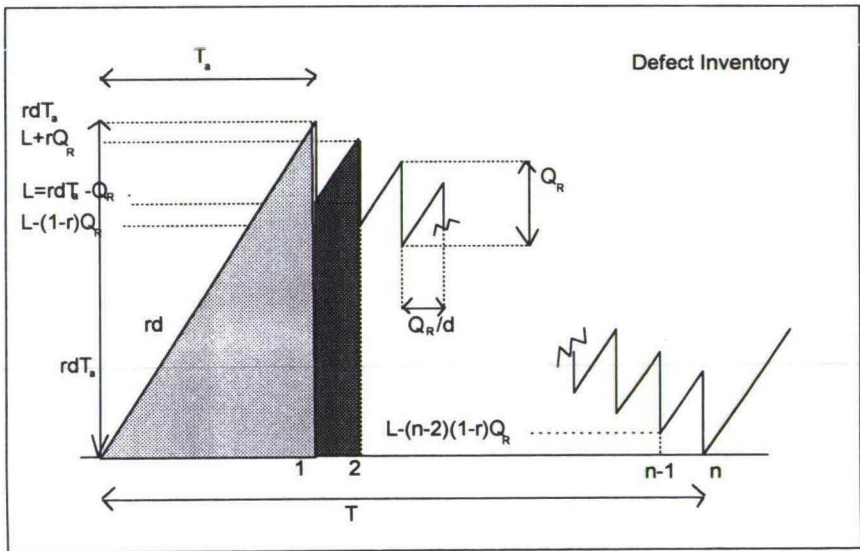
$$First\ Triangle\ Area = \frac{1}{2}\frac{(Q_P + Q_R)}{d}(rd\frac{(Q_P + Q_R)}{d})$$

$$= \left(\frac{r}{2d}\right)(Q_P + Q_R)^2$$

Illustration of the defect inventory curve from time point $t-t_R$ up to time point $t-t_R+T$ of figure 4

Total area for the (n-1) trapezoids is calculated as follows:

$$\frac{1}{2}\frac{(n-1)Q_R}{d}rQ_R + \frac{Q_R}{d}(L + L - Q_R(1-r) + L - 2Q_R(1-r) + \ldots + L - (n-2)Q_R(1-r))$$

$$= \frac{r(n-1)Q_R^2}{2d} + \frac{Q_R}{d}((n-1)L - \sum_{i=1}^{n-2} iQ_R(1-r))$$

$$= (n-1)\frac{Q_R}{2d}(rQ_R + 2L - (n-2)Q_R(1-r))$$

When this expression is worked out we have:

$$\frac{r}{2d}\left(\frac{r}{1-r}Q_P^2 - Q_PQ_R + \frac{Q_PQ_Rr}{1-r} - Q_R^2\right)$$

Thus the total area under the defect inventory curve can be written as:

$$A_2 = \frac{r}{2d}(Q_P^2 + 2Q_PQ_R + Q_R^2) + \frac{r}{2d}\left(\frac{r}{1-r}Q_P^2 - Q_PQ_R + \frac{Q_PQ_Rr}{1-r} - Q_R^2\right) =$$

$$\frac{r}{2d}\left[Q_P^2 + \frac{r}{1-r}Q_P^2 + 2Q_PQ_R - Q_PQ_R + \frac{rQ_PQ_R}{1-r} + Q_R^2 - Q_R^2\right] =$$

$$\frac{r}{2d}\left[\frac{1-r}{1-r}Q_P^2 + \frac{r}{1-r}Q_P^2 + \frac{1}{1-r}Q_PQ_R\right] =$$

$$\frac{r}{2d}\left[\frac{1}{1-r}Q_P^2 + \frac{1}{1-r}Q_PQ_R\right]$$

We may now write down the expression for total cost per cycle:

$$\text{TC per cycle} = A_P + nA_R + h_1A_1 + h_2A_2.$$

By replacing A1 and A2, and dividing TC per cycle by the system cycle time, we get the total cost

$$\text{TC per time unit} = \frac{A_Pd(1-r)}{Q_P} + \frac{A_Rrd}{Q_R} + \frac{h_1r}{2}\left[Q_R + \left(\frac{1-r}{r}\right)Q_P\right] + \frac{h_2r}{2}[Q_P + Q_R]$$

per time unit as follows:

As a result the optimal order quantities are:

$$Q_P^* = \sqrt{\frac{2A_Pd(1-r)}{h_1(1-r) + h_2r}}$$

and

$$Q_R^* = \sqrt{\frac{2A_Rd}{h_1 + h_2}}$$

Appendix B: Worked-out Expectations & Variance of Return Times

Let's consider day i. The net demand of that day is formed by the gross demand minus what is returned unused within the last five days. For each module which is returned unused on day i-1, it holds that with probability s it arrives on day i and with probability 1 - s on a later day.

Define the following help variable:

ss_{jj} = dummy variable representing the jj^{th} module which returns unused the next day (1) or on another day (0).

Hereby ss_{jj} has a binominal distribution with parameters $(n, p) = (1, s)$ and

$$jj = 1, ..., \sum_{j=1}^{d_{i-1}} h_j.$$

The number of modules which on day i is returned unused from day i - 1 is then:

$$\sum_{j=1}^{d_{i-1}} h_j$$

$$\sum_{jj=1} ss_{jj}$$

The number of modules returning unused from earlier days than day i -1, can be handled analogously. The returning days vary from one day till five days.

The expectation and variance of the net demand of day i can now be determined using independence for the variables d_i, h_j and ss_{jj}, identically distribution and independence of each other.

The Expectation:

$$x_i = d_i - \sum_{jj=1}^{\sum_{j=1}^{d_{i-1}} h_j} ss_{jj} - ... - \sum_{kk=1}^{\sum_{k=1}^{d_{i-5}} h_k} ww_{kk}$$

$$E\{x_i\} = E\{d_i - \sum_{jj=1}^{\sum_{j=1}^{d_{i-1}} h_j} ss_{jj} - ... - \sum_{kk=1}^{\sum_{k=1}^{d_{i-5}}} ww_{kk}\} =$$

$$E\{d_i\} - E\{\sum_{jj=1}^{\sum_{j=1}^{d_{i-1}} h_j} ss_{jj}\} - ... - E\{\sum_{kk=1}^{\sum_{k=1}^{d_{i-5}}} ww_{kk}\} =$$

$$E\{d_i\} - E\{\sum_{1}^{d_{i-1}} h_j\} E\{ss_{jj}\} - ... - E\{\sum_{k=1}^{d_{i-5}} h_k\} E\{ww_{kk}\} =$$

$E\{d_i\} - E\{d_{i-1}\} \, E\{h_j\} \, E\{ss_{jj}\} - ... - E\{d_{i-5}\} \, E\{h_k\} \, E\{ww_{kk}\} =$

$E\{d_i\} - E\{d_j\} \, es - ... - E\{d_j\} \, ew =$

$E\{d_i\} - eE\{d_i\} \, (s + ... + w) =$

$(1 - e) \, E\{d_i\}$

The Variance:

$$Var\{x_i\} = Var\{d_i - \sum_{jj=1}^{\sum_{j=1}^{d_{i-1}} h_j} ss_{jj} - ... - \sum_{kk=1}^{\sum_{k=1}^{d_{i-5}} h_k} ww_{kk}\} =$$

$$Var\{d_i\} + Var\{\sum_{jj=1}^{\sum_{j=1}^{d_{i-1}} h_j} ss_{jj}\} + ... + Var\{\sum_{kk=1}^{\sum_{k=1}^{d_{i-5}} h_k} ww_{kk}\} =$$

$$Var\{d_i\} + E\{\sum_{j=1}^{d_{i-1}} h_j\} \, Var\{ss_{jj}\} + E^2\{ss_{jj}\} \, Var\{\sum_{j=1}^{d_{i-1}} h_j\} + ... +$$

$$E\{\sum_{k=1}^{d_{i-5}} h_k\} \, Var\{ww_{kk}\} + E^2\{ww_{kk}\} \, Var\{\sum_{k=1}^{d_{i-5}} h_k\} =$$

$Var\{d_i\} + eE\{d_i\}s(1 - s) + s^2(E\{d_i\}e(1 - e) + e^2 Var\{d_i\}) + ... +$

$eE\{d_i\}w(1 - w) + w^2(E\{d_i\}e(1 - e) + e^2 Var\{d_i\}) =$

$Var\{d_i\} + E\{d_i\}e(1 - e) + e^2 Var\{d_i\} +$

$2e^2(st + su + ... + uw + vw) \, (E\{d_i\} - Var\{d_i\})$

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