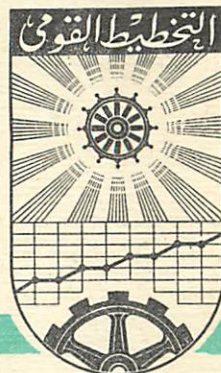


# ARAB REPUBLIC OF EGYPT

## THE INSTITUTE OF NATIONAL PLANNING



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Planning Strategies For Development  
Of New Items.

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## Introduction:

In the following we deal with parallel

- Planning strategies for the development of a new item. Let us assume that several proposals for developing the new items are available.

Usually one is interested to choose the best of these proposals with respect to some criterion. But it may happen that the data available at this point of the development process are very inaccurate and uncertain and therefore unreliable.

For example a proposal promising low costs and low time to bring the project to the end may turn out to be very expensive after its completion. In such situations a wrong decision may be avoided by pursuing a parallel path approach. Several, say  $m$ , of the proposals are pursued to a review-point at which point the best project is selected and brought to completion while the other still remaining approaches are stopped.

This is the simplest model of parallel path-approach; generalization to several review points, however, are possible and done in the literature. (See Marschak (3) ).

It is the purpose of this paper to answer the following question:

How much must the uncertainty at the review point be reduced in order that a parallel-approach is at all worth while to be pursued? A lower bound on the variation of the cost-estimate is obtained in order that



a parallel-approach with  $m$  proposals to start at the beginning of the project may be worthwhile at all, it is shown that this lower bound is attained only if the cost estimates are discrete, allowing only two values.

1- A General Model

Let us have a set  $\{1, 2, \dots\}$  of Research and development approaches which can start at a point  $t$ , a set  $F = \{i_1, i_2, \dots, i_m\}$  of  $m$  approaches of them are pursued to a review - point  $t + \theta$ , at which point the best project, i.e. that project having the smallest total money and time cost estimate is selected and brought to the end while the other remaining projects are stopped.

In order that such a procedure can work the cost-estimate must in some sense be consistent with the actual costs, i.e., there must be some relationship between cost-estimators and actual costs. This relationship is unbiasedness and is formulated as follows.

Let  $K_{i, t + \theta}$  be the total time and money-cost that finally is obtained by bringing proposal  $i$  from review-point  $t + \theta$  to completion and let moreover  $K_{t + \theta}^{(i)}$  be the total time and money-estimate obtained at the point  $t + \theta$ .

We again assume that  $K_{t + \theta}^{(i)}$  is an unbiased estimator of  $K_{t + \theta}^{(i)}$  is an unbiased estimator of  $K_{i, t + \theta}$  (2), (3) i.e., that

$$(1) \quad E(K_{i,t+\theta} / K_{t+\theta}^{(i)}) = (K_{t+\theta}^{(i)})$$

This assumption may seem strange since often in practice cost-estimates are much lower than actual cost. To make assumption (1) more realistic it may be assumed that

$$(1) \quad E(K_{i,t+\theta} / K_{t+\theta}^{(i)}) = g(K_{t+\theta}^{(i)})$$

where  $g$  is a monotonic non-decreasing function, e.g.  $g(x) = 3x$

It does not matter in our analysis if we replace assumption (1) by the assumption (1) by the assumption (1) i.e.  $K_{t+\theta}^{(i)}$  is replaced by  $g(K_{t+\theta}^{(i)})$  when ever it occurs.

Let  $\Gamma$  be a set of approaches and let  $W_j$  be the money cost which is necessary to bring approaches  $\delta \in \Gamma$  to review point  $t + \theta$ . If  $C_\Gamma$  is the total time and money.

- Cost which is necessary to follow a parallel-approach with approach-set

$\Gamma$ , then under assumption (1),

$$(2) \quad E(C_\Gamma) = \sum_{\delta \in \Gamma} E(W_\delta) = E(\min_{\delta \in \Gamma} K_{t+\theta}^{(\delta)})$$

Indeed, let

$\delta_0 \in \Gamma$  be such that

$$K_{t+\theta}^{(\delta_0)} = \min_{\delta \in \Gamma} K_{t+\theta}^{(\delta)}$$

then by (1) :

$$(3) C = \sum_{\delta \in \Gamma} W_{\delta} + K_{\delta, t+\theta}$$

$$(4) E(C) = \sum_{\delta \in \Gamma} E(W_{\delta}) + E(E(K_{\delta, t+\theta} | K_{t+\theta}^{(\delta)}))$$

$$= \sum_{\delta \in \Gamma} E(W_{\delta}) + E(K_{t+\theta}^{(\delta)})$$

$$= \sum_{\delta \in \Gamma} E(W_{\delta}) + E(\min_{\delta \in \Gamma} K_{t+\theta}^{(\delta)})$$

If  $\Gamma = (i_1, \dots, i_m)$  and

$$(5) F_{\Gamma}(x) = F_{i_1, \dots, i_m}(x) = P(\bigcap_{\delta \in \Gamma} \{K_{t+\theta}^{(\delta)} > x\})$$

then by using (4) (see Marochak (3)) we get

$$(6) E(C) = \sum_{\delta \in \Gamma} E(W_{\delta}) + \int_0^{\infty} F(x) dx$$

suppose that the projects are ordered according to increasing expected looking costs, i.e.:

$$E(W_1) \leq E(W_2) \leq \dots$$

We now make the following assumption, The distributions of the  $K_{t+\theta}^{(i)}$  are consistent with the value of  $E(W_i)$ . More precisely :

if  $E(W_i) > E(W_j)$ , we require that there is a higher probability that  $K_{t+\theta}^{(i)}$  exceeds a given value  $x$  than that  $K_{t+\theta}^{(j)}$  exceeds the value of  $x$  and this should hold for any  $x$ , given an arbitrary set of alternative approaches.

Definition (4) The given set of approaches is said to have a monotonous class of distribution function if for any subset of approaches

$\Gamma$  and pair  $(i, j)$ ,  $i, j \in \Gamma$  and any real number  $x$

$$(7) P(K_{t+\theta}^{(i)} > x | \bigcap_{\delta \in \Gamma} K_{t+\theta}^{(\delta)} > x) \geq P(K_{t+\theta}^{(j)} > x | \bigcap_{\delta \in \Gamma} K_{t+\theta}^{(\delta)} > x)$$

if  $i > j$

Now under the assumptions (1) and (7) we have

a)  $E(C_{\Gamma}^{vi}) \geq E(C_{\Gamma}^{vj})$

for any subset of approaches  $\Gamma$  if  $i \geq j$

b)  $\Gamma = \{1\}$  is the optimal set of approaches to be pursued if

(8)  $\int_0^{\infty} P(K_{t+\theta}^{(2)} \leq x, K_{t+\theta}^{(1)} > x) dx \leq E(W_2)$

(c) If there is a lost integer  $m \geq 2$  such that

$$E(W_m) \leq \int_0^{\infty} P(K_{t+\theta}^{(m)} \leq x, \prod_{i=1}^{m-1} K_{t+\theta}^{(i)} > x) dx$$

then  $\Gamma = (1, 2, \dots, m)$  is the optimal set of approaches to be pursued. From a we see that : under the monotony assumption it is always warthwhile to substitute a given approach by an approach possessing a lower cost estimate ; by such a substitution in the total expected time and money cost is not increases.

2 - Upper and lower bounds for the optimal number of approaches to be pursued .

In this section we simplify the general model of the pre - vious section by assuming that the cost estimates  $K_{t+\theta}^{(s)}$  are stochastically independent random variables . Under this assumption the optimality- criterion simplifies to

(9)  $\int_0^{\infty} P(K_{t+\theta}^{(m)} \leq x) \prod_{i=1}^{m-1} (1 - P(K_{t+\theta}^{(i)} \leq x)) dx \geq E(W_m)$

or we define

$$(10) \quad F_i(x) = P(K_{t+\theta}^{(i)} \leq x)$$

$$(11) \quad \text{to } \int_0^{\infty} F_m(x) \prod_{i=1}^{m-1} (1 - F_i(x)) dx \geq E(W_m)$$

The monotonicity - assumption implies that

$$(12) \quad 1 - F_i(x) \leq 1 - F_m(x) \quad ; \quad i = 1, 2, \dots, m-1$$

We now make the rather realistic assumption that all considered random variables (cost- estimates  $K_{t+\theta}^{(i)}$ ) are restricted to a finite interval  $(M_1, M_2)$  i. e. that

$$(13) \quad P(M_1 \leq K_{t+\theta}^{(i)} \leq M_2) = 1, \quad i = 1, 2, \dots$$

This implies that

$$F_m(x) = 0 \quad \text{if} \quad x \leq M_1$$

$$\text{and} \quad F_m(x) = 1 \quad \text{if} \quad x \geq M_2$$

using this and (12) we get from (11)

$$(14) \quad E(W_m) \leq \int_0^{\infty} F_m(x) \prod_{i=1}^{m-1} (1 - F_i(x)) dx$$

$$\leq \int_{M_1}^{M_2} F_m(x) \cdot (1 - F_m(x)) dx$$

it is necessary here to give the following well known facts.

1 - The function

$$(15) \quad f(p) = p^m(1-p) \quad 0 \leq p \leq 1$$

is monotonously increasing for  $p \in (0, m(m+1)^{-1})$  and monotonously decreasing for  $p \in (m(m+1)^{-1}, 1)$  i.e

$$\max_{0 \leq p \leq 1} f(p) = f\left(\frac{m}{m+1}\right) A_m = \left(1 + \frac{1}{m}\right)^{-m} \cdot \frac{1}{1+m}$$

$$(16) \quad = \left(1 + \frac{1}{m}\right)^{-(m+1)} \cdot \frac{1}{m}$$

$$(17) \quad \left((m+1)e\right)^{-1} \leq A_m \leq (me)$$

$$\lim_{m \rightarrow \infty} m \cdot A_m = e^{-1}$$

where  $e = \lim_{m \rightarrow \infty} \left(1 + \frac{1}{m}\right)^m = \sum_{m=0}^{\infty} \frac{1}{m!} = 2,71818$

that means, if the  $K_{t+\theta}^{\delta} \quad \delta = x, 2, \dots$

are stochastically independent random variables and  $p(M_1 \leq K_{t+\theta}^{(x)} \leq M_2) = 1$

then a necessary condition that there exist distribution function

$F_1(x), \dots, F_2(x)$  such that

$$(18) \quad F_i(x) = p(K_{t+\theta}^{(i)} \leq x) \leq F_{i-1}(x) = p(K_{t+\theta}^{(i-1)} \leq x)$$

for  $i = 2, 3, \dots, m$  and  $\sqrt{\quad} = i, 2, \dots, m$

is the optimal approaches to be pursued is that

$$(19) \quad M_2 - M_1 \gg E(W_m) (A_{m-1})^{-1}$$

$$(20) \quad \lim_{m \rightarrow \infty} (m+1) \left(1 + \frac{1}{m}\right)^m - e = -\frac{e}{2}$$

which yield to the approximation

$$(20) \quad (M_2 - M_1) (E(W_m))^{-1} \gg a_{m-1} \approx (m-1)e$$

where

$$a_m = (A_{m-1})^{-1} = m (1 + (m-1)^{-1})^m$$

and  $a_m \in (m-1)e, me$

To study the problem of (19) in the case of

$$M_2 - M_1 = (A_{m-1})^{-1} E(W_m)$$



it is necessary to make the more stringent assumption that all  $K^{(i)}$  are not only independent but also have all the same distribution  $F(x)$  but we consider  $K + 1$  - class - parallel - planning models i.e., we assume that  $F(x)$ , belong to a random variable  $X$  such that

$$N_1 < N_2 < \dots < N_{k+1} \text{ and } p(x = N_i) = P_i, i = 1, \dots, k+1 \text{ where of course } P_i \geq 0, 1 \leq i \leq k+1 \text{ and } \sum_{i=1}^{k+1} P_i = 1$$

let

$$(21) \quad P_i = 1 - \sum_{j=1}^i P_j \quad i = 1, 2, \dots, K$$

Then  $F(x)$  is equal to  $1 - P_i$  in the interval  $(N_i, N_{i+1})$  (Evidently

$$N_1 = M_1 \text{ and } M_2 = N_{k+1}$$

So we get from

$$(22) \quad \sum_{i=1}^k M_i^* (1 - P_i)^{P_i^m} \geq E(W_m)$$

where  $M_i^* = N_i + - N_i, i = 1, 2, \dots, k$

let us assume that  $M_1^*, M_2^*, \dots, M_{k-1}^*$

as well as  $P_1, \dots, P_k$  are given what is the lowest value of  $M_k^*$

such that we can find a real number  $P_k > 0$  (or equivalently a  $P_x$  such

that  $P_k \leq P_{k-1}$ ) with

$$\int_{M_1}^{M_2} F(x) (1 - F(x))^{m-1} dx = E(W_m)$$

to hold? Evidently

$$(23) H_m(P_{k-1}) = \max_{P_k \leq P_{k-1}} (1 - p_k) p_k^{m-1}$$

$$= \begin{cases} P_{m-1} & \text{if } P_{k-1} \geq (m-1)^{-1} \\ (1 - P_{k-1}) p_{k-1}^{m-1} & \text{if } P_{k-1} \leq (m-1)^{-1} \end{cases}$$

So the stated problem has a solution if and only if

$$(24) \sum_{i=1}^{k-1} M_i^* (1 - p_i) p_i^{m-1} + M_k^* h_m(P_{k-1}) \geq E(W_m)$$

or

$$(25) M_k^* h_m(P_{k-1}) \geq E(W_m) - \sum_{i=1}^{k-1} M_i^* (1 - p_i) p_i^{m-1}$$

$$(26) \text{ i.e. } M_k^* (E(W_m) - \sum_{i=1}^{k-1} M_i^* (1 - p_i) p_i^{m-1}) (h_m(P_{k-1}))^{-1}$$

$$= M_k^*, \min$$

$$(27) M_2^* - M_1^* = \sum_{i=1}^k M_i^* \geq (h_m(P_{k-1}))^{-1} (E(W_m) + \sum_{i=1}^{k-1} M_i^* (h_m(P_{k-1}) - (1 - p_i) p_i^{m-1}))$$

Specially if  $M_1^* = M_2^* = \dots = M_{k-1}^* = M_k^*, \min$  we get

$$M^* = E(W_m) (h_m(P_{k-1}) + \sum_{i=1}^{k-1} (1 - p_i) p_i^{m-1})^{-1}$$

and

$$(28) M_2^* - M_1^* \geq k M_k^*, \min = k E(W_m) (h_m(P_{k-1}) + \sum_{i=1}^{k-1} (1 - p_i) p_i^{m-1})^{-1}$$

if  $k = 2$  we get

$$M_2 - M_1 \geq 2 M_2^*, \min =$$

$$\begin{cases} 2E(W_m) (A_{m-1} + P_1(1 - P_1)^{m-1})^{-1} \\ \text{if } P_1 \leq m^{-1} \\ E(W_m) (P_1(1 - P_1)^{m-1})^{-1} \\ \text{if } P_1 \geq m^{-1} \end{cases}$$

(29) will be plotted as a function of  $P_1$  for  $m = 1$  and  $E(W_m) = 1$  later on .

it may also happen that a certain strategy  $m_0$  will never apply for given values of  $M_1^*, M_2^*, \dots, M_{k-1}^*, P_1, P_2, \dots, P_{k-1}$  because the strategy  $m = m_0 + 1$  is always superior to the strategy  $m = m_0$ , what ever may be the value of  $P_k$ . This can happen if and only if

$$(30) \quad M_k^* (1 - P_k) P_k^{m_0} \geq E(W_{m_0+1}) - \sum_{i=1}^{k-1} M_i^* (1 - P_i) P_i^{m_0}$$

For all  $P_k \leq P_{k-1}$

Specially  $P_k = 0$  implies

$$(31) \quad E(W_{m_0+1}) - \sum_{i=1}^{k-1} M_i^* (1 - P_i) P_i^{m_0} \leq 0$$

if  $M_1^* = M_2^* = \dots = M_{k-1}^*$  (equidistance of cost estimates) then

(29) becomes

$$(32) \quad M \geq \left( \sum_{i=1}^{k-1} (1 - P_i) P_i^{m_0} \right)^{-1} E(W_{m_0+1})$$



and thus

$$(33) M_2 - M_1 = (k-1) M_{k-1}^* + M_k^* \gg (k-1) E(W_{m_0+1})$$

$$\left( \sum_{i=1}^{m_0} (1-P_i) (P_i^{m_0})^{-1} + M_k^* \right)$$

if more over  $M^* = M_k^*$ , too and  $K \geq 2$ , we get

$$(34) (M_2 - M_1) (E(W_{m_0+1})) \gg 2 \cdot M^* \gg 2(P_1 (1 - P_1^{m_0}))^{-1}$$

it will be also plotted as a function of  $P_1$  for  $m_0 = 1$ .

For large  $m$  (and if  $P_1 \gg (m+1)^{-1}$  in general it is twice the minimum - value of  $M_2 - M_1$  for which the strategy  $m_0 + 1$  will apply at all; while (34) gives the minimum values of  $M_2 - M_1$  for which no strategy  $m \leq m_0$  will apply. Our computations and tables will also reveal to this situation.

3 - 1 The computation of probability intervals corresponding to given optimal strategies.

Given a certain set of values  $M_1^*, M_2^*, \dots, M_k^*$ ,

$P_1, P_2, \dots, P_{k-1}$  the question may arise how the probability intervals for  $P_k$  can be computed for which a given strategy  $m \geq 2$  is optimal. The interval in which  $m = 1$  is the optimal strategy is then evidently the interval  $(0, P_{k-1}) = \bigcup_{m=2}^{\infty} I_m$ , if  $I_m$  denote the interval in which strategy  $m$  is optimal). We have evidently

$$(35) P_k = P_{k-1} - P_k$$

implying  $P_k \leq P_{k-1}$

By (24) for the given values,  $P_k$  and hence  $P_k$  optimal if  $m$  is the last integer such that

$$(36) \quad (1 - P_k) P_k^{m-1} \geq N_k^* - 1 \quad (E(W_m) - \sum_{i=1}^{k-1} M_i^*) \\ (1 - P_i) P_i^{m-1} = N_m^*$$

If  $N_m^*$  happens to be smaller or equal to zero, then any  $P_k \leq P_{k-1}$  satisfies the inequality (36). let us denote by  $J_m$  the set of values  $P_k \leq P_{k-1}$  such that inequality (36) is met .

If  $J_m = (a, b)$  , then evidently  $J_m^{(0)} = (P_{k-1} - b, P_{k-1} - a)$

is the  $P_k$ - interval satisfying - (36) . Then

$$J_m^{(0)} \supseteq J_{m+1}^{(0)} \quad \text{and} \\ (37) \quad I_m = J_m^{(0)} - J_{m+1}^{(0)}$$

We know from the last paragraph that there is a lower bound for  $N_m^*$  in order that  $J_m^{(0)} \neq \emptyset$  , namely that

$$(38) \quad N_m^* \leq h_m(P_{k-1}) = \begin{cases} A_{m-1} & \text{if } P_{k-1} > (m-1) m^{-1} \\ P_{k-1}^{m-1} & \\ P_{k-1} (1 - P_k) & \text{if } P_{k-1} \leq (m-1) m^{-1} \end{cases}$$

If  $N_m^* \leq 0$  then evidently  $J_m = (0, P_{k-1})$ ,

$$J_m^{(0)} = (0, P_{k-1}) = (0, 1 - \sum_{i=1}^{k-1} P_i)$$

now let us assume that  $0 < N_m^* < h_m(P_{k-1})$

if  $N_m^* = h_m(P_{k-1})$ , then  $P_k = P_{k-1}$  is the only element of  $J_m^{(0)}$  in which case the  $k+1$  class-parallel planning - model degenerates to a  $k$  - class-parallel-planning model) We now make use of the results of the last paragraph, namely that  $g_{m-1}(p) = (1-p)p^{m-1}$  is monotonously increasing in  $(0, m^{-1}(m-1))$  and monotonously decreasing in  $(m^{-1}(m-1), 1)$

The maximum is at  $P = (m-1) m^{-1}$  a saddle - point at  $(m-2) m^{-1}$

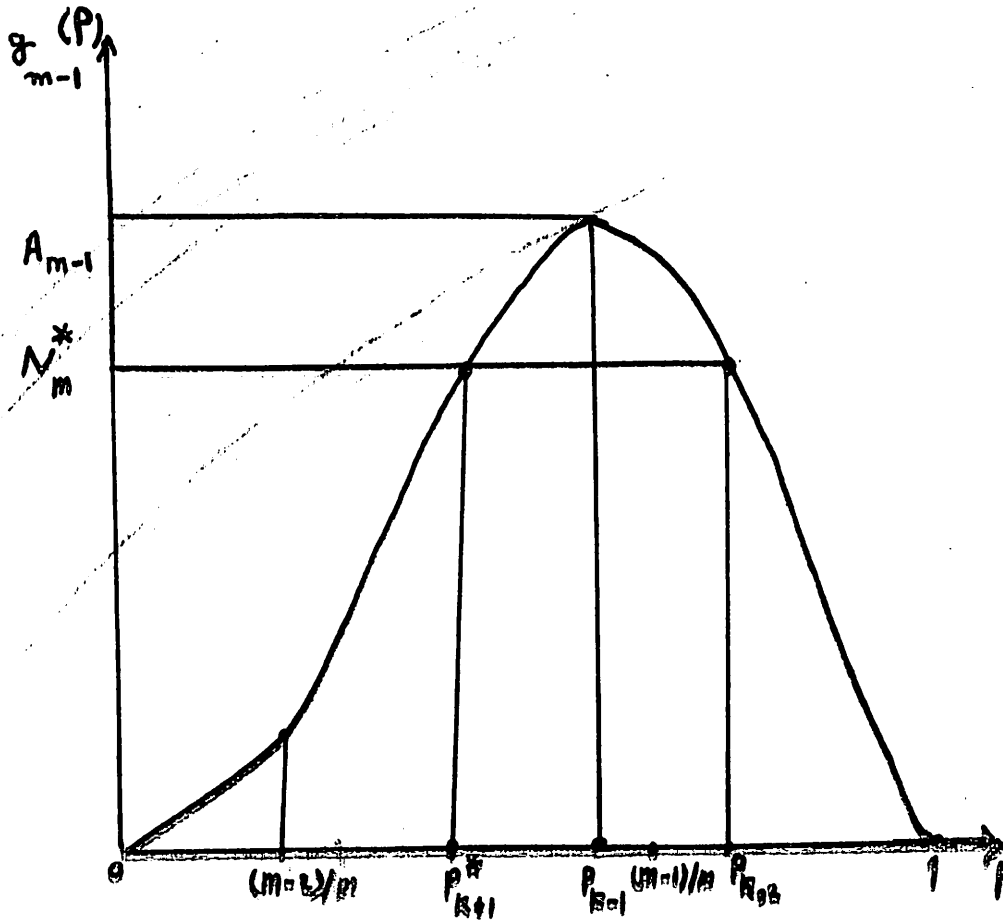


Fig 1 = Situation A



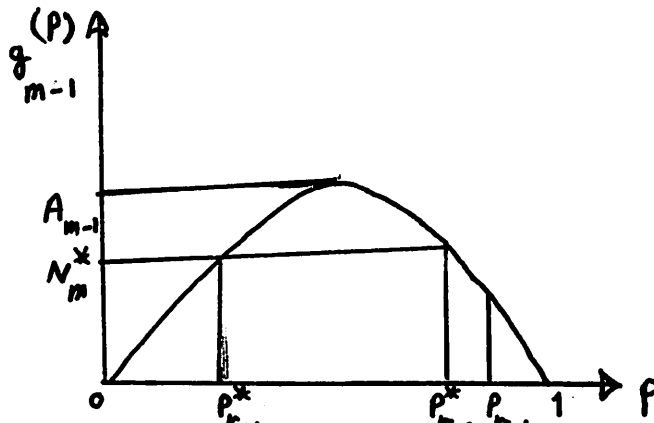


Fig 2 - Situation B

If  $0 < N_m^* < h_m(P_{k-1})$ , there will exist a diagram and analysis of  $g_{m-1}(p)$  show it - two values  $P_{k,1}^*, P_{k,2}^*$  such that  $P_{k,1}^* < P_{k,2}^*$  and therefore  $(1-P_{k,2}^*)(P_{k,2}^*)^{m-1} = (1-P_{k,1}^*)(P_{k,1}^*)^{m-1} = N_m^*$  thus

Thus

$$(1-P_k^*) P_k^{m-1} > N_m^* \text{ if } P_k \in (P_{k,1}^*, P_{k,2}^*) .$$

$$N_m^* < h_m(P_{k-1}) \text{ implies } P_{k,1}^* < P_{k-1}$$

In situation A (fig 1).  $P_{k,2}^* > P_{k-1}$  hence

$$(39) J_m^* = (P_{k,1}^*, P_{k-1}), J_m^{(0)} = (0, P_{k-1} - P_{k,1}^*)$$

In situation B (fig 2)

$$P_{k,2}^* > P_{k-1} \text{ and hence}$$

$$(40) J_m^* = (P_{k,1}^*, P_{k,2}^*), J_m^{(0)} = (P_{k-1} - P_{k,2}^*, P_{k-1} - P_{k,1}^*)$$

In general we have

$$(41) J_m^* = (P_{k,1}^*, \min(P_{k-1}, P_{k,2}^*))$$

$$(42) J_m^{(0)} = (P_{k-1} - \min(P_{k,2}^*, P_{k-1}), P_{k-1} - P_{k,1}^*)$$

$$= (\max(0, P_{k-1} - P_{k,2}^*), P_{k-1} - P_{k,1}^*)$$

3 - 2 Computing procedure

Compute  $N_m^*$  starting with  $m = 2$  and  $J^{(0)}$  according to

$$(43) \quad J_m^{(0)} \left\{ \begin{array}{l} \phi \quad \text{if } N_m^* > h_m^*(P_{k-1}) \\ (0) \quad \text{if } N_m^* = h_m^*(P_{k-1}) \\ \max(0, P_{k-1} - P_{k,2}^*) \cdot P_{k-1} - P_{k-1}^* \quad \text{if } 0 < N_m^* < h_m^*(P_{k-1}) \\ (0, P_{k-1}) \end{array} \right.$$

where  $P_{k,1}^*$  denotes the smaller and  $P_{k,2}^*$  denotes the larger of the two roots of the equation  $p^{m-1}(1-p) = N_m^*$ , provided

$$0 < N_m^* < 1. \quad \text{If } J_m^{(0)} \neq \phi$$

go to  $m+1$ , if  $J_m^{(0)} = \phi$  stop the computation.

If  $m = m_0$ , then

$$(44) \quad \begin{aligned} I_{m_0} &= \phi, \quad I_{m_0-1} = J_{m_0-1}^{(0)} \\ I_m &= J_m^{(0)} - J_{m-1}^{(0)} \quad m = 2, 3, \dots, m_0 - 2 \\ I_1 &= (0, P_{k-1}) - \bigcup_{r=2}^{m_0-1} I_r \end{aligned}$$

The only thing that now must be still done is the computation of the two roots of the equation  $p^{m-1}(1-p) = P_m^*$  provided

$$0 < N_m^* < A_{m-1}$$

This problem will be solved by considering the following theorem (4)

a) let

$$A_{m-1} = \varepsilon_{m-1} ((m-2) m^{-1}) = 2 m^{-1} (1-2 m^{-1})^m$$

and

$$P_0 = (m-2) m^{-1} \text{ if } 0 < N_m^* \leq \hat{A}_{m-1},$$

$$P_0 = (m-1) m^{-1} \text{ if } A_{m-1} > N_m^* > \hat{A}_{m-1}$$

and more over

$$(45) \quad P_{n+1} = (m-1)^{-1} \left[ (m-2) P_n + N_m^* \left\{ P_n^{m-2} (1-P_n)^{-1} \right\} \right]$$

, n = 0, 1, 2, .... Then

$$P_n > P_{n+1} \text{ and } \lim_{n \rightarrow \infty} P_n = P_1^*$$

where  $P_1^*$  is the smaller of the two roots of the equation

$$P^{m-1} (1-P) = N_m^*$$

(b) let  $\hat{P}_0 = (m-1) m^{-1}$  and

$$(46) \quad \hat{P}_{n+1} = 1 - N_m^* \hat{P}_n^{-(m-2)}, \quad n = 0, 1, 2, \dots$$

then

$$\hat{P}_{n+1} \geq \hat{P}_n \text{ and } \lim_{n \rightarrow \infty} \hat{P}_n = P_2^*$$

the larger of the two roots of the equation  $P^{m-1} (1-P) = N_m^*$

de tailed proof in (1)

We have the following error bounds for a :  $\dots$

$$P_n - P_1^* \leq (P_{n+1} - P_n) h_0(P_n) \text{ if } P_0 = (m-1) m^{-1}$$

$$P_n - P_1 \leq (P_{n+1} - P_n) h_1(P_n) \text{ if } P_0 = (m-2) m^{-1}$$



Where

$$h_0(P_n) = (1 - P_n) (m-1 - m P_n)^{-1}$$

$$h_1(P_n) = (1 - P)^2 ((m-1) - m P_n)^{-1}$$

$$\cdot P_{nn}^{m-1} (N_m^*)^{-1}$$

For (b)

$$P_n^* - \hat{P}_n \quad (\hat{P}_{n+1} - P_n) h_2(\hat{P}_m)$$

Where

$$b_2(\hat{P}_n) = \hat{P}_n (m \hat{P}_m - (m-1))^{-1}$$

#### 4 - Graphical and Numerical Illustrations

In (20) it had been shown that a parallel - approach with  $m$  approaches pursued to review - point can be optimal strategy if

$$(M_2 - M_1) (E(W_{m_0}))^{-1} \gg a_{m_0} - 1 \approx (m_0 - \frac{1}{2}) e$$

where  $M_2 - M_1$  is the variation of the cost - estimate and  $E(W_{m_0})$  the expected cost of carrying approach  $m$  to the review - point .

more over, we know that  $a_{m-1} \approx (m-1) e$  .

In ( table 1 )  $a_{m_0}$  and  $(m_0 - \frac{1}{2}) e$  as well as  $(m_0 - 1) e$  and  $m_0 e$

are listed it turns out that even for  $m_0 = 2$  the error between

$a_{m_0}$  ( =4 ) and  $(m_0 - \frac{1}{2}) e$  is less than 2 . It may also be noted that

computing  $a_{m_0}$  by logarithm was according to the formula .

$$a_{m_0} = \exp ( m \log m_0 - (m_0 - 1) \log (m_0 - 1) )$$

It has shown in section 2 that if

$a_{m_0} = (M_2 - M_1) / E(W_{m_0})$ , then there is only one distribution function  $F(x)$ , concentrated in  $(M_1, M_2)$ , such that  $m = m_0$  can be the optimal number of approaches to be pursued, namely the distribution which takes as values only  $X = M_1$  (with probability  $m_0^{-1}$ ) and  $X = M_2$  (with probability  $1 - m_0^{-1} = (m_0 - 1) m_0^{-1}$ )

if this very special two class problem can be excluded, then there must be a much higher value of  $(M_2 - M_1) / E(W_{m_0})$  in order that  $m = m_0$  can act as optimal strategy.

To win a further insight into the nature of this problem, let us consider that we have an equidistant three - class parallel - strategy model. i. e. that  $P(x = M_1) = P_1$ ,  $P(x = M_1 + (M_2 - M_1) / 2) = P_2$

$$P(x = M_2) = 1 - P_1 - P_2, \text{ where}$$

$$P_1, P_2 \geq 0$$

If  $P_1 > 0$  is given then necessary for the existence of some

$P_2 \geq 0$  such that  $m = m_0$  may act as optimal strategy is that see(29)

$$(47) \quad (E(W_{m_0}))^{-1} (M_2 - M_1) \geq h_{m_0}(P_1) \quad \left\{ \begin{array}{l} 20_{m_0} (1 + a_{m_0} (p_1 (1 - P_1)^{m_0 - 1} - 1) \\ \text{if } P_1 \leq m_0^{-1} \\ (P_1 (1 - P_1)^{m_0 - 1})^{-1} \\ \text{if } P_1 \geq m_0^{-1} \end{array} \right.$$

Note that if  $P_1 \geq m_0^{-1}$  and the equality - sign holds in (47), then

$P_2 = 0$  is the only value meeting the required condition, so that the

$n_0$	$(m_0 - 1)e$	$a_{m_0}$	$a_{m_0}$ together Camp	$(m_0 - \frac{1}{2})e$	$m_0 e$	relative error of $(m_0 - \frac{1}{2})e$
2	2,718	4	3,999	4,077	5,436	2%
3	5,436	6,75	6,735	6,795	8,154	1%
4	8,154	9,481	9,575	9,8513	10,872	3%
5	10,872	10,872	12,095	12,231	13,950	2%
6	13,590	13,590	14,933	14,949	16,308	1,3%
7	16,308	16,308	17,64	17,667	19,026	0,9%
8	19,026	20,371	20,375	20,385	21,744	0,7%
9	21,744	23,091	23,07	23,103	24,462	0,5%
10	24,462	25,811	25,835	25,821	27,180	0,4%
11	27,180	28,531	28,539	28,535	29,898	0,3%

Table 1: Minimal number of  $(M_2 - M_1)E (W_{m_0})$ , ratios of cost-estimates Range and expected inspection cost, that is necessary in order  $m = m_0$  can be the optional number of approaches to be pursued.

problem degenerates in this case to a two class problem, if  $P_1 \rightarrow 1$ , then  $h_{m_0}(P_1) \rightarrow \infty$

This is quite clear because if  $P_1=1$ , then we have a one-class problem in which all uncertainty is removed and some in this case there will

be no need for a parallel-strategy  $h_{m_0}(P_1)$  has minimum at  $P_1 = m_0^{-1}$  with minimum value  $h_{m_0}(m_0^{-1}) = m_0^a$

But the corresponding value of  $P_2$ , if  $(E(W_m))^{-1}(M_2 - M_1) = m_0^a$  is  $P_2 = 1 - m_0^{-1}$  implying

$$P(x = M_2) = 0$$

So the problem degenerates to a two-class problem. The same holds if  $P_1=0$ : value  $h_m(0) = 2 a_m$  is not really correct since in this case the distribution is concentrated in  $((M_1 - M_2) / 2, M_2) = (M_1^*, M_2^*)$  and so  $(M_2^* - M_1^*) / E(W_{m_0}) \gg a_{m_0}$  must hold in order that  $m = m_0$  can act as optimal strategy.

As we can see from (fig 3)  $h_{m_0}(P_1)$  has been plotted for  $m_0 = 2$  also the curve  $I_{m_0}$  is plotted this curve is equal to

$$(48) I_{m_0}(P_1) = 2(P_1(1 - P_1)^{m_0-1})^{-1}$$

and in minimal number of  $(M_2 - M_1) / E(W_{m_0})$  given  $P_1$ , in order that the strategy  $m = m_0 - 1$  will be never applied as optimal strategy whatever is the value of  $P_2$ .

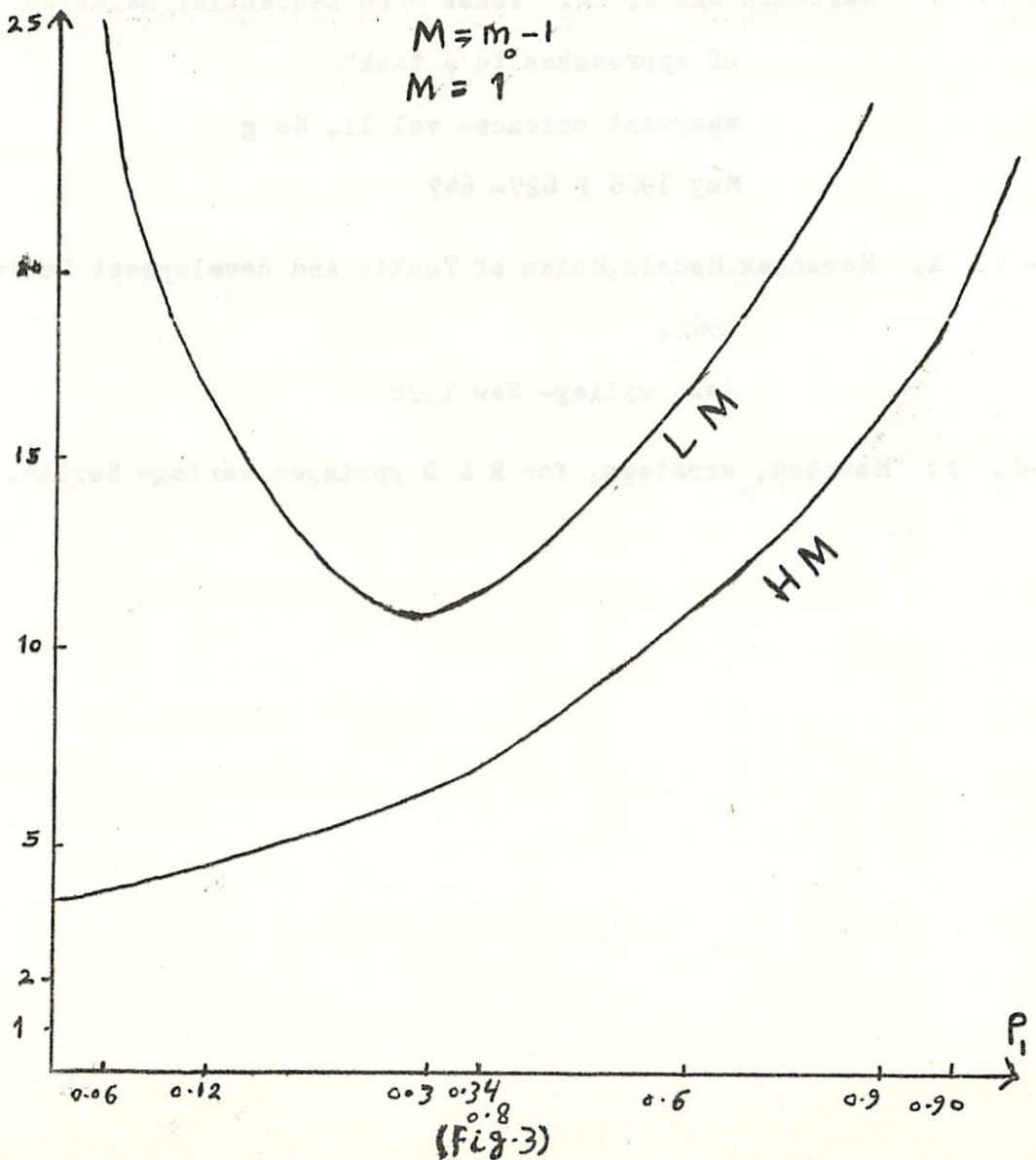
If  $(M_2 - M_1) / E(W_{m_0}) \gg I_{m_0}(P_1)$  then either  $m = m_0$  or  $m = m_0 + 1$ ,  $m_0 + 2 \dots \dots \dots$

will be applied as optimal strategy.

If  $P_1 \geq m_0^{-1}$  then  $I_{m_0}(P_1) / h_{m_0}(P_1) = 2$

If  $P_1 < m_0^{-1}$  this ratio will be much larger and approach infinity if  $P_1$  approach zero. This is quite clear for if  $P_1 = 0$ .

the problem again degenerates to a two- class problem





More material can be found in (4)

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