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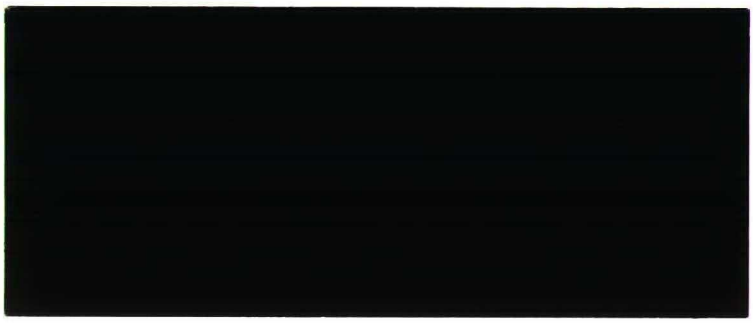

SAMPLING FOR QUALITY INSPECTION AND CORRECTION: AOQL PERFORMANCE CRITERIA

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ABSTRACT

The Average Outgoing Quality Limit (AOQL) is a property of a sampling plan leading to inspection of the whole population, if the sample shows a number of defective items k exceeding an acceptance number k_o. The literature shows how this constant k_o can be chosen such that the expected value of $\tilde{p}$, the fraction of defectives after inspection and possible correction, does not exceed a prespecified constant $\tilde{p}_m$. The present paper estimates several other criteria ignored in the literature. These estimates are based on an extensive Monte Carlo simulation. The main conclusion is that the AOQL scheme is useful in practice, including applications in auditing, Yet the probability that the yearly average $\bar{\tilde{p}}$ exceeds $\tilde{p}_m$ is sizable, if the true underlying fraction p exceeds $\tilde{p}_m$ "mildly".

The paper further investigates the effects of splitting the yearly population into subpopulations and the effects of underestimating p, as is often done in practice.

1. INTRODUCTION: AOQL

AOQL sampling plans were introduced by Dodge and Romig around 1930. These plans are discussed in the monograph by Hald (1981, pp. 116-124). Their application to auditing is studied by Kriens and Veenstra (1985). Recently interest in quality control has been stimulated by the Japanese management philosophy; see Cross (1984). We can summarize this sampling scheme as follows. The goal as introduced by Dodge and Romig, is to guarantee a minimum quality of the outgoing populations expressed as a maximum for the average fraction of defectives in the population. Kriens and Veenstra (1985) split up the yearly population into a number of subpopulations. The quality of a yearly population - before sampling and correction - is quantified by p, the fraction of "defective items" in the yearly population. The Number of items (defect plus correct) per Year is (say) NY, for example, a company produces NY cars; in auditing, accounts are sampled and NY is measured in dollars per years; see Kriens and Veenstra (1985, p. 387). Consequently, after inspection and correction the minimum quality corresponds to a maximum value for the expected value of the remaining fraction of defectives $\tilde{p}$ (random variables are underscored).

The sampling scheme has the following steps (also see Table 1 later on).

(i) The expected yearly population is divided into a number S of subpopulations, for example, S = 52 corresponds to production per week. These subpopulations may have dif-

ferent sizes, in expectation and certainly in realization. We denote the realized size of the subpopulation in subperiod s by N_s (s = 1, ...,S).

(ii) From each (realized) subpopulation a sample of size n is taken (n depends on several parameters, as we shall see).

(iii) Per sample (of size n) the number of defective items $\underline{k}$ is determined by inspection; obviously $\underline{k}$ is random. And the integer values k satisfy: $0 \leq k \leq n$.

(iv) If and only if k exceeds a critical constant k_o (which varies with n; see step ii) then the whole subpopulation is inspected and, by assumption, all defective items in the subpopulation are corrected (in auditing, defectives are errors which can often be removed by corrective actions; Hald (1981, pp. 311-312) discusses imperfect inspection and correction of items). If, however, $k \leq k_o$ then the defective items in the sample are corrected. So after sampling the quality of the subpopulation is improved, unless no defectives at all were found (k = 0).

After this last step the fraction of defectives per subpopulation $\tilde{\underline{p}}$ should satisfy the minimum-quality requirement $\tilde{p}_m$. So given a correct selection of the sampling plan's parameters n and k_o (see next paragraph), $\tilde{\underline{p}}$ should satisfy the condition $E\left(\tilde{\underline{p}}\right) \leq \tilde{p}_m$. Obviously, if the original fraction of defectives (before sampling) was very good already (say, p = 0), then $E\left(\tilde{\underline{p}}\right) \leq p$. If this quality was very bad ($p >> \tilde{p}_m$), then the sampling plan implies that sampling is (nearly) always followed by inspection and correction of the whole subpopulation so that (0≈) $\tilde{p} << \tilde{p}_m$. See Figure 1 where p^* is the "least favorable" value of p.

Obviously $\underline{k}$ follows the hypergeometric distribution with parameters n, p and N_s. The critical constant k_o and n can be computed such that the condition $E\left(\tilde{\underline{p}}\right) \leq \tilde{p}_m$ holds; moreover the expected costs are minimized. The original tables in Dodge

and Romig (1959), however, contain some inaccuracies; also see Hald (1981, p. 124). Therefore we use the tables recently computed by Kriens and Winters (1988); also see Veenstra and Buysse (1985) and Van Batenburg, Kriens and Veenstra (1987). Table 1 illustrates some typical results. (Tables for very small $\tilde{p}_m$-values are given in Ross, 1984.)

In practice the before-sampling fraction p is unknown and often only the left-most columns in tables like Table 1 are used (low p). Even if p is estimated wrongly, the quality constraint $E\left[\tilde{p}\right] \leq \tilde{p}_m$ is satisfied; the expected costs, however, may increase. Moreover, practitioners usually conjecture that the chance of a bad yearly quality is negligible, i.e., if $\bar{\tilde{p}}$

Table 1: Sample size n and acceptance number k_o depending on before-sampling fraction p, subpopulation size N, and quality limit $\tilde{p}_m$ (here $\tilde{p}_m$ = 1%).

Subpopulation size N	Before-sampling fraction p					
	0-0.02	...	0.21-0.40	...	0.81-1.00	
N	n	k_o	n	k_o	n	k_o
1-25	All	0	All	0	All	0
26-50	22	0	22	0	22	0
...						
801-1000	35	0	80	1	120	2
1001-2000	36	0	80	1	180	3
...						
20001-50000	85	1	255	4	990	15
50001-100000	85	1	255	4	1520	22

denotes the average yearly outgoing quality then

$$P\left[\bar{\tilde{p}} > \tilde{p}_m\right] \approx 0. \qquad (1.1)$$

This conjecture is the focus of our simulation. (Hald (1981, p. 310) gives analytical approximations for this probability.) Moreover, it hardly takes more computer time to estimate how bad $\bar{\tilde{p}}$ is *if* the constraint $\bar{\tilde{p}} < \tilde{p}_m$ is violated. Therefore we also estimate the following conditional expectation:

$$E\left[\bar{\tilde{p}} - \tilde{p}_m \middle| \bar{\tilde{p}} > \tilde{p}_m\right]. \qquad (1.2)$$

This paper has the following contributions:

(i) It examines the effects of splitting the yearly population (NY) into S subpopulations. For example, a higher S leads to a lower expected quality violation $E(\bar{\tilde{p}} - \tilde{p}_m | \bar{\tilde{p}} > \tilde{p}_m)$ (see Figure 4).

(ii) It estimates not only the yearly average $\bar{\tilde{p}}$ (Figure 2) but also the probability of a quality violation $P(\bar{\tilde{p}} > \tilde{p}_m)$ (Figure 3). That probability may be as high as 40%, which is certainly not negligible!

(iii) It estimates the effects of underestimating the before-sampling fraction p: in practice one often uses only the left-most columns of the tables needed for the AOQL scheme. This practice may result in higher costs (Figure 5) while the probability of a quality violation may increase (Figure 3).

(iv) It adds some additional insight. For example, higher variability in the before-sampling fraction p (over subpopulations) gives additional protection (see Section 2). Estimation of p is important; the paper gives a simple estimation scheme based on the AOQL scheme itself (Section 3).

2. DESIGN OF MONTE CARLO EXPERIMENT

As Table 1 showed, the sample size n and the acceptance number k_o are completely determined by the subpopulation size N_s, the before-sampling fraction p, and the quality limit $\tilde{p}_m$. That subpopulation size N_s depends on the yearly population size NY and on the number of subperiods S. In the simulation we study three values for S, namely 4, 13, and 52 which correspond to quarters, "months", and weeks. Our selection of the yearly population size NY is based on the experience of one of the authors with auditing applications: NY is 10,000 or 100,000 or 1,000,000. Obviously the expected subpopulation size $E(\underset{\sim}{N}_s)$ equals NY/S. We assume that $\underset{\sim}{N}_s$ follows a uniform distribution with expected value NY/S; its range is such that the coefficient of variation is always (roughly) 6%, which is an arbitrarily selected value.

We selected the following six values for the quality limit $\tilde{p}_m$: 0.1%, 0.5%, 1%, 2%, 5%, 10%. Selection of the before-sampling fraction p in the simulation should be related to the quality limit $\tilde{p}_m$, as we can see as follows. There are no tables available for $p > 2\,\tilde{p}_m$. This, however, is no problem if only the left columns of the tables are used (see Section 1). Obviously if p is very high, then the scheme is useless, i.e., sampling is (nearly) always followed by inspection of the whole subpopulation; therefore we restrict our simulation to $p \leq 6\,p_m$. Obviously not all subpopulations must have the same p, even

if all subpopulations have the same expected value $E(\underline{p})$. Therefore we sample $\underline{p}$ in the simulation. As Figure 1 demonstrates, the performance $E(\tilde{\underline{p}})$ improves as p deviates from the least favorable value p^*. In preliminary simulation experiments we sampled $\underline{p}$ from a distribution with a high variance, and indeed $E(\tilde{\underline{p}})$ decreased (not further reported in this paper). Therefore we concentrate our simulation on worst case situations, that is, $\underline{p}$ has a small range. We further assume that $\underline{p}$ is uniformly distributed with a range of only $0.2\ \tilde{p}_m$. We do change the expected value $E\left[\underline{p}\right]$; as we explained above, we vary p between 0 and $6\ \tilde{p}_m$. So we sample $\underline{p}$ from the uniform distribution between 0 and $0.2\ \tilde{p}_m$, between $0.2\ \tilde{p}_m$ and $0.4\ \tilde{p}_m$, ... , between $5.8\ \tilde{p}_m$ and $6\ \tilde{p}_m$. (the figures do not extend to $p = 6\ p_m$ because the pattern is already clear from figures with a smaller range of p).

Summarizing, we simulate 1620 factor combinations using only the left-most columns of the tables ("practitioner's approach") and we simulate 540 combinations with the optimal $\left[n, k_o\right]$ combinations ("theoretical approach").

There is an important technical issue in the simulation: how often should we simulate each factor combination in order to obtain reliable estimates of performance criteria such as $P\left[\tilde{\underline{p}} > p_m\right]$? By definition, one replicate yields a binomial variable (say) $\underline{x}$ with $q = P(\underline{x} = 0) = P\left[\tilde{\underline{p}} > \tilde{p}_m\right]$. Using the normal approximation to the binomial distribution, it is straightforward to derive the number of replications needed to estimate q with either a relative precision of 10% or an absolute precision of 0.001; also see Kleijnen (1987, pp. 46-51). This approach shows that at most 16,221 replications are needed to satisfy either the relative precision or the absolute precision

requirement, with 90% probability; this maximum of 16,221 occurs when q = .01. Actually we do not know q. So we substitute the "current" estimate for q after at least 100 replications, i.e., we substitute the estimate $\hat{q}_r$ available after r replications where r = 101, 102, ... The average number of replications turns out to be roughly 1000. We emphasize that the simulation not only estimates the performance criterion $q = P\left[\tilde{\underline{p}} > \tilde{p}_m\right]$ but several more criteria. The main criterion, however, is q so that we concentrate on q to select the number of replications.

It takes 40 hours of computer time to simulate 1620 + 540 factor combinations, each combination replicated roughly 1000 times. Computer time would exceed this sizable value, had we not introduced the following technical refinement. The number of defectives $\underline{k}$ has a hypergeometric distribution. The binomial distribution provides a good approximation provided $n << N_s$ which is often the case (but not always: if NY is small then $n > N_s$ may occur); see Table 1. The Poisson distribution is a good approximation to the binomial distribution, if p is small; also see Hald (1981, p. 203). We simulate the Poisson distribution using the subroutine in Naylor et al. (1966, p. 114); this Poisson program runs 20 times faster than the hypergeometric program on our computer (a VAX 780 running under VMS). We use the multiplicative congruential random number generator with multiplier 13^{13} and modulo 2^{59}, developed and tested by NAG (Numerical Algorithms Group, United Kingdom).

3. MONTE CARLO RESULTS

The Monte Carlo experiment yields a mass of data. We analyze these data through regression analysis (using SAS). Preliminary plots look like a gamma function (also see Figure

1). Therefore we fit such a type of non-linear regression model for $\bar{\tilde{p}}$ versus p; see Figure 2 when "Practice" refers to the "practitioner's approach" which uses only the left-most columns of the tables, and "Theory" refers to the optimal (n,k_0) combinations. Its R^2 adjusted for the number of explanatory variables, is higher than 0.95. Figure 2 looks like the theoretical Figure 1, i.e., there is a least favorable value for p and $\bar{\tilde{p}}$ remains below $\tilde{p}_m$. This result is not surprising, but it verifies the correctness of our simulation program.

If the before-sampling fraction p satisfies $p \leq \tilde{p}_m$ then obviously $q = P\left[\bar{\tilde{p}} > \tilde{p}_m\right] = 0$. If, however, $p > \tilde{p}_m$ then we again fit a function like the gamma function; see Figure 3, with $R^2 = 0.99$ for the theoretical case and 0.74 for the practitioner's approach. So there is a sizable chance (up to 40% in Figure 3) of violating the quality constraint $\bar{\tilde{p}} \leq \tilde{p}_m$, if the "practitioner's approach" is followed. We repeat, however, that our simulation concerns a worst case, since the fraction p of the subpopulation is sampled from a uniform distribution with a small range (see Section 2).

If $\bar{\tilde{p}} > \tilde{p}_m$ then we wonder how bad the quality violation is: $E\left[\bar{\tilde{p}} - \tilde{p}_m \middle| \bar{\tilde{p}} > \tilde{p}_m\right]$; see Figure 4. It is interesting that smaller subperiods (higher S) give extra protection.

Next we consider the costs of the sampling plans. The AOQL scheme implies that all N_s units (of a subperiod) are inspected if $k > k_o$. Figure 5 shows the fraction of the subpopulations which are rejected and fully inspected. That fraction increases drastically if $p > \tilde{p}_m$. Obviously the practitioner's approach is more expensive. We add that the curves are hardly affected by S, the number of subperiods (not displayed). We

also note that specification of cost functions is rather arbitrary so that we use the fraction in Figure 5 as a rough indicator; for specific cost functions we refer to Ercan et al. (1974), Hald (1981) and Schneider et al. (1988).

Our simulation shows that it is important to have a good idea about p, the before-sampling fraction of defectives. Therefore we suggest to obtain an estimate of p, using $\hat{p} = k/n$ if $k \leq k_o$ and $\hat{p} = K/N_s$ if $k > k_o$ where K denotes the number of defectives in the subpopulation (of size N_s). As time goes on, we obtain the estimators $\hat{p}_t$ which can be combined; for example, we may weigh the $\hat{p}_t$ with the sample sizes n_t or the subpopulation sizes N_t (if $k \leq k_o$ or $k > k_o$ respectively). If $\hat{p}_t$ shows serial correlation or non-stationary behavior, then we may apply time series techniques. A different approach using prior distributions is discussed by Hald (1981, pp. 15-21, 125-138, 335, 424-425).

4. CONCLUSIONS

The AOQL sampling plan is indeed used in practice (see Kriens and Veenstra, 1985). In that practice it is assumed that if the expected yearly fraction of defectives after inspection and correction $E(\tilde{p})$ meets the quality constraint $\tilde{p}_m$ then the probability of exceeding the constraint $\tilde{p}_m$ is negligible: $P\left[\bar{\tilde{p}} > \tilde{p}_m\right] \approx 0$. Figure 3 (based on simulation data analyzed by regression) shows that actually this probability is sizable, if the before-sampling fraction p is higher than the limit $\tilde{p}_m$ but not extremely high (if $p < \tilde{p}_m$ then obviously there is no chance that the yearly average $\bar{\tilde{p}}$ exceeds $\tilde{p}_m$; if $p >> \tilde{p}_m$ then most times sampling is followed by inspection of the whole subpopulation). If in practice p varies much over subperiods, then $P\left[\bar{\tilde{p}} > \tilde{p}_m\right]$ decreases (we simulated worst case situations: small

range of p). Figure 4 shows that increasing the number of periods S decreases the magnitude of the expected quality violation. Underestimating p is not wise: it does not give extra quality protection (in Figure 3 the "Practice" curve dominates the "Theory" curve); yet more inspection work is done (Figure 5). So in practice one should build up knowledge about p. One can get an estimate of p from the sampling procedure itself: if $k \leq k_o$ then $\hat{p} = k/n$; else $\hat{p} = K/N_s$. To reduce and control p itself means that the inspection costs decrease (see Figure 5); the expected value of the quality violation also decreases (Figure 4). The probability of a quality violation (Figure 3) and the average quality (Figure 2) deteriorate if the decreasing p approaches a least favorable value from above; pushing p below that value gives best results.

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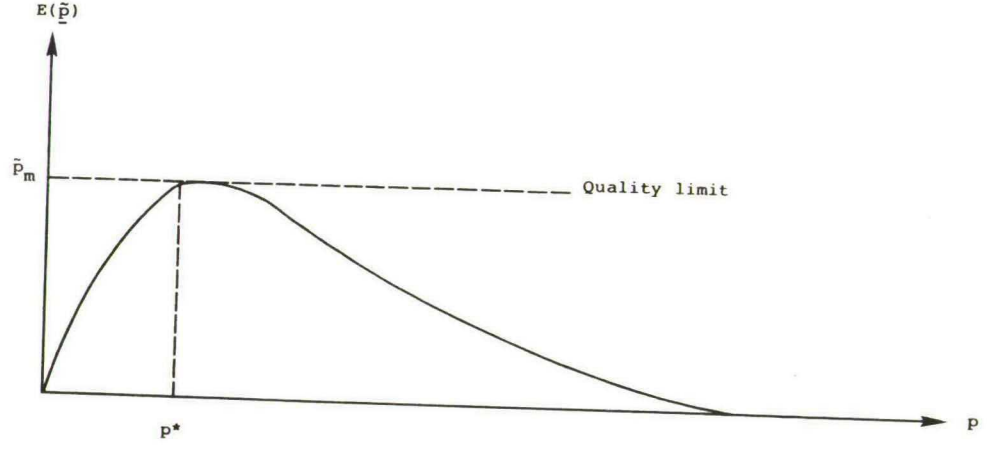

Figure 1: Expected fraction of defectives after sampling $E(\tilde{p})$ versus fraction before sampling p (different scales on different axes).

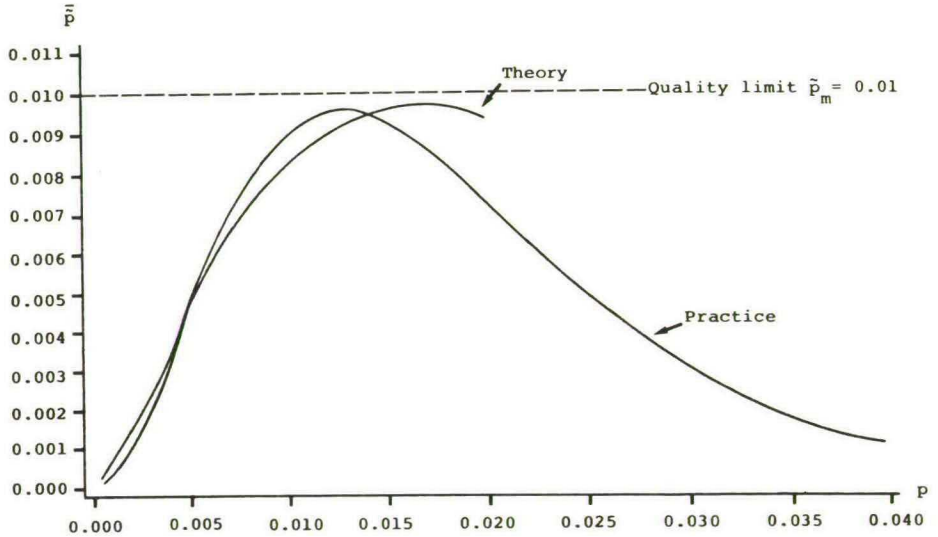

Figure 2: Average yearly outgoing quality $\bar{\bar{p}}$ versus fraction of defectives before sampling p (yearly population NY = 1,000,000; subperiods S = 52).

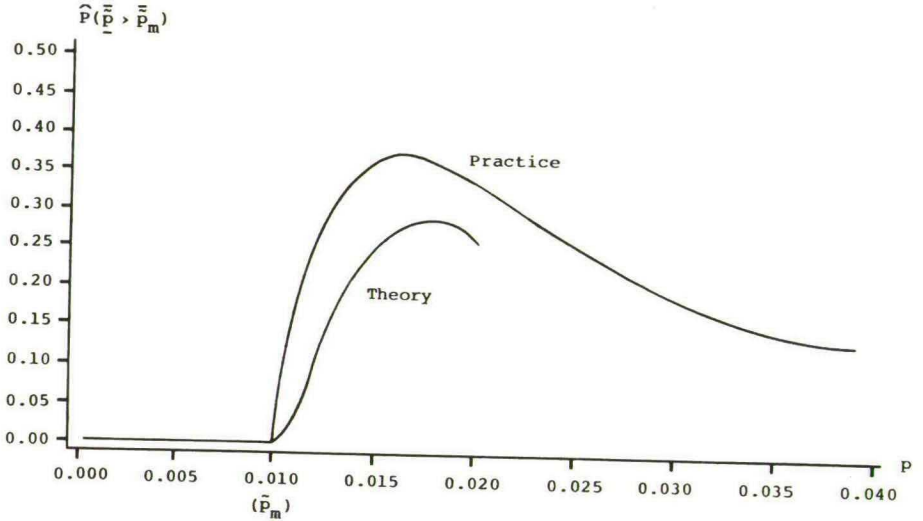

Figure 3: Estimated probability of quality violation, $P(\bar{\bar{p}} > \tilde{p}_m)$ (NY = 100,000; S = 52).

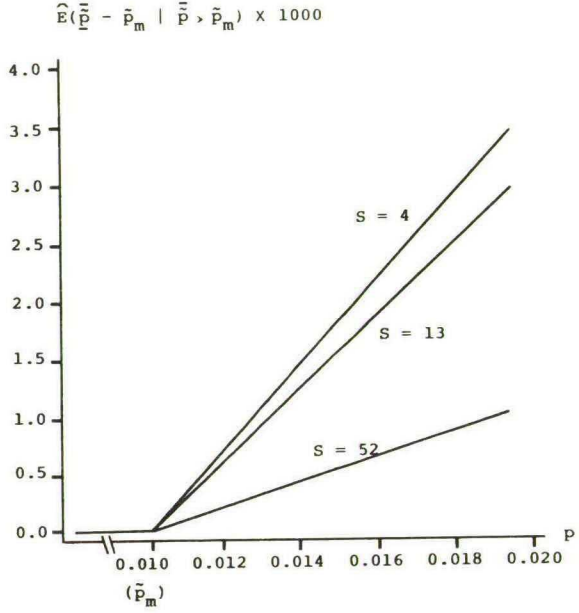

Figure 4: Estimated value $\hat{E}$ of quality violation, $E(\bar{\tilde{p}} - \tilde{p}_m \mid \bar{\tilde{p}} > \tilde{p}_m)$ in theoretical approach (NY = 1,000,000).

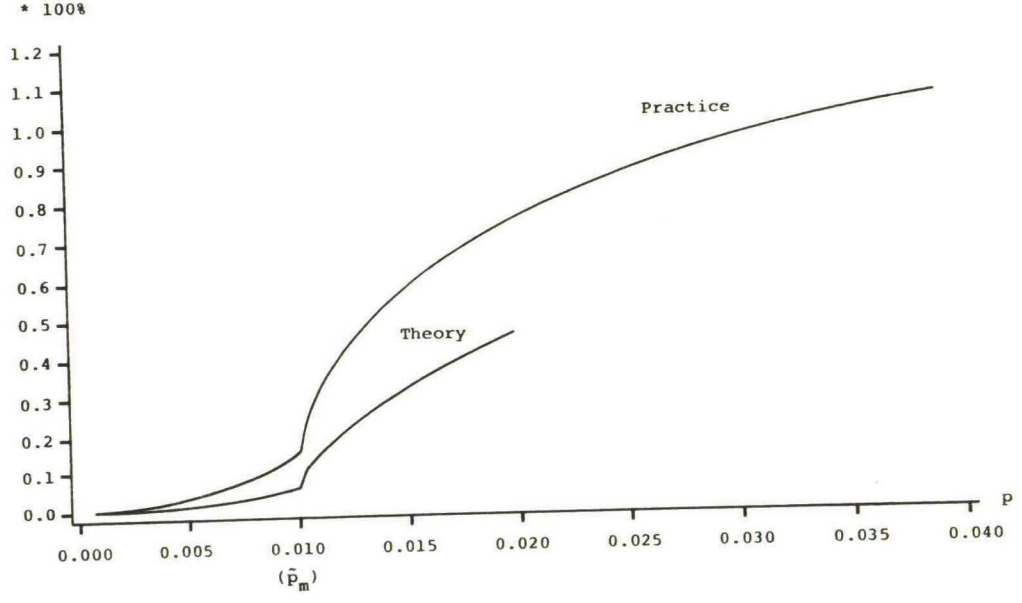

Figure 5: Estimated fraction of sub-populations, fully inspected (NY = 1,000,000 ; S = 52).

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