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KK Suresh
Professor and Head, Department of Statistics, Bharathiar University, Coimbatore- 641 046, Tamil Nadu, India

K Usha
Ph.D Research Scholar, Department of Statistics, Bharathiar University, Coimbatore- 641 046, Tamil Nadu, India

Correspondence
K Usha
Ph.D Research Scholar, Department of Statistics, Bharathiar University, Coimbatore- 641 046, Tamil Nadu, India

Construction and selection of Bayesian double sampling plans indexed through quality levels

KK Suresh and K Usha

Abstract
In acceptance sampling plans, the decisions on either accepting or rejecting a specific batch is still a challenging problem, in order to provide a desired level of production for customers as well as manufactures. In this paper, a new acceptance sampling design is double sampling plan which based on gamma -Poisson distribution and the procedures for selection of Bayesian double sampling plan indexed with relative slopes through incoming and outgoing quality levels are associated with their specified risks, which describe the degree of sharpness of the OC curve, are considered towards designing of sampling plans. Further comparison made with existing sampling plan.

Keywords: Double sampling plan, Gamma-Poisson distribution, Acceptable quality level, Limiting quality level, Operating Ratio, Relative Slopes.

1. Introduction

Since the beginning of various statistical concepts, methods and techniques are used to furnish lot by lot acceptance sampling plan. Inspection of the lot and final product is very necessary to ensure good quality. In fact the theory of sampling inspection pays more attention to improve the quality and reduce cost in terms of minimum sample size. In this scenario industrialists are able to bring innovative production with the help of Bayesian sampling plan, which is more effective than existing sampling plan, taking smaller inspection cost and efficiency over sample size.

The basic assumption in all the sampling plans is that the lot or process fraction defective is constant, which specifies the production process is stable. However, in real-life situations, the lots formed from a process will have quality variations which are due to random fluctuations. These variations are classified as within-lot variation and the other is between-lot variation. When the second type of variation is more than the first type of variation, the fraction defective items in the lots will vary continuously. In such cases, the conventional sampling plans cannot be applied. It is very important to note that acceptance sampling plans based on Bayesian methodology can be used when the experimenter has prior knowledge on the process variation to make a decision about the disposition of the lot.

The prior distribution describes the user belief to the sample, about the defectives from lot-to-lot. A decision to accept or reject the lot based on posterior distribution which combines the user prior knowledge of lot-to-lot variations with sampling inspection results. Bayesian sampling plan has a clear picture on the consequences associated with the selection of particular prior distribution. Thus, the pitfalls in the selection of a prior distribution have been pointed out by Case and Keats (1982) [2].

Calvin (1984) [1] has presented clearly and concisely the meaning of 'how and when to perform Bayesian Acceptance Sampling'. These procedures are suited to the sampling of lots either process or assembly operations, that contain assignable causes. Such causes may be unknown and awaiting isolation, known but irremovable due to the state of limitations, or known but uneconomical to remove. Further, theoretically if any major shift requires reassessment of the sampling plan, the accurate sampling risks were to be maintained.

A set of tables presented by Oliver and Springer (1972) [7] based on assumption of Beta prior distribution with specific posterior risk, to achieve minimum sample size which avoids the issue of estimating cost parameters. It is generally true that, Bayesian plan requires smaller sample size than conventional sampling plan with the same producer and consumer risk. Hamaker and Vanstrik (1955) [5] studied the efficiency of double sampling attributes using indifference quality level and presented expressions for p_0 and h_0. Dodge and Romig (1959) [3] have presented tables for double sampling plan indexed by AOQL and LTPD. Suresh (1993) [13] has presented and constructed tables for the selection of double sampling plan indexed through (p_1,h_1) and (p_2,h_2) involving incentive and filter effects.

Suresh and Saminathan (2010) [11] have studied designing of Repetitive deferred sampling plan indexed through relative slopes and compared with Repetitive group sampling plan. Latha (2002) [6] studied the Bayesian single sampling plan indexed with various quality levels and relative slopes at indifference quality levels. Suresh *et al* (2013) [10] have studied designing of Bayesian Repetitive Deferred Sampling Plan (BRDS) indexed through incoming and outgoing quality levels with their relative slopes on the OC curve. Balamurali *et al* (2012) [8] have developed Bayesian double sampling plan that uses two quality levels. This plan is better than single sampling plan in terms of minimum ASN and lesser ASN than existing sampling plans. Suresh and Usha (2016) [12] have studied Bayesian double sampling plan using minimum angle method which is better than Bayesian single sampling plan in terms of minimizing tangent θ and two risks.

Based on the above, the present work is attempted for Bayesian double sampling plan indexed through relative slopes at specified quality levels and comparison made with Bayesian single sampling plan (BSSP) with their quality levels. The present work would be worthy and useful in the area of quality control towards minimum sample size and efficiency through inspection cost.

2. Bayesian Double Sampling Plan

In general settings, *DSP* plan is authentic for application of attribute sampling inspection. However, this plan will especially be useful for product characteristics towards cost or involving destructive testing. A double sampling plan can significantly reduce the costs for sampling inspection related to single-sampling plan for lots with very low or very high proportion defective because a decision can be made after taking the first sample. If the decision requires two samples, the sampling cost can be greater than those of single-sampling plan.

Operating Procedure as follows

a. Select a random sample of size n_1 and observe the number of nonconforming units, d_1.
b. If $d_1 \le c_1$ accept the lot. If $d_1 > c_1$, then reject the lot. If $c_1 < d_1 \le c_2$, take a second sample of size n_2 and observe the number nonconforming units, d_2.
c. If the $d_1 + d_2 \le c_2$ accept the lot otherwise reject the lot.

Gamma-Poisson distribution, which is also known as the negative binomial distribution, is one of the most widely used models in acceptance sampling plans. When the production process produces output in a continuous stream and observed number of defects (or nonconformities) in the sample drawn from this process is distributed as Poisson with parameter np, where n is the sample size and p is the average number of defects per unit (Hald, 1981) [4]. According to Schilling (1982) [9], the Poisson distribution is an appropriate model for the number of nonconforming items in the sample when the ratio of sample size to the population size is less than 10%, is (n/N) n is large and p<0.10 is small such that np<5. Double Sampling Plan is specified with constants n_1 and n_2. It is assumed that $n_1 = n_2 = n$. Under the conditions of applications of Poisson model, the probability of acceptance of the double sampling plan given by

$$P_a(p) = \sum_{d_1=0}^{c_1} \frac{e^{-np}(np)^{d_1}}{d_1!} + \sum_{d_1=c_1+1}^{c_2} \frac{e^{-np}(np)^{d_1}}{d_1!}\left[\sum_{d_2=0}^{c_2-d_1} \frac{e^{-np}(np)^{d_2}}{d_2!}\right] \tag{1}$$

According to gamma distribution, the natural conjugate prior for sampling from the Poisson distribution, the function of prior distribution p is denoted by

$$f(p/t,s) = \frac{e^{-tp} t^s p^{s-1}}{\Gamma s}, \quad 0 \le p < \infty, t, s > 0 \tag{2}$$

where t is scale parameter and s is shape parameter. If $E(p) = \mu$ is given the scale parameter is obtained by $t = \frac{s}{\mu}$

Here s is specified from the prior information about the production process. The posterior distribution for nonconformities is reduced under gamma-Poisson distribution. When the production is unstable, the nonconforming item (d) and average number of defects p are independently distributed. According to Hald (1981), the nonconforming items (d) can be developed under the process average $\mu < 0.1, \frac{\mu}{s} < 0.2$ is given by

$$P(d : n\mu, s) = \frac{(s+d-1)!}{d!(s-1)!}\left(\frac{n\mu}{s+n\mu}\right)^d \left(\frac{s}{s+n\mu}\right)^s \qquad d = 0, 1, \ldots. \tag{3}$$

In order to continue this, the probability of acceptance of the double sampling plan under gamma-Poisson model is given by

$$\overline{P} = \sum_{d_1=0}^{c_1} \frac{(s+d_1-1)!}{d_1!(s-1)!}\left(\frac{n\mu}{s+n\mu}\right)^{d_1}\left(\frac{s}{s+n\mu}\right)^s + \sum_{d_1=c_1+1}^{c_2} \frac{(s+d_1-1)!}{d_1!(s-1)!}\left(\frac{n\mu}{s+n\mu}\right)^{d_1}\left(\frac{s}{s+n\mu}\right)^s \left[\sum_{d_2=0}^{c_2-d_1} \frac{(s+d_2-1)!}{d_2!(s-1)!}\left(\frac{n\mu}{s+n\mu}\right)^{d_2}\left(\frac{s}{s+n\mu}\right)^s\right] \tag{4}$$

3. Selection of Bayesian Double Sampling (BDSP)

A double sampling plan gives similar levels of consumer and producer risk but require less sampling in the long run than a single sampling plan which is given in conventional sampling plan. Bayesian double sampling plan also better than Bayesian single sampling plan, further comparison are given for $BDSP$ and $BSSP$.

3.1 Designing Plans For Given AQL, LQL, α and β

Table 1 is used to design Bayesian Double Sampling Plan for given $AQL(\mu_1), LQL(\mu_2), \alpha$ and β

The steps utilized for selecting Bayesian Double Sampling Plan are as follows:

1. To design a plan for given $(AQL, 1-\alpha)$ and (LQL, β) first calculate the operating ratio μ_2/μ_1
2. Find the value in Table 1 under column for α and β which is closest to the desired ratio.
3. Corresponding to the located value of μ_2/μ_1 the values of s, c_1, c_2 can be obtained.
4. The sample size can be obtained as $n\mu_1/\mu_1$ where $n\mu_1$ can be obtained against the located value of μ_2/μ_1.

Selection of BDSP through (AQL, LQL)

Example 1

Table 1 is used to construct $BDSP$ when AQL and LQL quality levels are given. μ_1=0.04 and μ_2 =0.30, calculate $LQL/AQL = 7.5$. The values corresponding to this is approximately equal to this calculating operating ratio Table 1 under column headed μ_2/μ_1 is 7.6815. The corresponding to this $n\mu_1, s, c_1$ and c_2 read as 0.6128, 2, 0 and 3 respectively. Now $n = n\mu_1/\mu_1 = 15.32 \approx 15$. Hence, the Bayesian DSP parameters are given $AQL = 0.04$ and $LQL = 0.30$ are $n = 15, c_1 = 0, c_2 = 3$ and $s = 2$.

3.2 Designing of Bayesian Double Sampling Plan indexed through Relative Slopes

Designing procedures for quality levels namely, Acceptable Quality Level (AQL), Indifference Quality Level (IQL) and Limiting Quality Level (LQL) are considered with their corresponding relative slopes (denoted by h), to describe the degree of sharpness for the OC curve.

Selection of BDSP Relative slope at AQL, IQL and LQL

Example 2

Table 1 is used to design plans for $BDSP$ indexed with μ_1 and h_1. For example, given $\mu_1 = 0.01$ and $h_1 = 0.05$, from Table 1 under column headed h_1, located value is equal to or just greater than specified h_1, that is 0.0537. Corresponding to this h_1, the values of parameters are associated with $n\mu_1 = 0.2015, c_1 = 0, c_2 = 1, s = 2$. From this one can obtain the sample size as $n = n\mu_1/\mu_1 \approx 20$. Thus the parameters are $n = 20, s = 2, c_1 = 0, c_2 = 1$.

Example 3

Table 1 is used to design plans for $BDSP$ indexed with μ_0 and h_0. For example, given $\mu_0 = 0.05$ and $h_0 = 0.12$, from Table 1 under column headed h_0 located value is equal to or just greater than the specified h_0, which is 1.2907. Corresponding to this h_0, the values of parameters are associated with $n\mu_0 = 1.1048$, $c_1 = 0, c_2 = 1, s = 4$. From this one can obtain the sample size as $n = n\mu_0/\mu_0 \approx 22$. Thus the parameters are $n = 22, s = 4, c_1 = 0, c_2 = 1$.

Example 4

Table 1 is used to design plans for $BDSP$ indexed with μ_2 and h_2. For example, given $\mu_2 = 0.04$ and $h_2 = 2.2$ from Table 1 under the column headed h_2 located value is equal to or just greater than the specified h_2, which is 2.2719. Corresponding to this h_2, the values of parameters are associated with $n\mu_2 = 0.8910, s = 8$. From this one can obtain the sample size as $n = n\mu_2/\mu_2 \approx 22$. Thus the parameters are $n = 22, s = 8, c_1 = 0, c_2 = 1$.

4. Comparative study on Single and Double Sampling Plan under Bayesian Methodology

Table 2 is shows that Bayesian single sampling plan and Bayesian double sampling plan for given various parametric values of 's' and relative slope at indifference quality levels.

4.1 Selection through AQL and LQL

In Table 2 the values of $BSSP$ $(n\mu_1, n\mu_2, n\mu_0, h_0)$ are given with reference to Latha (2002) for compare the values of $BDSP$.

Example

For given value of $\mu_1 = 0.015$ and μ_2, OR= μ_2/μ_1 = 8.9333

$BSSP$ when $s = 7, s = 7$, $n\mu_1$ = 0.7584 and n =51

$BDSP$ when $c_1 = 0$, $c_2 = 1, s = 7, n\mu_1$ = 7.8842 and n =28

4.2 Relative slope at Indifference Quality Levels

Example

Given $\mu_0 = 0.039$ and $h_0 = 1.15$, $c = 3$ and $s = 5$

$BSSP$ when h_0 =1.1567, $n\mu_0 = 3.9310, s = 5, c = 3$ and $n = 101$

$BDSP$ when h_0 =2.2503, $n\mu_0 = 1.5485, c_1 = 0, c_2 = 3$ and n =40

It is observed that the both plan are quite similar in nature of sampling procedures. If their OC curves are identical and two plans would be considered as matched. The proposed plan is better than Bayesian single sampling plan in terms of minimizing the sample size.

5. Construction of Tables

The relative slope is,

$$h = -\frac{\mu}{P_a(\mu)} \frac{dP_a(\mu)}{d\mu} \qquad (5)$$

Differentiating the equation (4) with respect to μ and their corresponding values $n\mu_1, n\mu_2$ and $n\mu_0$ are substituted in the equation (5) for the relative slopes at $\mu = \mu_1, \mu_0, \mu_2$, the values of h_1, h_0, h_2 are obtained in Table 1.

Table 1: Certain Parametric Values for Bayesian Double Sampling Plan

s	c_1	c_2	μ_1	μ_0	μ_2	h_1	h_0	h_2	μ_2/μ_1
2	0	1	0.2015	1.2155	4.707	0.0537	1.0314	5.293	23.3598
	0	2	0.3961	1.4868	4.7071	0.1775	1.3613	5.2931	11.8836
	0	3	0.6128	1.6705	4.7072	0.366	1.5888	5.2932	7.6815
	0	4	0.8417	1.7932	4.7073	0.6016	1.7417	5.2933	5.5926
	0	5	1.0781	1.8735	4.7074	0.8689	1.8419	5.2935	4.3664
	0	6	1.3195	1.9246	4.7075	1.1567	1.9058	5.2936	3.5676
	0	7	1.3637	1.9561	5.1422	1.2105	1.9451	5.8069	3.7708
	0	8	1.4401	1.9749	5.1423	1.3039	1.9686	5.807	3.5708
	0	9	1.486	1.9859	5.1424	1.3604	1.9824	5.8071	3.4606
4	0	1	0.2038	1.1048	3.379	0.0992	1.2907	3.7821	16.5800
	0	2	0.4105	1.379	3.7421	0.3168	1.6798	4.0502	9.1160
	0	3	0.647	1.5668	3.7422	0.6292	1.9345	4.0503	5.7839
	0	4	0.9019	1.8563	3.7423	0.9954	2.3036	4.0503	4.1494
	0	5	1.1682	1.9311	3.7424	0.382	2.394	4.0504	3.2036
	0	6	1.443	1.9737	3.7425	1.7678	2.4446	4.0505	2.5936
	0	7	1.4662	1.9963	3.7426	1.7722	2.4711	4.0506	2.5526
	0	8	1.5182	2.0075	3.7427	1.8697	2.4842	4.0506	2.4652
	0	9	1.5422	2.0128	3.7428	1.9018	2.4904	4.0507	2.4269
6	0	1	0.2047	1.0707	3.043	0.155	1.7646	4.1625	14.8657
	0	2	0.4161	1.3468	3.0431	0.49	2.2683	4.1626	7.3134
	0	3	0.6612	1.5368	3.3872	0.9584	2.5846	4.344	5.1228
	0	4	0.9274	1.6549	3.3873	1.487	2.7675	4.3441	3.6525
	0	5	1.2076	1.7206	3.3874	2.0202	2.8645	4.3441	2.8051
	0	6	1.498	1.9197	3.3875	2.5222	3.1378	4.3442	2.2613
	0	7	1.5454	1.9371	3.3876	2.5983	3.1602	4.3442	2.1921
	0	8	1.6005	1.9446	3.3877	2.6846	3.1698	4.3443	2.1167
	0	9	1.6243	1.9477	3.3877	2.7211	3.1737	4.3443	2.0856
8	0	1	0.2051	1.0541	0.891	0.2124	2.2719	4.7907	4.3442
	0	2	0.4191	1.3341	2.8911	0.6698	2.8985	4.7908	6.8984
	0	3	0.669	1.5228	3.2263	1.3008	3.2809	4.9059	4.8226
	0	4	0.9417	1.64	3.2264	1.9972	3.4931	4.9059	3.4261
	0	5	1.23	1.703	3.2265	2.6787	3.6002	4.906	2.6232
	0	6	1.5291	1.7326	3.2266	3.2927	3.6489	4.906	2.1101
	0	7	1.5303	1.7447	3.2267	3.295	3.6685	4.906	2.1085
	0	8	1.5762	1.7448	3.2268	3.3797	3.6686	4.906	2.0472
	0	9	1.5941	1.7492	3.2268	3.412	3.6757	4.906	2.0242

Table 2: Comparison between Bayesian SSP and DSP

	BSSP						BDSP						
s	c	$n\mu_1$	$n\mu_0$	$n\mu_2$	μ_2/μ_1	h_0	c_1	c_2	$n\mu_1$	$n\mu_0$	$n\mu_2$	μ_2/μ_1	h_0
1	1	0.2280	2.4142	18.4868	81.0825	0.5859	0	1	0.1976	1.4810	9.8330	49.7621	1.7681
	2	0.5833	3.8473	27.9766	47.9626	0.6181	0	2	0.3751	1.7567	9.8335	26.2157	2.2389
	3	0.8979	5.2852	37.4671	41.7275	0.6361	0	3	0.5671	1.9403	9.8340	17.3409	2.5608
	4	1.2186	6.7250	46.9579	38.5343	0.6488	0	4	0.7650	2.0698	9.8345	12.8556	2.7911
	5	1.5443	8.1658	56.4488	36.5530	0.6544	0	5	0.9667	2.1629	9.8350	10.1738	2.9581
	6	1.8722	9.6071	65.9398	35.2205	0.6599	0	6	1.1710	2.2310	9.8355	8.3992	3.0810
	7	2.2016	11.0488	75.4309	34.2619	0.6640	0	7	1.1778	2.2311	9.8360	8.3512	3.0812
	8	2.5320	12.4907	84.9220	33.5395	0.6671	0	8	1.2364	2.2312	9.8365	7.9558	3.0814
	9	2.8620	13.9327	94.4131	32.9885	0.6697	0	9	1.2747	2.2313	9.8370	7.7171	3.0815
2	1	0.3131	2.0000	8.2150	26.2376	0.7500	0	1	0.2015	1.2155	4.7070	23.3598	1.0314
	2	0.6617	3.1850	12.0292	18.1792	0.8277	0	2	0.3961	1.4868	4.7071	11.8836	1.3613
	3	1.0422	4.3732	15.8198	15.1792	0.8732	0	3	0.6128	1.6705	4.7072	7.6815	1.5888
	4	1.4376	5.5629	19.5994	13.6334	0.9037	0	4	0.8417	1.7932	4.7073	5.5926	1.7417
	5	1.8410	6.7531	23.3732	12.6959	0.9224	0	5	1.0781	1.8735	4.7074	4.3664	1.8419
	6	2.2492	7.9438	27.1435	12.0681	0.9408	0	6	1.3195	1.9246	4.7075	3.5676	1.9058
	7	2.6605	9.1346	30.9115	11.6187	0.9532	0	7	1.3637	1.9561	5.1422	3.7708	1.9451
	8	3.0740	10.3257	34.6777	11.2810	0.9631	0	8	1.4401	1.9749	5.1423	3.5708	1.9686
	9	3.4891	11.5169	38.4433	11.0181	0.9712	0	9	1.4860	1.9859	5.1424	3.4606	1.9824
3	1	0.3245	1.8838	6.3615	19.6040	0.8277	0	1	0.2030	1.1402	3.7630	18.5369	1.0935
	2	0.7003	3.0000	9.1637	13.0854	0.9375	0	2	0.4053	1.4130	4.1472	10.2324	1.4351
	3	1.1171	4.1190	11.9321	10.6813	1.0053	0	3	0.6344	1.5990	4.1473	6.5374	1.6644
	4	1.5542	5.2391	14.6847	9.4484	1.0553	0	4	0.8793	1.7196	4.1474	4.7167	1.8105
	5	2.0026	6.3598	17.4283	8.7028	1.0933	0	5	1.1342	1.9806	4.1475	3.6568	2.1185
	6	2.4581	7.4808	20.1666	8.2041	1.1155	0	6	1.1399	2.0284	4.1476	3.6386	2.1736
	7	2.9183	8.6021	22.9011	7.8474	1.1367	0	7	1.1921	2.0559	4.1477	3.4793	2.2051
	8	3.3818	9.7234	25.6331	7.5797	1.1538	0	8	1.2161	2.0710	4.1478	3.4107	2.2224

	9	3.8477	10.8449	28.3634	7.3715	1.168	0	9	1.2260	2.0790	4.1479	3.3833	2.2315
5	1	0.3353	1.7976	5.2107	15.5404	0.9034	0	1	0.2043	1.0842	3.1720	15.5262	1.5209
	2	0.7389	2.8631	7.3817	9.9901	1.0540	0	2	0.4138	1.3594	3.1721	7.6658	1.9655
	3	1.1950	3.9310	9.5086	7.9570	1.1567	0	3	0.6553	1.5485	3.1722	4.8408	2.2503
	4	1.6788	5.0000	11.6130	6.9174	1.2285	0	4	0.9167	1.6671	3.5236	3.8438	2.4191
	5	2.1791	6.0694	13.7043	6.2890	1.2897	0	5	1.1911	1.7348	3.5237	2.9584	2.5119
	6	2.6901	7.1392	15.7872	5.8686	1.3328	0	6	1.4746	1.7696	3.5238	2.3897	2.5586
	7	3.2083	8.2090	17.8644	5.5682	1.3696	0	7	1.5119	1.7697	3.5239	2.3308	2.5587
	8	3.7318	9.2791	19.9374	5.3426	1.4001	0	8	1.5657	1.7859	3.5240	2.2508	2.5802
	9	4.2592	10.3491	22.0075	5.1671	1.4259	0	9	1.5896	1.7860	3.5241	2.2170	2.5803
7	1	0.3405	1.7624	4.7894	14.0658	0.9408	0	1	0.2050	1.0612	2.9550	14.4146	2.0159
	2	0.7584	2.8072	6.7277	8.8709	1.1157	0	2	0.4178	1.3380	3.2940	7.8842	2.5805
	3	1.2356	3.8544	8.6156	6.9728	1.2391	0	3	0.6656	1.5287	3.2941	4.9491	2.9294
	4	1.7454	4.9025	10.4770	6.0026	1.3372	0	4	0.9354	1.5288	3.2942	3.5217	2.9295
	5	2.2757	5.9511	12.3223	5.4147	1.4107	0	5	1.2201	1.6463	3.2943	2.7000	3.1267
	6	2.8183	7.0000	14.1570	5.0232	1.4663	0	6	1.5153	1.9043	3.2944	2.1741	3.5110
	7	3.3708	8.0490	15.9844	4.7420	1.5159	0	7	1.5711	1.9202	3.2945	2.0969	3.5325
	8	3.9301	9.9081	17.8065	4.5308	1.5578	0	8	1.6722	1.9268	3.6238	2.1671	3.5411

6. Conclusions

The present work is mainly related to the construction and selection of $BDSP$ through various quality levels and relative slopes. In order to build confidence among producer and consumer towards minimize the sample size and risks. The effectiveness of this procedure is evaluated by comparing its results with those of obtained from optimal Bayesian acceptance sampling plan. Tables provided here with tailor-made, handy ready-made can be used in the industrial shop-floor condition. This result would be assistance in the field of quality control to develop new plans and procedures for engineer and plan designers.

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