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Original Article

A New Development of Variable-Attribute Relational Complete Chain Sampling Plan(RCCSP) for Quality Control Engineers

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Abstract - *In this modern world, competition for quality plays a significant role in production. Everybody prefers only high-quality products. Therefore quality control engineers need new Variable-Attribute sampling plans to satisfy customers and producers. To achieve this, a new variable-attribute plan is designed in this unit. The efficiency of the plan is examined by finding the OC values. The OC values of the proposed plan are compared with that of the combined modified chain sampling plan. The chance of acceptance (P_A) and other connected measures of the plan are given. The plan is indexed through AQL and LQL, and the parameters are found using the python program. Tables are designed to make choosing the plan simple.*

Keywords - *AQL, LQL, OC values, P_A, RCCSP, The python program*.

1. Introduction

Offline quality control and process control approaches have played a significant role in recent decades, with the acceptance sampling procedure remaining a vital tool for many practical quality control systems. Acceptance sampling is a statistical measure used to aid in deciding whether a product or batches should be issued for consumer use. In industries, sampling plans are commonly used to compute process characteristics and determine disposition. In the practice and theory of acceptance sampling, variable sampling is extremely important. The interesting quality criteria are consistently evaluated as the baseline prerequisites for variable sampling. The main advantages of the variable sampling plan are that it achieves a similar operating characteristics (OC) curve with a smaller sample size than attribute sampling methods. As a result, the variable acceptance sampling method requires fewer samples. The variable sampling method provides more useful data than attribute sampling. As a result, the protection is achieved with significantly smaller sample size. Variable sampling is critical in lowering inspection costs when destructive testing is used.

Furthermore, the variable sampling technique has some drawbacks compared to the attribute sampling process. The sample strategies are far more difficult to implement than the assumptions and attributes on which they are based, which may or may not be fulfilled or understood. The inspection cost of each item based on quality is lower than the variables. Because of the decreased cost, the basic recording technique may merely record the number of test failing units rather than variable measurements. Furthermore, in today's quality control system, some significant causes are no longer relevant because measurements are performed using automated test equipment. Even automated test equipment can do simple evaluation and data collection, which is typically necessary for variable sampling. Author et al. [1] discuss the variable sampling process and show that the acceptance sampling by variables is inappropriate when some investigators are interested in fraction non-conforming batches (incoming). However, the author et al. [2] proved that the variable sampling is also optimal. The traditional variable sampling process is investigated by various authors and is available for acceptance sampling. For the MIL scheme, the author et al. [3] modeled certain tables for plan selection parameters for various acceptable quality levels (AQL). When the SD of the process is unknown, the author et al. [4] designed a variable sampling plan based on the normal distribution. Author et al. [5] discuss a variable sampling plan for ensuring the product quality when the product quality characteristics undergo normal distribution with certain unknown SD and offer a procedure for evaluating the non-central distribution. Author et al. [6] provide a process for predicting the unknown sigma variable sampling process from the known variable sampling process. Author et al. [7] modeled a table for choosing the variable single sampling plan parameters that deal with the OC curve of the MIL scheme. Author et al. [8] modeled a double sampling process using variables with OC curves that match the equivalent single sampling plan-based OC curves. Author et al. [9] discuss the acceptance sampling that deals with certain traditional variable sampling plans. Author et al. [10] give a table for variable double sampling process when the SD process is unknown. The author extended the work with chain sampling for variable inspection. Moreover, he did not concentrate on any table with easier plan execution. However, the author restricts the discussion to some known SD. Therefore, this work attempts to model a table for easier execution of chain sampling to inspection variables with normal quality characteristics distribution for unknown and known SD cases. Author et al. [11] introduced the chain sampling concept for various applications that deal with attribute quality characteristics. Various authors investigate the properties and characteristics of the chain sampling process. It comes under various conditional sampling processes, such as multiple dependent sampling plans. In this process, the rejection and acceptance are based not only on the sampling but also on the sampling outcomes from the previous steps. The chain sampling method is appropriate for a Type B circumstance, such as sampling from a continuous process with high expectations for the same quality offered for inspection in each production order serially. The authors provide the characteristics and operating process of the attributes chain sampling plans [12].The OC curve, which assesses consumer and producer risk, is used to assess the efficacy of the acceptance sampling plan. It is critical to determine whether the variable plan shape is concave for a specific acceptable quality level. It is appropriate to improve the curve shape when the variable plan has an unsatisfactory OC curve, such as the zero acceptance number attributes plan. [13] discusses a broader study using the OC curve of the sampling variable plan with well-known SD. Enhancing the discriminating power of the OC curves is always necessary. It is possible with increased sampling size; nevertheless, destructive testing is unlikely and costly. Modeling a conditional sampling process is another option. The author et al. [14] extended the concept of chain sampling to variables inspection based on all of these notions. They are not provided with any tables for parameter selection and are only given the standard deviation. This project aims to provide industrial application plan tables for unknown and known SD scenarios. Author et al. [15] have also shown an approximation technique for estimating the plans of unknown SD instances. Author et al. [16] discussed reliability analysis of a system operating at reduced capacity with repair priority to a boiler, author et al. [17] presented a novel approach for Satellite image classification using an optimized deep convolutional neural network. Author et al. [18] showed optimization of injection pressure and injection timing of a diesel engine fuelled with an optimized blend of B25 cotton seed oil biodiesel. On the other hand, these studies present various methods for estimating the unknown sigma chain sampling strategy. Author et al. [19] analyzed the work in a Garment Industry in Laranjal. Planning and Programming of the Production of a Micro-Company of Bags and Bags were done by the author et al. [20]. Soundararajan (21,23) contributed to the study of single sampling plans and Chain sampling plans in 1971. Then in 1978, he submitted the procedures and tables for the construction and selection of chain sampling plans (Chsp -1). Author et al. [22] analyzed the Markov chains' application to evaluate the Operating Characteristics of chain sampling inspection plans. In 1955 Clark (24) studied the OC Curves for Chsp -1; the equivalence of OC functions for Certain Conditional sampling plans was discussed by Raju (25). The technique's most significant advantages are greater producer protection and a low average sample number (ASN). To use the variables chain sampling strategy, the following assumptions are true. This unit creates a new variable-attribute plan to accomplish this. The OC values are used to assess the plan's efficiency.

The work is structured as follows: Section 2 extensively analyzes various existing methods. In section 3, the methodology is explained. The numerical analysis and discussion of the anticipated model are provided in section 4. The summary of the work is given in section 5.

2. Literature Review

In 1967, Schilling provided a common method for determining the OC of the variable-attribute sample design. Based on Schilling's work, Govindaraju introduced Chsp1 for the given AQL and LQL in 1990. Suresh and Deva Arul developed a combined sampling plan with chain samples as the attribute plan in 2002. Deva Arul and Edna showed mixed sampling designs inv2011 for high-value or destructive items. Since then, in 2012, the same authors made a chain sampling plan for attribute quality traits. They developed an exploration algorithm in 2019 to identify expensive or disruptive products with mixed quality characteristics in batches. A sampling plan of the relational chain [RCPD (0, i)] is proposed to determine the attribute quality in 2017 by Devaarul and Vijila.

The acceptance sampling strategy is a method of evaluating random product samples used in quality control and improvement. It is an important component of quality management for business and industrial operations and aids decision-making. It's used to improve product quality during the manufacturing process. Acceptance sampling allows for a variety of sample procedures for the application of attribute quality attributes. Chain sampling (Chsp) is one of the sampling strategies for rejecting and accepting quality qualities with traditional features. The testing process can be quite costly and damaging in some cases. Hence sampling schemes with smaller sample sizes are usually employed. The general acceptability number for these smaller sample size proposals is zero. Some sampling programs include a zero-tolerance for unwanted results. OC curves are also convex throughput. As the fraction of defective turns to be larger than zero, the chance of acceptances begins to reduce extremely quickly. It is frequently unjust to the producer, and certain cases are based on correcting inspection. It necessitates that the consumer copes with more items, implying acceptable quality. The author requested a substitute method known as chain sampling in specific cases. Chain sampling is an alternative to typical single sample plans with zero acceptance numbers. It is especially optimal in a specific situation involving some samples with high demand and physical and economic challenges in obtaining the sample. Certain characteristics with' i'and 'n,' where n is the sample size and 'iI' is the number of subsequent samples with zero defects, classify the chain sampling strategy. When testing is damaging or expensive, a chain sampling plan is required. Under certain conditions, with a constant succession of the stable producer, the chain sampling plan aids sample size reduction.

3. Methodology

A variable sampling plan determines how close the process's specification or nominal limit performs. The attributes plans either reject or accept a lot, whereas the variable plans provide information regarding how well or poorly the process is carried out.

3.1. Construction of Variable-Attribute Sampling Plan using Relational Complete Chain Sampling Plan As Attribute Plan

The combined sampling plan with relational complete chain sampling as an attribute plan is constructed with the parameters s_1, s_2, k, and i, where,

s_1 = Current Sample Size

k = Variable Factor for a lot to be accepted

s_2 = Later Sample Size.

i = No. of batches to be chained

3.2. Measures of the Sampling Plan

Chance (Probability of acceptance):

$$P_A = P_{s_1}(\bar{x} \leq E) + \quad P_{s_1}(\bar{x} > E)\sum_{x=0}^{i} P_{x,r_2} P_{0,r_2}^{x} \quad (1)$$

Average sample number:

$$ASN = s_1 + s_2 P_{s_1}(\bar{X} > E) \quad (2)$$

Average outgoing quality:

$$\text{AOQ} = \frac{p}{N}[P(\bar{x} \leq E)(N - s_1) + (P_a - P(\bar{x} \leq E))(\text{N} - s_1 - s_2)] \quad (3)$$

Average total inspection:

$$A\,TI = ASN + (N - s_1 - s_2)(1 - PA) \quad (4)$$

3.3. Construction of Variable-Attribute Sampling Plan Indexed Through AQL

The method for constructing the variable-attribute sampling plan with Relational Complete Chain sampling as an attribute plan to satisfy (p_1, γ_1), i and the current sample size s_1, on the OC curve, is shown below;

1. If the plan is not dependent, adopt the following procedure.
2. Find the acceptance limit of the variable inspection and fix the sample size s_1
3. Now determine γ_1'' the chance of acceptance given to the attribute plan connected with the later stage sample as,

$$\gamma_1'' = \frac{\gamma_1 - \gamma_1'}{1 - \gamma_1'} \quad (5)$$

4. Determine the suitable later-stage sample of size s_2 and index i from the relation.

$$\sum_{x=0}^{i} P_{x,s_2} P_{0,s_2}^{x} = \gamma_1'' \quad (6)$$

A python application is built to solve the equations and build the tables.

Table 1: For the known AQL, the values of the first stage variable criteria 'k' and the second stage sample size s2 (using relational chain sampling plan as attribute plan in the later stage) are shown in Table 1. γ_1=0.950, γ_1'=0.65.

Table 1. AQL analysis

p_1	Values of s_2					Values of k			
	i=1	i=2	i=3	i=4	i=5	s_1=5	s_1=10	s_1=15	s_1=20
0.001	137	74	49	37	30	2.933	2.98	3.002	3.015
0.002	69	37	25	19	15	2.713	2.76	2.782	2.795
0.003	46	25	17	13	10	2.583	2.63	2.652	2.665
0.004	35	19	13	10	9	2.483	2.53	2.552	2.565
0.005	28	15	10	9	6	2.403	2.45	2.472	2.485
0.006	23	13	9	7	5	2.343	2.39	2.412	2.425
0.007	20	11	7	7	5	2.283	2.33	2.352	2.365
0.008	18	10	6	6	4	2.243	2.29	2.312	2.325
0.009	16	9	6	5	3	2.193	2.24	2.262	2.275
0.010	14	7	5	5	3	2.153	2.20	2.222	2.235

Illustration: If a manufacturing technique has a one-percentage-defective rate, create a combined sampling plan with relative chain sampling as the characteristic plan, a chance of acceptance of o.95, and chaining batches of i= 3.

Solution: It is for the reason that the chance of acceptance is 95%. Let γ_1'=0.65; the current stage chance of acceptance. Then, the later stage chance of acceptance will be γ_1" = 0.86. If the current stage sample size $s_1 = 10$, from the table, we get $s_2 = 5$. Hence, the parameters of combined sampling are:

$$(s_1, s_2, i, k) = (10, 5, 3, 2.20)$$

3.4. Method of interpreting a lot

The pseudocode for interpreting the variables is provided below:

Pseudocode:

1. Consider a random sample of length s_1=10 from the lot.
2. Accept the lot, if the sample mean is less than or equal to E=U-2.153σ
3. If the sample mean is greater than E= U-2.153σ, consider a later sample of size s_2=5 here, U is the Upper specified value.
4. Examine the later stage sample of size s_2=5 and determine the number of faults((d)
5. Accept the current batch if d = i=zero.
6. If d =i= one, accept the current batch only if the previous batch has no faults. Otherwise, reject it.
7. If d =i= two, accept the current batch only if the previous two batches have no faults. Otherwise, reject it.
8. If d = i = three, accept the current batch only if the previous three batches have no faults. Otherwise, reject it.

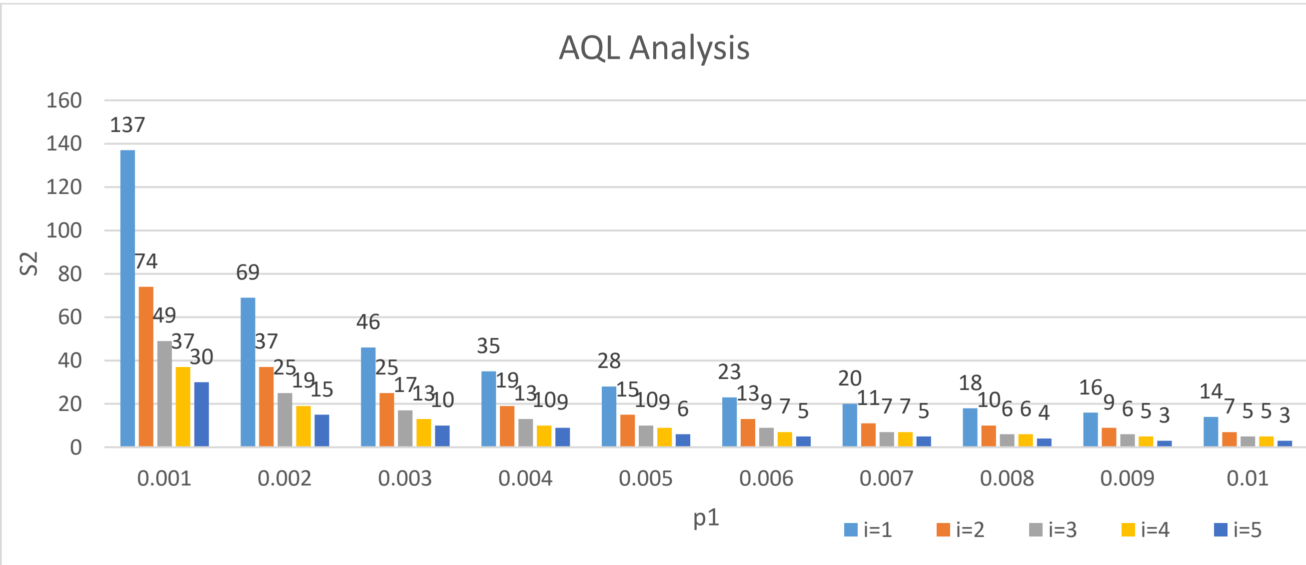

Fig. 1 AQL Analysis

3.5. Construction of Variable-Attribute Sampling Plan Indexed Through LQL

The method for constructing the variable-attribute sampling plan with Relational Complete Chain sampling as an attribute plan to satisfy (p_2, γ_2), i and the current sample size s_1, on the OC curve, is shown below;

1. If the plan is not dependent, adopt the following procedure.

2. Find the acceptance limit of the variable inspection and fix the sample size s_1

3. Now determine γ_2'' the chance of acceptance given to the attribute plan connected with the later stage sample as,

$$\gamma_2'' = \frac{\gamma_2 - \gamma_2'}{1 - \gamma_2'} \tag{7}$$

4. Determine the suitable later-stage sample of size s_2 and index i from the relation.

$$\sum_{x=0}^{i} P_{x,s_2}\, P_{0,s_2}^{x} = \gamma_2'' \tag{8}$$

A python application is built to solve the equations and build the tables.

Table 2: For the known AQL, the values of the first stage variable criteria 'k' and the second stage sample size s2 (using relational chain sampling plan as attribute plan in the later stage) are shown in Table 2. γ_2=0.05, γ_2'=0.035.

Table 2. LQL analysis

p_2	VALUES OF s_2					VALUES OF k			
	i=1	i=2	i=3	i=4	i=5	n_1=5	n_1=10	n_1=15	n_1=20
0.01	247	171	122	93	74	3.1295	2.8924	2.7873	2.7247
0.02	124	86	61	47	37	2.8495	2.6124	2.5073	2.4447
0.03	83	57	41	31	25	2.6895	2.4524	2.3473	2.2847
0.04	62	43	31	24	19	2.5595	2.3224	2.2173	2.1547
0.05	50	35	25	19	15	2.4495	2.2124	2.1073	2.0447
0.06	42	29	21	16	13	2.3595	2.1224	2.0173	1.9547
0.07	36	25	18	14	11	2.2895	2.0424	1.9373	1.8747
0.08	31	22	16	12	10	2.2195	1.9724	1.8673	1.8047
0.09	28	19	14	11	9	2.1395	1.9124	1.8073	1.7447
0.10	25	18	13	10	8	2.0795	1.8524	1.7473	1.6847

Illustration: If a manufacturing technique has a six-percentage-defective rate, create a combined sampling plan with relative chain sampling as the characteristic plan, a chance of acceptance of o.05, and chaining batches of i= 3.

Solution: It is for the reason that the chance of acceptance is 5%. Let γ_2'=0.035; the current stage chance of acceptance. Then, the later stage chance of acceptance will be γ_2" = 0.0155. If the current stage sample size $s_1 = 10$, from the table, we get $s_2 = 21$. Hence, the parameters of combined sampling are:

$$(s_1, s_2, i, k) = (10, 21, 3, 2.1224)$$

3.6. Method of interpreting a lot

The pseudocode for interpreting the variables through LQL is provided below:

Pseudocode:

1. Consider a random sample of length s_1=10 from the lot.
2. Accept the lot if the sample means.is less than or equal to E=U-2.1224σ
3. If the sample means is greater than E=U-2.1224σ, consider a later sample of size s_2=21 here. U is the Upper specified value.
4. Examine the later stage sample of size s_2=5 and determine the number of faults (d)
5. Accept the current batch if d = i=zero.
6. If d =i= one, accept the current batch only if the previous batch has no faults. Otherwise, reject it.
7. If d =i= two, accept the current batch only if the previous two batches have no faults. Otherwise, reject it.
8. If d = i = three, accept the current batch only if the previous three batches have no faults. Otherwise, reject it.

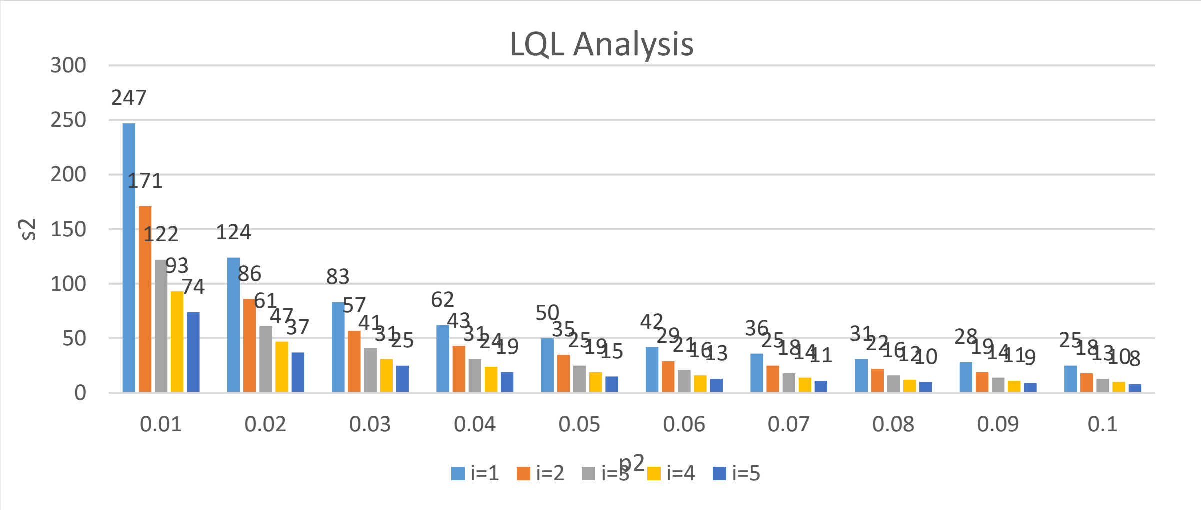

Fig 2. LQL Analysis

4. Comparison of OC(Operating Characteristic) Values

The OC Values of the combined (variable-attribute) plan with modified chain Sampling as attribute plan in the second stage and the OC values of the combined plan using relative complete chain sampling as attribute plan in the later stage are compared. The OC curves are shown below in Table 2.

Table 3. OC values

P	$s_1=5$, $s_2=10$ & i=1 (Attribute plan in the later stage-Relative complete chain sampling plan)	$s_1=5$, $s_2=10$ & i=1 (Attribute plan in the later stage-Modified Chain sampling plan)
	P_A	P_A
0.001	0.99995	0.99967
0.005	0.99876	0.9850
0.01	0.99535	0.97123
0.03	0.98348	0.96381
0.05	0.92691	0.90560
0.2	0.71019	0.66562
0.3	0.67003	0.58125
0.5	0.42451	0.40381

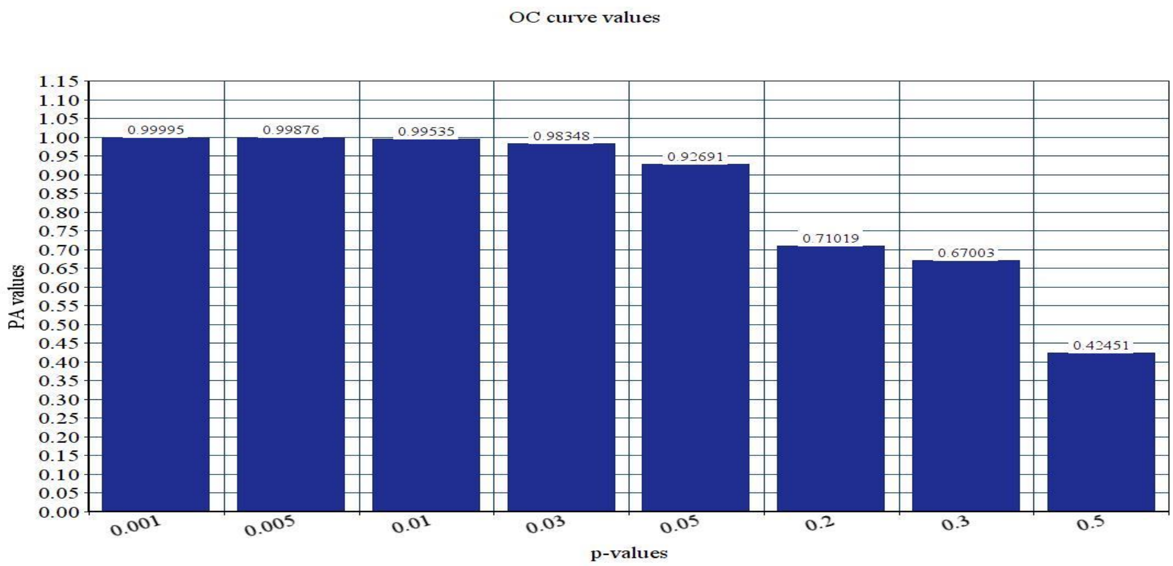

Fig. 3 OC Curve Values (RCCSP)

A huge part of the prevailing dependent process; moreover, the chain past lot outcomes when defective units are predicted with the current lot. For instance, the traditional ChSP plan merely chains previous lot outcomes when the defective units are monitored with the current sample. It specifies that the accessible historical quality evidence is not completely used. For this cause, the changes with ChSp plans are modified over the MChSP (modified ChSP) plan. These plans are explored with a quality historical level with non-conformities observed and outcomes in a lower sample size than the one needed for ChSP plans. Moreover, the plans are utilized for attribute inspection, and selection is monitored under the Poisson model

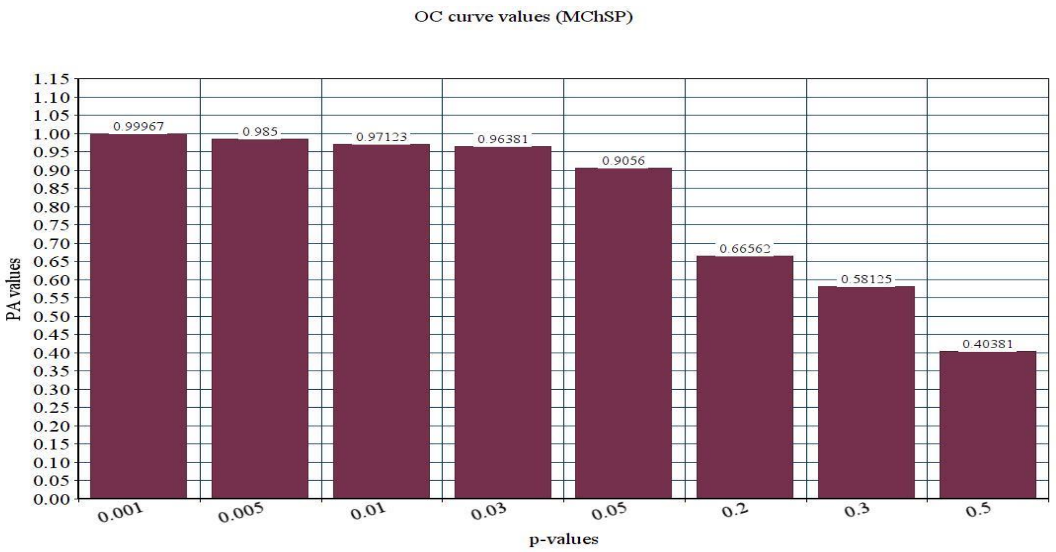

Fig. 4 OC Curve Values (MChSp)

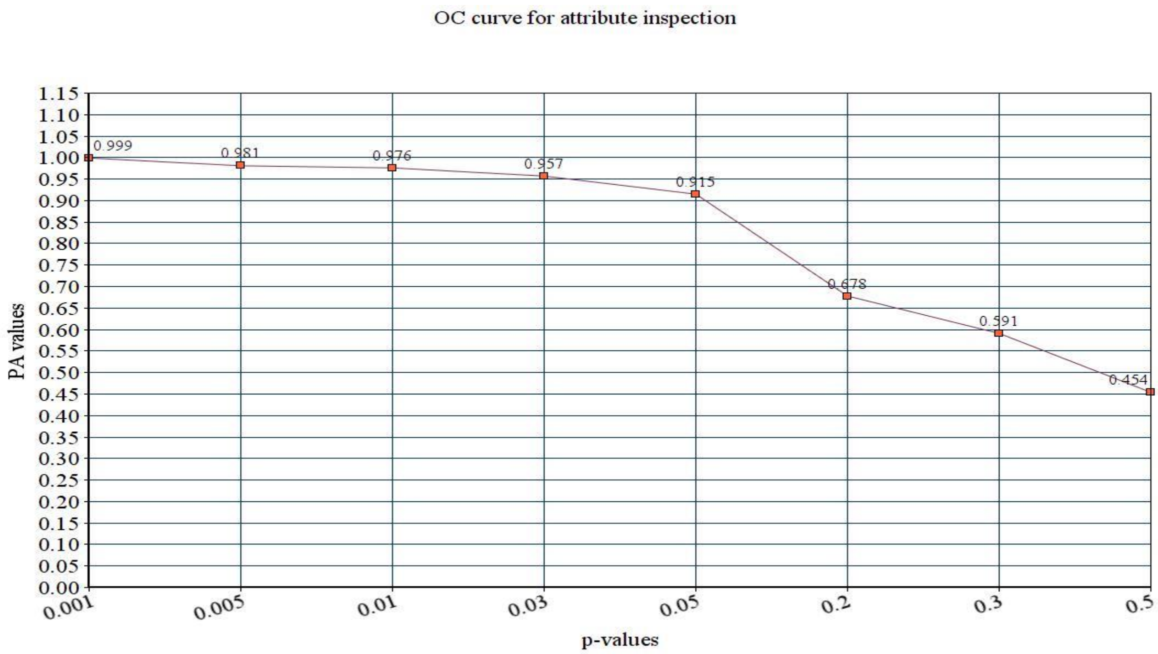

Fig. 5 OC curve for attribute inspection (RCCP)

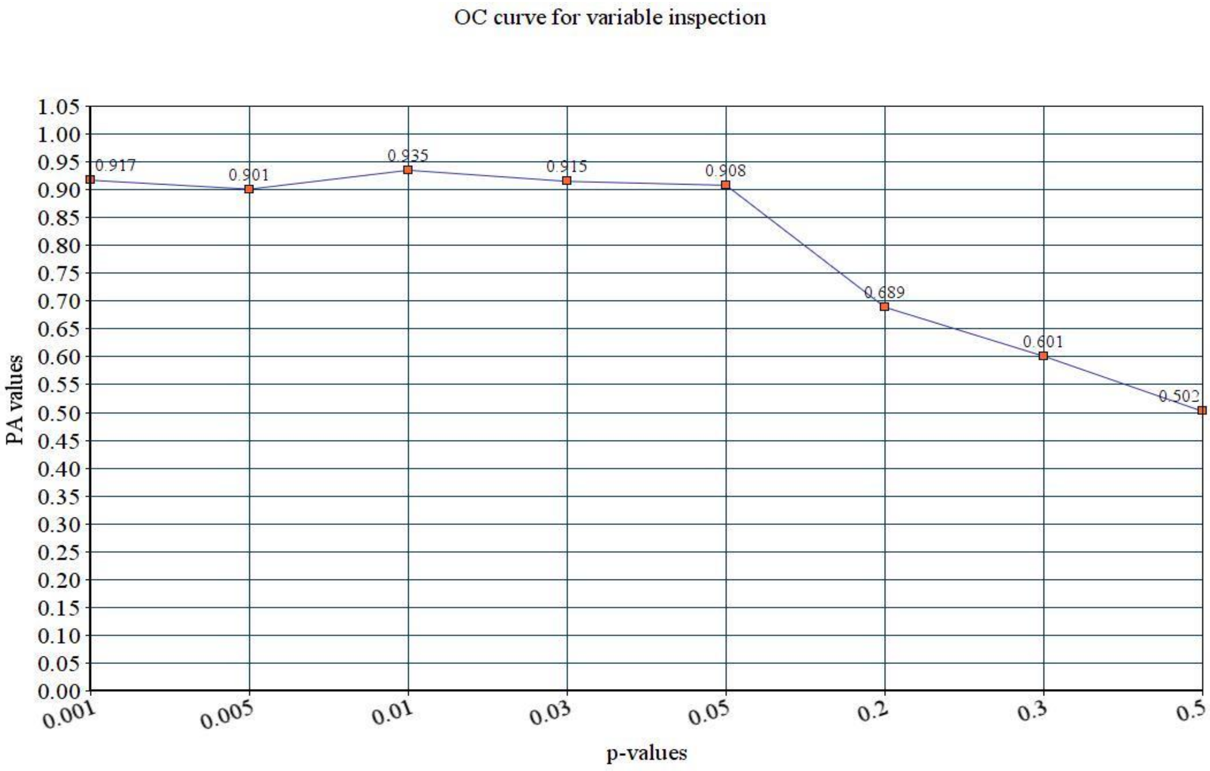

Fig. 6 OC curve for variable inspection (RCCP)

This research explains the Variable-Attribute Relational Complete Chain Sampling Plan(RCCSP). The comparison is shown in Figures 1 to 4, suitable for both variables and attributes inspection. The attributes sampling process is based on the Poisson model, and the variable sampling plans adopt some quality characteristics with normal distribution with known variance. The procedures that facilitate the design of these plans and various analytical properties of OC curves are provided. Specifically, it is represented that the OC curve of this RCCSP plan always shows some inflection point. The mixed RCCP sampling plans are depicted for examining the attribute and variable inspection. For this cause, it is considered that lots are acquired from the constant streaming of lots of processes with some unknown and constant fraction defective p. Moreover, the OC-curve dependency is provided concerning the plan parameters. The curve turns to be steeper when the number of chained sample outcomes i increases.

5. ASN (Average Sample Number) Values of Combined RCCSP

Table. 4 ASN values

ASN values of Combined RCCSP s_1=5, s_2=16, i=1, β_1=0.95, β_1'=0.65.									
p	0.005	0.006	0.007	0.008	0.009	0.01	0.05	0.09	0.1
$P_A(p)$	0.99647	0.99498	0.99325	0.99129	0.98910	0.98671	0.79047	0.55534	0.50321
ASN	8	9	10	10	11	11	19	21	21

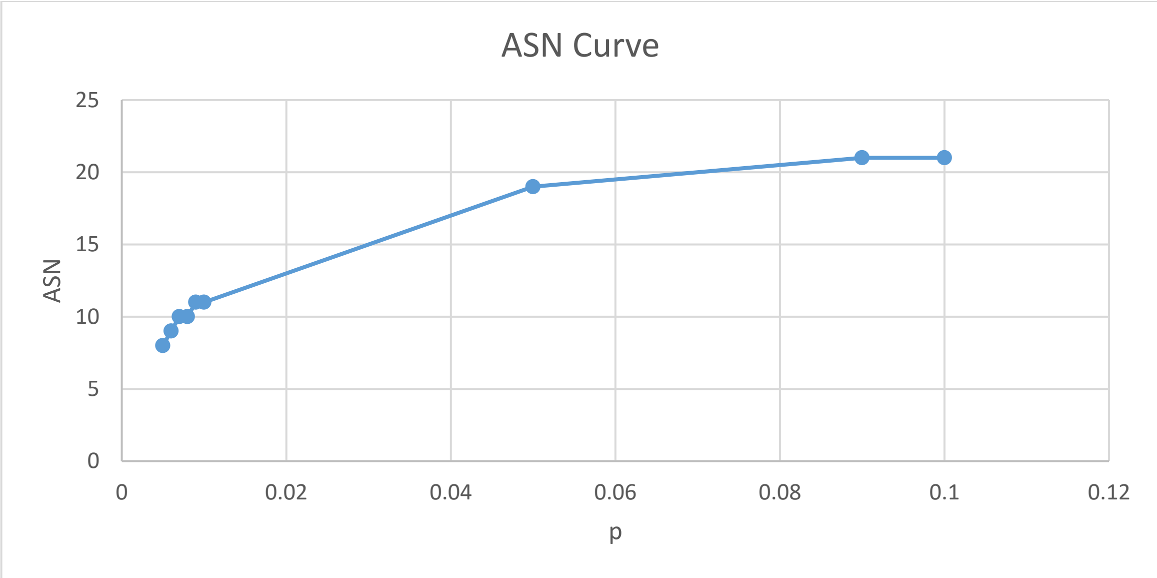

Fig. 7 ASN Curve

6. Results and Discussion

It is discovered that, in attribute testing, sample size reduces as the number of chained lots rises. Additionally, it has been discovered that the Variable-Attribute RCCSP plan produces a small sample size in attribute testing with a high acceptance probability. Since the testing is based on both variables and attributes, this inspection approach might satisfy customers. The new algorithm has been made user-friendly for quality control. Tables are created depending on the designing process to assist quality control engineers. It has been demonstrated that the proposed sampling scheme is more sensitive to quality decline.Table 1,2& Fig 1,2 reflect the AQL&LQL analysis.From Table 5, it is noted that this plan yields a small average sample number so that the cost and duration of the inspection are economical compared with the pure attribute or pure variable inspection.

7. Conclusion

Hence in this module, an attribute-variable sampling plan is evolved with a relational complete chain sampling plan as an attribute plan. The plan is indexed through AQL, and the parameters are estimated through a python program. The OC values of the proposed plan suggest that for good quality batches, the chance of acceptance is very high, and for poor quality batches, the chance of acceptance is very low. Hence it satisfies both producer and customer in a better manner. Also, the OC values of the proposed plan are more than that of the combined modified chain sampling plan.

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