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RESEARCH PAPER

A Simulation-Based Approach for Designing an Innovative Double Sampling Plan for Two Stages Process

Amir-Mohammad Golmohammadi[1]*, Ali Shahabi[2], Hamidreza Abedsoltan[3], Fazel Hajizadeh Ebrahimi[4]

[1] *Assistant Professor, Department of Industrial Engineering, Arak University, Arak, Iran.*
[2] *Assistant Professor, Department of Industrial Engineering, Central Tehran Branch, Islamic Azad University, Tehran, Iran.*
[3] *M.Sc., School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran.*
[4] *Assistant Professor, Department of Industrial Engineering, Qom University of Technology, Qom, Iran.*

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Abstract

One of the main aspects of the production industry is the optimization of acceptance sampling plans. Sampling plan performance depends on many uncertain factors that are difficult to model, especially in a multi-stage process. Therefore, it requires an innovative procedure to optimize it. This study presents an innovative double sampling plan for a multi-stage process based on discrete event simulation (DES) toward proposing an applicable plan to the inspection of the product whose accepting probability follows the hypergeometric distribution for a finite lot without replacement. This paper focuses on the five economic parameters of a double sampling plan that are determined by minimizing the average sample number (ASN) with the help of DES results and optimization methods. Several experiments based on DES were tested to determine the regression function of the ASN simulation study was carried out using Enterprise Dynamic software (ED). Our economic statistical lot acceptance sampling plan based on minimizing the average sample number has been developed to determine the acceptance parameters including the first acceptance number, first rejection, number, first sample size, second sample size, and second acceptance number in a multi-stage process. According to all runs of the simulation model, we concluded at a 95% level of confidence that ASN ranges from 530.16 to 554.93, which is given in detail in the paper.

Keywords:
Double Sampling Plan, Multi Stages Process, Average Sample Number, Optimization, Discrete Event Simulation.

Introduction

Sampling in industrial statistics terminology, in general, is concerned with the opting of a random subset of goods to predict characteristics of the whole production. Hence acceptance/rejection sampling technique is used to determine if a production lot of material meets the desired technical specifications. Two gains of sampling in comparison with measuring the whole lot are faster data collection and lower cost. Acceptance sampling plans have several applications in various industries. Not only can the sampling be used to determine the quality of new products, but also it can be used to determine the quality of returned products for remanufacturing (Abedsoltan et al., 2022). The higher the quality of the returned product,

* Corresponding author: (Amir-Mohammad Golmohammadi)
Email: a-golmohammadi@araku.ac.ir

the easier the remanufacturing will be. Additionally, it can be helpful in quality and risk decisions (Ahmed et al., 2024). Also, its use in manufacturing is undeniable (Tashkandy et al., 2023). For instance, Wang (2023) demonstrated the application of sampling for food quality and safety validation.

Lot quality sampling is a random sampling methodology, originally developed by Dodge and Romig in 1944 as a method of quality control in industrial production to provide less information but often requires substantially smaller sample sizes (Schilling and Neubauer, 2009).

A significant method in statistical quality control is the lot acceptance sampling plan (LASP). It contains a set of rules to make decisions in acceptance/rejection of a multiple or consecutive sampling approach, or even a given lot, to take other samples and then iterate the decision process which usually occurs at finished products, semi-finished products, or incoming raw materials. Acceptance sampling plans are vital to inspect final products, although all stages of the manufacturing process are monitored (Aslam et al., 2013). Balamurali and Aslam (2014) examined the performance of their presented skip-lot sampling plan system by Markov chain formulation. They demonstrated that their methodology was efficient in comparison with other methodologies.

This study applied discrete event simulation to make the objective function and then solved the optimization problem to determine the economic parameters of the double sampling plan. Our economic statistical lot acceptance sampling plan based on minimizing the average sample number has been developed to determine the acceptance parameters including the first acceptance number, first rejectable, number, first sample size, second sample size, and second acceptance number in a multi-stage process.

Literature Review

It is imperative for corporates to have an effective model for sampling plans to monitor the quality of products. Taking a simulation approach and optimization brings about economic goals. Wu et al. (2017) presented two types of variables quick switching sampling (VQSS) system. This system is developed based on a popular process capability index. Additionally, for solving the plan parameters for the VQSS system, a minimization model was presented. Finally, they examined, discussed, and compared the performance of two types of VQSS. Aslam (2019) employed the neutrosophic interval method in an attribute sampling plan by proposing a real example. Bhattacharya and Aslam (2020) considered exponential distribution for quality in their proposed sampling plan. The single sampling plans and multiple dependent state sampling were the two special cases of the proposed sampling plan. Moreover, Yüksel et al. (2022) to the determination of the reasons for production interruptions presented a three-phased acceptance sampling model. A multiple sampling plan is also another type of sampling. In practice, the approach is complex (Wu et al., 2023).

Commonly, the LASP falls into some categories; single, double, multiple, and sequential. The second sample in the double sampling plan possibly will be required. Finally, the results of both samples will be combined to make the final decision based on deduced information.

Another common classification stemmed from the nature of the variable; continuous or discrete data. Attribute sampling plan (ASP) displays data that result from inspection based on adherence to a given standard that may be expressed as conforming or nonconforming and counting a number of non-conformities and variables sampling plan (VSP) displays values follow-on from the measurement of a continuous variable (Montgomery, 2001).

To cope with designing quality assurance specifications in construction, ASP plays a significant role. Additionally, ASP is widely used in the acceptance of raw materials because it does not include complex statistical calculations for the processing data (Cheng and Chen, 2007).

The design of a LASP depends on some properties such as 1) Acceptable quality level (AQL), 2) Reject able quality level (RQL), 3) Type I Error (α or Producer's Risk), 4) Type II Error (β or Consumer's Risk), (Schilling and Neubauer, 2009).

The proper design of LASP is the ability of the sampling plan to access the low probability of α and β that depend on acceptance parameters. Usually, the power of the LASP increases with the sample size; so, it may be convenient to increase the sample size, but this is expensive and time-consuming. Thus, in the optimization process, there should be a trade-off between α and β and sample size (Cheng and Chen, 2007).

Frequently there are two distinct approaches for the design of acceptance sampling plans; (1) constraint statistical approach that performs the sampling plan with just respect to the producer's risk and customer's risk, and (2) economic design that focuses on minimizing the average sample number (ASN)or cost function subject to statistical properties simultaneously. Kandasamy et al. (2019) devised a series of deferred state sampling plans utilizing the Truncated Poisson distribution to mitigate risk through the careful consideration of sample size.

Schilling and Neubauer (2009) described practical procedures for acceptance of sequential, multiple, single, and double sampling using different types of data. Moreover, they interpreted the necessity of probability theory for an in-depth understanding. An economic objective and statistical constraint for attribute single sampling plan and optimized it using a genetic algorithm (GA) proposed by Kaya, 2009. Later, Engin et al (2008) developed the previous algorithm using lingual terms and fuzzy logic. Cheng and Chen (2007) presented a genetic-based algorithm for their proposed multi-objective economic design for double sampling plans.

Wu et al. (2012) devised a variable inspection scheme for resubmitted lots that relies on the process capability index (CPK). Their study demonstrated that the resubmitted sampling plan outperforms the single sampling plan in terms of the operating characteristic (OC) curve. Furthermore, they solved a pair of non-linear simultaneous equations to determine the sample size and critical acceptance value while considering the producer's risk and the customer's risk.

Aslam et al. (2013) also developed a variable inspection scheme for resubmitted lots based on CPK, with an emphasis on minimizing the average sample number (ASN) under similar conditions as the previous study. They proposed a variable sampling approach for repetitive group sampling based on a loss function and determined the parameters by minimizing the average sample number subject to both producer and customer risk. More recently, Fayomi and Khan (2024) presented the group acceptance sampling plan for 'Another Generalized Transmuted-Exponential Distribution. Balamurali and Jun (2007), for variable inspection, demonstrate multiple dependent state sampling plans (MDS) which is an economic design with minimizing sample size subject to producer and customer's risk.

Jafari Jozani and Mirkamali (2010), to deal with single sampling plans for attributes based on statistics, presented the maxima nomination sampling (MNS) technique.

However, the double sampling plan has not been well-studied. Thus, this study develop an attribute double sampling plan based on the optimization of ASN in multi-stage production. There are many uncertain factors in designing an optimization model so there is no direct procedure for solving the model.

In the operations management area, simulation is the second most widely used technique and there is an increased interest in hybrid modeling as a real-world approach to deal with systems complexity (Jahangirian et al., 2010). Therefore, in this study, we investigate a specific application field of simulation in quality management. Mourtzis (2020) Survey various simulation tools and gaps of each simulation approach in manufacturing systems. Brailsford et al. (2019) reviewed studies in the hybrid simulation modeling field. They mentioned that hybrid simulation is a new but rapidly growing area in operational research. Moreover, they introduced healthcare, manufacturing, and supply chains as the main application areas for hybrid simulation. Chen et al. (2022) proposed a modeling method for discreet events simulation and examined their model by a case study to validate it. As a result, they concluded that their method has better performance than manual simulation. Chakraborty et al. (2024) used the single and double-sampling methods to obtain optimal sample size. Rasay et al. (2020) presented various sampling plans in quality control and reliability testing, including single sampling (SS), double sampling (DS), sequential sampling, and repeated group sampling (RGS).

The complexity of the production line together with the stochastic nature of quality needs a discrete event simulation modeling technique to determine the parameters of the economic sampling plan. Several experiments based on DES were tested to determine the regression function of the ASN simulation study was carried out using Enterprise Dynamic software (ED). Our economic statistical LASP based on minimizing average sample number has been developed to determine the acceptance parameters including first acceptance number (c1), first rejectable, number (r), first sample size (n1), second sample size (n2), and second acceptance number (c2) in multi-stage process

This study is organized as follows,

Part 3 describes the procedure of the double sampling plan and details of the process, and part 4 presents the methodology for solving the problem. The simulation modeling approach is investigated in part 5 where the model layout and performance measure are presented. Part 6 includes the experiment design and simulation results. Part 7 shows the optimization procedure and mathematical modeling and the conclusion is discussed in the final section.

Procedure of double sampling plan (DSP) in multi stage process

This article is mainly purposed to present an effective model by taking a simulation approach and optimization, toward designing DSP in two stage production line to detect the best sampling plan for economic goals. DSP is the most important procedure. Initially, a random sample of n1 from the lot should be taken. Three possibilities exist after testing the first sample which include: no decision, reject the lot, and accept the lot. If the number of observed defective equal to or less than the acceptance number of the first sample (C1) accept the lot and release it to the next stage of the process, if it is bigger than the first rejectable number (r1), reject the lot and if the outcome is no decision, take the second sample with n2 items. The rectification inspection process involves accepting a lot if the summation of the number of observed defects in two samples is less than the second acceptance number (C2), and rejecting the lot if this condition is not met. In the event of rejection, the entire lot is subject to examination and any non-conforming items are replaced with acceptable ones. This procedure is represented by the double sampling plan, as illustrated in Figure 1.

LASP can be used between companies and customers or at different stages of the production process with the same company (Engin O., Celik A., Kaya I., 2008). In this paper, the DSP procedure is applied to the multistage processes in the same company.

In second station, the production time is normally distributed with standard deviation and mean of 0.2 and 1 minutes and quality of products follow normal probability with standard deviation and mean of 5 and 60 and acceptance standard is 60 ± 3. Each piece produced in the first stage have to be tested before entering second station. If the result of test is accepted the lot, all package will transport to next station, otherwise all products will be sent to 100% inspection and only accepted products will be transferred to next station. The procedure of sampling in every stage is same and based on double sampling plan. Fig.2 shows the conceptual model of manufacturing process.

Methodology

The complexity in production line together with the stochastic nature of quality needs discrete event simulation modeling technique to determine parameters of economic sampling plan. Several experiments based on DES were tested to determine regression function of ASN simulation study was carried out using Enterprise Dynamic software (ED). The designed simulation model works as a solution evaluation module. The detailed description of the developed event-driven simulation model is presented in work of Shahabi et al. (2022). The simulation model is developed based on an object-oriented modeling paradigm using a commercial ED simulator.

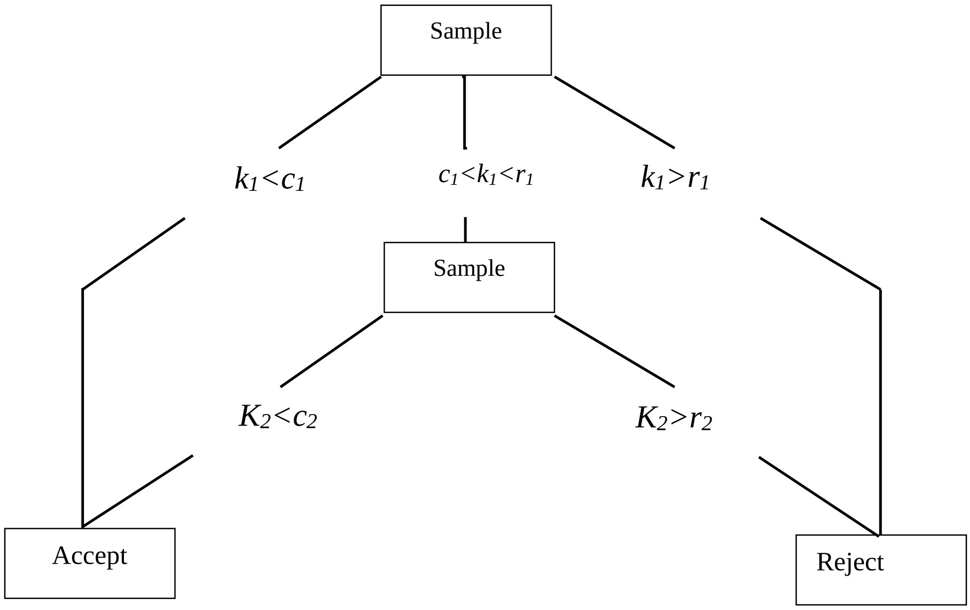

Fig 1. Operation procedure of proposed double sampling plan

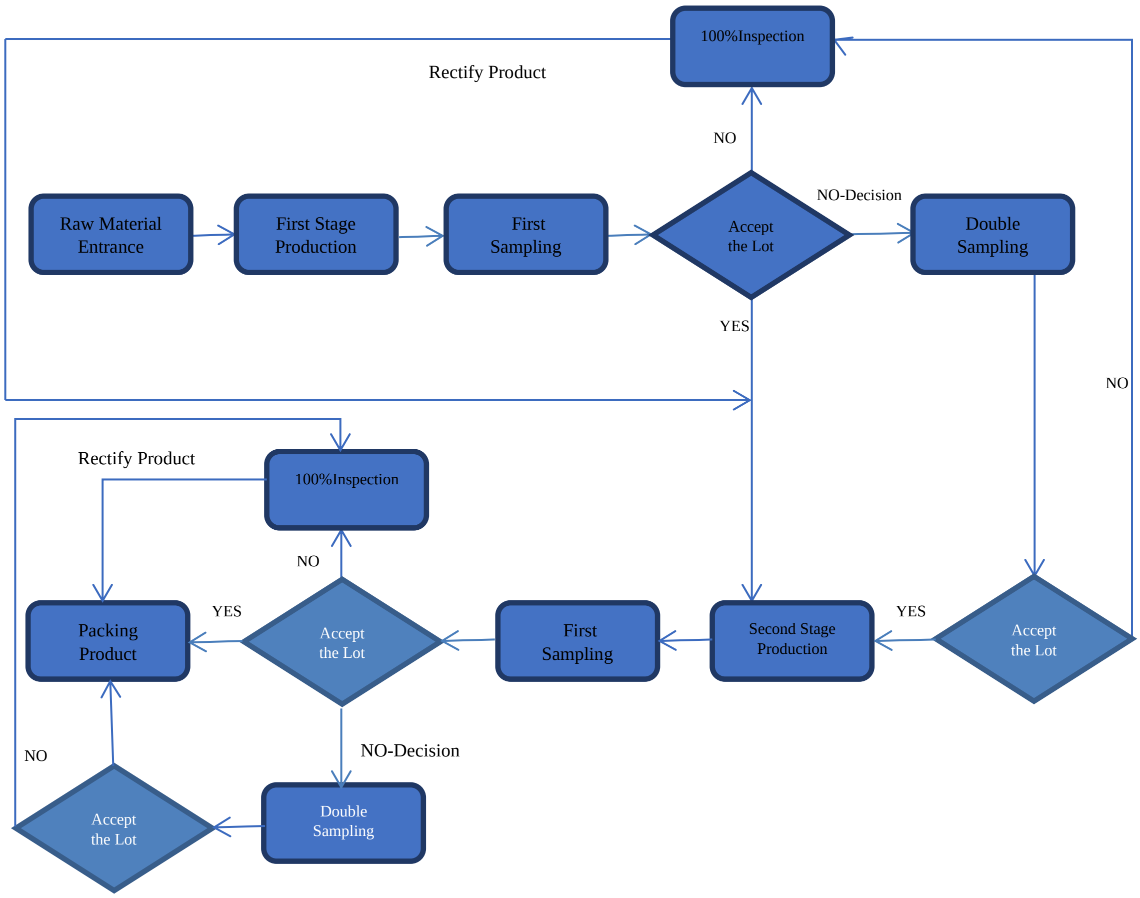

Fig 2. Conceptual model of manufacturing process

Our economic statistical LASP based on minimizing average sample number has been developed to determine the acceptance parameters including first acceptance number (c1), first rejectable, number (r), first sample size (n1), second sample size (n2), and second acceptance number (c2) in multi stage process. Fig.3 shows the methodology of determining economic parameters of DSP in two stages manufacturing. First, according to the conceptual model, a simulation models designed to find performance measures or ASN, afterwards the suitable number of experiments is designed for exploring the relation between performance measure and DSP parameters based on regression. At the end of procedure, the optimal variables based on optimization technique are designed.

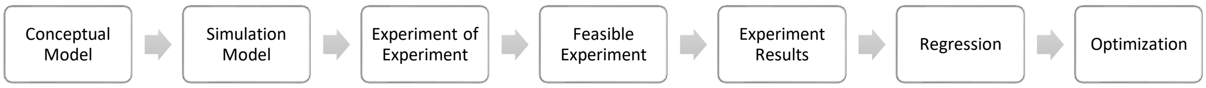

Fig 3. Methodology of determining parameters of DSP

Simulation Modeling

To solve this problem, we developed a simulation model using DES. The simulation approach places significant emphasis on the modeling of the effects of stochastic events within production systems, including but not limited to product quality, arrival time, and sampling plan. The fundamental model construction is facilitated through the utilization of ED software, which is widely recognized as a highly effective tool for discrete event simulation and the numerical experiments are performed on a Laptop with an Intel Core i7-6567U processor at 3.60 GHz and 16 gigabytes of RAM. The model consists of some atom namely: source, server, inspection atom, sink and finally, the data atom. Fig. 4 depicts the layout model illustrating the two-stage process.

The simulation model is described based on following atom:
Source: This atom shows the raw material inflow into the production line
Server: These atoms show the first and second production stage in production line
Inspection procedure: For designing double sampling plan, new atoms are designed. Here, two sub-atoms are integrated into the model; the first sampling and second sampling plan that commands on Event is based on below;

- Set the number of defects to zero
- Count the number of defective products
- Check acceptance of the lot base on first sampling plan
- Move defective products to
- Count the number of accepted lots

100%inspection: This atom directs the non-conforming items to the scrap atom after inspection.
Scrap: non-conforming products are collected in this atom
Products: accepted item are collected in this atom

As mentioned before, we are looking for optimal ASN, so suitable statics or performance measures is average sample number that can be calculated based on equation 1.

$$ASN = \sum_{stage=1}^{2} \text{input of 100\%inspection}_{stage} + \text{number of first sampling}_{stage} \times n1_{stage} + \text{number of second sampling}_{stage} \times n2_{stage} \tag{1}$$

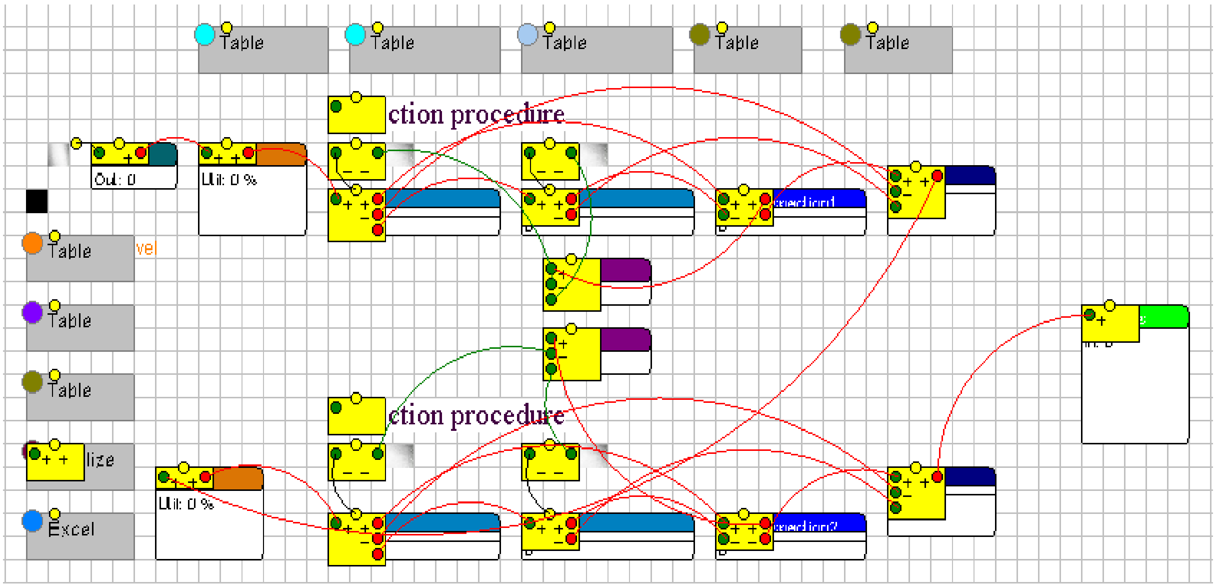

Fig 4. ED simulation models for double sampling plan at two stage process

Simulation Conclusions

To assess the interaction of the ASN with the independent variable (n1, n2, c1, c2, r1) 80 experiments were formulated. The experiments assess the effect of alternative scenarios. Thus, the scenarios are formulated to answer the following research questions:

1) To determine the relation between average sample number, sample size, acceptance number and reject number
2) To achieve minimum ASN

According to all runs of simulation model, we concluded at 95% level of confidence that ASN is ranged from 530.16 to 554.93, which is given in details along with a designed experiment in Table 1. It should be noted that any run time period is equal to 8-hour work-shift and 30-day work and Warm-up Period has been considered as 8hours per any run.

Table 1. Result of Experiments

Run	First Stage/Second Stage					ASN	Run	First Stage/Second Stage					ASN
	n_1	c_1	r_1	n_2	c_2			n_1	c_1	r_1	n_2	c_2	
1	16	2	4	12	2	546.04	19	16	2	6	12	2	530.16
2	16	2	4	12	2	546.67	20	16	2	4	12	2	547.67
3	14	2	4	12	2	537.67	21	16	2	6	12	2	534.24
4	17	3	5	11	4	551.13	22	16	2	4	12	4	547.22
5	17	3	5	13	3	548.85	23	17	3	5	11	4	548.42
6	16	2	4	10	2	545.48	24	16	2	4	12	2	546.12
7	18	2	4	12	2	554.93	25	16	2	4	12	0	546.15
8	16	2	4	12	2	546.02	26	16	2	4	12	2	547.57
9	15	3	5	11	3	539.4	27	15	3	5	11	3	538.29
10	16	2	4	10	2	546.41	28	15	3	5	13	4	534.68
11	15	3	5	13	4	537.97	29	16	2	4	12	0	547.83
12	17	3	5	13	3	549.61	30	16	0	4	12	2	546.07
13	16	2	4	12	4	545.95	31	16	2	4	12	2	546.4
14	16	2	4	14	2	546.11	32	16	0	4	12	2	547.05
15	16	2	4	12	2	545.14	33	14	2	4	12	2	537.17
16	16	2	4	14	2	545.58	34	18	2	4	12	2	554.28
17	16	2	4	12	2	547.37	35	16	2	4	12	2	547.44
18	16	2	4	12	2	546.11	36	16	2	6	12	2	530.16

Optimization Procedure

The intricacy of product pathways renders analytical optimization models inadequate, thereby necessitating the implementation of discrete event simulation to furnish optimal and cost-effective sampling parameters through optimization function. Using the data in Table 1, regression analysis generates an equation to describe the relationship between predictor variables and the response variable.

The statistical significance of a coefficient is evaluated through the p-value, which tests the null hypothesis that the coefficient is equal to zero. In Table 2, it is observed that the predictor variables of n_1, c_1, r_1, and c_2 exhibit statistical significance as their respective p-values are less than 0.1. Conversely, the p-value for n_2 is 0.4, exceeding the standard alpha level of 0.1, and thus, indicating a lack of statistical significance.

Table 2. Regression Analysis ASN versus n_1; c_1; r_1; n_2; c_2

Predictor	Coef	SE Coef	T	P	VIF
Constant	493.979	7.516	65.72	0.00	
n_1	4.8504	0.3587	13.52	0.00	1.00
c_1	1.1696	0.5452	2.15	0.04	1.49
r_1	-6.2255	0.5991	-10.39	0.00	1.38
n_2	-0.2721	0.3587	-0.76	0.45	1.00
c_2	0.5083	0.3634	1.40	0.10	1.36

With eliminating n_2 based on Table 3 we can see that the predictor variables of n_1, c_1, r_1, c_2 are significant and VIF test show that all variable are independent.

Using residual plots, you can assess the observed error is not consistent with stochastic error so quadratic regression is used for more fitting that final results are shown in Table 4 and R-Sq(adj)= 95.8%, so regression equation (equation 2) 95.8% fit relationship between variables and the response.

Table 3. Regression Analysis ASN versus n_1; c_1; r_1; c_2

Predictor	Coef	SE Coef	T	P	VIF
Constant	490.714	6.118	80.21	0.00	
n_1	4.8504	0.3561	13.62	0.00	1.00
c_1	1.1696	0.5413	2.16	0.03	1.49
r_1	-6.2255	0.5949	-10.47	0.00	1.38
c_2	0.503	0.3609	1.41	0.10	1.36

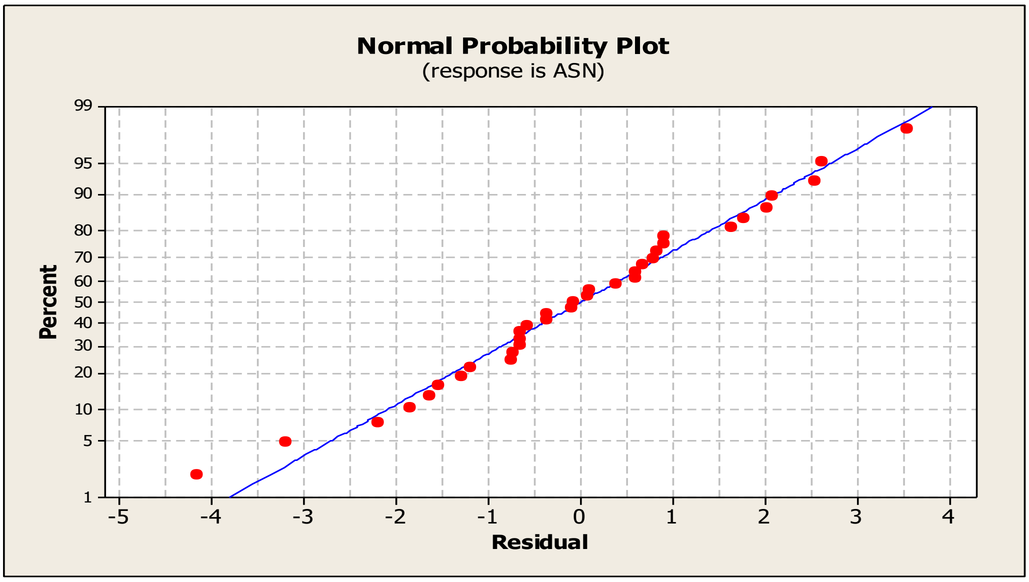

Fig 5. Residual Plot

Table 4. Regression Analysis: ASN versus c_1; r_1; c_1; n_1; c_1^2; c_1n_2

Predictor	Coef	SE Coef	T	P	VIF
Constant	547.971	1.828	314.53	0.0	
c_1	-34.261	2.079	-16.48	0.0	53.75
r_1	-7.1028	0.4121	-17.24	0.0	1.61
c_1^2	1.4394	0.2411	5.97	0.0	9.42
n_1c_1	2.06243	0.09586	21.51	0.0	30.25
c_1n_2	-0.14110	0.09586	-1.47	0.1	17.45
S = 1.11792	R-Sq = 96.4%		R-Sq(adj) = 95.8%		

This section presents the mathematical model and associated notations, as well as an economic statistical sampling plan predicated on the average sample number. This plan is designed to ascertain the acceptance parameters for a multi-stage process, including the first sample size (n_1), second sample size (n_2), first acceptance number (c_1), first rejectable number (r), and second acceptance number (c_2).

Specifically, we aim to achieve the minimum value of average sampling plan, at the rest of this section decision variable and mathematical model is presented.

Decision Variables

n_1	first sample size
n_2	second sample size
c_1	acceptance number of the first sample
r_1	rejected number of the first sample
c_2	acceptance number of second sample

Model

$$Min\ ASN = 575 - 34.3\,c_1 - 7.1r_1 + 1.44\,c_1^2 + 2.06n_1c_1 - 0.141c_1n_2 \tag{2}$$

<u>*s.t.*</u>

$$n_1 \geq r_1 \tag{3}$$
$$r_1 - 2 \geq c_1 \tag{4}$$
$$n_1 \geq c_1 \tag{5}$$
$$n_2 \geq c_2 \tag{6}$$
$$c_2 \geq r_1 - 1 \tag{7}$$

The solution obtained from LINGO14 optimization software and the optimal results are indicated in Table 5.

Table 5. Optimal Solution

n_1	c_1	r_1	n_2	c_2
10	4	6	15	5

Conclusion

Attribute double sampling plans are a crucial component of quality control. The design of an Attribute double sampling plan necessitates the predefinition of acceptance quality limit (AQL), rejectable quality limit (RQL), and associated α and β risks to explore acceptance parameters (n_1, n_2, c_1, r, c_2) that conform to the AQL-α and RQL-β on the operating characteristic curve. However, producers may prioritize total sample size reduction over other considerations. On the other hand, there are many stochastic events such as the quality of products and sampling plans that make it so complex. To oppose this situation, this study applied discrete event simulation to make the objective function and then solve the optimization problem to determine the economic parameters of the double sampling plan. The scenarios are formulated to answer the following research questions,

- To determine the relation between the average sample number, sample size, acceptance number, and reject number
- To achieve minimum ASN

According to all runs of the simulation model, we concluded at 95% confidence that ASN ranges from 530.16 to 554.93, which is given in detail along with a designed experiment in the paper. It should be noted that any run time period is equal to an 8-hour work shift and 30-day work and Warm-up Period has been considered as 8 hours per any run.

In future research, consideration of reliability can be effective. Also, consideration of risks and using of game theoretical methodologies can be an interesting topic. In addition, more empirical studies are needed to validate these methodologies. Case studies can have a positive influence on making a better decision.

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