



Fuzzy Sampling Strategy Based on IPD

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Abstract

If a production process modification is implemented with the intention of enhancing product quality, IPD models a suitable probability distribution for the number of sample defects. If a manufacturing process intervention is done with the purpose of increasing product quality, IPD models a suitable probability distribution for the sample's total number of defects. When the production process with the interference parameter is considered, fuzzy sampling plans based on IPD are found to be more effective than the current strategy. The Intervened Poisson distribution is used to develop single sampling strategy for such lots when there is ambiguity regarding the percentage of defective items. With fuzzy probability, the plan's operating characteristic curve is obtained. The mean of outgoing quality is derived using fuzzy parameters.

Keywords: Fuzzy OC; FAOQ; fuzzy probability; fuzzy Poisson distribution; Fuzzy OC band; fuzzyIPD(fIPD)

1. Introduction

Acceptance sampling plans were created using a crisp figure for the fraction of defectives. Strategies for sampling inspections are typically created with the quality standards and associated acceptability and rejection risks. The AQL, LQL, and producer and customer risk indices are commonly used when creating sampling strategy. Every sampling has an OC curve that represents the performance of the sampling strategy, i.e., high or low value, where the fIPD-OC curve is produced by plotting the probability of approval, $Pacc(p)$ against the given criteria of the lot process quality.

There is a chance of interference during the production process. In such a case, IPD shows the apposite probability distribution for the count of faults, and by estimating the value of the interference parameter "r," the probability of acceptance can be computed [13]. The uncommon event p's mean may vary if the production process is altered in an effort to improve the quality of the final product. In this instance, the appropriate probability distribution for the sample's count of faults is modeled by IPD. Using IPD-based plans has the benefit of giving information on the effectiveness of preventive measures taken, which is not relevant in the distribution of poisons. The IPD plan facilitates the creation of a better sampling plan when an intervention modifies the production process during sampling inspection. Because the quantity of flawed is not always identified exactly in practical applications, a fuzzy parameter is used and sample plans are produced using an intervening Poisson distribution. Because the quantity of flawed is a fuzzy number, the plan's operational characteristic curve is a strip with higher and lesser boundaries. The mean of the rare event p may alter if a change is made to the production process with the purpose of enhancing product quality. The apposite probability distribution for the count of faults in the sample in this case is modeled by the InPD. The benefit of using InPD-based programs is that they offer information on the effectiveness of the preventive measures, which is not available in the current poison distribution system. Reliability analysis, queuing issues, and epidemiological studies are just a few of the many applications that frequently employ InPD-based probability models [15]. Azarudheen & Veerakumari, (2017) designed sampling strategy using Intervened Poisson distribution[7]. Veerakumari (2019) introduced sampling plans based on Intervened Poisson distribution

[13]. Shanmugam (1985; 2001) derived IPD and studied its medical applications [14]. Radhakrishnan and Sekkizhar (2007) and Sampath Kumar et al. (2012) have developed sampling plans based on Intervened random effect Poisson distribution [12]

Literature Review: Mixed sample plans for second quality lots were developed by Devaarul and Jemmy Joyce (2010) [9]. Ezzatallah Baloui Jamkhaneh Bahram Sadeghpour Gildeh, and Gholamhossein Yari (2009) created the acceptance single sample plan with a Poisson distribution and fuzzy parameters, [3][4]. Ezzatallah Baloui Jamkhaneh and Bahram Sadeghpour Gildeh(2012) developed the Acceptance Double Sampling Plan Using Fuzzy Poisson Distributi [5]. Fuzzy Sampling plan based on ZTPD was developed by Jemmy Joyce(2020) [10]

2. Methodology

The ambiguous probability band of approval using IPD and its measures are derived using fuzzy parameter and probability laws. The computations are done using python programming and the plots are done using seaborn package.

2.1. Fuzzy probability distribution

Suppose that $\tilde{K}_i, \tilde{k}_i, i=1, \dots, k$ are ambiguous numbers and that the likelihood of the outcome $X = x_i$ equals \tilde{K}_i . We refer to the discrete fuzzy probability function of the random variable X as \tilde{P} and $\tilde{P}(\{x_i\}) = \tilde{K}_i$ where the support of \tilde{K}_i is $[0, 1]$, and there are $k_i \in \tilde{K}_i[\alpha]$ such that $\sum_{i=1}^n k_i = 1$. $\sum_{i=1}^n k_i = i$ That is, we can choose k_i in $\tilde{K}_i[\alpha]$, all α so that a discrete probability distribution can be obtained. Let $B = \{x_1, \dots, x_k\}$ be the subset of X and for

$0 \leq \alpha \leq 1$. define $\tilde{P}(B)[\alpha] = \{\sum_{i=1}^n k_i | S\}$ where S denotes the assertion $k_i \in \tilde{K}_i[\alpha]$ $1 \leq i \leq n$.

$$\sum_{i=1}^n k_i = 1$$

2.2. Acceptance fuzzy Single Sampling strategy based on IPD

When the percentage of defective items is ambiguous, and many large size N items need to be inspected, the parameters to consider are n , the size of sample of fIPD; c , the approval number of fIPD; and d , the quantity of faults in the sample. The lot is accepted or refused depending on whether the count of faulty units is less than or equal to the approval number of fIPD The count of faulty units follow fuzzy intervened Poisson distribution with parameter $\tilde{\lambda} = n\tilde{p}$ and hence the ambiguous likelihood mass function is derived below [17] – [20], with alpha cut of the ambiguous number as $[A_c]$,

$$\tilde{P}(x)[A_c] = \left\{ \frac{((1+r)^x - r^x)}{e^{r\tilde{\lambda}}(e^{r\tilde{\lambda}} - 1)^x} \tilde{\lambda}^x / \tilde{\lambda} \in \tilde{\lambda}[A_c] \right\} \quad x = 1, 2, 3, \dots$$

The count of faulty units in the sample with fuzzy probability is

$$\tilde{P}[A_c] = [P^L[A_c], P^U[A_c]]$$

The number of defective units in the sample with fuzzy probability using IPD is

$$\tilde{P}_{accp} = \left\{ \sum_{x=1}^c \frac{((1+r)^x - r^x)}{e^{r\tilde{\lambda}}(e^{r\tilde{\lambda}} - 1)^x} \tilde{\lambda}^x / \tilde{\lambda} \in \tilde{\lambda}[A_c] \right\} \tag{1}$$

$$P^L[A_c] = \min \left\{ \sum_{x=1}^c \frac{((1+r)^x - r^x)}{e^{r\tilde{\lambda}}(e^{r\tilde{\lambda}} - 1)^x} \tilde{\lambda}^x / \tilde{\lambda} \in \tilde{\lambda}[A_c] \right\} \tag{2}$$

$$P^U[A_c] = \max \left\{ \sum_{x=1}^c \frac{((1+r)^x - r^x)}{e^{r\tilde{\lambda}}(e^{r\tilde{\lambda}} - 1)^x} \tilde{\lambda}^x / \tilde{\lambda} \in \tilde{\lambda}[A_c] \right\} \tag{3}$$

Fuzzy Average Outgoing Quality:

$$FAOQ[A_c] = [FAOQL[AC], FAOQL[AC]]$$

$$FAOQL[AC] = \min(\tilde{p} \cdot \left\{ \sum_{x=1}^c \frac{((1+r)^x - r^x)}{e^{r\tilde{\lambda}}(e^{r\tilde{\lambda}} - 1)^x} \tilde{\lambda}^x / \tilde{\lambda} \in \tilde{\lambda}[A_c] \right\})$$

$$FAOQU[AC] = \max(\tilde{p} \cdot \left\{ \sum_{x=1}^c \frac{((1+r)^x - r^x)}{e^{r\tilde{\lambda}}(e^{r\tilde{\lambda}} - 1)^x} \tilde{\lambda}^x / \tilde{\lambda} \in \tilde{\lambda}[A_c] \right\})$$

The band of fuzzy operating characteristic function: Table 1: fIPD-fuzzy probability of acceptance sampling strategy is calculated using (1) and the fuzzy OC band is obtained. For n=10, c=1, r=0.01 and $\tilde{p} = (\kappa, 0.02 + \kappa)$, the fIPD-fuzzy probability of acceptance is calculated and given below:

Table 1: Comparative analysis

κ	\tilde{p}	\tilde{P}_{accp} { using IPD }	\tilde{P}_{accp} { using PD }
0.01	[0.01,0.03]	[0.8549202, 0.9498828]	[0.963063687, .9953211598]
0.02	[0.02,0.04]	[0.8100512, 0.9015263]	[0.938448064, 0.982476903]
0.03	[0.03,0.05]	[0.7669029, 0.8549202]	[0.90979599, 0.963063687]
0.04	[0.04,0.06]	[0.7254557, 0.8100512]	[0.878098618, 0.93844806]
0.05	[0.05,0.07]	[0.6856871, 0.7669029]	[0.844195016, 0.909795989]
0.06	[0.06,0.08]	[0.6475716, 0.7254557]	[0.808792135, 0.87809861775]
0.07	[0.07,0.09]	[0.6110814, 0.6856871]	[0.772482354, 0.844195016]
0.08	[0.08,0.1]	[0.051805728, 0.6475716]	[0.735758882, 0.8087921354]
0.09	[0.09,0.11]	[0.054997326, 0.6110814]	[0.699029276, 0.7724823535]
0.1	[0.1,0.12]	[0.05761859, 0.5761859]	[0.662627266, 0.73575888234]
0.2	[0.2,0.22]	[0.059713764, 0.3068368]	[0.354570107, 0.4060058497]
0.3	[0.3,0.32]	[0.061325496, 0.1525415]	[0.171201257, 0.19914827347]
0.4	[0.4,0.42]	[0.058999072, 0.07170318]	[0.077976999, 0.09157819444]
0.5	[0.5,0.52]	[0.042143808, 0.03226406]	[0.034202699, 0.04042768199]

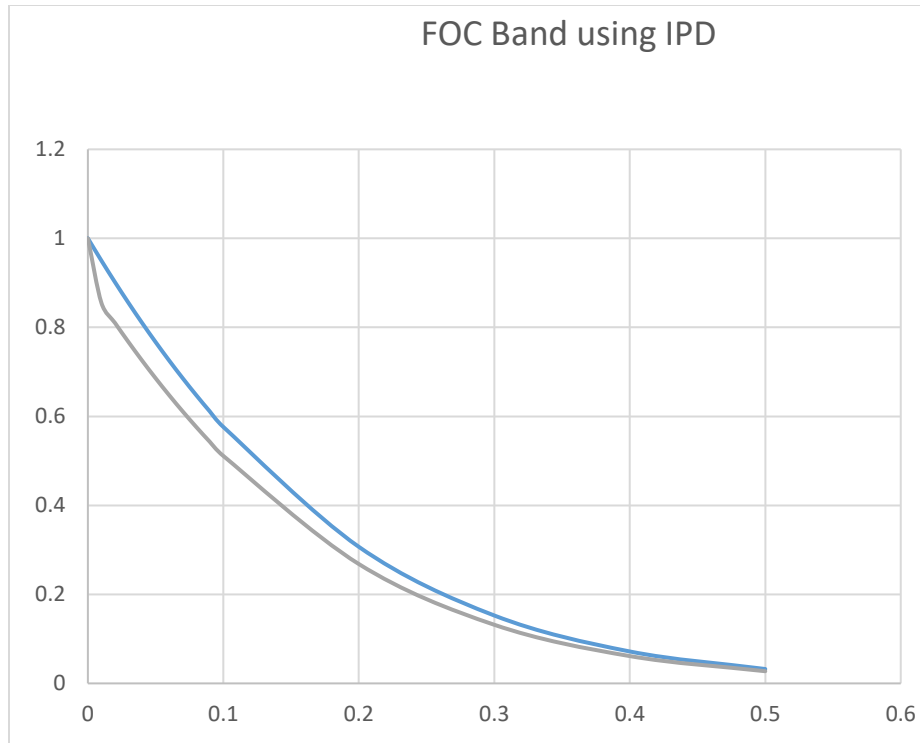


Figure 1: Graph of FOC band using IPD

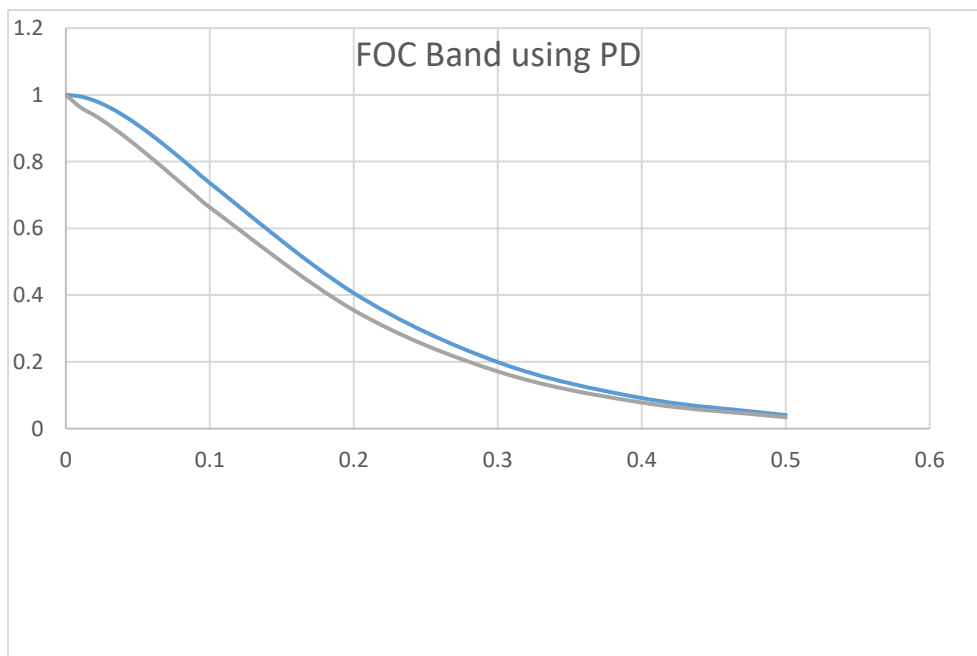


Figure 2: Graph of FOC band using PD

Table 2: For $n=10, c=2, r=0.01$ and $\tilde{p} = (\kappa, 0.02 + \kappa)$, the fIPD-fuzzy probability of acceptance is calculated and given below:

κ	\tilde{p}	\tilde{P}_{accp} {using IPD}	\tilde{P}_{accp} {using PD}
0.01	[0.01,0.03]	[0.9857229, 0.9983269]	[0.996400507, 0.9998453469]
0.02	[0.02,0.04]	[0.9753017, 0.9934819]	[0.992073668, 0.9988515187]
0.03	[0.03,0.05]	[0.9624632, 0.9857229]	[0.985612322, 0.99640050681]
0.04	[0.04,0.06]	[0.9474452, 0.9753017]	[0.976884712, 0.99207366813]
0.05	[0.05,0.07]	[0.9304773, 0.9624632]	[0.965858416, 0.98561232203]
0.06	[0.06,0.08]	[0.9117808, 0.9474452]	[0.952577404, 0.97688471224]
0.07	[0.07,0.09]	[0.8915678, 0.9304773]	[0.9371430660, 0.965858415874]
0.08	[0.08,0.1]	[0.8700408, 0.9117808]	[0.919698603, 0.952577403928]
0.09	[0.09,0.11]	[0.8473926, 0.8915678]	[0.900416281, 0.937143065702]
0.1	[0.1,0.12]	[0.799453, 0.8700408]	[0.879487099, 0.919698602928]
0.2	[0.2,0.22]	[0.5690728, 0.6198103]	[0.62271375, 0.67667641618]
0.3	[0.3,0.32]	[0.3466329, 0.38593]	[0.379903741, 0.42319008112]
0.4	[0.4,0.42]	[0.1926372, 0.2179777]	[0.210237987, 0.23810330555]
0.5	[0.5,0.52]	[0.1000051, 0.1145374]	[0.10878665, 0.12465201948]
0.7	[0.7,0.72]	[0.02338677, 0.02722378]	[0.025473508, 0.0296361638805]

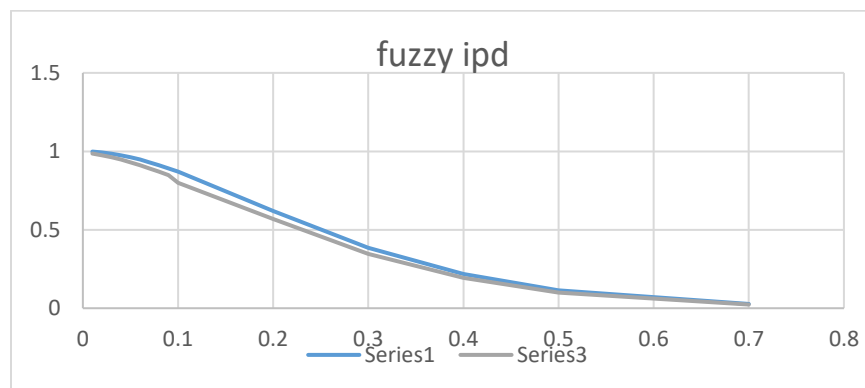


Figure 3: Fuzzy ipd

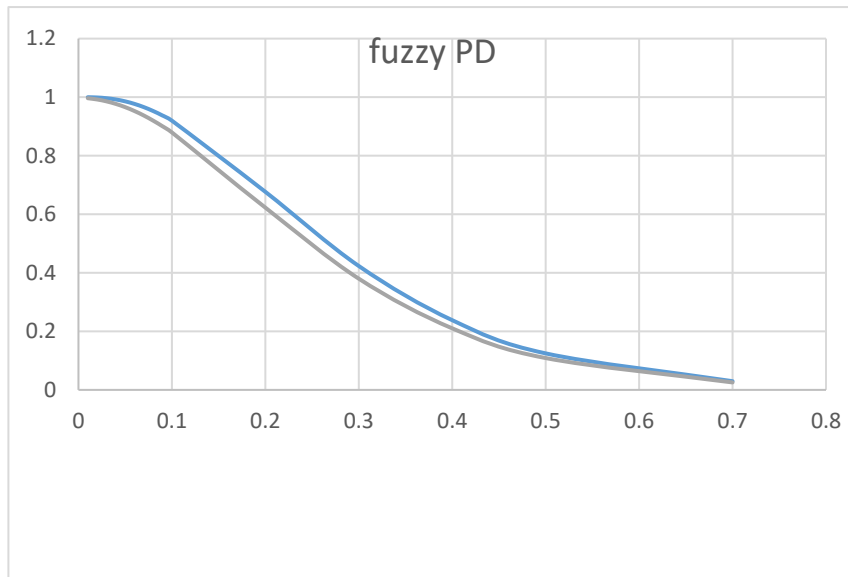


Figure 4: Fuzzy PD

Table 3: For $n=10, c=3, r=0.01$ and $\tilde{p} = (\kappa, 0.02 + \kappa)$, the fIPD-fuzzy probability of acceptance is calculated and given below:

κ	\tilde{p}	\tilde{P}_{accp} {using IPD}	\tilde{P}_{accp} {using PD}
0.01	[0.01,0.03]	[0.9989353,0.999958]	[0.999734189, 0.999996153]
0.04	[0.04,0.06]	[0.9922914,0.9975576]	[0.996641931, 0.99922374862]
0.06	[0.06,0.08]	[0.9829481,0.9922914]	[0.990920142, 0.9966419311]
0.1	[0.1,0.12]	[0.9501732,0.9689815]	[0.966231032, 0.9810118431]
0.2	[0.2,0.22]	[0.7919575,0.8305662]	[0.819352422, 0.85712346]
0.3	[0.3,0.32]	[0.5782104,0.6216753]	[0.602519724, 0.64723188878]
0.4	[0.4,0.42]	[0.3783513,0.4149798]	[0.39540337, 0.4334701203]
0.5	[0.5,0.52]	[0.2271533,0.2530443]	[0.238065499, 0.265025915]
0.7	[0.7,0.72]	[0.06794673,0.07734721]	[0.071917118, 0.0817654162447]
0.8	[0.8,0.82]	[0.03471812,0.03982434]	[0.036999864, 0.04238011199]

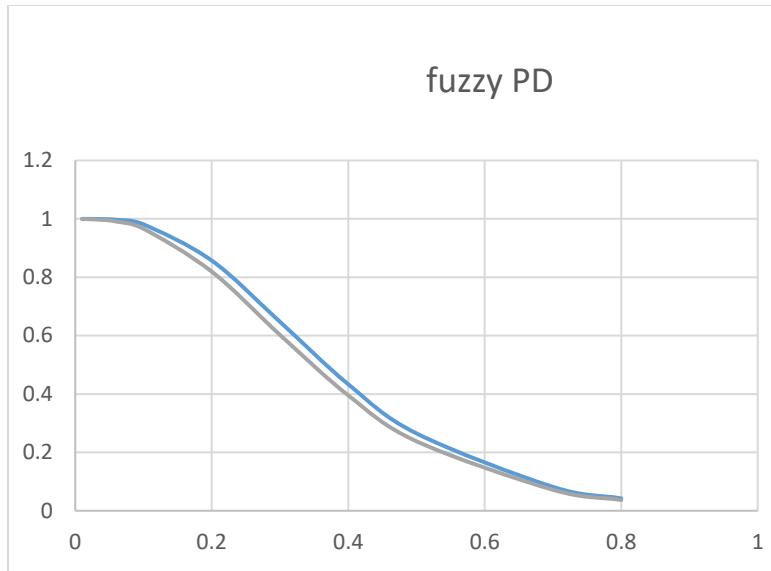


Figure 6: Fuzzy PD

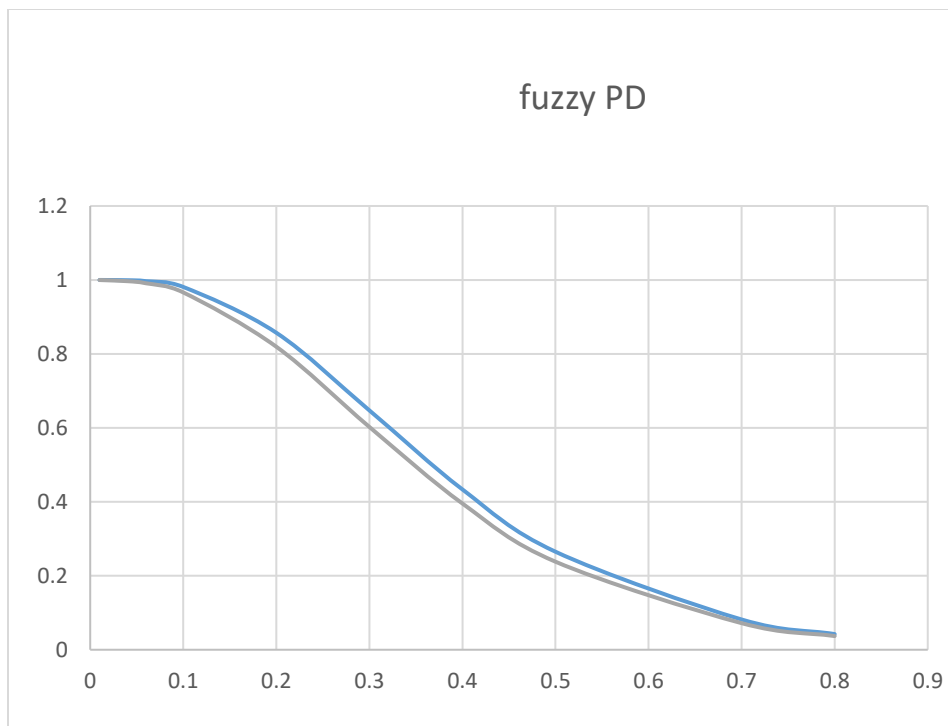


Figure 7: Fuzzy IPD

Table 4: For $n=10$, $c=1$, and $c=2$ $r=0.01$ and $\tilde{p} = (\kappa, 0.02 + \kappa)$, the fIPD-fuzzyAOQ is calculated and given below:

κ	\tilde{p}	FAOQ {using IPD,c=1}	FAOQ {using IPD,c=2}

0.01	[0.01,0.03]	[[0.009498828,0.028496484]	[0.009983269,0.029571687]
0.02	[0.02,0.04]	[0.018030526,0.036061052]	[0.019869638,0.039012068]
0.03	[0.03,0.05]	[0.025647606,0.04274601]	[0.029571687,0.04812316]
0.04	[0.04,0.06]	[0.032402048,0.048603072]	[0.039012068,0.056846712]
0.05	[0.05,0.07]	[0.038345145,0.053683203]	[0.04812316,0.065133411]
0.06	[0.06,0.08]	[0.043527342,0.058036456]	[0.056846712,0.072942464]
0.07	[0.07,0.09]	[0.047998097,0.061711839]	[0.065133411,0.080241102]
0.08	[0.08,0.1]	[0.051805728,0.06475716]	[0.072942464,0.08700408]
0.09	[0.09,0.11]	[0.054997326,0.067218954]	[0.080241102,0.093213186]
0.1	[0.1,0.12]	[0.05761859,0.069142308]	[0.08700408,0.09593436]
0.2	[0.2,0.22]	[0.06136736,0.067504096]	[0.12396206,0.125196016]
0.3	[0.3,0.32]	[0.04576245,0.04881328]	[0.115779,0.110922528]
0.4	[0.4,0.42]	[0.028681272,0.030115336]	0.08719108,0.080907624]
0.5	[0.5,0.52]	[0.01613203,0.016777311]	0.0572687,0.052002652]

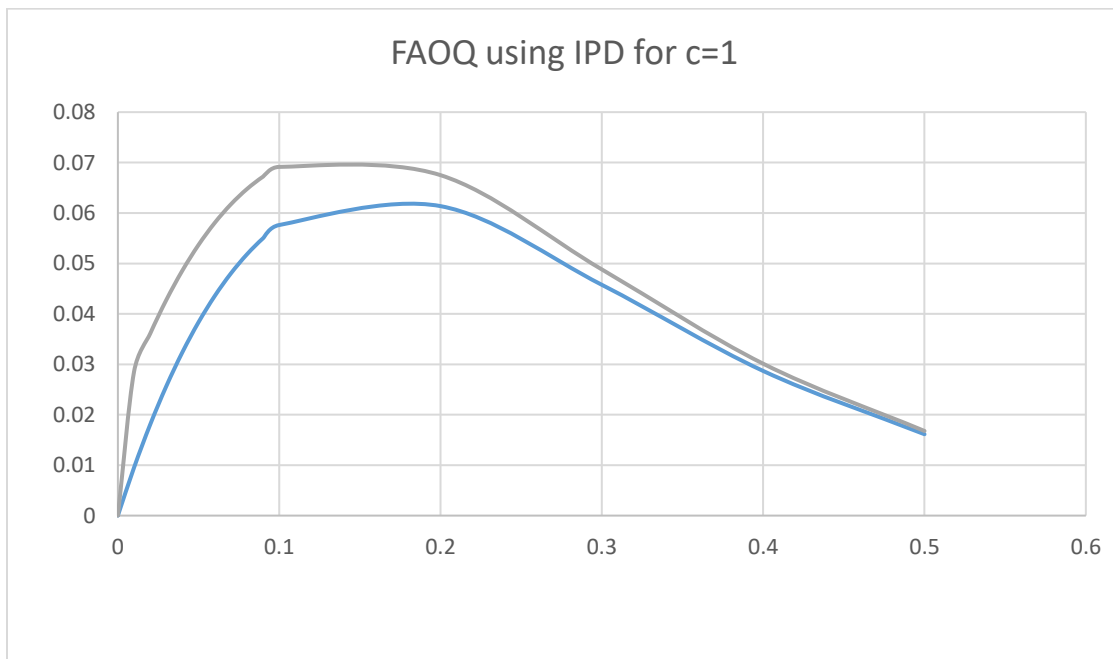


Figure 7: FAOQ using IPD for c=1

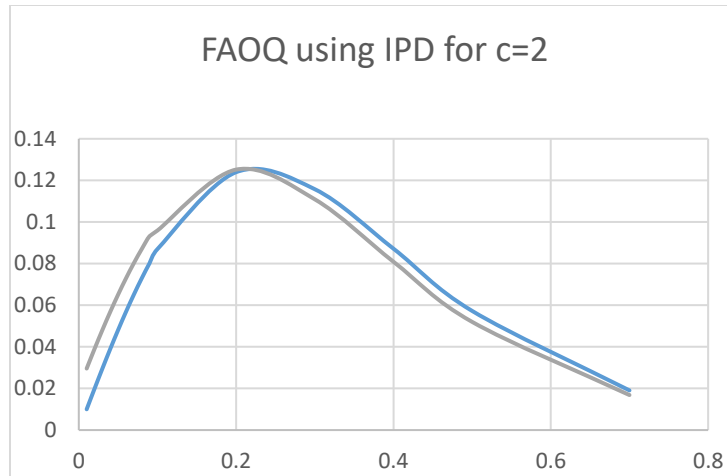


Figure 8: FAOQ using IPD for c=2

Table 5: For n=10, c=3, r=0.01 and $\tilde{p} = (\kappa, 0.02 + \kappa)$, the fIPD-fuzzyAOQ is calculated and given below:

κ	\tilde{p}	FAOQ {using IPD,c=3}	κ	\tilde{p}	FAOQ {using IPD,c=3}
0.01	[0.01,0.03]	[0.00999958, 0.029968059]	0.3	[0.3,0.32]	0.18650259, 0.185027328]
0.04	[0.04,0.06]	[0.039902304, 0.059537484]	0.4	[0.4,0.42]	0.16599192, 0.158907546]
0.06	[0.06,0.08]	[0.059537484, 0.078635848]	0.5	[0.5,0.52]	0.12652215, 0.11811971]
0.1	[0.1,0.12]	[0.09689815, 0.114020784]	0.7	[0.7,0.72]	0.054143047, 0.048921646]
0.2	[0.2,0.22]	[0.16611324 0.17423065]	0.8	[0.8,0.82]	0.031859472, 0.028468858]

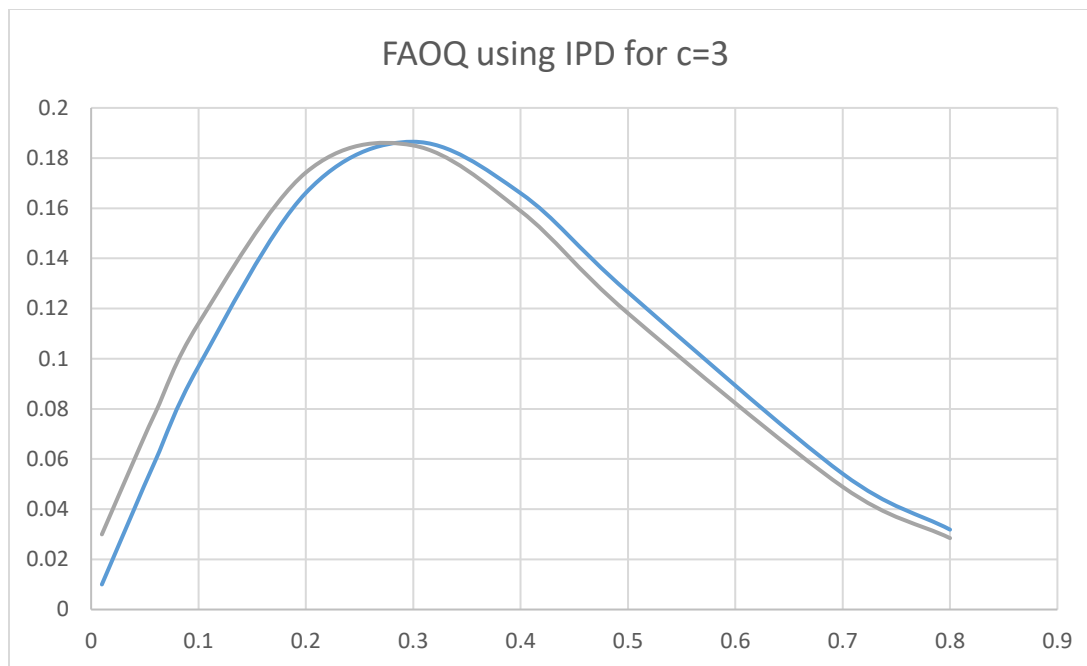


Figure 9: FAOPQ using IPD for c=3

3. Results and Discussions

The fIPD-fuzzy probability of acceptance of the sampling strategy, is calculated for $c=1$ using python programming and tabulated in table 1. A comparison is given in table 1 with fuzzy OC band using Poisson distribution and it is visualized that the Fuzzy OC band of fuzzy sampling strategy using IPD in figure 1 is closer to Ideal OC band than the fuzzy OC band of fuzzy sampling strategy using Poisson distribution. The fIPD-fuzzy probability of acceptance of the sampling strategy, is calculated for $c=2$ using python programming and tabulated in table 2. A comparison is given in table 1 with fuzzy OC band using Poisson distribution and it is visualized that the Fuzzy OC band of fuzzy sampling strategy using IPD in figure 3 is closer to Ideal OC band than the fuzzy OC band of fuzzy sampling strategy using Poisson distribution. The fIPD-fuzzy probability of acceptance of the sampling strategy, is calculated for $c=3$ using python programming and tabulated in table 1. A comparison is given in table 1 with fuzzy OC band using Poisson distribution and it is visualized that the Fuzzy OC band of fuzzy sampling strategy using IPD in figure 4 is closer to Ideal OC band than the fuzzy OC band of fuzzy sampling strategy using Poisson distribution. From the following figure 10 also it is clear that fuzzy probability band of IPD is better than fuzzy probability band of Poisson distribution.

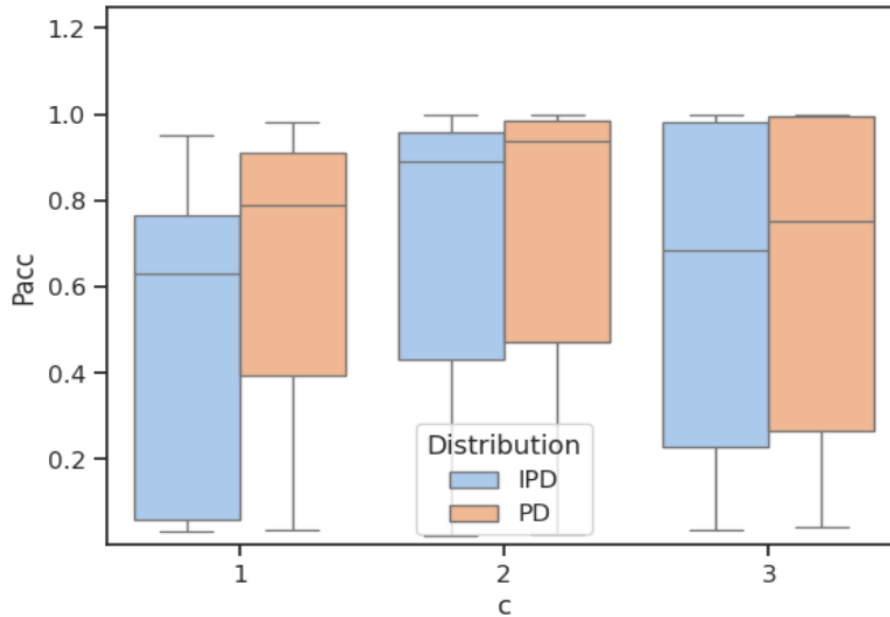


Figure 10: Comparison FOC band

The fIPD-fuzzyAOQ band is calculated and tabulated in Table 4 for $c=1$ and $c=2$ and in Table 5 for $c=3$. The graphical representation clearly indicates a good outgoing quality that as the quantity 'c' surges the girth of the Fuzzy FAOQ strip decreases.

4.1. Example based on Application

In a high-tech vehicle manufacturing industry, to increase quality, the corporation employs 1% of robots in the manufacturing process. The fraction non-conformities lie between 1% and 3%. Determine fuzzy probability of acceptance and fuzzy acceptable outgoing quality for acceptance number $c=2$. Solution: From Table 2, the fuzzy probability of acceptance is $[0.9857229, 0.9983269]$ and using table 4, fuzzy acceptable outgoing quality $[0.009983269, 0.029571687]$ for $n=1$

5. Conclusion

In this work, a fIPD-fuzzy single sampling plan with an intervention parameter is designed, and the fIPDfuzzy probability of acceptance is derived, using an intervened Poisson distribution. For different values of the acceptance constant, the FOC band graph is provided. With fuzzy probability, a strip with higher and lesser limits is produced when the fraction of defective is not precisely known. It is found that the FOC band using IPD turns out to be better than the existing FOC band using Poisson distribution. The FAOQ band shows that the band width is wider for lesser values of acceptance constants.

References

- [1] Buckley.J.J., "Fuzzy probability: new approach and application," Physical Verlag, Heidelberg, Germany, 2003
- [2] Buckley.J.J., "Fuzzy probability and statistics," Springer Verlag, 2006
- [3] Ambeth Kumar, V.D. (2017). Automation of Image Categorization with Most Relevant Negatives. Pattern Recognition and Image Analysis, 27(3), 371–379.
- [4] Baloui Jamkhaneh, Bahram Sadeghpour Gildeh, Gholamhossein Yari,"Acceptance single sampling plan with fuzzy parameter", Vol8, No.2, pp47-55, 2011.

- [5] Kumar, I., Kumar, A., Kumar, V.D.A. et al. (2022) Dense Tissue Pattern Characterization Using Deep Neural Network. *Cogn Comput* 14, 1728–1751.
- [6] Azarudheen.S & Pradeepa Veerakumari.K (2019) Selection of Tightened-Normal-Tightened sampling scheme under the implications of intervened Poisson distribution, *Pakistan journal of statistics and operation research* ,15 (1), 129-140.
- [7] Azarudheen.S & Pradeepa Veerakumari.K (2017). Designing of Skip lot sampling plan (SkSP – 3) with Single Sampling Plan as reference plan under the conditions of Intervened Poisson distribution. *Asia Matematika*, 1 (1),23-29.
- [8] Kumar, V.D.A., Sharmila, S., Kumar, A. et al. (2023). A novel solution for finding postpartum haemorrhage using fuzzy neural techniques. *Neural Comput & Applic.* 35(33), 23683–23696
- [9] Devaarul, S. & Jemmy Joyce, V. (2010). Selection of Mixed Sampling Plans for Second Quality Lots. *Economic Quality Control, Germany*, 25, 31 – 42.
- [10] Jemmy Joyce, V and Rebecca Jebaseeli Edna, k. (2020) Fuzzy sampling based on ZTPD. *Advances in Mathematics: Scientific Journal* 9(4), 1161-64. <https://doi.org/10.37418/amsj.9.4.16>
- [11] Kumar, C.S., Shibu, D.S.(2011) Modified intervened Poisson distribution. *Statistica* 71, 489–499
- [12] Radhakrishnan, R & Sekkizhar J(2007) Construction of sampling plans using Intervened random effect Poisson distribution. *International journal of Statistics and management systems* 12(1-2)88-97.
- [13]. Balakrishnan, Chitra, and V. D. Ambeth Kumar. (2023). IoT-Enabled Classification of Echocardiogram Images for Cardiovascular Disease Risk Prediction with Pre-Trained Recurrent Convolutional Neural Networks. *Diagnostics* 13(4), 775
- [14] R. Shanmugam (1985) An intervened Poisson distribution and its medical application, *Biometrics* 41, 1025-1029.
- [15] V. Jemmy Joyce et al.(2021) Designing Mixed Sampling Plan Based On IPD, *Journal of Management Information and Decision Sciences*, Vol.24(special issue 4),1-6
- [16] Hemamalini, Selvamani, and Visvam Devadoss Ambeth Kumar. (2022). Outlier Based Skimpy Regularization Fuzzy Clustering Algorithm for Diabetic Retinopathy Image Segmentation. *Symmetry*, 14(12), 2512
- [17] Ezzatallah Baloui Jamkhaneh, Bahram Sadeghpour Gildeh, Gholamhossein Yari, “Acceptance single sampling plan with fuzzy parameter with the using of Poisson Distribution”, Vol.37, pp1111-1115, 2009
- [18] Sathya Preiya, V., and V. D. Ambeth Kumar. (2023). Deep Learning-Based Classification and Feature Extraction for Predicting Pathogenesis of Foot Ulcers in Patients with Diabetes. *Diagnostics* 13(12), 1983.
- [19] Dhanavanthan, P, (2000) Estimation of the parameters of compound intervened Poisson distribution, *Biometrical Journal*, 42, 315-320
- [20] Pradeepa Veerakumari, K & Azarudheen, S(2017). Evaluation of Single Sampling Plan under the conditions of Intervened Poisson distribution, *Communications in Statistics – Simulation and Computation* 46(8), 6106-6114.
- [21] Sherubha, “Graph Based Event Measurement for Analyzing Distributed Anomalies in Sensor Networks”, *Sādhanā*(Springer), 45:212, <https://doi.org/10.1007/s12046-020-01451-w>
- [22] Ezzatallah Baloui Jamkhaneh and Bahram Sadeghpour Gildeh, “Acceptance Double sampling plan using fuzzy Poisson distribution”, *World Applied Sciences Journal* 16 (11), pp1578-1588, 2012.
- [23] S. Hemamalini, V. D. Ambeth Kumar, R. Venkatesan, S. Malathi. (2023). Relevance Mapping based CNN model with OSR-FCA Technique for Multi-label DR Classification. *Journal of Fusion: Practice and Applications*, 11 (2), 90-110.
- [24] C. S. Manigandaa, V. D. Ambeth Kumar, G. Rangunath, R. Venkatesan, N. Senthil Kumar. (2023). De-Noising and Segmentation of Medical Images using Neutrophilic Sets. *Journal of Fusion: Practice and Applications*, 11 (2), 111-123.
- [25] Sumithra, M., Naveen, G., Buvaneswari, B., Sridharan, K., D., V.. Effective Drive an Autonomous Vehicle, The Environment Characteristics Are Extracted Via Intelligent Image Processing. *Journal of Intelligent Systems and Internet of Things*, vol. 7, no. 1, 2022, pp. 40-50. DOI: <https://doi.org/10.54216/JISIoT.070104>

- [26] Piyush K. Pareek, Pixel Level Image Fusion in Moving objection Detection and Tracking with Machine Learning “,Fusion: Practice and Applications, Volume 2 , Issue 1 , PP: 42-60, 2020
- [27] Shivam Grover, Kshitij Sidana, Vanita Jain, “Egocentric Performance Capture: A Review”, Fusion: Practice and Applications, Volume 2, Issue 2 , PP: 64-73, 2020.
- [28] Abdel Nasser H. Zaied, Mahmoud Ismail and Salwa El- Sayed, A Survey on Meta-heuristic Algorithms for Global Optimization Problems, Journal of Intelligent Systems and Internet of Things, Volume 1 , Issue 1 , PP: 48-60, 2020
- [29] Mahmoud H.Alnamoly, Ahmed M. Alzohairy, Ibrahim M. El-Henawy, “A survey on gel images analysis software tools, Journal of Intelligent Systems and Internet of Things, Volume 1 , Issue 1 , PP: 40-47, 2021.