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Verifiable Ideal Guard Point Standard For Air Pollution: A Statistical Analysis

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ABSTRACT
The Ideal Standard can be characterized as a proclamation about the number of inhabitants in toxin which is set with no strategy by which consistency is to be tried or screened. For instance, with the Best Standard, we can't register the likelihood that a specific checking site will be in control in the approaching year. Barnett and O'Hogan (1997) presented the idea of the Factual Obvious Ideal Norm (SVIS). The thought is to join the Optimal Norm with a genuinely based rule of execution. To this end, conventional factual apparatus might be utilized. We might utilize Neyman Pearson's Approach of Speculation testing to build SVIS. In this paper, we develop SVIS because of the Neyman Pearson Speculation testing system and research the Air Nature through SVIS.

KEYWORDS:
SPRT, Operating Characteristic, Ideal Standard. Air pollution, Standard, Realizable standard, Statistically Verifiable Ideal Standard (SVIS), Exceedences,

MSC: 62P12, 62B05

1. INTRODUCTION

The construction of SVIS using either hypothesis testing or a confidence interval approach. These SVIS were constructed by imposing the constraints on $P(X)$ (or φ_{1-t} quantile of the distribution of X). These SVIS can be described as single-level SVIS as these provide benefits of doubt either to the compiler or regulator. If we set the hypothesis $I_o : \omega \le \omega_0$, the regulator has to give strong evidence to reject the hypothesis. If we set $I_o : \omega \ge \omega_0$ then the compiler will need strong evidence to reject the hypothesis. That is complier will need to maintain the pollution level below to ω_0. In this manner, from the above conversation, we see that there is an irreconcilable situation as the single-level SVIS allows being vindicated either to the controller or polluter. Thus, we want SVIS which can deal with both the polluter and controller risk. To this end, we want a twofold level SVIS. Barnett (1979) examined the idea of genuinely certain ideal gatekeeper point guidelines (SVIGPS) which are twofold level SVIS. The thought behind the idea of SVIGPS can be portrayed underneath. To cover the two dangers, we accept that the polluter and controller both consent to think twice about it. So instead of setting the single-level standard ω_0 both the regulator and polluter are ready to set upper and lower guard points respectively around the old single standard level ω_0. The regulator sets an upper guard point above ω_0 at ω_2 with the assurance that at this level, pollution will be detected with probability $1-\tau$ (a is small) Polluter sets a guard point below ω_0 at ω_1 with the assurance that for compliance the probability is $1-\upsilon$ where υ is small. A defined standard is fair to both regulator and polluter for some appropriate value of ω_1, ω_2, τ and υ. When $\omega > \omega_2$ the probability of failing the standard is not less then $1-\tau$ and when $\omega < \omega_1$, the probability of compliance of the standard is not less then $1-\upsilon$. When ω is between ω_1 and ω_2 then there is uncertainty and we need more information in terms of observations. Hence for specified τ and υ, the concept of SVIGPS can be explained statistically as below:
If the mean pollution level ω of the pollutant exceeds ω_2 then the probability of failing the standard is at least $1-\tau$ and the population is declared as out of compliance. If the mean pollution level ω is below ω_1 then probability is at least $1-\upsilon$ for compliance of the population. To develop the above-explained SVIGPS, we will use the hypothesis testing framework based on the sequential probability ratio test (SPRT) developed by A. Wald (1947). We know that in the Neyman Person hypothesis testing approach, it is impossible to control both types of error (risk) τ and υ i.e. τ and υ cannot be made arbitrarily small for the fixed value of sample size n (say). In the sequential testing approach, the sample size is not fixed and both types of error (risk) τ and υ can be controlled. Thus, in this paper, we shall construct SVIGPS based on a hypothesis testing framework using a sequential probability ratio test.

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2. SEQUENTIAL PROBABILITY RATIO TEST (SPRT)

In this part, we will examine SPRT for testing basic invalid speculation against a straightforward elective theory with the assistance of the probability capability.

Let X be an irregular variable having a likelihood dissemination capability

$$f(x,\varphi);\ \varphi \in \delta;\ x \in R;\ \delta = \{\varphi_0, \varphi_1\}$$

Suppose we wish to test the hypothesis

$$I_0 : \varphi = \varphi_0 \text{ versus}$$

$$I_1 : \varphi = \varphi_1$$

$$\text{and } \{X_i, i \ge 1\}$$

is a sequence of random variables generated through simple random sampling from the probability density function $f(x,\varphi)$. The SPRT $\phi(x)$ for testing I_0 versus I_1 can be described below:

At the nth stage of the experiment if

1. $\gamma_n(x) \ge A$

stop sampling with the rejection of I_0

2. $\gamma_n(x) \le B$

stop sampling with acceptance of I_0

3. $B < \gamma_n(x) < A$

continue sampling by taking one more observation

where

$$\gamma_n(x) = \frac{L(x,\varphi_1,n)}{L(x,\varphi_0,n)},$$

$$L(x,\varphi_1,n) = \prod_{i=1}^{n} f(x_i, \varphi_j), \quad j = 0,1$$

and A and B are some constants that are obtained in such a way that SPRT has the specified strength (α, β)

where

$\eta = P[Type\ 1\ error] = P[Reject\ \mathrm{I}_0 \mid I_0\ is\ true]$ and $\upsilon = P\ [Type\ II\ error] = P[Reject\ \mathrm{I}_0 \mid I_1\ is\ true]$

SPRT can also be understood in another way in terms of S_n as below:

At the n[th] stage of sampling if

1. $S_n \ge a$

Stop sampling with rejection I_0. Where $a = log\ A$

2. $S_n \leq b$

Stop sampling with acceptance of I_0, Where $b = log\, B$

3. $b < S_n < a$

The result is uncertain and another observation is taken.

Where

$$S_n = \Sigma V_i = log\ [\gamma_n(x)] \text{ and}$$

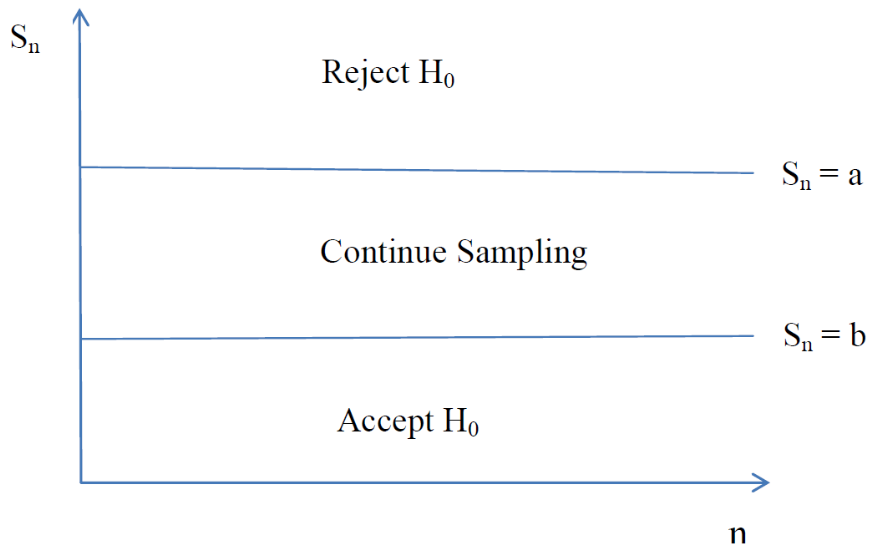
$$V_i = log \frac{f(x, \varphi_i)}{f(x, \varphi_0)}$$

Along these lines, to distinguish high contamination occasions as they happen, we gather perceptions consecutively, and consistency testing is finished after every perception is gotten

Beneath we give the graphical portrayal of SPRT for testing

$$I_0 : \varphi = \varphi_0 \text{ senus}$$

$$I_1 : \varphi = \varphi_1 \text{ in terms of } S_n .$$



Graphical Representation of SPRT

According to Wald (1947), some important properties of SPRT are as follows:

1. $A \leq \frac{1-\upsilon}{\tau}$ and $B \geq \frac{\upsilon}{1-\tau}$

If $A \leq \frac{1-\upsilon}{\tau}$ and $B \geq \frac{\upsilon}{1-\upsilon}$

then $\tau' + \upsilon' \leq \tau + \upsilon$ where (τ', υ') is the actual strength of SPRT for

$A = \frac{1-\upsilon}{\tau}$ and $B = \frac{\upsilon}{1-\tau}$ is the required strength.

2. SPRT terminates ultimately with probability one.
3. The OC function L(θ) of SPRT is given by

$$L(\varphi) \geq \frac{A^{h(\varphi)} - 1}{B^{h(\varphi)} - A^{h(\varphi)}}$$

Where $A = \frac{1-\upsilon}{\tau}$ and $B = \frac{\upsilon}{1-\tau}$

The value of $h(\varphi)$ is so obtained such that

$$P\left[L^{h(\varphi)}\right] = 1,$$

$$P\left[\frac{f(x,\varphi_2)}{(x,\varphi_1)}\right]^{h(\varphi)} = 1$$

4. The ASN function $E(n \mid \theta)$ is given by

$$P(n \mid \varphi) \approx \frac{bL(\varphi) + a[1 - L(\varphi)]}{P_{\varphi}(P)}$$

5. For all tests of

$$I_0 : \varphi = \varphi_0 \text{ verses}$$
$$I_0 : \varphi = \varphi_1$$

having strength (τ, υ), the SPRT has the least possible values of $P(n \mid \varphi)$.

It is essential to take note of that the above property VI of SPRT is significant according to the hypothetical perspective. This property is demonstrated by Wald and Wolfowitz (1948).

3. CONSTRUCTION OF SVIGPS

In this segment, we will examine the development of SVIGPS through Wald's consecutive likelihood proportion test (SPRT) for

$$I_0 : \omega = \omega_1 \text{ against}$$

$$I_1 : \omega = \omega_2 \ (> \omega_1).$$

If the random variable

$$Y \sim lnN(\omega, \rho^2), \text{ then}$$

$$X = log\ Y \sim N(\omega, \rho^2)$$

The probability density function (pdf) of X is given by:

$$f(x,\omega,\rho) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left[-\frac{(\text{x-}\omega^2)}{2\sigma^2}\right] \quad \dots (1)$$

For the development of SPRT for testing

$$I_0: \ \omega = \omega_1 \text{ against}$$

$$I_1: \omega = \omega_2 ,$$

we assume that ρ^2 is known. If ρ^2 is known then without loss of any generality, we take $\rho^2 = 1$. For PRT observations are collected sequentially and at each stage of the experiment we compute ΣX_i. Then SPRT can be described in terms of

$$\Sigma X_i \text{ to test } I_0: \ \omega = \omega_1 \text{ against}$$

$$I_1: \ \omega = \omega_2 \ (> \ \omega_1).$$

Note that

$$V_i = ln\left[\frac{f(x_i,\omega_2)}{f(x_i,\omega_1)}\right]$$

$$V_i = ln\left[exp\left(-\frac{(x_i-\omega_2)^2}{2}+\frac{(x_i-\omega_1)^2}{2}\right)\right]$$

$$V_i = ln\left[exp\left(-\frac{1}{2}[\omega_1^2-\omega_2^2+2x_i(\omega_2-\omega_1)\right)\right] \quad \dots (2)$$

$$V_i = -\frac{1}{2}\left[\omega_1^2-\omega_2^2+2x_i(\omega_2-\omega_1)\right] \quad \dots (3)$$

$$S_n = \Sigma V_i = \Sigma x_i(\omega_2-\omega_1)+\frac{n}{2}(\omega_1^2-\omega_2^2) \quad .. (4)$$

Now for testing I_0 against I_1, the SPRT $\phi(x)$ can be stated as and below:

At the n[th] stage of sampling if

1. $S_n \geq a$

Stop sampling with the rejection of H_0

Where $$a = log\,A = log\,\frac{1-\upsilon}{\tau}$$

And

1. $S_n = \sum V_i$

$$= \sum x_1(\omega_2-\omega_1)+\frac{n}{2}(\omega_1^2-\omega_2^2)$$

$$= \sum x_1(\omega_2-\omega_1)+\frac{n}{2}(\omega_1^2-\omega_2^2) \geq a$$

$$= \sum x_1 \geq \frac{a - \frac{n}{2}(\omega_1^2 - \omega_2^2)}{(\omega_2 - \omega_1)} \qquad \dots (5)$$

2. $S_n \leq b$

$$\sum x_i \leq \frac{b - \frac{n}{2}(\omega_2^2 - \omega_1^2)}{(\omega_2 - \omega_1)} \qquad \dots (6)$$

Stop sampling with acceptance of H_0

Where

$$b = log\, B = log\, \frac{\upsilon}{1-\tau},$$

$$b < S_n < a$$

$$\frac{b - \frac{n}{2}(\omega_1^2 - \omega_2^2)}{(\omega_2 - \omega_1)} < \sum x_i < \frac{a - \frac{n}{2}(\omega_1^2 - \omega_2^2)}{(\omega_2 - \omega_1)} \qquad \dots (7)$$

The result is uncertain and another observation is taken.

4. OPERATING CHARACTERISTIC FUNCTION OF SPRT

The OC (Operating Characteristic) function of SPRT is given by

$$L(\omega) \approx \frac{A^{h(\omega)} - 1}{B^{h(\omega)} - A^{h(\omega)}} \qquad \dots (8)$$

where $A = \frac{1-\upsilon}{\tau}$ and $B = \frac{\upsilon}{1-\tau}$

The value of $h(\mu)$ is so obtained such that

$$P[L^{b(\omega)}] = 1,$$

$$P\left[\frac{f(x,\omega_2)}{f(x,\omega_1)}\right]^{h(\omega)} = 1$$

$$\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}(x-\omega)^2} \left(\frac{e^{-\frac{1}{2}(x-\omega_2)^2}}{e^{\frac{1}{2}(x-\omega_1)^2}} \right) dx = 1 \qquad \dots (9)$$

Simplifying equation (9), we get

$$h(\omega) = \frac{(\omega_2 + \omega_1) - 2\omega}{(\omega_2 - \omega_1)} \qquad \dots (10)$$

Now taking different values of $h(\omega)$. we shall get the different value of ω and by using equation (8), we get $L(\omega)$. OC function.

5. AVERAGE SAMPLE NUMBER FUNCTION OF SPRT

The ASN (Average Sample Number) function is approximately given by

$$P(n \mid \omega) \approx \frac{bL(\omega) + a[1 - L(\omega)]}{P_{\omega}(V)} \qquad \dots (11)$$

Where

$$a = log\, A = log\, \frac{1-\upsilon}{\tau},$$

$$b = log\, B = log\, \frac{\upsilon}{1-\tau}$$

$$P_{\mu}(V) = \frac{1}{2}(\omega_2 - \omega_1)(\omega_1 + \omega_2 - 2\omega) \qquad \dots (12)$$

Now putting the value from equation (5.12) in equation (5.11), we will get the ASN function. and

6. CONSTRUCTION OF SVIGPS FOR THE POLLUTANT NO_2

In this section, we illustrate the construction of SVIGPS with an example based on the test discussed in the above section. Specifically, we construct SVIGPS for the pollutant NO_2.

According to the NAAQ standard, 24 hourly monitoring values of the polluter NO_2 should not exceed 80 μg/m³. So instead of setting the single level standards at $\omega_0 = 80$ both regulator and polluter are ready to set upper and lower guard points respectively around the single standard level at ω_0.

Suppose the regulator set an upper guard point above ω_0 at 85 with the guarantee that at this level pollution will be detected with probability $1-\tau$ $(\tau = 0.05 \ \ say)$. And polluter set the guard point below po at 75 with the guarantee of compliance probability $1-\upsilon\left(\upsilon = 0.05\right)$Now we will construct SVIGPS as below:

Our test of the hypothesis will be:

$$I_0 : \omega = 75 \text{ against}$$

$$I_1 : \omega = 85.$$

The SPRT $\phi(x)$ for testing I_0 against I_1 can be described as below:

i) We will reject I_0 if

$$S_n \geq a$$

Where
$$0.15\,\Sigma x_i - 1.12\frac{n}{2} \geq a$$

$$\Sigma x_i \geq \frac{3.01 + 1.09\dfrac{n}{2}}{0.10}$$

Where
$$a = 3.01$$

ii) We will accept H_0 if $S_n \leq b$

$$0.15\Sigma x_i - 1.08\frac{n}{2} \le b$$

$$= \Sigma x_i \le \frac{-3.01 + 1.08\frac{n}{2}}{0.10};$$

Where $$b = 0.199$$

iii) The result is uncertain and another observation is taken if

$$b < S_n < a \text{ , } b^* < \sum x_i < a^* \text{ where}$$

$$a^* = \frac{3.01 + 1.08\frac{n}{2}}{0.10} \text{ and}$$

$$b^* = \frac{-3.01 + 1.08\frac{n}{2}}{0.10}$$

Now for the different stage of the experiment, the above test is described in the table below

Sampling Stage	**NO_2**	**Log NO_2**	$\sum x_i$	a^*	b^*	**Result**	**Conclusion**
1	43.01	4.011	4.011	29.008	-20.5	$b^* < \sum x_i < a^*$	Continue Sampling
2	42.04	3.727	7.485	33.25	-16.2	$b^* < \sum x_i < a^*$	Continue Sampling
3	41.2	3.718	11.2	37.625	-11.8	$b^* < \sum x_i < a^*$	Continue Sampling
4	51.09	3.928	15.13	42	-7.42	$b^* < \sum x_i < a^*$	Continue Sampling
5	48.88	3.889	19.02	46.375	-3.04	$b^* < \sum x_i < a^*$	Continue Sampling
6	43.08	3.756	22.78	50.75	1.333	$b^* < \sum x_i < a^*$	Continue Sampling
7	42.99	3.775	26.55	55.125	5.708	$b^* < \sum x_i < a^*$	Continue Sampling
8	38.99	3.664	30.22	59.5	10.08	$b^* < \sum x_i < a^*$	Continue Sampling
9	39.98	3.689	33.9	63.875	14.46	$b^* < \sum x_i < a^*$	Continue Sampling
10	40.95	3.716	37.62	68.25	18.83	$b^* < \sum x_i < a^*$	Continue Sampling
11	39.07	3.659	41.28	72.625	23.21	$b^* < \sum x_i < a^*$	Continue Sampling

12	39.92	3.692	44.97	77	27.58	$b^* < \sum x_i < a^*$	Continue Sampling
13	37.2	3.617	48.59	81.375	31.96	$b^* < \sum x_i < a^*$	Continue Sampling
14	38.06	3.634	52.22	85.75	36.33	$b^* < \sum x_i < a^*$	Continue Sampling
15	37.08	3.601	55.82	90.125	40.71	$b^* < \sum x_i < a^*$	Continue Sampling
16	34.9	3.562	59.38	94.5	45.08	$b^* < \sum x_i < a^*$	Continue Sampling
17	38.02	3.625	63.01	98.875	49.46	$b* < \sum x_i < a*$	Continue Sampling
18	30	3.397	66.41	103.25	53.83	$b* < \sum x_i < a*$	Continue Sampling
19	34.97	3.569	69.98	107.625	58.21	$b* < \sum x_i < a*$	Continue Sampling
20	34.88	3.57	73.55	112	62.58	$b* < \sum x_i < a*$	Continue Sampling
21	26.93	3.25	76.8	116.375	66.96	$b* < \sum x_i < a*$	Continue Sampling
22	33.07	3.533	80.33	120.75	71.33	$b* < \sum x_i < a*$	Continue Sampling
23	31.99	3.469	83.8	125.125	75.71	$b* < \sum x_i < a*$	Continue Sampling
24	32.9	3.512	87.31	129.5	80.08	$b* < \sum x_i < a*$	Continue Sampling
25	32.00	3.472	90.78	133.875	84.46	$b* < \sum x_i < a*$	Continue Sampling
26	40.01	3.695	94.48	138.25	88.83	$b* < \sum x_i < a*$	Continue Sampling
27	30.01	3.407	97.88	142.625	93.21	$b* < \sum x_i < a*$	Continue Sampling
28	29.99	3.421	101.3	147	97.58	$b* < \sum x_i < a*$	Continue Sampling
29	29.01	3.362	104.7	151.375	102	$b* < \sum x_i < a*$	Continue Sampling
30	33.98	3.529	108.2	155.75	106.3	$b* < \sum x_i < a*$	Continue Sampling
31	26.02	3.298	114.9	164.5	115.1	$\sum x_i < b*$	Accept H_0

The OC and ASN functions of the above test are described in figure 1 and figure 2 respectively.

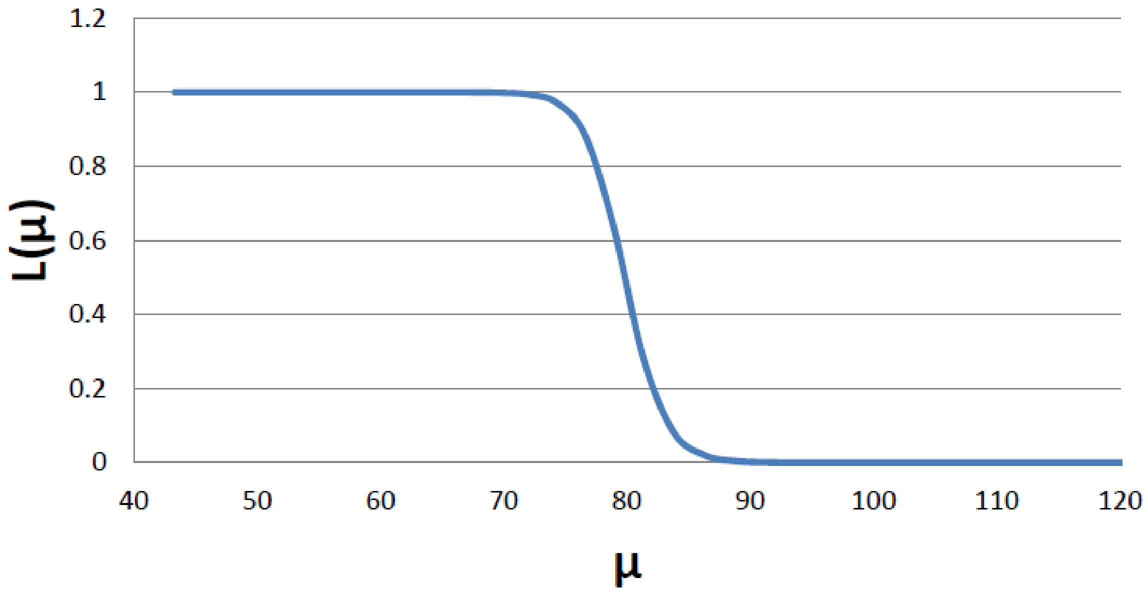


Figure 1: OC Curve for $I_0 : \omega_1 = 75,\ I_1 : \omega_2 = 85,\ \rho = 1,\ \tau = \upsilon = 0.05$

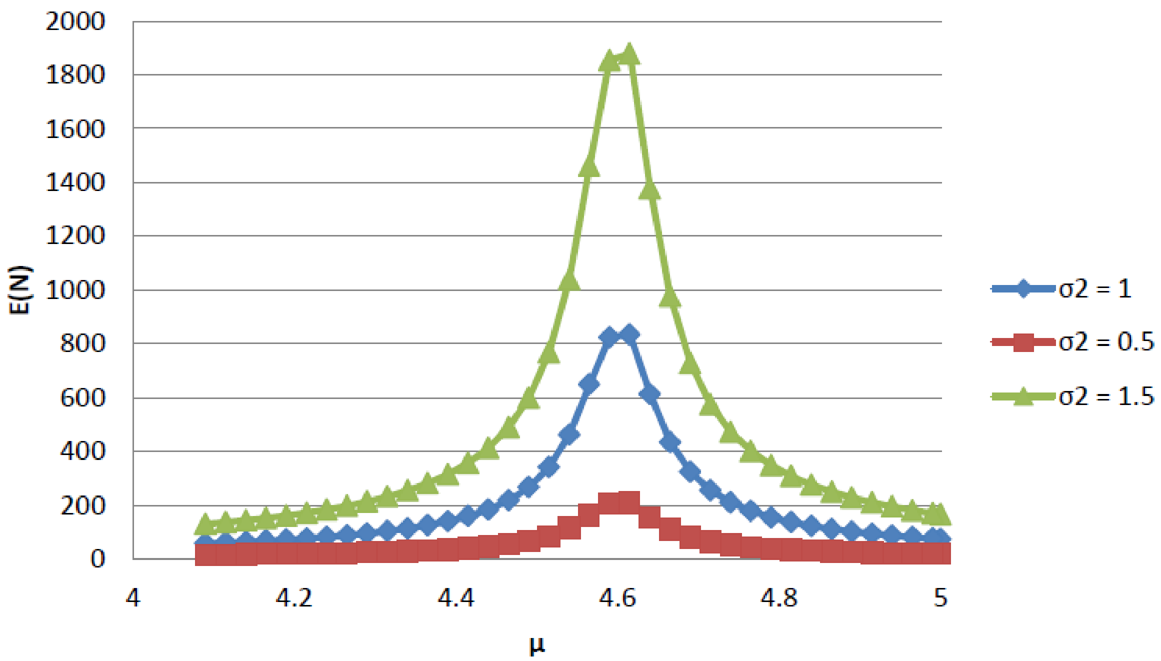


Figure 2: ASN Curve for $H_0 :\ \omega_1 =\ 75,\ \mathrm{I}_1 :\ \omega_2 =\ 85,\ \tau = \upsilon = 0.05$

7. CONCLUSION

The Air idea of a city is checked with the help of the Best Standard set by the Regulatory body. The Ideal Standard can be portrayed as a decree about the quantity of occupants in poison which is set with no technique by which consistency is to be attempted or screened. For example, with the Best Norm, we can't enroll the probability that a particular checking site will be in charge in the upcoming year. Barnett and O'Hogan (1997) introduced the possibility of the Genuine Clear Ideal Norm (SVIS). The idea is to get the Ideal Norm together with a truly based rule of execution. To this end, customary verifiable contraption may be used. We could use Neyman Pearson's Methodology of Theory testing to fabricate SVIS. In this paper, we foster SVIS on account of the Neyman Pearson Hypothesis testing framework and examine the Air Nature through SVIS.

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