

Optimisation of Signal Strength for a Detector under Noise Using Sigma Quality Approach

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Abstract Signal strength performance of a detector circuitry was evaluated under White Gaussian Noise (WGN). A component-based sigma quality improvement model was developed and utilized to assess the performance of the signal detector. The resulting model was implemented on MATLAB software. The results obtained revealed that reduction in probability of false alarm (P_{FA}), and probability of not meeting target were sustainable to detectable signal strength with increased signal energy-to-noise ratio. Greater signal strength performance was resulted from the deployment of sigma quality strategy. Generally, from the results it can be concluded that signal strength could be positively influenced by the application of six sigma component-based system. This showed that detector's signal sensing strength depended on circuitry components quality.

Keywords Signal, Strength, Quality, Component, Noise

1. Introduction

The presence of noise in signal is responsible for fading/interference [1, 2] and inaccuracy in signal detection [3, 4]. This noise needs to be reduced for optimal signal detection [5, 6, 7]. There are many research efforts in the areas of improved signal strength (detection) by noise reduction. These include detection-interpolation scheme [7], penalty function technique [8], minimax noise variance estimation [9], performance improved nonlinear detector of spread spectrum receiver [10], nonparametric dynamic model for monitoring changes in signal detection performance [11], synthetic antenna array concept for signal detection enhancement [12], algorithm based on sparsity hypotheses [13], successive interference cancellation architecture and channel decoding to treat the co-channel interference [14], Dynamic Spectrum Access (DSA) [15], and orthogonal frequency division multiplexing scheme for fading/ interference mitigation [1, 2]. Apart from Broumandan [12] that carried out research on enhancement of signal detection using synthetic antenna array concept, scanty studies were identified in applying the component-based circuitry for improved signal strength through increased signal energy-to-noise performance ratio. This study will close the gap mentioned.

2. Materials and Methods

In Figure 1, the detector circuitry system developed by Lawal [16] is given. The detector was embedded with buzzer and microcontroller circuitries to alert the users of signal detection or not. The circuit was developed on multism 11.0 CAD tools, the hardware implementation of the mobile phone detector/sniffer developed for single sniffer connected to the microcontroller that was linked with the liquid crystal display (LCD) that serves as information display unit for the activities of the developed sniffer to indicate phones sniffed and the position.

The design utilized 0.22 μ F disk capacitor (C_1) to capture the Radio Frequency (RF) signals from the mobile phones. The lead length of the capacitor is fixed at 18 mm with a spacing of 8 mm between the leads to get the desired frequency. The disk capacitor along with the leads acted as a small gigahertz loop antenna to collect the RF signals from the mobile phone. Op-amp IC (U_2) was used in the circuit as a current-to-voltage converter with capacitor C_1 connected between its inverting and non-inverting inputs. The output CMOS transistor was capable of swinging the output voltage to within 10 mV of either supply voltage terminal. Capacitor C_1 in conjunction with the lead inductance acted as a transmission line that intercepts the signals from the mobile phone. This capacitor created a field, stored energy and transferred the stored energy in the form of minute current to the inputs of (U_2). This had upset the balanced input of (U_2) and converted the current into the corresponding output

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voltage. Capacitor C_2 along with high-value resistor R_1 kept the non-inverting input stable for easy swing of the output to high state. Resistor R_2 provided the discharge path for capacitor C_2 . Feedback resistor R_3 made the inverting input high when the output became high. When the mobile phone signal was detected by C_1 , the output of U_1 became high and low alternately according to the frequency of the signal as indicated by LED1. Capacitor C_3 maintained the base bias of transistor Q_1 for fast switching action. This oscillation was indicated by the flashing of the LED and beeping of Buzzer. Capacitor carried energy in form of electromagnetic field. A slight change in field caused by the RF from phone due to noises disturbed the field and forced capacitor to release energy that the RF-signal detector circuit could sense by continuous sounding of the buzzer with the blinking of LED1. The control of the sniffer activities including the length of blinking time range was achieved using

microcontroller, intel8051series (Atmel 89c52) that accommodated simultaneous single and multiple cell phone detectors on RF-signal platform. This was not present in the identified former design [20]. The detection performance of the detector was affected by both internal noises (noise in circuit components) and external noises (noises due to environmental conditions, which are, humidity, temperature, barriers, etc.). The stated noises have ability to influence detection performance in two principal ways: detector detected signal and it was true detection, P_D ; and detector detected signal and it was false detection, P_{FA} (Figure 2). With special attention to internal noises-White Gaussian Noise (WGN), the detection performance was improved upon by reducing (removing) noises from the circuitry components using sigma quality-based statistical model (Figure 3).

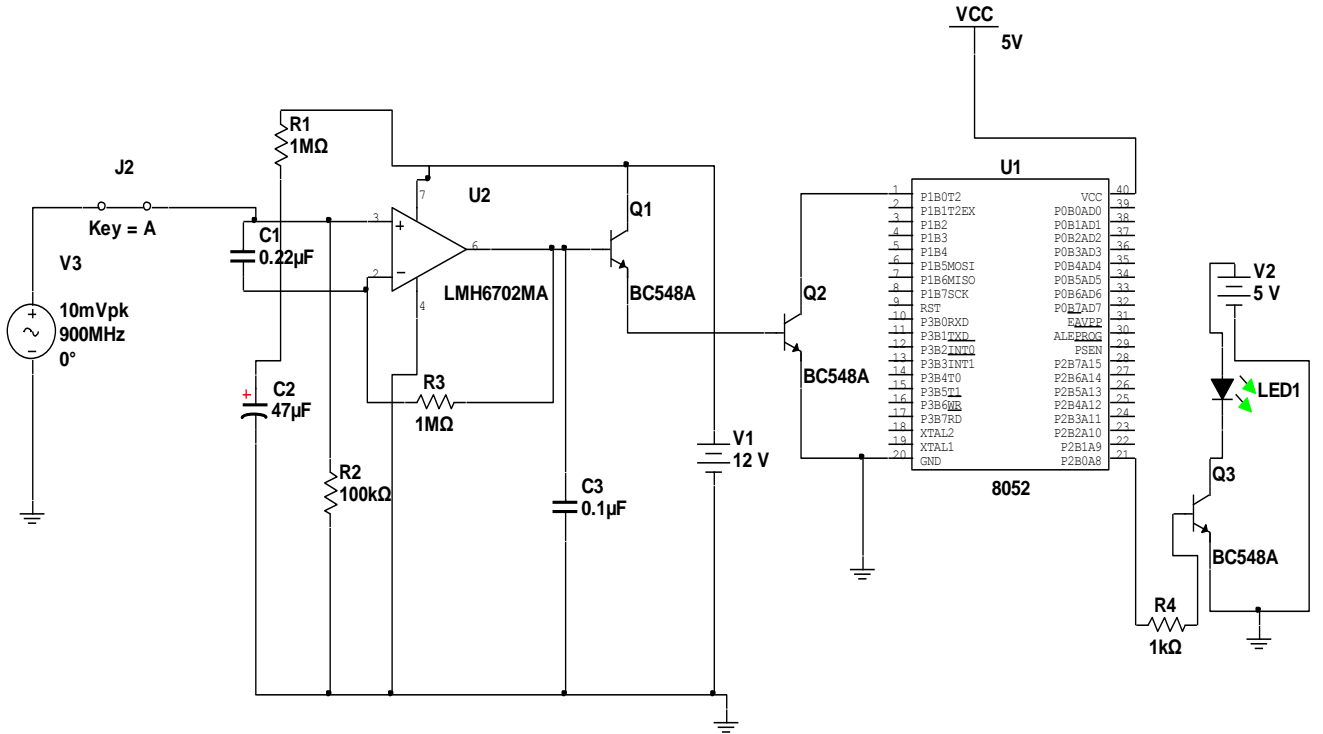


Figure 1. Detector circuit with buzzer and microcontroller

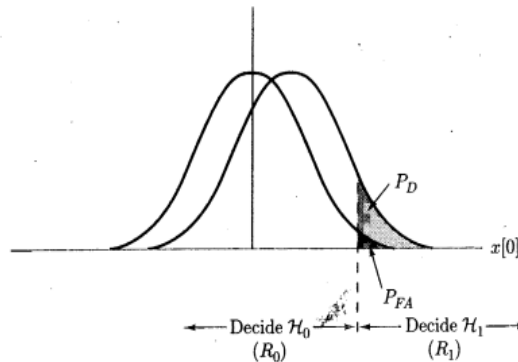


Figure 2. Decision region and probability

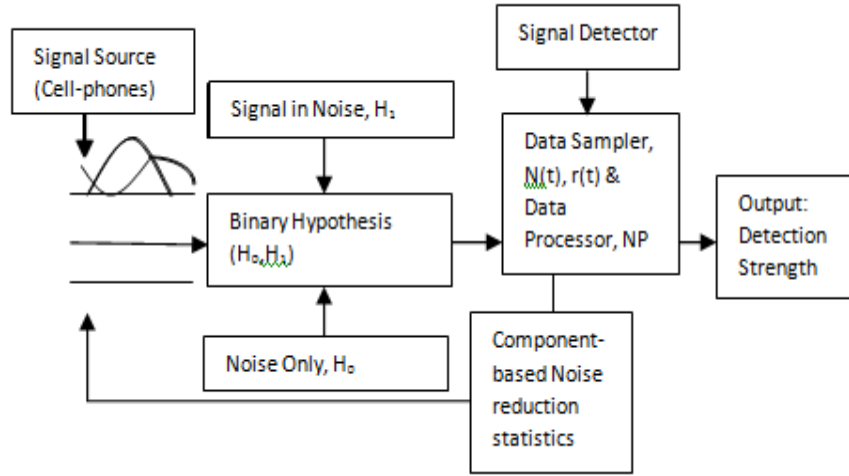


Figure 3. Signal strength improvement system

2.1. Modeling Approach

The block diagram of the proposed cell-phone signal detection improvement system is shown in Figure 3. The binary hypothesis based on right (true, H_1) or wrong (false, H_0) can fit adequately into detection problem. In Neyman-Pearson (NP) approach to cell-phone signal detection, let assume that a realization of a random variable whose probability density function (PDF) is either $N(0,1)$ or $N(1,1)$ is observed when the detector is being tested. The notation $N(\mu, \sigma^2)$ denotes a Gaussian PDF with mean μ and variance σ^2 . For a sustainable hypothesis testing on μ then the problem is to choose between two competing hypotheses expressed as follows [17]:

$$H_1 : \mu = 1, H_0 : \mu = 0 \quad (1)$$

Where H_0 is referred to as the null hypothesis (noise only) and H_1 as the alternative hypothesis (signal present in noise). This problem is known as a binary hypothesis test since we must choose between two hypotheses (Figure 2). The PDFs under each hypothesis with the difference in means may cause the PDF under H_1 to be shifted to the right. A reasonable approach might then be to decide H_1 if

$$x[0] > 1/2.$$

This is because if

$$x[0] > 1/2,$$

the observed sample is more likely.

If H_1 is true, or if $x[0] > 1/2$, it can be seen from Figure 2 that

$$p(x[0]; H_1) > p(x[0]; H_0).$$

The detector then compares the observed datum value with $1/2$, the latter being called the threshold. With this scheme, two types of errors can be identified. If H_1 is decided but H_0 is true, that is a Type I error. On the other hand, if H_0 decided but H_1 is true, then a Type II error is made. Those errors $P(H_i; H_j)$ indicates the probability of deciding H_i when H_j is true. For example,

$$P(H_1; H_0) = \Pr\{x[0] > 1/2; H_0\}.$$

These two errors are unavoidable to some extent but may be traded off against each other. The Type I error probability $P(H_1; H_0)$ is decreased at the expense of increasing the Type II error probability $P(H_0; H_1)$. It is not possible to reduce both error probabilities simultaneously. A typical approach then in designing an optimal detector is to hold one error probability fixed while minimizing the other. Let choose to constrain $P(H_1; H_0)$ to fixed value, say α . The problem of Eq. 1 can be viewed as an attempt to distinguish between the hypotheses:

$$H_0 : x[0] = w[0], H_1 : x[0] = s[0] + w[0]$$

Where $s[0] = 1$ and $w[0] \sim N(0,1)$, then the signal detection problem arise. Deciding H_1 when H_0 is true can be thought of as a false alarm. As a result, $P(H_1; H_0)$ is referred to as the probability of false alarm and is denoted by P_{FA} . To design the optimal detector there is need to minimize the other error $P(H_0; H_1)$ or equivalently to maximize $1 - P(H_0; H_1)$. The latter is $P(H_1; H_1)$ and in keeping with the signal, detection problem is called the probability of detection, denoted by P_D . This setup is termed the Neyman-Pearson (NP) approach to hypothesis

testing or to signal detection (Figure 2). The objective function is to maximize

$$P_D = P(H_1; H_1)$$

subject to the constraint

$$P_{FA} = P(H_1; H_0) = \alpha.$$

Based on the stated illustration P_{FA} can be constrained by choosing the threshold γ since

$$\begin{aligned} P_{FA} &= P(H_1; H_0) \\ &= \Pr\{x[0] > \gamma; H_0\} \\ &= \int_{\gamma}^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}t^2\right) dt \\ &= Q(\gamma) \end{aligned}$$

Meanwhile, the goal of a detector is to decide either H_0 or H_1 based on an observed set of data $\{x[0], x[1], \dots, x[N-1]\}$. This is a mapping from each possible data set value into a decision. A detector then may be thought of as a mapping from the data values into a decision. In particular, let R_1 be the set of values in R^N that map into the decision

$$H_1 \text{ or } R_1 = \{x : \text{decide } H_1 \text{ or } H_0\}.$$

This region is termed the critical region in statistics. The set of points in R^N that map into the decision H_0 is the complement set of

$$R_1 \text{ or } R_0 = \{x : \text{decide } H_0 \text{ or } H_1\}.$$

Clearly, $R_0 \cup R_1 = R^N$ since R_0 and R_1 partition the data space. The P_{FA} constraint then becomes

$$P_{FA} = \int_{R_1} p(x; H_0) dx = \alpha \quad (2)$$

In statistics, α is termed the significance level or size of the test. Now there are many sets R_1 that satisfy Eq. 2, the goal is to choose the one that maximizes

$$P_D = \int_{R_1} p(x; H_1) dx. \quad (3)$$

In statistics, P_D is called the power of the test and the critical region that attains the maximum power is the best critical region. The NP theorem indicates how to choose R_1 for a given $p(x; H_0)$, $p(x; H_1)$, and α [17]. Neyman-Pearson, NP theorem maximize P_D for a given $P_{FA} = \alpha$.

Then decide H_1 if

$$L(x) = \frac{p(x; H_1)}{p(x; H_0)} > \gamma \quad (4)$$

Where the threshold γ is found

$$\int_{\{x: L(x) > \gamma\}} p(x; H_0) dx = \alpha$$

For a general signal detection problem under White Gaussian Noise (WGN):

$$H_0 : x[n] = w[n] \quad n = 0, 1, \dots, N-1$$

$$H_1 : x[n] = A + w[n] \quad n = 0, 1, \dots, N-1$$

Where the signal is $s[n] = A$ for $A > 0$ $w[n]$ is WGN with variance σ^2 . The previous illustration (Eqs 1-4) is a special case where $A = 1$, $N = 1$, and $\sigma^2 = 1$. Also, note that the problem is a test of the mean of a multivariate Gaussian PDF. This is because under H_0 ,

$$x \sim N(0, \sigma^2 I),$$

while under H_1 ,

$$x \sim N(A1, \sigma^2 I),$$

where, 1 is the vector of all ones.

Hence, we have equivalently

$$H_0 : \mu = 0, \quad H_1 : \mu = A1.$$

This parameter test of the PDF interpretation is used in describing the signal detection problem. Then the signal detector decides H_1 if

$$\frac{\frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp\left[-\frac{1}{2\sigma^2} \sum_{n=0}^{N-1} (x[n] - A)^2\right]}{\frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp\left[-\frac{1}{2\sigma^2} \sum_{n=0}^{N-1} x^2[n]\right]} > \gamma.$$

Taking logarithm of both sides results in

$$-\frac{1}{2\sigma^2} \left(-2A \sum_{n=0}^{N-1} x[n] + NA^2 \right) > \ln \gamma$$

This simplifies to

$$\frac{A}{\sigma^2} \sum_{n=0}^{N-1} x[n] > \ln \gamma + \frac{NA^2}{2\sigma^2}.$$

Since, $A > 0$, then

$$\frac{1}{N} \sum_{n=0}^{N-1} x[n] \succ \frac{\sigma^2}{NA} \ln \gamma + \frac{A}{2} = \gamma'. \quad (5)$$

The signal based NP detector compares the sample mean

$$\bar{x} = (1/N) \sum_{n=0}^{N-1} x[n] \text{ to a threshold } \gamma'.$$

This is intuitively reasonable since \bar{x} may be thought of as an estimate of A. If the estimate is large and positive, then the signal is probably present. How large the estimate must be before declare that a signal is present depends upon concerns that noise only may cause a large estimate. To avoid this possibility, γ' can be adjusted to control P_{FA} , with larger threshold values to reduce P_{FA} .

To determine the detection performance the test statistic

$$T(x) = 1/N \sum_{n=0}^{N-1} x[n],$$

should be Gaussian under each hypothesis.

The means and variances are [17, 18]:

$$\begin{aligned} E(T(x); H_0) &= E\left(\frac{1}{N} \sum_{n=0}^{N-1} w[n]\right) \\ &= \left(\frac{1}{N} \sum_{n=0}^{N-1} E(w[n])\right) \\ &= 0. \end{aligned}$$

Similarly, $E(T(x); H_1) = A$ and

$$\begin{aligned} \text{Var}(T(x); H_0) &= \text{var}\left(\frac{1}{N} \sum_{n=0}^{N-1} w[n]\right) \\ &= \left(\frac{1}{N^2} \sum_{n=0}^{N-1} \text{var}(w[n])\right) \\ &= \frac{\sigma^2}{N} \end{aligned}$$

Similarly, $\text{Var}(T(x); H_1) = \frac{\sigma^2}{N}$

We have then

$$\begin{aligned} P_{FA} &= \Pr\{T(x) \succ \gamma'; H_0\} \\ &= Q\left(\frac{\gamma'}{\sqrt{\sigma^2/N}}\right) \end{aligned} \quad (6)$$

and

$$\begin{aligned} P_D &= \Pr\{T(x) \succ \gamma'; H_1\} \\ &= Q\left(\frac{\gamma' - A}{\sqrt{\sigma^2/N}}\right). \end{aligned} \quad (7)$$

P_D can be related directly to P_{FA} by noting that the Q function is monotonically decreasing since $1 - Q$ is a CDF, which is monotonically increasing. Thus, Q has an inverse denoted as Q^{-1} . As a result, the threshold is found from Eq. (5) as [17, 18],

$$\gamma' = \sqrt{\frac{\sigma^2}{N}} Q^{-1}(P_{FA})$$

$Q(x)$ is the probability of exceeding a given value (target) as:

$$Q(x) = \int_x^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} t^2\right) dt$$

From which,

$$Q(x) = \frac{1}{\sqrt{2\pi} x} \exp\left(-\frac{1}{2} x^2\right) dx$$

Then inverse, complementary Cumulative Distribution Function (CDF);

$$Q(x)^{-1} = 1 - Q(x) = \int_{-\infty}^x \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} t^2\right) dt$$

and

$$\begin{aligned} P_D &= Q\left(\frac{\sqrt{\sigma^2/N} Q^{-1}(P_{FA}) - A}{\sqrt{\sigma^2/N}}\right) \\ &= Q\left(Q^{-1}(P_{FA}) - \sqrt{\frac{NA^2}{\sigma^2}}\right). \end{aligned} \quad (8)$$

It is seen that for a given P_{FA} the detection performance would increase monotonically with NA^2/σ^2 , which is the signal energy-to-noise ratio (ENR) [17, 18]. In case of a hypothesis, testing problem called the mean-shifted Gauss-Gauss problem. It was observed the value of a test statistic T and decide H_1 if $T > \gamma'$ and H_0 otherwise, where, $\mu_1 > \mu_0$.

Hence, we wish to decide between the two hypotheses that differ by a shift in the means of T. If $T = \bar{x}$. Then for this type of detector, the detection performance is totally characterized by the deflection coefficient d^2 [17].

This is defined as

$$\begin{aligned} d^2 &= \frac{(E(T; H_1) - E(T; H_0))^2}{\text{var}(T; H_0)} \\ &= \frac{(\mu_1 - \mu_0)^2}{\sigma^2} \end{aligned} \quad (9)$$

In the case $\mu_0 = 0$, $d^2 = \mu_1^2/\sigma^2$ may be interpreted as a

signal-to-noise ratio (SNR). To verify the dependence of detection performance on d^2 we have that

$$\begin{aligned} P_{FA} &= \Pr\{T \succ \gamma'; H_0\} \\ &= Q\left(\frac{\gamma' - \mu_0}{\sigma}\right) \\ P_D &= \Pr\{T \succ \gamma'; H_1\} \\ &= Q\left(\frac{\gamma' - \mu_1}{\sigma}\right) \\ &= Q\left(\frac{\mu_0 + \sigma Q^{-1}(P_{FA}) - \mu_1}{\sigma}\right) \\ &= Q\left(Q^{-1}(P_{FA}) - \left(\frac{\mu_1 - \mu_0}{\sigma}\right)\right) \end{aligned}$$

And using Eq. (9), we have

$$P_D = Q\left(Q^{-1}(P_{FA}) - \sqrt{d^2}\right) \quad (10)$$

Since, $\mu_1 > \mu_0$. The detection performance is therefore monotonic with the deflection coefficient. Where,

$$d^2 = NA^2 / \sigma^2.$$

Each point on the curve corresponds to a value of (P_{FA}, P_D) for a given threshold γ' . By adjusting, γ' any point on the curve may be obtained. As expected as γ' increases, P_{FA} decreases but also does P_D and vice-versa. This type of performance summary is called the Receiver Operating Characteristics (ROC). This ROC also support the detection probability that relates $P_{FA} = P_r\{\text{detect}; H_0\}$ and $P_D = P_r\{\text{detect}; H_1\}$. An alternative way of summarizing the detection performance of a NP detector is to plot P_D versus P_{FA} .

The improvement on probabilities of signal detection P_D can be achieved through deployment of sigma quality statistic on components responsible for signal detection, namely, capacitors, transistors, resistors, antennae, etc. (Figures 1 and 3). Improvement strategies based on one-, two-, three-, four-, five-, or six-quality sigma (δ) could be imposed on the components as a whole [19]. The detection enhancement sigma (δ) is capable of removing noises with reduced probabilities of false alarms. With the new arrangement, Eq. (10) then becomes:

$$P_D = Q\left(Q^{-1}(P_{FA} \delta) - \sqrt{d^2}\right) \quad (11a)$$

Signal strength termed signal Energy-to-Noise Ratio (ENR) at a given probability of exceeding the target (threshold value) can be statistically estimated as

$$\text{ENR} = \{Q(Q^{-1}(P_{FA} \delta) - \sqrt{d^2})\} / P_{FA} \quad (11b)$$

2.2. Model Testing

Information on cell-phone signal detector of the type shown in Figure 1 was used for experimentation. The cell-phone detector was designed to detect RF-signals of the cell-phone in active mode located within radii 0-6m. The data generated from the experiment showed a representation of general detectors' behaviours with probabilities of false alarm ranging from 0 to 1. This indicated that when false alarm is 0, there is full (accurate) signal detection and if false alarm is 1, then detector is not functioning well. Therefore, accuracy of detection can be enhanced by reducing false alarm in order to improve detection accuracy. Reduction of false alarms was carried out by introducing component based sigma improvement strategies varied from one (1) to six (6) sigma under homogeneous behaviour of the system. In this arrangement, the range 0.69 to 0.0000034 would have reduced circuitry system failure probabilities [19]. The probability of exceeding the given value (target) $Q(x)$ was also assumed a failure range, 0 – 1. The distance (d) between means of the two densities of hypothesis (H_0, H_1) was taken in the range 0.5 to 2.0 in step of 0.5. Analysis of the optimized detection system was carried out on MATLAB computer software to determine the effect of sigma improvement system on the signal strength performance. The signal strengths generated based on signal energy-to-noise ratio (ENR) and its corresponding probabilities of false alarm are presented in Figures 4-10.

3. Results and Discussion

The results based on balanced probability of not exceeding the target of 0.5 were generated to illustrate performance of the system in terms of signal strength performance based on ENR under the influence of sigma quality. Figure 4 shows probability levels of false alarm with signal strength based on signal energy-to-noise ratio, at the probability of not exceeding the target (0.5). It can be seen from Figure 4 that at given probabilities of false alarm and meeting target, the signal strength performance increased monotonically with the signal energy-to-noise ratio at varying degrees depending on the value of distance, d (range from 0.5 to 2.0) between the two densities H_0 and H_1 . The results from Figure 4 showed that the signal strength (ENR4) monotonically and steadily increased fastest at distance 2.0. The fast rate of noise removal from the system has led to reduction in probabilities of false alarm from the detector.

Figures 5-10 revealed signal strengths (ENR1, ENR2, ENR3 and ENR4) and probabilities of false alarm (P_{FA}) outcomes for the densities distance 0.5, 1.0, 1.5 and 2.0 when component based sigma improvement circuitry was imposed on the system. The results obtained when detection system was treated with component-based improvement system based on single sigma (Figure 5) indicated a slight

improvement in signal strengths with reduction in probabilities of false alarm over untreated results given in Figure 4 which served as control.

Steadily and more satisfactorily improved signal detection performance was noticed and demonstrated by considerably higher monotonically increased signal strength as the system was moving from two-sigma (Figure 6), three-sigma (Figure 7), four-sigma (Figure 8), five-sigma (Figure 9) to six-sigma (Figure 10). The outcomes generally revealed that signal strength could be fully enhanced with the application of six-sigma component-based quality system. Signal strengths based on signal energy-to-noise ratios were running into thousands while the probabilities of false alarms were running close to zero with the application of six-sigma quality scheme. The outcomes have demonstrated a promising approach to effective noise removal from the communication system.

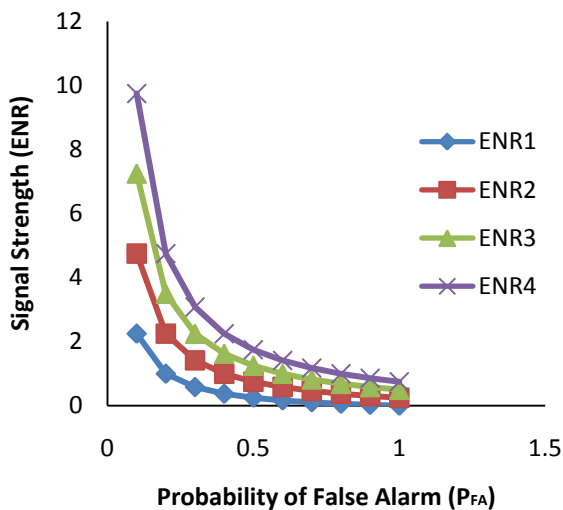


Figure 4. Signal strength without sigma improvement system

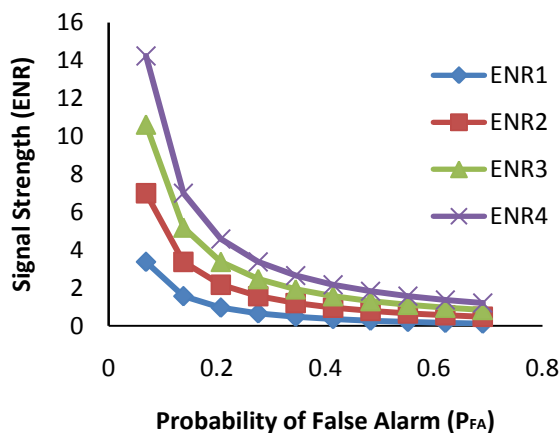


Figure 5. Signal strength with one-sigma improvement system

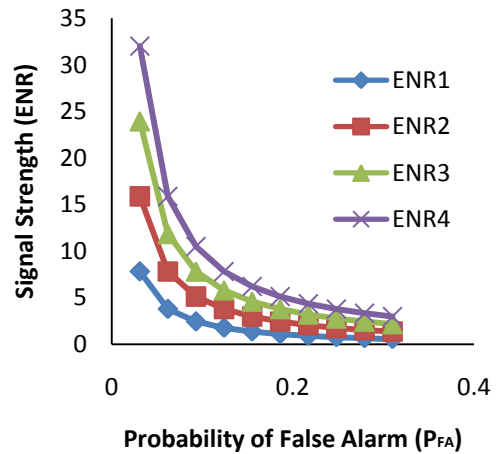


Figure 6. Signal strength with two-sigma improvement system

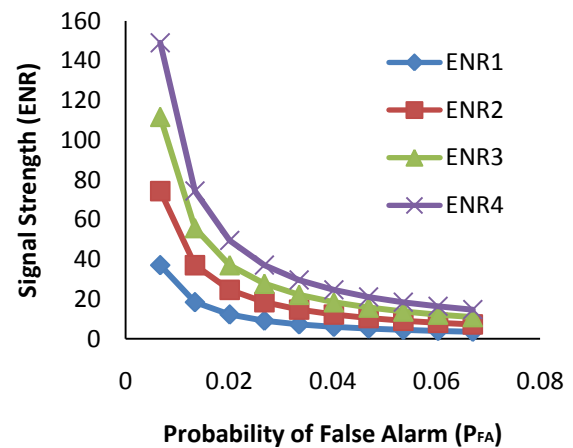


Figure 7. Signal strength with three-sigma improvement system

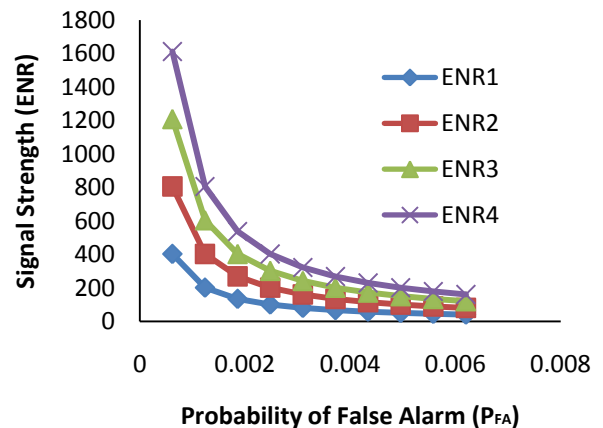


Figure 8. Signal strength with four-sigma improvement system

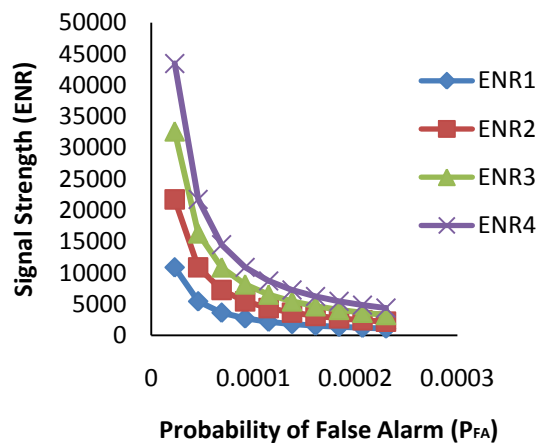


Figure 9. Signal strength with five-sigma improvement system

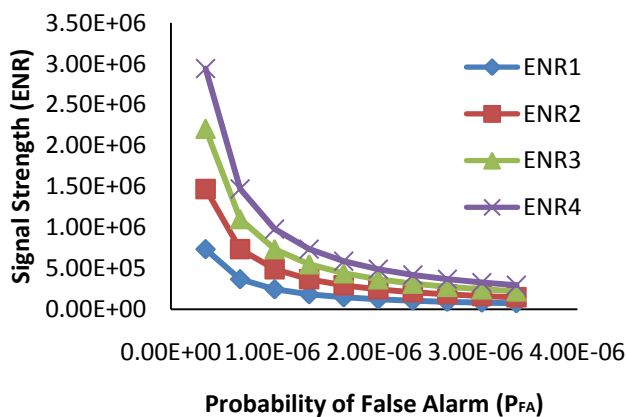


Figure 10. Signal strength with six-sigma improvement system

4. Conclusions

The detection circuit was developed to take care of signal detection strength/probability through incorporation of component-based sigma improvement system. Signal detection strength modeling was developed based on sigma quality improvement strategy. It can be generally concluded from the results of the study that signal detection performance could be fully strengthened with the application of six sigma component-based improvement system. The deployment of six-sigma quality system may demand high quality component-based circuitry. One cannot conclude yet on the strength of signal detection until thorough analysis of the components quality is carried out. Therefore, determination of signal detection strength would demand balancing the component quality with strength of signal being detected. These promising outcomes of improved signal strength due to decreased probability of false alarm through component-based sigma quality improvement strategy could break a new ground in simplifying the complex nature of electronics manufacturing systems of modern days.

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