Optimal Transmission Power of Target Tracking with Quantized Measurement in WSN

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Abstract

One of the important applications of the quality of monitoring (QoM) on target tracking in wireless sensor networks is reducing the overall power consumption in the monitoring / tracking procedures. We present, an optimal (sensor) transmission power problem is analytically formulated and its optimal solution is found such that a given constraint on the QoM is satisfied. Next, an optimum quantization system for the noise-corrupted sensor observations (measurements) is presented. In this scheme, sensor observations are first quantized into binary levels, and then transmitted to a fusion center where a final decision is made. The significant impact of optimizing the sensor's transmission power and quantizing its observations, is to provide for high QoM while reducing the overall power consumption in the monitoring / tracking procedures.
Numerical validation results show that, our suggested methods decreases energy consumptions in the sensor/fusion communication phases by the constraint binary message transmissions. This is well motivated by the bandwidth limitation of the communication links, and by the limited power budget of local sensors. On the other hand, the energy consumed in target tracking is minimized to an analytically optimal level while the target QoM level is satisfied all the time.

Key words: Wireless Sensor Networks (WSN); optimal transmission power; optimal message quantization; Power adaptation scheme; Quality of Monitoring (QoM).

1- Introduction

This paper presents first: an optimal sensing power that can guarantee, theoretically, error-free communications in WSNs. In traditional transmission scenarios, the system operating points lay in the feasible signal-to-noise ratio (SNR) regions. The objective of the scheme being presented is to improve the global probability of bit-error by compensating for the effect of fading along the communication channels through updating the effective sensor SNR required to optimize the detection performance [1], second; due to bandwidth and power limitations, each sensor node quantizes its observations into b_i –bits message, and transmits its locally processed data to the fusion center. Then, the fusion node estimates the state vector of the object based on the quantized observations.
A significantly important aspect of the sensor's power optimization scheme is that, it helps in reducing the number of Participating monitor nodes in the target tracking problem (QoM) [1] and also, in node selection procedures, aiming to select the most informative sensors in order to minimize the energy consumptions of monitoring and tracking.

2- Related work

Energy efficiency is another critical design factor in WSNs, because the sensor nodes are usually of low cost and are designed with strict restrictions on their power Consumptions Previous research works on WSNs range from general theoretic analysis, to proposing optimization solutions for the detection process [2], [6]. However, these works mostly neglect the effect of fading over the communication channels, which are an important issue in real environment and, ignoring it, may cause significant degradation of the performance of the detection process. For the purpose of energy conservation, it was shown in [7] that, when the network is subjected to a joint power constraint, having identical sensor nodes (i.e. all nodes using the same transmission scheme), is asymptotically optimal for binary decentralized detection. Efficient node power allocation to achieve a given performance has been considered by [8], [9]–[11]. In [11], the optimal power assignment problem was addressed with amplify-and forward processing at local sensor nodes. It was shown that, such an analog forwarding scheme is optimal in the single sensor case by Shannon's separation principle. It was also shown that, optimal power scheduling improves the mean squared error performance by a large margin compared to that achieved by uniform power allocation scheme. The minimum energy, decentralized estimation with correlated data was addressed in [10]. They exploited knowledge of the noise covariance matrix to optimal quantization levels at sensor nodes that the power, while meeting a given target mean-squared error.

3- Saving Power Consumption in the Target Tracking

3.1- Power Assignment Algorithm

Assume that the received signal strength at the fusion node [1] is given by,

$$U = |R|\sqrt{a} + n \tag{1}$$

Where, $\sqrt{a}$ denotes the transmitted power, R is the path gain (fading amplitude) between the sensor and the fusion node with n as an additive white Gaussian noise having standard deviation σ. The SNR, at the fusion node is therefore,

$$SNR = \gamma = \frac{|R|^2 a}{\sigma^2} \tag{2}$$

3.1.1- Optimal sensing power.

In the following, we derive an optimal sensing power that minimizes the power consumed by the sensor subjected to constraints on the performance metrics (α, β) (i.e., $QoM\,(\alpha,\beta)$). This, in effect, is a constrained optimization problem, can be formulated as follows,

$$\begin{cases} \text{Min}\ \sqrt{a}\ , \quad \text{such that} \\ QoM\,(\alpha,\beta) \le Q\,(|\frac{\log(\eta)\sigma}{R\sqrt{a}} - \frac{R\sqrt{a}}{2\sigma}|), \\ \sqrt{a} \ge 0, \end{cases} \tag{3}$$

The inequality in equation (3) above can be rewritten as follows,

$$\varphi \le |\frac{\log(\eta)\sigma}{R\sqrt{a}} - \frac{R\sqrt{a}}{2\sigma}|, \tag{4}$$

Where we defined, $\varphi = Q^{-1}(QoM\,(\alpha,\beta))$, hence, the optimization problem (3) can be rewritten as follows,

$$\begin{cases} \text{Min.}\sqrt{a}\ , \quad \text{such that} \\ \varphi \le (|\frac{\log(\eta)\sigma}{R\sqrt{a}} - \frac{R\sqrt{a}}{2\sigma}|), \\ \sqrt{a} \ge 0, \end{cases} \tag{5}$$

The optimization problem (5) can thus be reformulated using the Lagrange optimization scheme [12]-[13] as follows, then,
Assume the following objective function, F,

$$F = \sqrt{a} + \Gamma(\varphi \le |\frac{\log(\eta)\sigma}{R\sqrt{a}} - \frac{R\sqrt{a}}{2\sigma}|) \tag{6}$$

Where: Γ is the Lagrange multiplier, $\sqrt{a} = \frac{\sqrt{a_o}}{d}$. The optimal solution for the problem (6) is given by,

$$\sqrt{a_{o_{opt}}} = \frac{d\sqrt{(\sigma\varphi)^2 + 2\sigma\acute{\eta}} - d\sigma\varphi}{R} \tag{7}$$

Where $\acute{\eta} = \log(\eta)\,\sigma$, (Prove is in appendix),

Equation (7) gives the minimum (sensor) transmission power necessary to balance the effects of channel fading and noise. Substituting equation (7) into (2), gives the target SNR,

$$\sqrt{SNR_{trg}} = d\sqrt{\varphi^2 + 2\acute{\eta}/\sigma} - d\,\varphi \tag{8}$$

Where, $SNR_{trg} = \frac{|R|^2 a_{opt}}{\sigma^2}$

At this point, we can set a sensor selection strategy based on the following procedures:

a) A target SNR of the link between the sensor and the fusion center is computed using equation (8), based on the sensor location d,
b) Based on the received SNR at each sensor. It turns itself into active/inactive (participating/nonparticipating) in the target detection process,
c) Certainly, such a self sensor activation /deactivation procedure would leads to a significant reduction of the sensor energy along its life time.

3.1.2- Numerical Results

In this section, the performance of the proposed coverage and SNR assignment is validated through numerical examples.
As shown in Figure (1), the sensor's coverage d increases with the SNR according to Equation (8). For instance, the sensing range, d, is about 5m if α = 2%, $\beta' = 93\%$, SNR = 7.5 dB. However, at SNR = 9 dB, the sensing range covers up to 10m. Figure (1) depicts the sensing ranges for different detection metrics $(\propto, \beta')$.
In figure (2), we show an illustrative example on the optimum transmission power for the sensor-to-fusion communication link. In this example, the fading coefficient R, is set to unity (constant). This is done in order to highlight the effects of different communication metric values $(\propto, \beta')$ on the power assignment process. As expected, the higher the values of $(\propto, \beta')$, the higher is the transmission power necessary to compensate for the effects of the path losses over the communication range (i.e., twice the sensing range) as given by Equation (7). In Figure (3), we show the effect of channel fading on the optimum power assignment. As expected, in order to maintain a given target values of $(\propto, \beta')$, higher transmission power assignment becomes n

order to compensate for the effects both the fading and the path losses.

Figure (4), presents a practical implementation of the proposed (optimal) power assignment strategy. Assume that each sensor knows it's (discrete) relative location with respect to the fusion node. Assume further that, each sensor sends a pilot signal to the fusion node. Upon receiving the pilot signal from the sensor and, based on the measured channel characteristics, the fusion center performs an estimation of the optimum transmission power necessary to achieve the target $(\propto, \beta^{'})$ values and sends it as an update to the sensor. This way, our power assignment strategy would guarantee that the network operational point will always lies in the optimal SNR region.

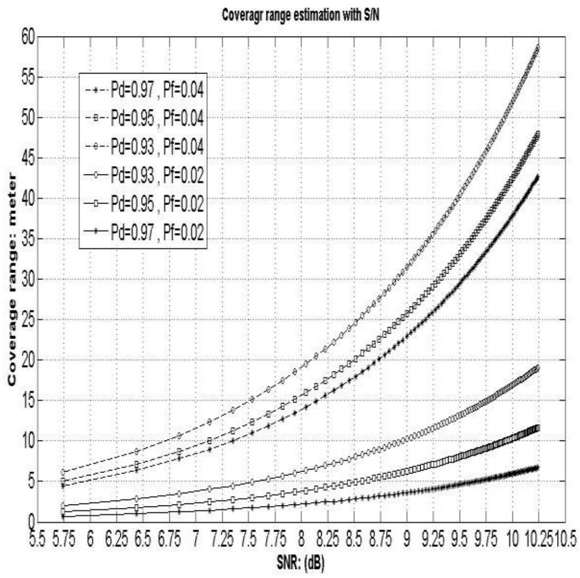

Figure (1): Coverage range estimation

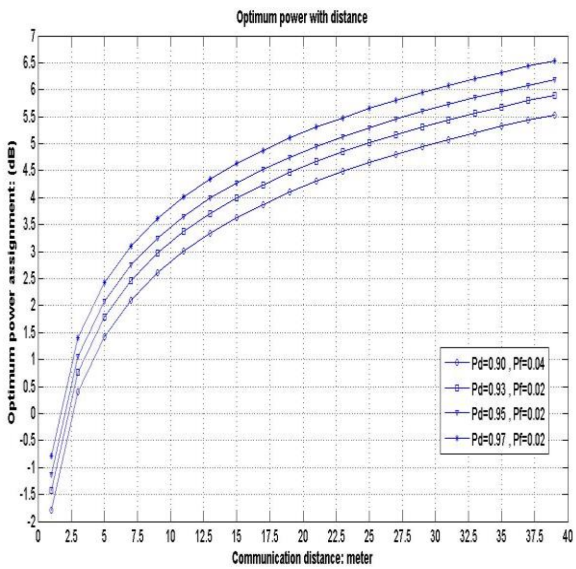

Figure (2): Optimum power assignment

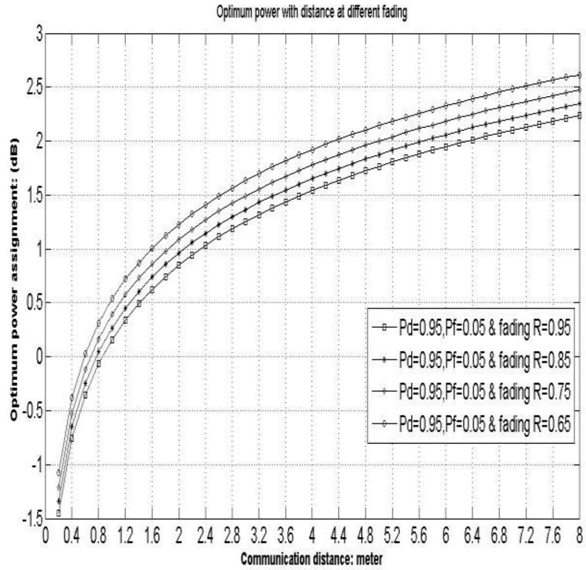

Figure (3): Effect of fading on the power assignment adding model

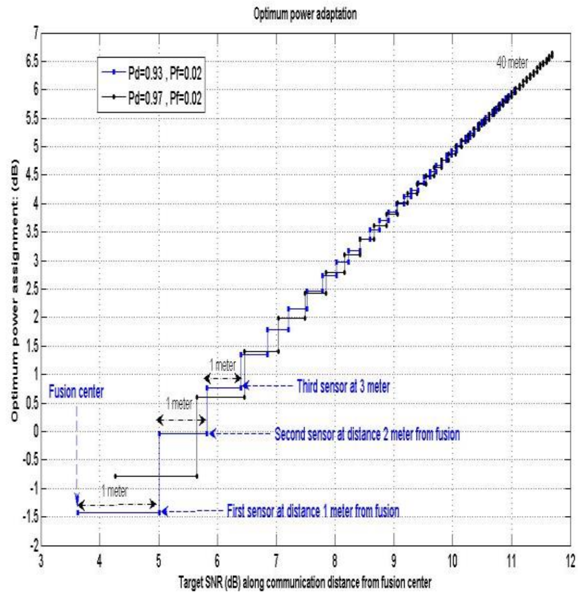

Figure (4): Target SNR(dB) along communication distance from fusion center

3.2- Optimal Message Quantization

Let the quantized message from the i-th sensor to fusion center [1] at time k be modeled as,

$$y_i(\mathrm{k}) + q_i \qquad (9)$$

Where: q_i is a zero mean quantization error with variance less than $\frac{W^2}{(2^{b_i}-1)^2}$ [14], and $(\frac{W}{2}, \frac{-W}{2})$ is the available signal amplitude range common to all sensors, $b_i$is the number of bits, to be determined later, and $L_i = 2^{b_i}$, is the i-th quantization points, these points are uniformly spaced and it follows,

$$\Delta = \frac{2W}{2^{b_i}-1}.$$

The quantization model in equation (9) and the uniform quantization error assumption are widely used in the literature due to their analytical tractability.

Assuming that, the channel noise is v_i, quantization noise q_i , are mutually independent. Therefore, the signal of i-th sensor can be express as,

$$u_i(k) = y_i(k) + q_i + v_i \qquad (11)$$

Let the noise $n_i = v_i + q_i$ is comprised of uncorrelated components and having zero means with variance,

$$\sigma_{n_i}^2 = \sigma_{v_i}^2 + \sigma_{q_i}^2 \qquad (12)$$

The covariance of quantization noise is,

$$\sigma_{q_i}^2 \leq \frac{W^2}{(2^{b_i}-1)^2} \qquad (13)$$

It is easy to see that, the accuracy of the quantized messages is better if the variance of the quantization noise is small which is equivalent to using larger number of bits. That is, we can make its upper bound small which, in turns, means more bandwidth is need. However, in WSNs, both the sensor power and the transmission bandwidth are limited. Hence, it is important to find the optimal quantization bits necessary to achieve a given performance measure such that, a constraint on the sensor's energy/power are satisfied.

3.2.1- Bit Assignment

In this section, we consider the quantization bit assignment problem, assuming that the channel between the i-th sensor and the fusion node experiences a path loss proportional to d_i^m, where d_i is the transmission distance between the i-th sensor and the fusion node. The energy consumed in the i-th sensor is,

$$E_i = \omega_i (2^{b_i} - 1) \qquad (14)$$

Where: ω_i is the energy density, in which $\omega_i = \rho' d_i^m \ln(\frac{2}{P_b})$, ρ' depends on the actual noise distribution [23], and P_b is the target bit error rate, assumed common to all sensor links.

At this point, our goal is to minimize the mean square transmission power while meeting a given total power consumption. This goal can be represented by the following optimization problem,

$$\begin{cases} \min \quad \sum_{i=1}^{N} \omega_i^2 B_i^2 \\ \text{s.t} \ \sum_{i=1}^{N} (\sigma_{v_i}^2 + \sigma_{q_i}^2) \leq D \\ \quad D \geq 0 \end{cases} \qquad (15)$$

Where: D > 0 is a given targeted upper bound on the noise variance, where

$$B_i^2 = (2^{b_i} - 1)^2.$$

3.2.2- The Optimal Solution

In order to facilitate the analysis, we relax the integer b_i to be a real positive number. As we did in previous section, the problem in equation (15) can be reformulated as a Lagrangian convex optimization,

$$F(\Gamma, B_i) = \sum_{i=1}^{N} \omega_i^2 B_i^2 + \Gamma^* \{ \sum_{i=1}^{N} \left(\sigma_{v_i}^2 + \frac{W^2}{B_i^2}\right) - D\} \qquad (16)$$

Letting $\partial F / \partial b_i = 0$ for all i ,

$$2\omega_i^2 B_{i_{opt}} - \Gamma^* \frac{2 B_{i_{opt}} W^2}{B_{i_{opt}}^4} = 0 \qquad (17)$$

$$2\omega_i^2 B_{i_{opt}} - \Gamma^* \frac{2W^2}{B_{i_{opt}}^3} = 0 \qquad (18)$$

And at the optimum solution, we should have,

$$D - \sum_{i=1}^{N} \left(\sigma_{v_i}^2 + \frac{W^2}{B_{i_{opt}}^2}\right) = 0 \qquad (19)$$

Combining equations (18) and (19) yields,

$$b_{i\,opt} = \log_2 \left[1 + \frac{W}{\omega_i} \sqrt{\frac{\Gamma^*}{2}}\right] \qquad (20)$$

Where: $\Gamma^* = \frac{2(W\sum_{i=1}^{N}\omega_i)^2}{(D - \sum_{i=1}^{N}\sigma_{v_i}^2)^2}$

Once the optimal, real-valued $b_{i\,opt}$ is computed, the associated bit loads can be obtained through simple upper integer rounding. Recall from equation (20) that the energy consumption of each sensor is proportional to the path loss d_i^m. Hence, larger energy consumptions correspond to sensors deployed far away from its fusion node.

3.2.3- Effect of Channel Fading on Quantization Bit Assignment

The relationship between the original signal of i-th sensor and the data received by the fusion node with fading is depicted in [1]. Therefore, equation (11) becomes,

$$u_i \text{ (k)} = \text{R } y_i \text{ (k)} + q_i + v_i \tag{21}$$

and from equation (14), the energy consumed in the i-th sensor under fading is,

$$E_i = \text{R } \omega_i \, (2^{b_i} - 1) \tag{22}$$

Where: R is the fading gain, ω_i is the energy density, $\omega_i = \rho' \; d_i^m \ln(\frac{2}{P_b})$.

3.2.4- Numerical Results

Recall from equation (11), that the energy consumption of each sensor is proportional to the path loss. Hence, large value of the energy consumptions correspond to sensors deployed far away from the fusion node. In light of this point, the optimal quantization bit assignment is intuitively attractive. Figure (5) illustrates the (optimally) assigned bits versus the path loss of the channel in terms of the coverage distance. As can be seen, the optimal number of bits is proportional to the expected path loss. This is intuitively reasonable since sensors with bad link conditions, should be allocated with more bits in order to improve the received message accuracy at the fusion center. Clearly, the same talking applies well for the channel noise. This is illustrated in Figure (6), in terms of the noise variance. Finally, Figure (7) shows the optimum bit assignments taking into account the bit error caused by the channel. To transmit, the binary bits, we must insure that a given probability of bit error is achieved at the fusion node.

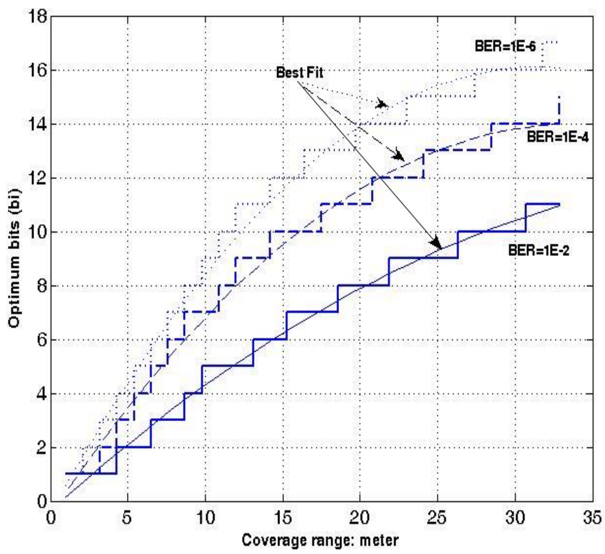

Figure (5): Optimum bit assignment with coverage range

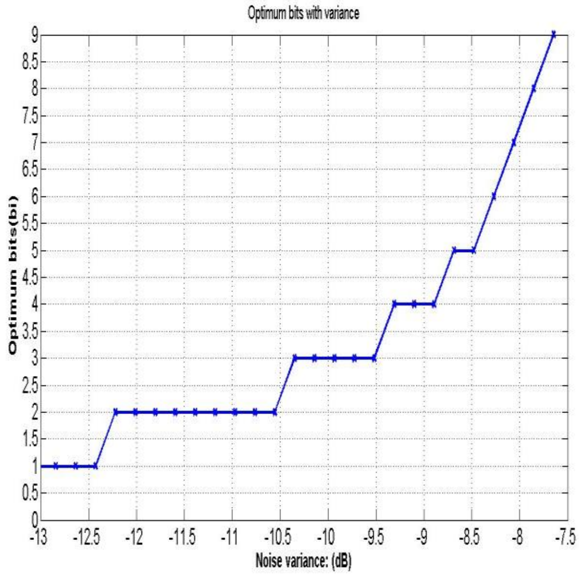

Figure (6): Effect of noise on optimum bit assignment

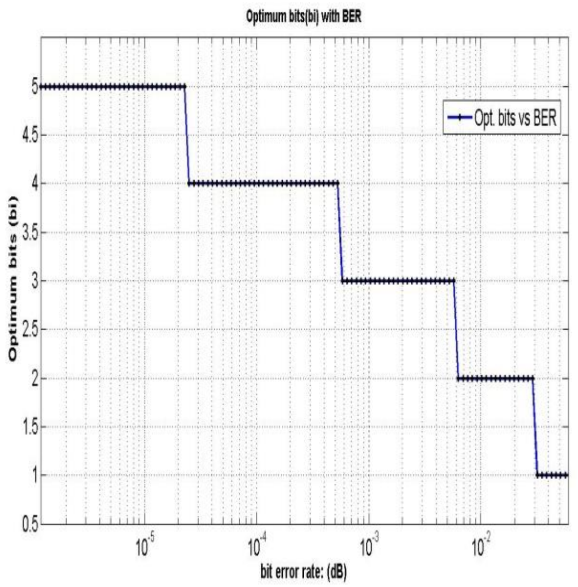

Figure (7): Effect of BER on optimum bit assignment

4- CONCLUSION

These days, energy saving in the monitoring (QoM) of mobile target tracking is considered as one of the important applications of wireless sensor networks.

We considered the optimal (sensor) transmission power problem such that a given constraint on the QoM is satisfied. The significant impact of optimizing the sensor transmission power is, to provide for high QoM while reducing the overall power consumption in the WSN. The scheme is designed with number of objectives: first, the moving target should be covered with predefined QoM level, at optimal transmission power; second, the channel quality is below a (computable) SNR threshold, the corresponding sensor will be completely shut off to save energy. In contrast, when the channel quality is good and the observation noise is low, the corresponding sensor will be active. Hence, the potential duty sensor(s) is the one who can receives a pre computed SNR level. As such, only some sensors will be eligible to participating in the target tracking routine, while others will have to abstain.

Along the same, energy saving line, we presented an optimal bit assignment scheme for the noise-corrupted sensor observations (measurements). In this scheme, sensor observations are first quantized into binary levels, and then transmitted to the fusion center where a final decision is made.

In very broad terms, we claim to have elaborated on the moving target tracking problem, but from different viewpoints. The objective has always been, to challenge the long held paradigm that high tracking quality (low tracking error) necessarily requires high power consumptions.

Numerical validation results show that, our suggested methods decreases energy consumptions in the sensor/fusion communication phases by the constraint binary message transmissions. This is well motivated by the bandwidth limitation of the communication links, and by the limited power budget of local sensors.

On the other hand, the energy consumed in target tracking is minimized to an analytically optimal level while the target QoM level is satisfied all the time.

Appendices

A constrained optimization problem, can be formulated as follows,

$$\begin{cases} \text{Min.} \sqrt{a} \ \text{, such that} \\ \varphi \le \left| \frac{\log(\eta)\sigma}{R\sqrt{a}} - \frac{R\sqrt{a}}{2\sigma} \right|, \\ \sqrt{a} \ge 0 \end{cases}$$

First we convert to the form

$$\begin{cases} \text{Min.} \sqrt{a} \ \text{, such that} \\ \left| \frac{\log(\eta)\sigma}{R\sqrt{a}} - \frac{R\sqrt{a}}{2\sigma} \right| \le -\varphi \\ \sqrt{a} \ge 0 \end{cases}$$

Using Lagrange: the object function is

$$F = \sqrt{a} + \Gamma \left(\left| \frac{\log(\eta)\sigma}{R\sqrt{a}} - \frac{R\sqrt{a}}{2\sigma} \right| \le -\varphi \right)$$

Put $\sqrt{a}$ =T

So we need $\frac{\partial F}{\partial T}$ = 0 , then after differentiations

$$1 - \Gamma\left(-\left(\frac{-\log(\eta)\sigma}{RT^2} - \frac{R}{2\sigma}\right)\right) = 0$$

$$\left(\frac{\log(\eta)\sigma}{RT} - \frac{RT}{2\sigma}\right) \le -\varphi$$

$$\Gamma \ge 0 \qquad (23)$$

From equation (23)

$$-2\sigma \log(\eta)\sigma + R^2(T_{opt})^2 = 2\varphi R(T_{opt})\sigma, \text{ then}$$

$$R^2(T_{opt})^2 + 2R(T_{opt})\varphi\sigma - 2\sigma\log(\eta)\sigma = 0$$

Put $\acute{\eta} = \log(\eta)\sigma$

$$R^2(T_{opt})^2 + 2\varphi R(T_{opt})\sigma - 2\sigma\acute{\eta} = 0$$

Then $T_{opt} = \frac{\sqrt{(\sigma\varphi)^2 + 2\sigma\acute{\eta}} - \sigma\varphi}{R}$,

Where:

$$R^2 \frac{(\sigma\varphi)^2 + 2\sigma\acute{\eta} - 2\sigma\varphi\sqrt{(\sigma\varphi)^2 + 2\sigma\acute{\eta}} + (\sigma\varphi)^2}{R^2} + 2R\sigma\varphi\frac{\sqrt{(\sigma\varphi)^2 + 2\sigma\acute{\eta}} - \sigma\varphi}{R} - 2\sigma\acute{\eta} = 0$$

Then

$$\sqrt{a}_{opt} = \frac{\sqrt{(\sigma\varphi)^2 + 2\sigma\acute{\eta}} - \sigma\varphi}{R}$$

$$\sqrt{a_o}_{opt} = \frac{d\sqrt{(\sigma\varphi)^2 + 2\sigma\acute{\eta}} - d\sigma\varphi}{R} \text{ ,(prove of equation (7))}$$

Where:

$$T_{opt} = \sqrt{a}_{opt} \text{ , } \sqrt{a}_{opt} = \frac{\sqrt{a_o}_{opt}}{d} \text{ ,}$$

$$\sqrt{SNR_{trg}} = d\sqrt{\varphi^2 + 2\acute{\eta}/\sigma} - d\varphi = \frac{R\sqrt{a}_{opt}}{\sigma}$$, (prove of equation (8))

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