Estimation of Primary Channel Gain and Interference Reduction for Spectrum Sharing in Cognitive Radio Networks

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Abstract:- To achieve spectrum allocation in cognitive radio grids, channel gain among primary transmitter and receiver is essential for cognitive transmitter. For CT to sense primary signals and to evaluate prime channel gain, new methods such as Maximum Likelihood estimator (ML) as well as Median Based estimator (MB) be proposed. ML principle is adopted to examine received prime signals, thus developed ML estimator. Then Median Based estimator is offered for reducing computational complication of ML estimator, such that CT can calculate interference temperature ofprime system and attain spectrum distribution. Through simulation outcomes, valuation error remains 0.015 in both estimators. To further decreasing unwanted noise, a level based reduction methodbe there used.

Keywords:- *Cognitive Radio, Channel gain, Maximum likelihood, Median based Estimation error, Interference.*

I. INTRODUCTION

Cognitive radio (CR) is a means of transmitting and receiving scheme that can spontaneously identify freely vacant channels in a wireless band. CR adjusts its transmission factors to allow further communications to run concurrently then also improve radio operating behavior. To utilize the radio spectrum more powerfully and to sustain most efficient usage of communications are the basic ideas of cognitive radio. A favorable candidate to manage spectrum shortage problem is cognitive radio and this technique also offer solution for spectrum scarcity. Therefore it is developed to solve current existing problems in future wireless communications.

Secondary users can enhance spectrum utilization efficiency by coexisting through primary users on under-utilized authorized band. Opportunistic spectrum access (OSA) and spectrum sharing (SS) are two ways to exist with licensed users. In OSA, secondary users can access band only if band is idle and have to vacate the band as soon as possible noseband is re-occupied. In SS, secondary users is capable of accessing band even when spectrum is occupied.

If demand of spectrum increases, frequency bands become further congested mainly in developed cities. So spectrum superiors are resulting diverse methodologies to spectrum sharing (SS). Band distribution involves other users as well as shares same band intended for different uses. In cognitive radio matrix, efficient spectrum sharing is very important. Spectrum sharing efficiency is improved by means of minimizing intrusion then, can attain spectrum distribution. To enhance spectrum operation efficiency cognitive radio should follow spectrum sharing policies.

II. LITERATURE SURVEY

Many researchers introduced an overview on cognitive radio, spectrum sharing aspects and techniques, primary channel gain estimation methods and so on. So there have been a number of surveys about this in the literature.

S.Haykin et.al [1] gives the idea of cognitive radio in wireless communication and also gives two primary objectives such as efficient use of band and highly consistent communication whenever and wherever needed.

The key element of cognitive radio is spectrum sharing. It is the simultaneous usage of a specific radio frequency band in a specific geographical area by a number of independent entities. [2] Mandeep Kaur et.al [2] gives a review on cognitive radio spectrum sharing aspects and techniques. Network architecture based spectrum sharing techniques in the cognitive radio mesh is classified into centralized and distributed spectrum sharing. Co-operative and non-cooperative spectrum sharing are the two types of spectrum sharing techniques based on allocation behavior. Based on the access technique the spectrum sharing techniques is grouped into overlay and underlay spectrum sharing.

Guodong Zhao et.al [3] explains about the primary channel gain estimation for spectrum distribution in cognitive radio network. Channel gain among primary receivers is assessed by cognitive transmitter using maximum likelihood (ML) estimator and median based (MB) estimator. So CT there able to calculate intrusion of primary system and attain spectrum distribution.

Y.C. Liang et.al [4] introduce two cognitive spectrum access models such as opportunistic spectrum access (OSA)

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model and concurrent spectrum access (CSA) model. In OSA model a CR user carries out spectrum sensing to detect spectrum holes. In CSA model a CR user and the active primary user (PU) is coexists in a licensed band and this model also requires the CR Tx to predict the interference power level that is received at the particular location and it is referred as spectrum sharing.

E. A. Jorswieck et.al [5] presented a complete assessment on spectrum sharing between operators in cellular wireless network in terms of network efficiency. The gain by sharing spectrum heavily depends on the chosen network scenario and the parameter settings. This article reports that spectrum sharing gains in the range between 10 and 100 percent and also demonstrates how equal-priority spectrum sharing in cellular networks improves spectrum efficiency, enhances coverage, increases user satisfaction, leads to increased efficiency for operators and decreases capital and operating expenditures.

L. Sboui et.al [6] briefly explains the achievable rate of the secondary cognitive user in a spectrum sharing multiple input multiple output (MIMO) uplink communication using a special precoding scheme. The secondary user (SU) utilize the unused eigenmodes of the primary user and shares the used ones with regard to both total power and interference temperature constraints. The main objective is to examine the maximum achievable rate for the SU over all channel realizations.

A. Ghasemi et.al [7] express the fundamental limits of dynamic spectrum sharing approach when channels vary due to fading. If the channels are vary due to fading, significant capacity gains may be achieved. In [8] L. Musavian et.al explains the capacity gains of spectrum sharing channels in Rayleigh fading environments. The capacity and optimum power allocation schemes are obtained to achieve the ergodic, outage and minimum rate channel capacities and also determined the corresponding capacities under joint peak and average received power constraints.

Y. Chen et.al [9] considered a cognitive radio system in fading wireless channels and proposed an opportunistic power control strategy for the secondary users. It is an alternative method to protect the primary user's transmission and to realize spectrum sharing between the primary user and the cognitive users. The main feature of this offered strategy is, cognitive users be able to make best use of its attainable communication level without demeaning the outage probability of licensed user through opportunistically adapting it's transmit power.

S. Wang et.al [10] designed an energy efficient and low complexity uplink transceiver for a new multiuser (MU) massive spatial modulation multiple input multiple output (SM-MIMO) system over frequency selective fading channels. In this paper, the multiuser detection (MUD) problem in massive MIMO can be solved by the generalized approximate message passing (GAMP) algorithm. And also construct a GAMP detector (GAMPD) that approaches to the performance of ML detection and outperforms minimum mean square error (MMSE).

Z. Rezki et.al [11] analyzing the optimal power allocation and the ergodic capacity of the secondary link under limited channel knowledge at the secondary transmitter and also proposed a spectrum sharing CR model under general fading channels with continuous probability density functions. And at certain interference constraints the licensed user and the unlicensed user share the same spectrum.

In [12]J. Dai et.al developed a simple and efficient clustering algorithm which is to address the mutual interfering issues among the unlicensed users (SUs) and to improve the spectrum utilization efficiency. in Zhang [13] proposed a proactive channel gain valuation methodology among unlicensed and licensed users using probing process. With this suggested methodology, unlicensed users are able to recognize the co-occurrence among licensed and unlicensed users.

Y.-C. Liang et.al [14] explains a practical cognitive beam forming scheme that utilizing a new idea of effective interference channel (EIC) and this scheme is used to minimize the effect of the resulted intrusion on PR transmissions. A. Melonakos et.al [15] presenting an interference mitigation techniques for MIMO wireless communication systems to perform spatial division multiple access with minimal co-operation between users. In this proposed technique, each user learns the null space of the interference channel to the other user by transmitting a learning signal and observing an affine function of the other user's interference plus noise power. In [16] Andrea. J. Goldsmith et. a proposed a tracking algorithm for reducing interference between neighboring groups in Coordinated Multi-point (CoMP) networks.

III. PROPOSED METHODOLOGY

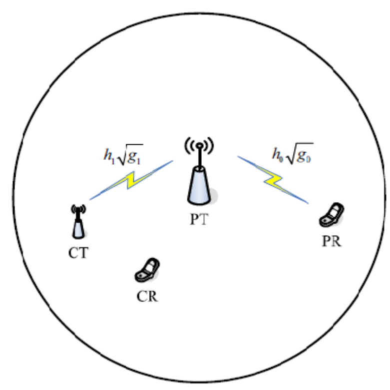

Fig 1:- System Model

The fig 1. shows system model which involves primary transmitter (PT), primary receiver (PR), cognitive transmitter (CT), and cognitive receiver (CR). On certain frequency band, PT is transmitting data to PR. CT aims to use similar frequency band at the same time and realize spectrum sharing (SS). Spectrum sensing phase and cognitive information transferring phase are two stages of spectrum sharing. CT receives primary signals in spectrum detecting phase to evaluate primary channel gain among PT and PR and do not transfer any cognitive data. CT uses assessed primary channel gain in cognitive data transmission stage, to calculate interfering temperature and conduct cognitive document transmissions.

A. Network Modelling

Block fading channels are considered between operators. Specifically $h_0$and g_0 are small scale block fading and channel gain coefficients between PT and PR respectively, channel between PT and PR is $h_0\sqrt{g_0}$. Likewiseh_1 and g_1 are small scale block fading andchannel gain coefficients between PT and CT respectively, channel between PT and CT is $h_1\sqrt{g_1}$. | h_i| (i = 0, 1) surveys a Rayleigh sharing with unit mean. Channel, h_i(i = 0, 1) remains persistent within all block and differs individually between dissimilar blocks. Gain, (i = 0, 1) is found by path loss model,

$$pl(di) = 128 + 37.6 \log_{10}(di),$$

For di ≥ 0.035 km, (1)

Where distance between two transceivers is denoted as di (km). The channel gaingi is,

$$gi = 10^{-12.8} di^{-3.76},$$

For di ≥ 0.035 km, (2)

for a given distance di,it remains constant all time. Thus CT estimate prime channel gain $g_0$sincePT to PR used for spectrum allocation.

B. Signal Modelling

PT transfers primary signals to PR in band detecting stage and at same time, CT accept sprimesigns to evaluate primary channel gain and do not transfer any cognitive information. In spectrum sensing phase, there is no common interfering occur among licensed and unlicensed users. Then model signal from PT to PR and from PT to CT, correspondingly.

- *Signal Modelling Between Primary Users*

The primary signal is denoted by$x_p$with unit power p_0. If PT transfers primary signal with unit power thenacknowledged signal at PR in block k is,

$$y_p(k) = h_0(k)\sqrt{g_0(k)p_0(k)}x_p(k) + n_p(k) \quad (3)$$

Where $n_p$symbolizes additive white Gaussian noise (AWGN) at PR with zero mean and varianceσ^2. Then, signal to noise ratio (SNR) of acknowledged prime signal at PR is,

$$\gamma_p(k) = \frac{|h_0(k)|^2 g_0 p_0(k)}{\sigma^2} \quad (4)$$

The PT spontaneouslymodifiesits transmit power to meet a assured target SNR γ_T at PR. Then PT's transmit power is,

$$p_0(k) = \frac{\gamma_T \sigma^2}{|h_0(k)|^2 g_0} \quad (5)$$

- *Signal modelling Between Secondary Users*

The received primary signal at CT in block k is,

$$y_c(k) = h_1(k)\sqrt{g_1(k)p_0(k)}x_p(k) + n_c(k) \quad (6)$$

Where n_c represents the AWGN at CT with zero mean and varianceσ^2. Then SNR of acknowledged prime signal at CT is,

$$\gamma_c(k) = \frac{|h_1(k)|^2 g_1 p_0(k)}{\sigma^2} \quad (7)$$

By substituting eqn. (5) into eqn. (7), γ_c(k) in eqn. (7) can be rewritten as,

$$\gamma_c(k) = \frac{\gamma_T g_1}{g_0} \frac{|h_1(k)|^2}{|h_0(k)|^2} \quad (8)$$

C. Gain Estimation Methods

For estimating primary channel gain among primary transceivers, the estimators such as Maximum Likelihood (ML) estimator and Median Based (MB) estimator are developed.

- *Maximum Likelihood (ML) Estimator*

The basic principle of ML estimator is, the primary signal comprises certain data about primary channel gain. Thus by sensing primary signal, CT be able to achieve primary channel gain. Every SNR of acknowledged primary signal at CT and primary channel gain g_0 is correlated. Therefore CT can measure SNR of acknowledged primary signal and evaluateg_0.

But, it is challenging to getg_0 directly from (8). Because all SNR in (8) is fluctuates independently among different blocks and likewise affected by arbitrary small scale fadings. Otherwise, the CT can measure altered SNRs of prime signals in numerous blocks and exploits haring awareness of small scale fading's to assessg_0. The ML criterion can powerfully extract common data from multiple files and achieve better for factors assessments. Therefore implement ML standard and cultivate ML estimator for CT to attain primary channel gain $g_0$among PT and PR. Through eliminating block index k in (8) gain g_0 is,

$$g_0 = \frac{g_1 \gamma_T \emptyset}{\gamma_c} \quad (9)$$

Where $\Phi = \frac{|h_1|^2}{|h_0|^2}$.

The fig 2. represents the flow chart showing the ML estimation method for to obtain the gain. The origin of ML estimation consist of two phases. Finding optimal value $\overline{g_0}$ is the first step and the next step is to compute $\dot{g}_0$ to obtain ML estimation.

Both h_0 and h_1 differin dividually among different blocks within K consecutive blocks. So CT can measure K independent samples of γ_c in accordance with the relation between h_0, h_1 and γ_c in equation (8). Then calculate the joint pdf and taking the log function of the samples and also approximated to $f1(\overline{g_0})$ which is a concave function of $\overline{g_0}$. Taking the first order and second order derivatives of the concave function and also obtain the optimal value which maximize the concave function. Then calculate $\dot{g}_0$ and obtain the ML estimation to find the primary channel gain.

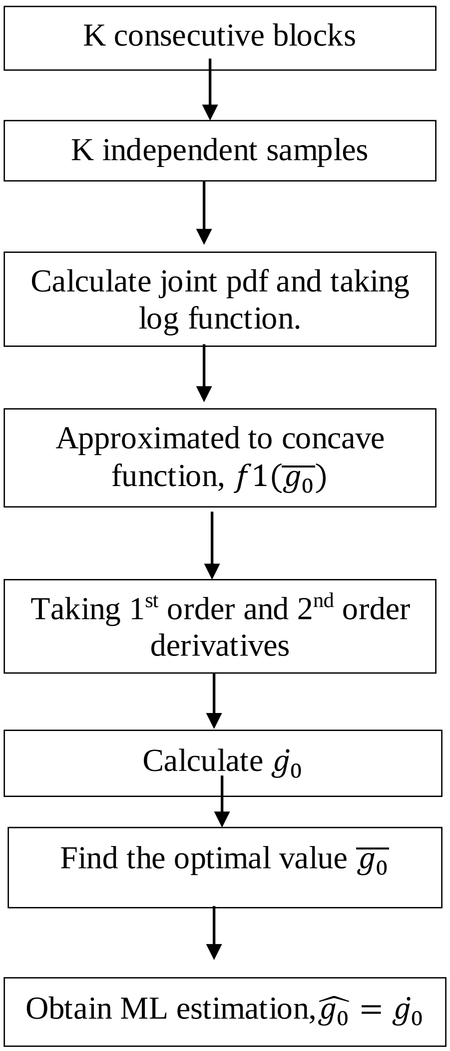

Fig 2:- Flow chart of ML estimation method

Median Based (MB) Estimator

A new estimator named MB estimator is introduced, which is to decrease the computational complications. The basic principle of MB estimator is, for arbitrary variable X with CDF $F_X(x)$, $x \epsilon$ R, if $x_{\frac{1}{2}}$ fulfills both,

$$F_X\left(x_{\frac{1}{2}}\right) = \Pr\left\{X \le x_{\frac{1}{2}}\right\} = \frac{1}{2} \qquad (10)$$

And

$$1 - F_X\left(x_{\frac{1}{2}}\right) = \Pr\left\{X \le x_{\frac{1}{2}}\right\} = \frac{1}{2} \qquad (11)$$

$x_{\frac{1}{2}}$ is the median of random variable X. There fore primary channel gain is,

$$g_0 = \frac{g_1 \gamma_T}{\gamma_{c,\frac{1}{2}}} \qquad (12)$$

The median $\gamma_{c,\frac{1}{2}}$ is a function of primary channel gain g_0. If $\gamma_{c,\frac{1}{2}}$ is obtainable to CT, g_0 can be directly designed. But, $\gamma_{c,\frac{1}{2}}$ is unknown to the CT. As an alternative, $\gamma_{c,\frac{1}{2}}$ is first estimate and then obtain g_0.

The fig 3. shows the flow chart of MB estimation method for estimating the primary channel gain.

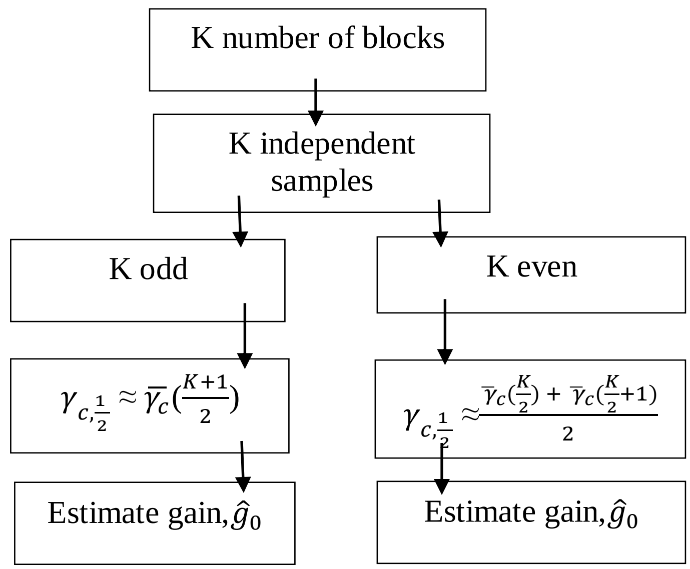

Fig 3:- Flow chart of MB estimation method

For K autonomous variables, CT can compute K independent samples of γ_c, ie, $\gamma_c(k)$ ($1 \le k \le K$). Approximate median $\gamma_{c,\frac{1}{2}}$ with sample median $\gamma^s{}_{c,\frac{1}{2}}$ of these K samples and with approximated $\gamma_{c,\frac{1}{2}}$, g_0 can be estimated. By arranging K samples in rising order, the K samples can be relabeled by $\overline{\gamma_c}(k)$ ($1 \le k \le K$), ie, $\overline{\gamma_c}(i) \le \overline{\gamma_c}(j)$ for $1 \le i \le j \le k$. Then for odd and even K, sample medians $\bar{\gamma}s_{c,\frac{1}{2}}$ is,

(i) For K stays odd: The sample median is $\bar{\gamma}s_{c,\frac{1}{2}} = \overline{\gamma}_c(\frac{K+1}{2})$, once K is odd,. Then, average of γ_c can be estimated as

$$\gamma_{c,\frac{1}{2}} \approx \overline{\gamma}_c(\tfrac{K+1}{2}) \qquad (13)$$

Byreplacing (13) into (12), MB estimator as,

$$\hat{g}_0 = \frac{g_1 \gamma_T}{\overline{\gamma}_c(\frac{k+1}{2})} (14)$$

(ii) For K stays even: The sample average is among $\overline{\gamma}_c(\frac{K}{2})$ and $\overline{\gamma}_c(\frac{K}{2}+1)$, when K is even,. Then, the median of γ_c can be approximated as

$$\gamma_{c,\frac{1}{2}} \approx \frac{\overline{\gamma}_c(\frac{K}{2}) + \overline{\gamma}_c(\frac{K}{2}+1)}{2} (15)$$

By equating (15) into (12), the MB estimator as,

$$\hat{g}_0 = \frac{2 g_1 \gamma_T}{\overline{\gamma}_c(\frac{K}{2}) + \overline{\gamma}_c(\frac{K}{2}+1)} \qquad (16)$$

As a result, the MB estimator can be shortened as, $\hat{g}_0$

$$\hat{g}_0 \hat{g}_0 \hat{g}_0 \hat{g}_0 = \begin{cases} \dfrac{g_1 \gamma_T}{\overline{\gamma}_c(\frac{k+1}{2})} \text{ for K is odd,} \\ \dfrac{2 g_1 \gamma_T}{\overline{\gamma}_c\left(\frac{K}{2}\right) + \overline{\gamma}_c\left(\frac{K}{2}+1\right)} \text{ for K is even,} \end{cases}$$

D. Comparison Between ML Estimator and MB Estimator

The ML estimator and MB estimator is related based on computational complications and estimation accuracy.

- *Computational Complication Contrast*

The computational complications of ML estimator is handled through resolving nonlinear equations. Mainly an iterative search algorithms are capable for obtaining results. Especially for a lesser error easiness, required number of repetitions is generally huge. But in place of MB estimator, primary channel gain can be assessed through only one step. As a result, MB estimator remains considerably easy than ML estimator in case of computational complication.

- *Estimation accuracy contrast*

The ML estimator outputs an estimation of g_0 by exploiting all SNR samples but MB estimator simply use sample median to evaluate g_0. Mainly, a large SNR $\gamma_c(k)$ gives small measurement error and a small SNR yields large measurement error. Therefore, suggested estimators are do better once average SNR at CT is enormous, and execute bad when average SNR is small. MB estimator is capable of removing lesser SNR quantities and increase valuation accuracy, when average SNR is small. The MB estimator also eliminates large SNR quantities and reduce valuation accuracy, when average SNR is large. Therefore, when average SNR at CT is huge, ML estimator is probable to overtake MB valuation in terms of assessment accuracy and when average SNR at CT is small MB estimator is higher to ML estimator.

Generally, ML system is well performed than any other schemes under the same SNR. But the performance of ML scheme may possibly be inferior than other schemes, if SNRs are altered at dissimilar schemes. The MB estimator eliminates low SNR samples whereas ML estimator uses very SNR samples. Then, this one is conceivable that average SNR of MB estimator is higher than ML estimator. So MB estimator may well performed than ML estimator in terms of valuation accuracy.

E. Estimation Error And Interference Temperature

The estimation error is the difference among an estimated value and true value of a parameter. Estimation error, ϵ is defined as

$$\epsilon = \frac{10 \log_{10} \hat{g}_0 - 10 \log_{10}(g_0)}{10 \log_{10}(g_0)} (17)$$

The interference temperature *PI* is related to $P_{max,}$ θ, γ_T.And by detecting modulation and coding scheme (MCS) of primary signal, γ_T can be known at the CT. P_{max} is the distinctive value of primary transmitter and can be known by previous information at CT. Outage probability, θ relates to precise γ_T andwell-known by the CT once γ_T is acquired. The power of AWGN is σ^2 and is also obtainable at the CT. Hence CT can compute *PI* with $P_{max,}$ θ, γ_T, g_0.Interference temperature, *PI* is defined as,

$$PI = \frac{-P_{max}\, g_0 \ln(1-\theta)}{\gamma_T} - \sigma^2 \ (18)$$

F. Level Based Reduction of Interference

For the level based reduction of interference effect on ML estimator and MB estimator, initially compute interference temperature of true value, ML estimator and MB estimator. Then set two levels, level 60 and level 120. And check the conditions like, if the calculated interference level of ML estimator and MB estimator is greater than or less than level 60 and level 120. If the calculated intrusion level of ML estimator and MB estimator is greater than level 60 and level 120, reduce some signals from that intrusion level. If the interference level of ML estimator and MB estimator is less than level 60 and level 120, there is no reduction for calculated interference.

IV. RESULTS

The simulation outcomes show performance of suggested ML and MB estimators.

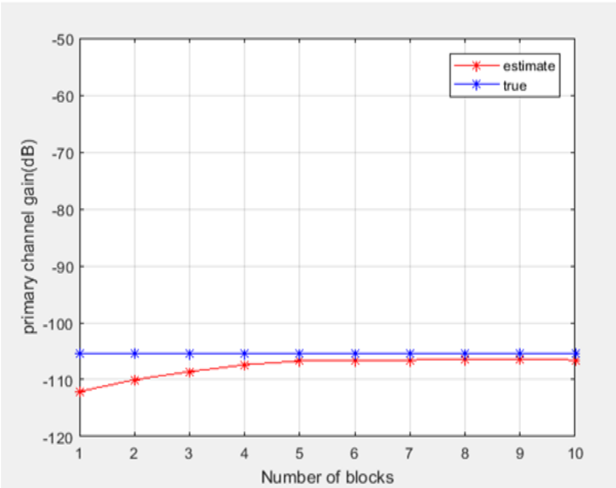

Fig 4:- Evaluation between accurate value of primary channel gain and assessment value with MB estimator

The fig 4. gives contrast among true value of primary channel gain and assessment value with MB estimator. The figure demonstrates that estimation value of MB estimator, $\hat{g}_0$reaches to true value,g_0 as number of blocks, K raises.

The fig 5. enlightens estimation error with number of signal samples, J. Here, J varies from 1 to 10. As number of signal samples rises, estimation error of ML estimator and MB estimator declines. Since, a large J might lead to lesser measurement error for all SNR and decreases valuation error of primary channel gain. When J is large, measurement error of all SNR can be disregarded.

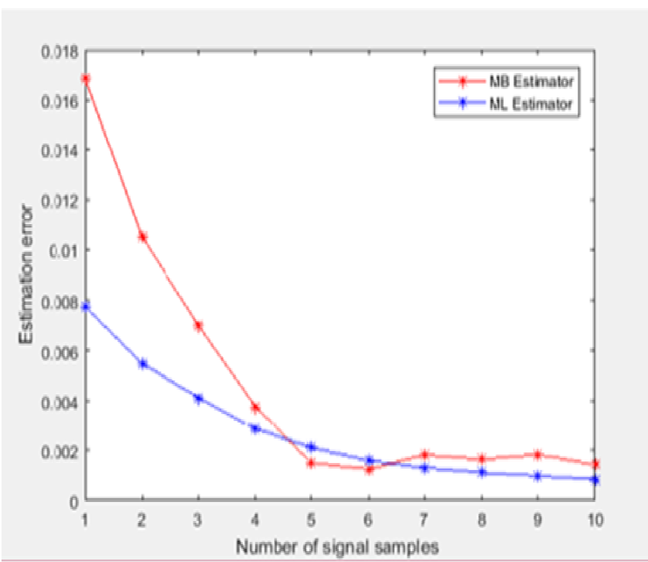

Fig 5:- Estimation errors with number of signal samples, J

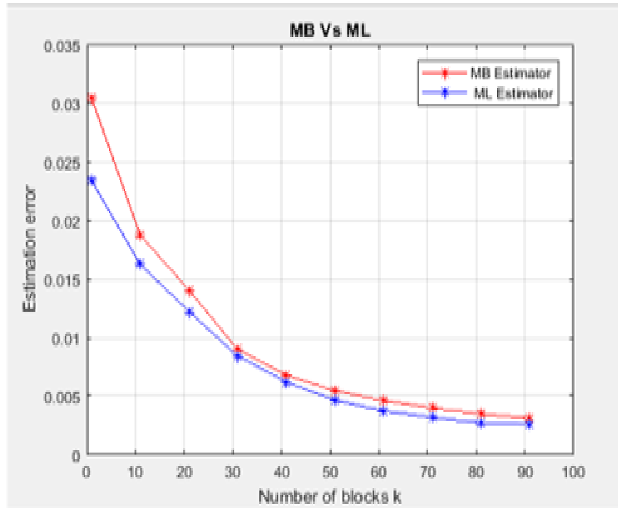

Fig 6:- Estimation errors with number of blocks

The fig 6. shows estimation errors with number of blocks, K. Here K varies from 10 to 100. Estimation errors ofML estimator and MB estimator decreases as number of blocks, K raises.

Fig 7:- represents estimation error with normal SNR of measured primary signal at CT. Distance between PT and PR and between PT and CT are fixed as 0.25 km. So average SNR at PR and CT are same. The valuation error of ML estimator and MB estimator declines, as normal SNR at CT raises from 2 dB to 12 dB and remains persistent when normal SNR at CT go beyond 12 dB. The valuation error affected through measurement error of all SNR at CT can be discounted, if normal SNR at CT raise.

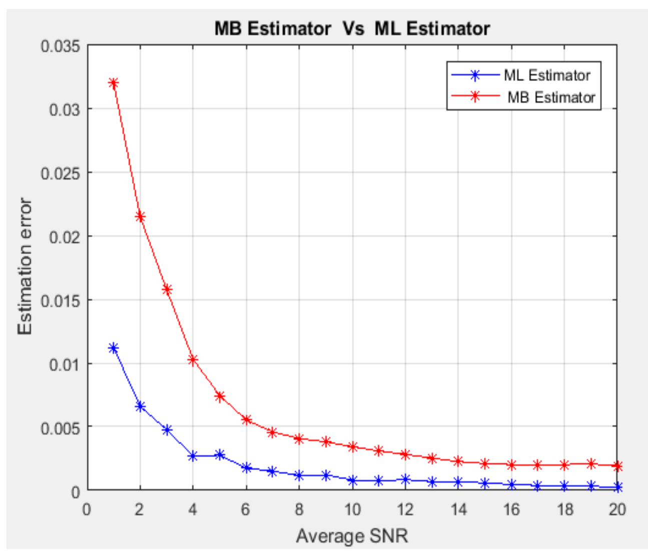

Fig 7:- Estimation error with average SNR

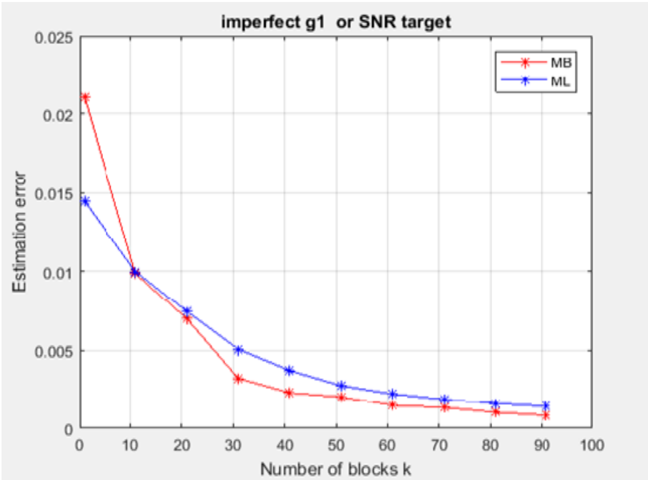

Fig 8:- Estimation error with imperfect g1 or SNR target

The fig 8. demonstrate the estimation error with imperfect g1 or SNR target. Imperfect factors mean that error of parameter is equally disseminated. When either g1 or SNR target is imperfect, ML estimator and MB estimator is reduced as K grows from 10 to 100. The effects of imperfect g1 and or γ_T onvaluation accuracy can be declinedviarising K for an assessment. When g1 and orγ_T are imperfect, MB estimator performed better than ML estimator. When g1 and or γ_T are perfect, ML estimator is higher than MB estimator.

The fig 9. demonstrates effects of ML estimator and MB estimator on attainable rate of cognitive transmission. CT uses primary channel gain to compute interfering temperature of primary link and controls transmit power before transmitting cognitive data.

The cognitive communication may interrupt outage probability of primary communication, if estimation errors exists. The CTs transmit power should be reduced to satisfy outage probability. Thereby achievable rate performance of ML estimator and MB estimator is attained. If estimated primary channel gain is perfect, achievable rate performance was also provided.

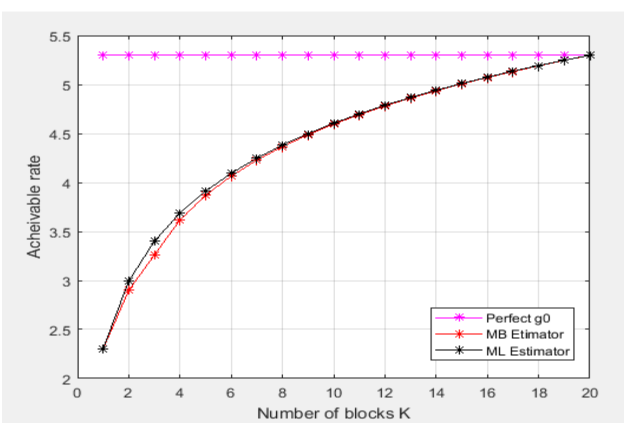

Fig 9:- Effects of ML and MB estimator on attainable rate

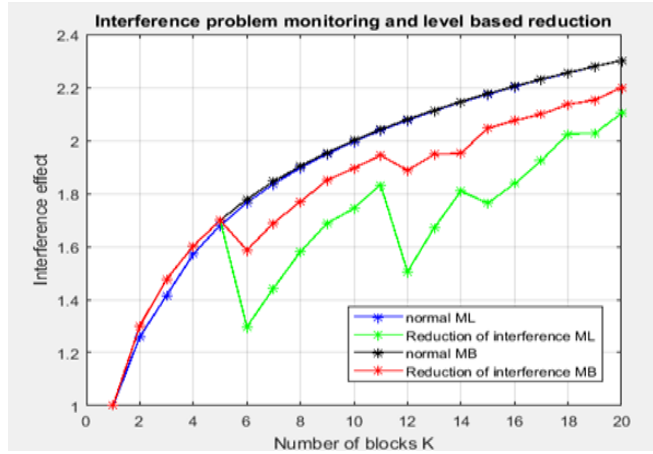

Fig 10:- Interference effect and level based reduction

As K raises, achievable rate of both estimators rises and reaches to value with perfect primary channel gain. The estimation value come close to perfect and may lead to an exact valuation, when K is enormous. Attainable rate of ML estimator perform better than attainable rate of MB estimator.

Fig 10. represents interference effect and level based reduction of interference. Graph shows that, interference level of both ML estimator and MB estimator is reduced from level of normal ML estimator and MB estimator. The interference problem can be reduced by level based reduction.

V. CONCLUSION

The gain valuation methods such as ML estimator and MB estimator are proposed for CT to attain primary network gain. Thereby CT can compute interfering temperature of prime system. Channel gain among prime transceivers stays essential for CT to achieve spectrum sharing in cognitive radio matrix. For further minimizing interference effect, a level reducing method is used. If primary signal sensed at CT is weak, ML estimator will perform better than MB estimator related to accuracy else MB estimator is better in accordance to both computational complication plus assessment accuracy. As per simulation outcomes, evaluation errors of both estimators is 0.015.

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