A New Extended Kalman Filtering for Shadow/Fading Power Estimation in Mobile Communications

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Abstract - This paper proposes a New Extended Kalman filter (NEKF) approach to improve local mean power estimation. The method is being validated using a GUI system model and then compared to existing methods, Kalman Filter (KF) with Gaussian and Non-Gaussian noise environments. Our analysis is showing that NEKF is a more accurate method in most situations. NEKF can accurately estimate the parameters and predict states in discrete nonlinear state-space for modeling shadow power.

Index Terms – Extended Kalman Filter; Fading Channel, Handoff, Kalman Filter, local mean, multipath, power estimation, shadowing, state space.

1.0 INTRODUCTION

High performance shadow/fading power estimation methods are very important for use in power control of mobile device and base station handoff. Wireless mobile communications has become an essential part of life, creating the need for research.

Mobile communication performance is affected to a large degree by fading. Fading is defined as the variation in attenuation of a signal over a particular transmission medium.

There are two main causes of fading between a mobile station (MS) and a base station (BS) [1-3]. One is multipath propagation, where the received signal strength fluctuates due to multiple paths, and shadowing (Local Mean), where the transmitted signal is lost through physical phenomena, such as absorption, refraction (Figure 1), scattering and diffraction. Shadowing is caused by obstacles, such as buildings or trees along the path of a signal from the base station (BS) to the mobile station [1-3]. Signal is affected by objects along the path of the signal as it gets reflected thus taking different paths changing the amplitude and phase, resulting in increased or decreased power at the receiver. As the mobile device (Figure 1) is moving relative to the base station the Doppler shift (Figure 2) is causing the received frequency to change in comparison to the emitted frequency. Improving the shadow power estimation and reducing the estimation error more users can be accommodated in the system.

For mobile users, frequently occurring fading dips will cause unnecessary and capacity degrading, retransmissions. To

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achieve a high throughput over fading channels, adaptive methods for adjustment of (e.g. the modulation alphabet, and the coding complexity) can be used [4-6].

These techniques require accurate shadow power estimation and prediction to combat time-variability.

Weighted sample average estimators of local mean power, are currently used in many wireless communication system providers [4, 30, 31, 34].

Window based estimators work best under the assumptions that the shadow power process is constant over the duration of the averaging window [1]. In reality shadow power varies with time due to fading, which causes deterioration of these estimates as the window size increases beyond a certain value. The window size depends on several variables. One variable is the vehicles velocity v, and sampling period Ts. There are other shadow fading characteristics that affect the optimal window size [23].

The Kalman Filter (KF) algorithm can be used for linear systems. There are continuous and discrete KF methods. KF is an optimal recursive estimator, for stochastic linear dynamic systems are minimized by the Mean Squared Error (MSE) method. Wiener-Kolmogorov filter was the predecessor that Kalman filter [2]. While KF can be applied to linear systems is not a good solution for systems with nonlinearities. NEKF Techniques have been proposed to modify KF to be applied to nonlinear systems. For example, NEKF has been proposed in nonlinear systems estimations by linearizing the estimated variables through deriving Jacobian matrices [2]. However, NEKF may not be a good choice in system with high nonlinearity, or systems that are very difficult to calculate their Jacobian matrices.

This paper has been organized as follows. Section 1 is an introduction. Section 2 explains the new method of Extended Kalman Filter (NEKF) used for determining Shadow power in mobile station. Section 3 explains the non linear state space model theory. Section 3.1 Multipath and Linear Kalman Filter 1st order. Section 4 is the measurements, simulations and results. Section 5 is the conclusion. Section 6 is future work.

Although statistical methods for parameter estimation of linear models in dynamic mobile communication systems have been developed, the estimation of both states and parameters of non linear dynamic systems remains also challenging and is being addressed in this paper.
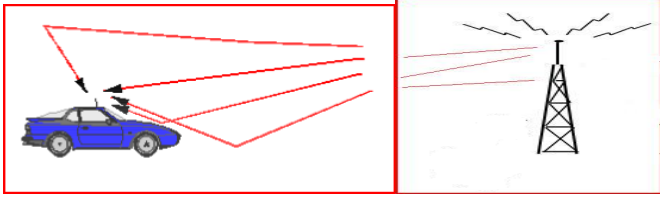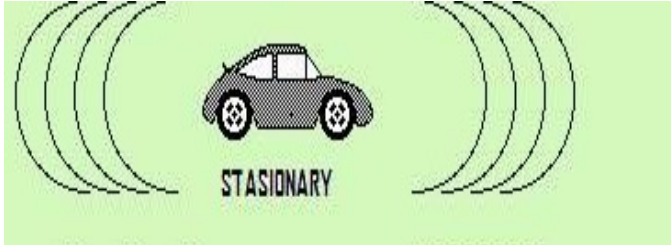
Figure 1: MS Refraction from BS

Figure 2: Doppler shift effect

2.0 EXTENDED KALMAN FILTER THEORY

KF is a form of a linear algorithm for the optimal recursive estimation of system state with specific set of output equations. Kalman filter equations can be separated into two parts [6]; the time update equations and the measurement update equation. The Process state is estimated at some time with feedback using measurements that contain noise as it can be shown in equation 4. The time update equations can also be called predictor equations while the measurement equation can be called corrector equations.

K_k: Kalman Gain
R: Environment noise covariance
Q: System noise covariance
P: Error covariance

$$x_{k+1} = f(x_k) + g(x_k, u_k) \qquad (1)$$

$$y_k = h(x_k) \qquad (2)$$

2.1 Time Update "Predicted"

Project the state ahead

$$\hat{x}_k^- = J_x \hat{x}_{k-1} + J_u u_{k-1} \qquad (3)$$

Project the error covariance ahead

$$P_k^- = J_x P_{k-1} J_x^T + Q \qquad (4)$$

2.2 Measurement Update "Corrected"

Compute the Kalman gain

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1} \qquad (5)$$

Update estimate with measurement z_k

$$\hat{x}_k = \hat{x}_k^- + K_k \left[z_k - h(\hat{x}_k^-) \right] \qquad (6)$$

Update the error covariance

$$P_k = (I - K_k H_k) P_k^- \qquad (7)$$

Initial estimates for $\hat{x}_{k-1}$ and P_{k-1}

where:
K_k: Kalman Gain
R: Environment noise covariance
Q: System noise covariance
P: Error covariance

The Extended Kalman Filter (NEKF) is the non linear extension of Kalman Filter (KF). NEKF is therefore suitable to take into account the non-linearity of the shadow power system model [7-9]. NEKF is a well known method and standard that has been considered in the theory of nonlinear state estimation [10]. KF and NEKF are known to be recursive data processing algorithms that estimate current mean and covariance. NEKF is reprocessing data at every time step without the need of storing previous measurements. The state distribution along with the mean and the covariance are being propagated analytically using a first order linearization. The predicted state estimation $\hat{x}_k^-$ for a linearized nonlinear process is expressed as follows:

$$\hat{x}_k^- = J_x \hat{x}_{k-1} + J_u u_{k-1} \qquad (8)$$

The following expression is representing the error covariance P_k^- of the predicted state estimation:

$$\hat{x}_k^- = J_x \hat{x}_{k-1} + J_u u_{k-1} \qquad (9)$$

where Q_{k-1} is the process noise, and $J_f(x_{k-1}^-)$, $J_f^T(x_{k-1}^-)$ are the Jacobian matrix and its transpose respectively. As it can be seen below J_f is the Jacobian matrix with partial derivative of all the state estimates:

$$J_f = \begin{pmatrix} \dfrac{\partial f_1}{\partial y_1} & \dfrac{\partial f_2}{\partial y_2} & \cdots & \dfrac{\partial f_n}{\partial y_n} \\ \vdots & & \ddots & \vdots \\ \dfrac{\partial f_n}{\partial y_1} & \dfrac{\partial f_n}{\partial y_2} & \cdots & \dfrac{\partial f_n}{\partial y_n} \end{pmatrix} \qquad (10)$$

$$J_y = \begin{pmatrix} \dfrac{\partial y_1}{\partial x_1} & \dfrac{\partial y_2}{\partial x_2} & \cdots & \dfrac{\partial y_n}{\partial x_n} \\ \vdots & & \ddots & \vdots \\ \dfrac{\partial y_n}{\partial x_1} & \dfrac{\partial y_n}{\partial x_2} & \cdots & \dfrac{\partial y_n}{\partial x_n} \end{pmatrix} \qquad (11)$$

Jacobian J_f and J_y matrices are shown in 10 and 11. K_k the weighting gain is defined by taking into account the measurement error that are due to the process noise as it can be seen in equation (3). The measurement matrix H_k is the Jacobian and R_k is the measurement noise. The gain K_k is directly proportional to H_k and inversely proportional to the measurement noise R_k. Expression (5) shows that the gain decreases to minimize the weight of the noise on the next estimate when the measurement noise increases while other factors are negligible. The predicted state estimation $\hat{x}_k^-$ is corrected by taking the effect of the measurements into account. The actual measurement z_k is compared to the

predicted measurement $h(\hat{x}_k^-)$ and scaled by the relevant component of the measurement information, and inversely proportional to the measurement noise R_k. This expression (4) is significant. It shows that the gain decreases to minimize the weight of the noise on the next estimate, when the measurement noise grows and other factors are negligible.

$\hat{x}_k^-$ is the predicted state estimation. It's corrected by taking the effect of the measurements. z_k is the defined as the actual measurement and it is compared to the predicted measurement $h(\hat{x}_k^-)$ and adjusted by scaled K_k weighting gain (4).Equation (5) is expressing the correction phase of the algorithm. The error covariance is updated as shown in equation (6). The parameters of the model were varied in order to test robustness.

3.0 NONLINEAR STATE-SPACE MODEL THEORY
In control theory nonlinear state-space Model (NSSM) is a powerful tool for modeling of an unknown noisy system [10]. Nonlinear dynamical factor analysis (NDFA) scales only quadratic ally with the dimensionality of the observation space, so it is also suitable for modeling systems with fairly high dimensionality [10]. In NSSM, the observations have been generated from the hidden state y_i.
Linearization of the state-space equation by making the first order Taylor expansion around the current estimate $x_{i|i-1}$.
We have a linear state-space model of x_i. The state x_i can be estimated recursively using the solution of a normal linear state-space model.

3.1 Multipath and Non-Linear section Kalman Filter 2nd order
The Non-Linear KF 2nd order model is based on the following equations:
Prediction step:

$$\begin{bmatrix} \hat{S}_{1(n|n-1)} \\ \hat{S}_{2(n|n-2)} \end{bmatrix} = A \begin{bmatrix} \hat{S}_{1(n|n-1)} \\ \hat{S}_{2(n|n-2)} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} \hat{S}_{1(n|n-1)} \\ \hat{S}_{2(n|n-1)} \end{bmatrix} \quad (16)$$

$$M_{(n|n-1)} = A[M_{(n|n-1)}]A^T + Q \quad (17)$$

KALMAN GAIN:

$$\quad (18)$$

$$K_{(n)} = (M_{(n|n-1)}H^T (M_{(n|n-1)})H^T + \sigma_H^2$$

UPDATE STEPS:

$$\begin{bmatrix} \hat{S}_{1(n|n)} \\ \hat{S}_{2(n|n)} \end{bmatrix} = \begin{bmatrix} \hat{S}_{1(n|n-1)} \\ \hat{S}_{2(n|n-2)} \end{bmatrix} + K \left(P_{(n)} - H \begin{bmatrix} \hat{S}_{1(n|n-1)} \\ \hat{S}_{1(n|n-1)} \end{bmatrix} \right) \quad (19)$$

$$M_{(n|n)} = (I - K_{(n)}H)(M_{(n|n-1)}) \quad (20)$$

$$S^* = H \begin{bmatrix} \hat{S}_{1(n|n)} \\ \hat{S}_{2(n|n)} \end{bmatrix} \quad (21)$$

S^* Is the optimal estimate of the second order shadow process

In order to stabilize continuous and discrete-time systems one has to use time-dependent or discontinuous feedback controls. On the other hand, the criterion of stabilization in the class of R_x^n piecewise-constant feedbacks is established. The piece wise-constant (figure 3) feedback is associated with a piece wise-constant function of the form u – u(x) where x   R. Piecewise constant is used in the nonlinear form (figure 4) for the coefficient α.
The coefficient α is given by the following equations:

$$S(n) = a_2 S(n-2) + a_1 S(n-1) + \varphi_n \quad (22)$$

$$a_1 = e^{\frac{vT_s}{X_{c1}}} \quad (23)$$

$$a_2 = e^{\frac{vT_s}{X_{c2}}} \quad (24)$$

where a_1 and a_2 are shadow power coefficients. $S(n)$ is $S(nT_s)$, $\varphi(n)$ is zero mean white Gaussian noise with variance σ_ϕ^2 that equals to $(1-a^2)*\sigma_s^2$ where the mean $E[S(n)]$ decreases monotonically as n increases.
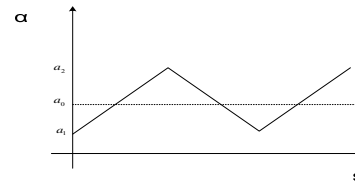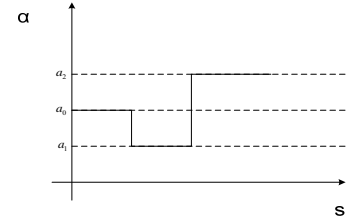

Figure 3: Linear as coefficient constant.

Figure 4: Nonlinear as coefficient piecewise constant.

4.0 GUI MEASUREMENT SIMULATION AND RESULTS
A Graphical User Interface (GUI) was developed to better assist with varying the different parameters. In Figure 5 a flow chart of the GUI identifies the different sections of the code.
Several simulations were executed. After running multiple simulations the results can be shown in Figures 6,7,8, 9.10,11,12,13,14. Clearly the NEKF applied on the incoming signal is performing as expected. The results show that the NEKF are very close to the incoming signal.
It's shown also that NEKF performs satisfactory within the range of -5dB to 5dB. Non-Gaussian noise distributions can be modeled as additive zero-mean Gaussian distributions.
Even though the computational complexity of NEKF is higher than the KF the results are satisfactory. The assumption made when using KF is that the shadow process is driven by white Gaussian noise. It's a window free approach when multipath is white [1].

There are two scenarios that are being taken into account. One scenario is the suburban were the shadow process coefficient can be regarded as constant for a wide range of velocities due to a large X_c with X_c being the correlation distance [1].As an example, in the case $X_c = 500m$ when the velocity v is in the range from 5 to 80km/hr while the sampling period can be chosen as $T_s = 0.01s$,in which case a is between [.9841, 0.9990].

The other scenario is the urban (Figure 12) case with a small X_c and large range in velocity v.

Figure 5 is the flow chart of the graphical interface (GUI)
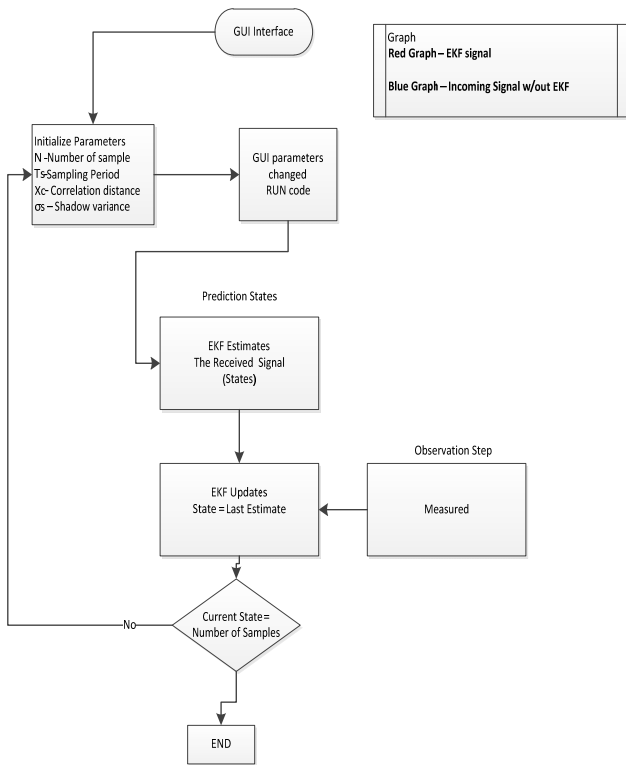
Figure 5: GUI Flow Chart.
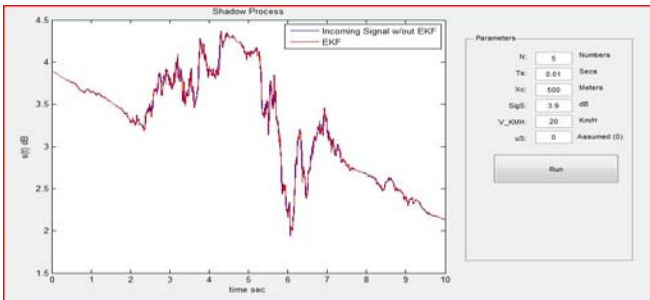
Figure 6: Simulink GUI estimation mean =0 variance = 3.9
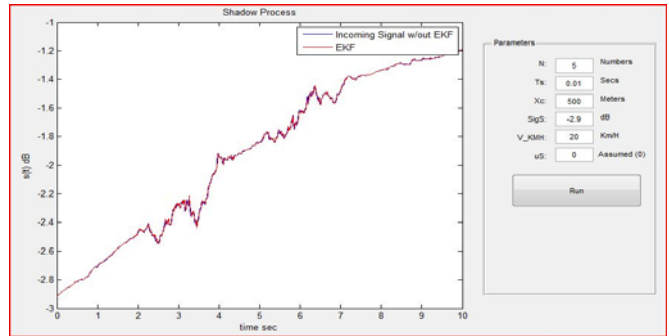
Figure 7: Simulink GUI estimation S(t) = -2.9 db

Simulink GUI was also created to give us the ability of changing the parameters and being able to see the results as in figure 7.
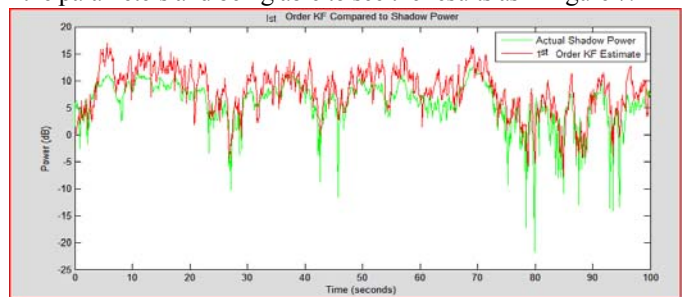
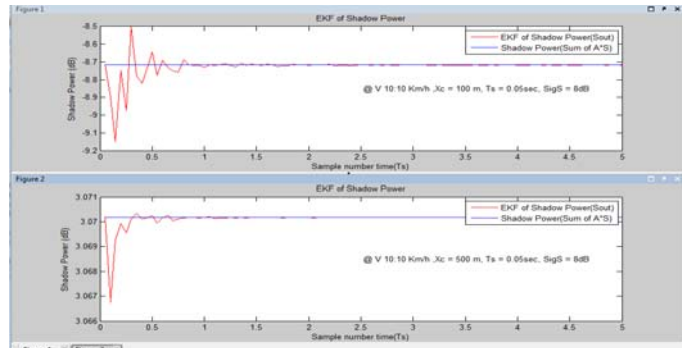

Figure 8: Compare 1st order KF with actual Shadow Power.

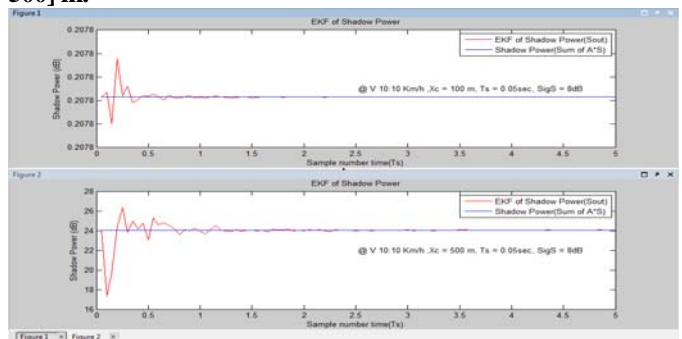**Figure 9: NEKF of Shadow Power at low speeds range [100 500] m.**

Figure 10:. NEKF ofShadow Power at low speedsrange [100- 500] m.
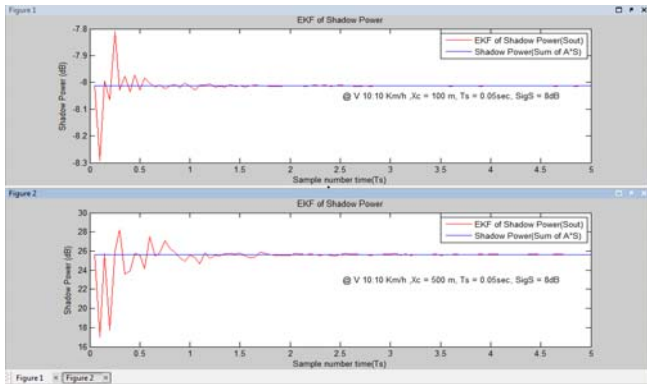
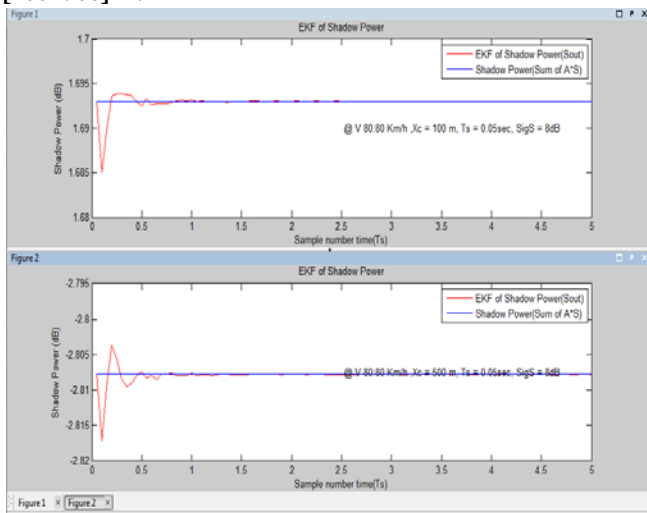**Figure 11: NEKF of Shadow Power at low speedsrange [100- 500] m.**

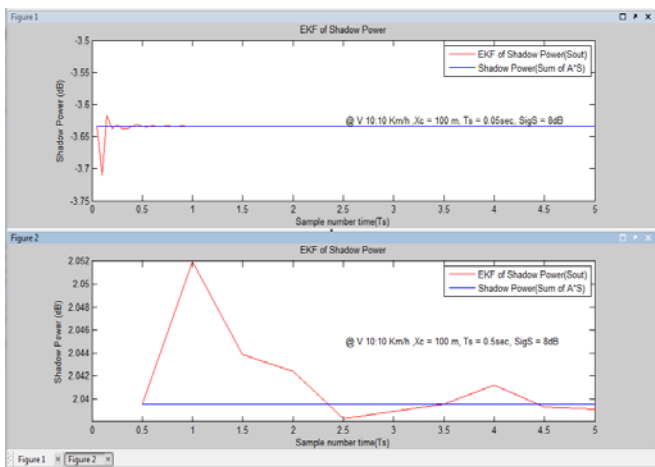**Figure 12: NEKF of Shadow Power at high speedsdistance [100 -500] m.**

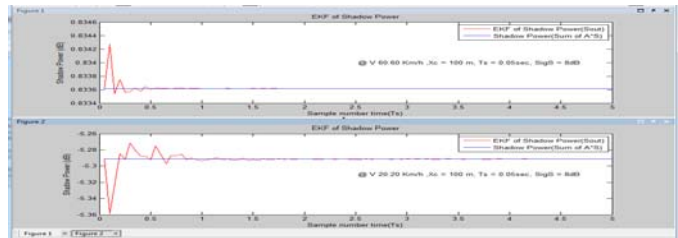**Figure 13: NEKF of Shadow Power at low speeds Time sample[.05 .5] sec.**

Figure 14: NEKF of Shadow Power Velocity [20 60] Km/h.

5.0 CONCLUSION

In this paper, the NEKF method has been proposed to optimize the performance of the shadow/fading power estimation. Simulation results show that the incoming signal is being tracked in a satisfactory manner. Increasing the shadow power variance has a direct affect in increasing the noise level seen in the shadow power estimate. Having mean =0 and variance = 3.9 then we receive 0 signal on the average (though there is a probability Shadow can be very small according to distribution) increases the noise. The major variables that are considered in this paper are; X_c which is the effective correlation distance, T_s the sampling period, v the vehicle velocity, a the correlation coefficient. In a suburban scenario, the shadow process coefficient which is a factor of the effects of environmental diversity that plays a role in wireless communications is regarded as constant for a wide range of velocities due to the fairly large X_c. X_c is the correlation distance with v being vehicle velocity and T_s the sampling period. For example, in the case X_c = 500m when the velocity is in the range from 5 to 80km/hr, the sampling period can be chosen as T_s= 0.01s, in which case a is between [.9841, 0.9990].The results have also shown that this method is more efficient when implemented in both multipath affected signals. NEKF performs significantly better than KF while preserving their structures. Parameters have been changed to simulate conditions of typical urban areas as well as rural ones. The implementation of NEKF in this paper can be used in other wireless communication devices besides the cellular phones [32].

6.0 FUTURE WORK

1. Apply the approach to larger and more complex nonlinear (NL) models and joint state/parameter estimation.
2. Extend the analysis to higher order non-Gaussian channel models.
3. Assess the impact and effects of path loss including multiusers in shadow-fading environment.

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