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Communication Channel Model Between Two Neighbors in UAV Networks

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Abstract

Unmanned aerial vehicle (UAV) networking is evolving as a major state of the art research field, thanks to the foreseen revolution in its applications. Enhancing the performance of such networks requires developing a channel model between any couple of neighbors within the UAV network. In this paper, we present a statistical signal reception model for the shadowed communication channel between two neighbors in a UAV network. In this model, we consider both the shadowing effect and the small scale fading effect. Focusing on the applications where a UAV network could be considered as a rural environment, the shadowing is considered as a line of sight (LOS) lognormal one, where the LOS component is shadowed by obstacles present within the path between two network nodes. The presented model relates the power spectral density of the received signal to noise ratio (SNR) per symbol with the physical path parameters, which could be measured in real time.

Keywords: Loo's model, lognormal shadowed distribution, Nakagami model, path loss, rice fading, shadowing, UAV network

Abbreviations: MGF, moment generating function; **LMS,** land mobile satellite; **LOS,** line of sight; **PDF,** probability density function; **SER,** symbol error rate; **SNR,** signal to noise ratio; **UAV,** Unmanned aerial vehicle

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INTRODUCTION

Tremendous advantages of Unmanned aerial vehicle (UAV) networking pave the way toward untethered applications. Major concerned areas include research, commercial, and public domains.
Greenhouse monitoring can be accomplished using a set of UAVs as a mobile sensory platform. The design, construction, and validation of such approach are predicted in ref.[1]
Another scenario of applications is about the task of locating a targeted object continuously using one or more UAVs, whereby; the track should be rapidly updated and should not be lost for any reason. Such scenario is sketched in ref.[2] In ref.,[3] detecting springs using a team of UAVs is described.

Many research centers are working on enhancing the operation of the UAV network at every composing sector. Among these sectors, the wireless channel presents a serious challenge for researchers, as it is a fundamental part of the communication system, which – in turn – is the main part of the network. For example, each node within the network needs to find the best next hop in order to forward data, this need to have, as exact as it gets, knowledge about the links between nodes and the qualities of those links, which means determining the effects of the wireless channel between nodes.[4] The precise channel model will give accurate information about the routes; hence, forwarded information will reach its final destination within optimized delay and minimum corruption. Also, It is mandatory to find the type of fading within the channels (slow/fast, flat/frequency selective) which will play a main role in determining the best techniques for the communication system of the nodes. Because of all of those reasons and others (decide about the fading margin in the link budget, calculate the channel capacity which affect the used bit rate, etc.), a lot of work has been conducted in order to find the optimal channel model between network nodes.[5,6]

Using the information collected in real time from the propagation environment, fade statistics for communication paths between network nodes could be calculated with the help of the available fundamental theory. Actually, in most cases the knowledge about fade dynamics is so little; so one should use measurements or simulation in order to gather data which is often case specific. On the other hand, in order to simulate the operation of the network and how information will be routed between nodes, it is very important to create a channel simulator. As a main reason for this simulator, a routing metric, which is related to the channel model, should be studied using simulators in order to be evaluated and enhanced before actually used.[4–7]

The remaining sections in this paper are organized as follows. In second section we present a study for the physics and statistics included within the communication channel between any two network nodes. In third Section, the complex received signal model is introduced and the probability density function (PDF); of the SNR per symbol is calculated. In order to use this PDF in real time, we reparameterize it into other format; this format uses the parameters that could be estimated in real time. In section fourth, symbol error rate (SER); for the ideal coherent MPSK modulations is calculated. Discussion of numerical and simulation results is shown in section below. Finally, we finish this paper with some concluding remarks and future aspects.

PHYSICS AND STATISTICS OF UAV NETWORKS PROPAGATION CHANNEL

Because of the dynamic nature of the communication channel between nodes within UAV networks, the transmitted signals within this type of channel are affected by random shadowing effects. The main sources of this shadowing are the nonhomogeneous obstacles that exist within the direct line of sight (LOS) signal path and causes changes in the transmitted electromagnetic waves. Considering no multipath effects, which is generated within the local environment, the received signal will be composed of a number of dominant components resulted from the diffraction and refraction of the waves within the wireless link. But as these components reach the receiving node, they will be affected by the multipath effects that result from local reflections and scattering resulted from the geometry and design of the UAV node.[8]

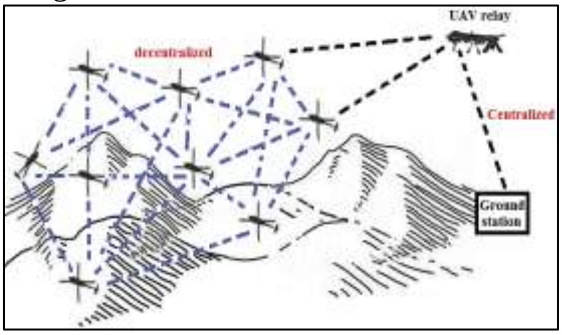

Fig. 1. *Decentralized UAV Network With Centralized UAV Relay.*

Most applications use the decentralized control scheme in order to deploy multiple UAVs as a network.[9–10] But a lot of applications need to have the UAV network close to the earth surface (low altitudes) in order to have clear and more precise information about the area they cover, besides, the area to be covered will mostly be far away from the control center or base station, thus, hybrid centralized and decentralized solutions are used where a repeater UAV (may be more than one) is used to connect the UAV network to the control center.[11–13] The overall topology is illustrated in Figure 1. As the UAV network will be close to the ground surface, then the wireless link between the UAV nodes could suffer from strong shadowing effects; this will actually affect the LOS or specular component. It is clear that shadowing caused by obstacles within the environment where the network works will have great effects on the network performance. For that, in order to reach the perfect design for the hardware of each node such as:

The antenna types and receiver technologies.[14]

1. Optimize routing protocols.[15,16]
2. Enhance task allocation procedures.[4]
3. Increase the performance of positioning schemes to be used in UAV network communications.[7]

The shadowing effects should be taken into account when we formulate the statistical model that describes the received signal envelope.

Looking at the results which was found in land mobile satellite (LMS) communications, where the channel suffer from both shadowing and small scale fading, and where the shadowing affects only the LOS components,[17,18] we can notice that the studied communication channel is the same as it is between UAV nodes, see Figure 2.

Both could be considered as rural environments, both suffer from shadowing on the LOS component, and both suffer from same multipath conditions. Using these results we derive a model for the communication channel between two neighbor nodes within the UAV network and relate it with real time estimated parameters.

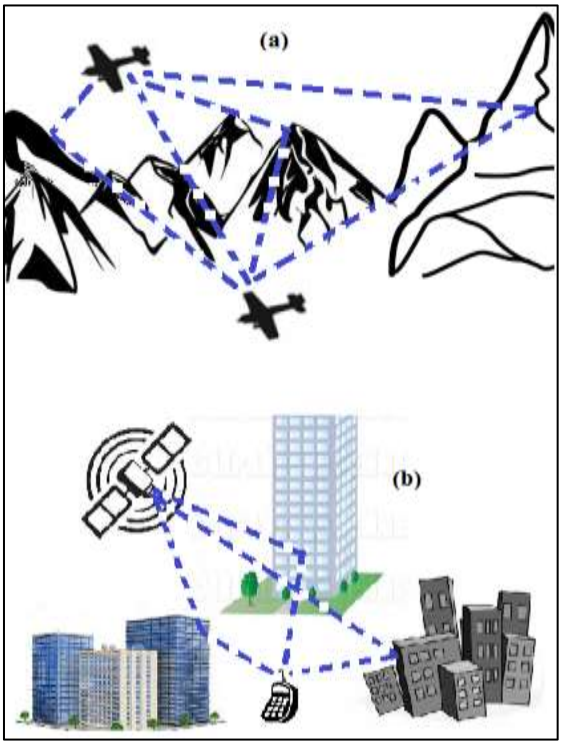

***Fig. 2**. Proposed Approach (a) The Wireless Channel Within UAV Networks in Rural Environments. (b) The LMS Wireless Channel.*

In the model proposed in this paper, we assume the presence of scattered waves together with the LOS signal component; this is identical to the phenomenon observed in Rician fading.[19] The difference between the proposed model and the Rician one is that the LOS component is assumed to be random with lognormal distribution because of the shadowing effect.

This study is aiming at finding a channel model that could be used to calculate the channel quality depending on the channel parameters estimated in real time. The resulting performance metric, which is the SER, will be used by different network nodes in order to build their routing tables efficiently.

Using this routing metric will increase the total network efficiency.

A STATISTICAL MODEL FOR SHADOWING IN UAV NETWORK COMMUNICATIONS CHANNELS

In order to build a communication channel model for the wireless channel between the network nodes, as we have seen in the previous section, we have to consider three different types of fading models; these models shall be used to describe different fading phenomenon within the wireless channel:

1. The first model we have to consider is the large scale path loss model, which is used to characterize the average received signal strength at the receiving node.
2. The second model we have to include is the shadowing model. This model is used in order to estimate the fluctuation in the received signal power because of the electromagnetic large obstacles within the wireless channel.
3. Finally, the small scale fading model should be involved. Actually, it is used to characterize the fluctuation in the received signal envelope which is resulted because of scattering near the receiving node.

Large-Scale Fading

According to the free space path loss model, the received signal power formula can be written according to the Friis power transmission formula as follows:[20]

$$P_r = P_t G_t G_r \left(\frac{\lambda}{4\pi d}\right)^2 \quad \text{Eq. (1)}$$

where d is the distance between the two nodes, G_r and G_t are the antenna gains of receiving node and the transmitting node, respectively, P_r, P_t are the transmitted and received power, respectively, and λ is the wavelength of the carrier frequency. This means that the received signal power decays as d^{-2}.

In most cases, the network will work in a nonfree space environment, because of that it is better to use the generalized path loss model which could be written in decibel units as:

$$PL(dB) = PL_{ref}(dB) + \alpha 10 \log\left(\frac{d_{ref}}{d}\right) \quad \text{Eq. (2)}$$

where PL is the path loss for a given distance d, is the path loss exponent which depends on the environment clutter and could be estimated previously using collected information about the area where the UAV will be placed and work and information about their heights, and PL_{ref} refers to the path loss at a reference distance d_{ref} which is also determined according to the used antennas at the two communicating nodes.[21] Usually PL_{ref} is the free space path loss gain at the distance d_{ref} when we use omnidirectional antennas (this is the case of UAV nodes), so we can write the following formula for the average received signal power:

$$\bar{S} = P_t \left(\frac{\lambda}{4\pi d_{ref}}\right)^2 \left(\frac{d_{ref}}{d}\right)^{\alpha} \quad \text{Eq. (3)}$$

where $G_t = G_r = 1$ considering omnidirectional antennas to be used on nodes.

The value of α ranges from 2 to 6 for outdoor environments,[21] where it equals 2 in free space (assuming there is a line of sight between the communicating nodes). It depends on several factors:[21,22] the heights of the two communicating nodes, the situation of the ground (flat or other), quantity of particles in the air, atmospheric conditions, the volume of obstacles within the communication channel environment, and others. Usually it is assumed to be equal to 4 if we cannot estimate its value, where it is better to use empirical methods to estimate its value as these methods take into consideration the used frequency and antenna heights.[22,23] In the case of UAV networks it is usually estimated taking both the surrounded environment and the application into consideration. As there is always a LOS between UAVs, its value will be typically between 2 and 4. As an example, in ref.[24] they set the path loss exponent to 3.5 to consider the effect of obstacles between two UAVs, while in refs.[16–25] they set it to 2 considering good LOS conditions between UAVs. In ref.[26,27] they set it to 3.

Received Signal Envelope

According to the discussion above, it is principal to consider that the received signal envelope in UAV network communications channels suffers from the same effects that exist in Rician fading.[19] Actually, a lot of researches have used this assumption to model the small scale fading between UAVs.[5,14,16,28] Also, we are going here to use Rician fading to model the multipath fading between network nodes, except that in our situation, the LOS component is a random variable with lognormal distribution, and this is in order to take the shadowing effects into consideration within the channel model. Assuming narrowband stationary model, and according to the definition of the scatter and the LOS components provided earlier, the low pass equivalent complex envelope of the received signal could be written as follows:[29]

$$\mathrm{R(t)} = W(t)\exp\big(j\emptyset(t)\big) + A(t)\exp(j\emptyset_0) \qquad \text{Eq. (4)}$$

where *W(t)* is the amplitude of the scatter component, and it is a stationary random process that follows a Rayleigh distribution, this will be shown in the hereafter, and *A(t)* is the amplitude of the LOS component and it is assumed to be lognormal distributed. In this model, ϕ_0 is the deterministic phase of the LOS component and $\phi(t)$ is the stationary random phase process with uniform distribution over the range $[-\pi,\pi)$. *A(t)* and *W(t)* are independent random processes, and they are also independent of $\phi(t)$.

Rician Effect

If *A(t)* is initially held constant, then the conditional PDF of the received signal envelope $R(t) = |R(t)|$ is a PDF of Rician distribution:[19]

$$f_{R|A}(r|a) = \frac{r}{b_0}\exp\left(-\frac{r^2+a^2}{2b_0}\right) I_0\left(\frac{ar}{b_0}\right) \qquad \text{Eq. (5)}$$

where $2b_0 = E[W^2]$ represents the average scattered power due to the multipath components, and $I_0(.)$ is the modified Bessel function of the first kind and zeroth order.

In order to find the distribution of W, we can let a tend to 0. Using the approximation of the value of Bessel function when its argument is small,[30] and from Eqs. (6), (9), and (7):

$$I_{\nu-1}(x) \approx \frac{\left(\frac{x}{2}\right)^{\nu-1}}{\Gamma(\nu)} \qquad \text{Eq. (6)}$$

Taking $x = \frac{ar}{b_0}$ and $\nu = 1$, then as a tend to 0; we have:

$$I_0\left(\frac{ar}{b_0}\right) \approx \frac{1}{\Gamma(1)} = 1 \qquad \text{Eq. (7)}$$

Using Eq. (7) into (5) and after some mathematical manipulation gives:

$$f_{R|A}(r|a) = \frac{r}{b_0}\exp\left(-\frac{r^2+a^2}{2b_0}\right) \qquad \text{Eq. (8)}$$

When we let a tend to 0, this means that we concentrate the power only in the scatter components, where no power will be exist in the LOS component. This means that the received signal in Eq. (4) will be related only to W, and so the conditional probability density function we have in Eq. (8) will equal the probability density function of W, and this gives that:

$$f_W(w) = \frac{w}{b_0} \exp\left(-\frac{w^2}{2b_0}\right), \quad w \geq 0 \quad \text{Eq. (9)}$$

Using Eq. (8) and letting a equals zero, we find that the above equation is equivalent to the Rayleigh distribution[19] from Eqs. 2 to 6:

$$f_W(w) = \frac{2w}{\mathrm{p}} \exp\left(-\frac{w^2}{\mathrm{p}}\right) \quad \text{Eq. (10)}$$

Shadowing Effect

In order to determine the distribution of the received signal envelope at the time where the LOS component is a lognormal distributed random variable, we can use the conditional mathematical expectation "theorem of total probability":

$$f_R(r) = E_A\left[f_{R|A}(r|a)\right]$$

$$f_R(r) = \int_0^\infty f_{R|A}(r|a) f_A(a)\, da \quad \text{Eq. (11)}$$

where $E_A[.]$ Is the expectation with respect to A. Eq. (11) gives:

$$f_R(r) = \frac{r}{b_0} \int_0^\infty \exp\left(-\frac{r^2 + a^2}{2b_0}\right) I_0\left(\frac{ar}{b_0}\right) f_A(a)\, da \quad \text{Eq. (12)}$$

where

$$f_A(a) = \frac{1}{a\sqrt{2\pi d_0}} \exp\left[-\frac{(\ln a - \mu)^2}{2d_0}\right] \quad \text{Eq. (13)}$$

Here, μ=E[ln(A)] and $d_0 = Var[\ln(A)]$, $Var[.]$ is the variance, are the mean and the variance of the lognormal distribution, respectively.

Eq. (12) is related to $2b_0$, the mean of $\ln(A)$, and the variance of $\ln(A)$. In practice and in real time situations we need to estimate the channel behavior using measurements that are collected by the network node, this is done in order to calculate the cost of the link between a node and its neighbors, which will be then used to choose the best path to forward data. From these measurements we can estimate the shadowing variance.[31,32] and the Rician factor.[33–36] So we have to relate the parameters of this equation with the shadowing variance ($\sigma^2_{X_{dB}}$) and the Rician factor (K).

As the LOS component is a random variable, then the LOS power component is also a random variable, and so the Rician factor is also a random variable, this is because the Rician factor K, which is related to a and b_0 through the relationship $K=a^2/2b_0$, is simply the ratio of the total power of the dominant components (a^2) to the total power of the scattered waves ($2b_0$). Thus, in real time, we actually estimate the average Rician factor (K_r), and we have to relate the parameters of (12) with this average value.

As proved in ref.,[22] the shadow fading component in the received power is a zero-mean Gaussian random variable added to the path loss when it is expressed in dB. In order to characterize the shadowing effect we have to estimate or measure the variance of the path loss which will also be expressed in dB. Taking the shadowing effect into consideration, without the multipath effect, we can rewrite Eq. (2) as follows:

$$PL(dB) = PL_0(dB) + \alpha 10 \log\left(\frac{d_0}{d}\right) + X(dB) \quad \text{Eq.14}$$

where X(dB) is the zero-mean Gaussian distributed random variable that represents the shadowing effect and whose variance will be denoted $\sigma^2_{X_{dB}}$. The shadowing variance ($\sigma^2_{X_{dB}}$) could be estimated by empirical measurements in real time.[22] We have to relate all our parameters with $\sigma^2_{X_{dB}}$ and K_r in order to evaluate any required quantity using the actual measured parameters.[33–36]

In order to relate the parameters of Eq. (12) which are (d_0, μ, b_0) with the parameters which we can estimate in real time (d, $\sigma^2_{X_{dB}}$, K_r), we first need to find the average Rician factor in the channel, this could be done by taking the first moment of the Rician factor probability density function. For that we will start by finding the PDF of the Rician factor in the channel.

Assuming that the variation of the LOS component follows Eq. (13), it is possible to perform a transformation of variables to find the distribution of k. Using the relationship $k=a^2/2b_0$, it follows that $a^2=2b_0k$. To obtain the PDF of the transformed variable k, we must evaluate:

$$f_K(k) = f_A\left(\sqrt{2b_0k}\right)\left|\frac{da}{dk}\right| \quad \text{Eq. (15)}$$

which, in turn, gives

$$f_K(k) = \frac{1}{2k\sqrt{2\pi d_0}} \times \exp\left[-\frac{\left(\ln\sqrt{2b_0k}-\mu\right)^2}{2d_0}\right] \quad \text{Eq. (16)}$$

or,

$$f_K(k) = \frac{1}{k\sqrt{2\pi(4d_0)}} \times \exp\left[-\frac{\left(\ln k-(2\mu-\ln(2b_0))\right)^2}{2(4d_0)}\right] \quad \text{Eq. (17)}$$

We can see that this is the PDF of a log-normal variable and we can deduce that:

$$\mu_{\ln k} = \ln K_r - 2d_0 \quad \text{Eq. (18)}$$

$$Var[\ln(k)] = 4d_0 \quad \text{Eq. (19)}$$

Using the first moment relation of the log-normal PDF,[37] we can find that:

$$K_r = \frac{\Omega}{2b_0} \quad \text{Eq. (20)}$$

where Ω is the average power of the LOS component. It is also the second moment of the LOS component.

Recall that the Rayleigh and lognormal random processes are additive, then the mean of the received power is the sum of the mean power of the LOS component and the average power of the multipath component, $\bar{S} = \Omega + 2b_0$, and using (20), then:

$$\Omega = \frac{K_r}{1+K_r}\bar{S} \quad \text{Eq. (21)}$$

$$2b_0 = \frac{\bar{S}}{K_r+1} \quad \text{Eq. (22)}$$

Using equation (3) we find:

$$2b_0 = \frac{P_t\left(\frac{\lambda}{4\pi d_{ref}}\right)^2\left(\frac{d_{ref}}{d}\right)^{\alpha}}{K_r+1} \quad \text{Eq. (23)}$$

$$\Omega = \frac{K_r}{1+K_r}P_t\left(\frac{\lambda}{4\pi d_{ref}}\right)^2\left(\frac{d_{ref}}{d}\right)^{\alpha} \quad \text{Eq. (24)}$$

The second order moment of the LOS received component can be written as[37]:

$$\Omega = \exp[2\mu + 2d_0] \quad \text{Eq. (25)}$$

which gives:

$$\mu = \frac{(\ln\Omega - 2d_0)}{2} \quad \text{Eq. (26)}$$

and so,

$$\mu = \frac{1}{2}\ln\left(\frac{K_r}{1+K_r}P_t\left(\frac{\lambda}{4\pi d_{ref}}\right)^2\left(\frac{d_{ref}}{d}\right)^{\alpha}\right) - d_0 \quad \text{Eq. (27)}$$

Now we have to find the relation between d_0 and the real time estimated parameters. The shadowing variance is the variance of the ratio $\frac{P_t}{S_a}$ in dB,[21,22–38,39] where S_a is the received LOS component power, so, in order to relate d_0 with the shadowing variance we can estimate in real time, it is sufficient to find the distribution of the ratio $\Psi_{dB} = 10\log\frac{P_t}{S_a}$. As it is proved in

Appendix (I), the PDF of Ψ_{dB} is:

$$f_{\Psi_{dB}}(\Psi_{dB}) = \frac{1}{\sqrt{2\pi(4\zeta^2 d_0)}} exp\left[-\frac{\left(\Psi_{dB}-(10\log P_t - 2\zeta\mu)\right)^2}{2(4\zeta^2 d_0)}\right] \quad \text{Eq. (28)}$$

which means, as it is expected, that Ψ_{dB} is normally distributed with variance: $\sigma^2_{X_{dB}}=4\zeta^2 d_0$, where $\zeta=10/\ln(10)$. This means that we can relate d_0 to $\sigma^2_{X_{dB}}$using the relation:

$$d_0 = \sigma^2_{X_{dB}}/4\zeta^2 \quad \text{Eq. (29)}$$

Eq. (23), (27), and (29) could now be used to calculate all of the required measurements (PDF, CDF, SER, and others) depending on measurements in real time operation.

Substituting Eq. (13) into (12) gives:

$$f_R(r) = \frac{r}{\sqrt{2\pi d_0}b_0}\int_0^{\infty}\frac{1}{a}\exp\left(-\frac{b_0(\ln a-\mu)^2 + d_0(r^2+a^2)}{2d_0b_0}\right) \times I_0\left(\frac{ar}{b_0}\right)da \quad \text{Eq. (30)}$$

Eq. (30) is the PDF of the received signal envelope within the shadowed Rician communication channel observed in UAV networks between any two neighbors. This is the PDF of the Loo's statistical model for land mobile satellite communications channels derived in ref.,[17] but here we could relate the Loo's parameters with those we can estimate in real time working.

Using the change of variable ($S=r^2$) where S is the received signal power, and as $\frac{dr}{ds}=\frac{1}{2r}$ we can find the PDF of the received power as follows:

$$f_S(s)=\frac{1}{2b_0\sqrt{2\pi d_0}}\int_0^\infty \frac{1}{a}\exp\left[-\frac{(\ln a-\mu)^2}{2\times d_0}\right]\exp\left(-\frac{s+a^2}{2b_0}\right)\times I_0\left(\frac{a\sqrt{s}}{b_0}\right)da \quad \text{Eq. (31)}$$

In order to calculate the SER within the wireless link, we need to find the PDF of the SNR or equivalently the PDF of the ratio of symbol energy to the noise power spectral density ($\gamma=\frac{sT_s}{N_0}$). This can be done by using change of variable on Eq. (31). The change of variable we could use is:

$$f_\gamma(\gamma)d\gamma=f_S(s)ds \quad \text{Eq. (32)}$$

and so,

$$f_\gamma(\gamma)=\frac{N_0}{T_s}f_S(s)=\frac{N_0}{T_s}f_S\left(\frac{N_0}{T_s}\gamma\right) \quad \text{Eq. (33)}$$

Knowing that $\bar{\gamma}=\frac{T_s}{N_0}\bar{S}$ we have $\frac{T_s}{N_0}=\frac{\bar{\gamma}}{\bar{S}}$ and so, $f_\gamma(\gamma)=\frac{\bar{S}}{\bar{\gamma}}f_S\left(\frac{\bar{S}}{\bar{\gamma}}\gamma\right)$ which gives:

$$f_\gamma(\gamma)=\frac{\bar{S}}{2\bar{\gamma}\sqrt{2\pi d_0}b_0}\int_0^\infty \frac{1}{a}\exp\left[-\frac{(\ln a-\mu)^2}{2d_0}\right]\exp\left(-\frac{\frac{\bar{S}}{\bar{\gamma}}\gamma+a^2}{2b_0}\right)\times I_0\left(\frac{a}{b_0}\sqrt{\frac{\bar{S}}{\bar{\gamma}}\gamma}\right)da \quad \text{Eq. (34)}$$

Eq. (34) is the probability density function of the SNR per symbol when the average SNR per symbol is $\bar{\gamma}$, the shadowing variance is $\sigma^2_{X_{dB}}$, and the average Rician factor is K_r.

SER CALCULATION

The following relation could be used to calculate the SER depending on the PDF of the SNR per symbol[21]:

$$SER=\int_0^\infty P_s(\gamma)f_\gamma(\gamma)d\gamma \quad \text{Eq. (35)}$$

where $P_s(\gamma)$ is the probability of symbol error in Additive White Gaussian Noise (AWGN) channels with SNR per symbol γ. In this paper we will use MPSK modulation with ideal coherent detection as it is widely used in UAV networks. We know that, for ideal coherent MPSK, the probability of symbol error in AWGN channels is[21]:

$$P_s(\gamma)=2Q\left(\sqrt{2\gamma}\sin\left(\frac{\pi}{M}\right)\right) \quad \text{Eq. (36)}$$

where M is the modulation order. So the SER could be found from Eq. (34) as follows:

$$SER=\frac{\bar{S}}{b_0\bar{\gamma}\sqrt{2\pi d_0}}\int_0^\infty Q\left(\sqrt{2\gamma}\sin\left(\frac{\pi}{M}\right)\right)\int_0^\infty \frac{1}{a}\exp\left[-\frac{(\ln a-\mu)^2}{2d_0}\right]\times\exp\left(-\frac{\bar{S}\gamma+\bar{\gamma}a^2}{2b_0\bar{\gamma}}\right)I_0\left(\frac{a}{b_0}\sqrt{\frac{\bar{S}\gamma}{\bar{\gamma}}}\right)da\,d\gamma \quad \text{Eq. (37)}$$

It is better to normalize the parameters within Eq. (37) in order to get a relation which is independent of the received signal power, and so independent of distance, transmitted power, bit rate, and bandwidth, and to be related only with the average SNR per symbol. Because of that it is better to use the following normalization:

$$a_n=a/\sqrt{\bar{S}} \quad \text{Eq. (38)}$$

$$2b_{0n}=\frac{1}{K_r+1} \quad \text{Eq. (39)}$$

$$\mu_n=\frac{1}{2}ln\left(\frac{K_r}{1+K_r}\right)-d_0 \quad \text{Eq. (40)}$$

The normalization defined by Eqs. (36), (37), and (38) keeps the statistics properties unchanged (see Appendix II).

Knowing that $\ln(a_n)-\mu_n=\ln(a)-\mu$, we can write Eq. (37) as follows:

$$SER = \frac{1}{b_{0n}\bar{\gamma}\sqrt{2\pi d_0}} \int_0^{\infty} Q\left(\sqrt{2\gamma}\sin\left(\frac{\pi}{M}\right)\right) \times \int_0^{\infty} \frac{1}{a_n} \exp\left[-\frac{(\ln a_n - \mu_n)^2}{2d_0}\right] \exp\left(-\frac{\gamma + a_n{}^2}{2b_{0n}\bar{\gamma}}\right) \times I_0\left(\frac{a_n}{b_{0n}}\sqrt{\frac{\gamma}{\bar{\gamma}}}\right) da_n\, d\gamma \quad \text{Eq. (41)}$$

Eq. (41) represents the probability of errors that could exist in the received signal at the receiving node when the used modulation is MPSK, and when the average received SNR per symbol is $\bar{\gamma}$, knowing that the shadowing variance in the communication channel between the two nodes is $\sigma^2_{X_{dB}}$ and the average Rician factor is K_r. All the parameters in Eq. (41) could be calculated using Eq. (23), (27), and (29).

Actually, it is very difficult to find a closed form formulas for Eq. (41), and in order to calculate it we have to use numerical solutions as the “trapz” function available in MATLAB. This is very complicated and time consuming when implemented on the UAV boards. For that, it is better if we could find an acceptable approximation to be used in order to write a closed form formula for the SER.
In ref.,[18] another shadowed Rician model has been proposed where the shadowing is also considered as LOS shadowing, which means that the shadowing affects only the LOS component, but it is characterized as a Nakagami-m distributed random variable. Assuming narrowband stationary model, this model uses the same low pass equivalent complex envelope of the received signal shown in Eq. (4), except that *A(t)* here follows a Nakagami-m distribution. The multipath component is characterized by the Rayleigh distribution too. It has been shown that the model in ref.[18] provides a similar fit to the Loo’s model, and it is considered as an acceptable approximation for it without losing in the characteristics of the channel model. Thus we can use this approximation in order to find a closed form formula for the SER.

The Nakagami-m model has been proposed in ref.[40] According to this model the amplitude of the LOS component is distributed according to Nakagami-m distribution:

$$f_A(a) = \frac{2m^m a^{2m-1}}{\Omega^m \Gamma(m)} \exp\left(-\frac{ma^2}{\Omega}\right), a \geq 0 \quad \text{Eq. (42)}$$

where $\Gamma(.)$ is the Gamma function, and $m = \frac{\Omega^2}{Var[S_a]} \geq 0$ is the Nakagami parameter.

In order to model the different types of LOS conditions in a variety of UAV networks channels, we will let m to change from 0 to infinity. In the traditional Nakagami model for multipath fading,[19] m changes over the limited range of m≥0.5. The case of m=0,$f_A(a) = \delta(a)$, corresponds to urban areas where the LOS is totally obstructed, while the case of infinity m, $f_A(a) = \delta(a - \sqrt{\Omega})$, corresponds to open areas with no LOS obstructions. These two extreme cases do not exist in real practical situations, thus, moderate values of m which corresponds to rural areas where the LOS component is partially obstructed, case of UAV networks, are expected.

In order to use this approximated model, we have to relate its parameters (Ω, m, b_0) with the parameters we can estimate in real time (d, K_r, $\sigma^2_{X_{dB}}$). Actually we have already related b_0 and Ω with d and K_r by Eq. (23) and Eq. (24), respectively. Now we only need to relate *m* with the parameters that could be estimated in real time. Using the second-order matching used in ref.[18] we get the following relation that relates *m* with d_0:

$$d_0 = \frac{\Psi'(m)}{4} \quad \text{Eq. (43)}$$

where Ψ'(.) is the first derivative of the psi function Ψ(.).[41] Using Eq. (29) and (43) we get the relation that relates m with $\sigma^2_{X_{dB}}$:

$$\sigma^2_{X_{dB}} = \zeta^2 \Psi'(m) \quad \text{Eq. (44)}$$

So, from the real time estimated parameters we can find b_0 and Ω using Eq. (23) and (24), respectively, and find m numerically using Eq. (44).

Now we have to find a closed form formula for the SER. In order to do that, we have to find the PDF of the received SNR per symbol.

Using Eq. (5) and (42), we can use the conditional mathematical expectation $\int_0^\infty f_{R|A}(r|a) f_A(a) da$, which gives the PDF of the received signal envelope:

$$f_R(r) = \frac{r}{b_0}\exp\left(-\frac{r^2}{2b_0}\right)\int_0^\infty \exp\left(-\frac{a^2}{2b_0}\right) I_0\left(\frac{ar}{b_0}\right) \times \frac{2m^m a^{2m-1}}{\Omega^m \Gamma(m)} \exp\left(-\frac{ma^2}{\Omega}\right) da \quad \text{Eq. (45)}$$

and so,

$$f_R(r) = \left(\frac{2b_0 m}{2b_0 m + \Omega}\right)^m \frac{r}{b_0}\exp\left(-\frac{r^2}{2b_0}\right) \times {}_1F_1\left(m; 1; \frac{\Omega r^2}{2b_0(2b_0 m + \Omega)}\right), for\ r \geq 0 \quad \text{Eq. (46)}$$

where ${}_1F_1(.;.;.)$ is the confluent hypergeometric function.[41]

The PDF of the received power could be then determined from Eq. (46) as follows:

$$f_S(s) = \left(\frac{2b_0 m}{2b_0 m + \Omega}\right)^m \frac{1}{2b_0}\exp\left(-\frac{s}{2b_0}\right) \times {}_1F_1\left(m; 1; \frac{\Omega s}{2b_0(2b_0 m + \Omega)}\right), for\ s \geq 0 \quad \text{Eq. (47)}$$

As we have seen before, $f_\gamma(\gamma) = \frac{\bar{S}}{\bar{\gamma}} f_S\left(\frac{\bar{S}}{\bar{\gamma}}\gamma\right)$, then we can find the PDF of γ as follows

$$f_\gamma(\gamma) = \left(\frac{2b_0 m}{2b_0 m + \Omega}\right)^m \frac{\bar{S}}{2b_0\bar{\gamma}}\exp\left(-\frac{\bar{S}\gamma}{2b_0\bar{\gamma}}\right) \times {}_1F_1\left(m, 1, \frac{\Omega \bar{S}\gamma}{2b_0\bar{\gamma}(2b_0 m + \Omega)}\right) \quad \text{Eq. (48)}$$

The moment generating function (MGF) could be found using the table of integrals in[42] as follows:

$$M_\gamma(s) = \frac{(2b_0 m)^m \left(1 + \frac{2b_0}{\bar{S}}\bar{\gamma}s\right)^{m-1}}{\left[(2b_0 m + \Omega)\left(1 + \frac{2b_0}{\bar{S}}\bar{\gamma}s\right) - \Omega\right]^m} \quad \text{Eq. (49)}$$

In order to eliminate $\bar{S}$ from the equations we can use Eq. (39) together with the following normalization (using Eq. (21)):

$$\Omega_n = \frac{\Omega}{\bar{S}} = \frac{K_r}{1+K_r} \quad \text{Eq. (50)}$$

With this normalization, we can find that the Nakagami parameter m will keep its value without any changes, as it is the square of the ratio of two power quantities.

Equation (49) could be rewritten using the normalization defined by Eqs. (39) and (50) as follows:

$$M_\gamma(s) = \frac{(2b_{0n} m)^m (1 + 2b_{0n}\bar{\gamma}s)^{m-1}}{[(2b_{0n} m + \Omega_n)(1 + 2b_{0n}\bar{\gamma}s) - \Omega_n]^m} \quad \text{Eq. (51)}$$

Based on the MGF, we can find the SER for a number of modulation schemes in uncorrelated fading channels.[19] For the MPSK modulation we can find the SER using Eq. (51) as follows:[42]

$$SER = \frac{(2b_0 m)^m G_{1,MPSK}^{m-1}}{4G_{2,MPSK}^m} F_1\left(\frac{1}{2}, 1-m, m; 2; \frac{1}{G_{1,MPSK}}, \frac{2b_0 m}{G_{2,MPSK}}\right)$$
$$+\frac{\sqrt{w}(2b_0 m)^m G_{1,MPSK}^{m-1}}{\pi G_{2,MPSK}^m} F_D^3\left(\frac{1}{2}, -\frac{1}{2}, 1-m, m; \frac{3}{2}; w, \frac{w}{G_{1,MPSK}}, \frac{2b_0 m w}{G_{2,MPSK}}\right) \qquad \text{Eq. (52)}$$

where

$$G_{1,MPSK} = 1 + \frac{2b_0\bar{\gamma}}{\bar{S}} g_{MPSK}, \qquad \text{Eq. (53)}$$
$$G_{2,MPSK} = 2b_0 m + \frac{2b_0\bar{\gamma}}{\bar{S}} g_{MPSK}(2b_0 m + \Omega), \qquad \text{Eq. (54)}$$
$$g_{MPSK} = \sin^2\left(\frac{\pi}{M}\right), \qquad \text{Eq. (55)}$$
$$w = 1 - g_{MPSK}, \qquad \text{Eq. (56)}$$

where F_D^n is the Lauricella function,[43] and F_1=F_D^2 is the Appell hypergeometric function. Eq. (52) could be rewritten using the normalization defined by Eq. (39) and (50) as follows:

$$SER = \frac{(2b_{0n} m)^m G_{1n,MPSK}^{m-1}}{4G_{2n,MPSK}^m} F_1\left(\frac{1}{2}, 1-m, m; 2; \frac{1}{G_{1n,MPSK}}, \frac{2b_{0n} m}{G_{2n,MPSK}}\right) + \frac{\sqrt{w}(2b_{0n} m)^m G_{1n,MPSK}^{m-1}}{\pi G_{2n,MPSK}^m} \times$$
$$F_D^3\left(\frac{1}{2}, -\frac{1}{2}, 1-m, m; \frac{3}{2}; w, \frac{w}{G_{1n,MPSK}}, \frac{2b_{0n} m w}{G_{2n,MPSK}}\right) \qquad \text{Eq. (57)}$$

where:

$$G_{1n,MPSK} = 1 + 2b_{0n}\bar{\gamma} g_{MPSK}, \qquad \text{Eq. (58)}$$
$$G_{2n,MPSK} = 2b_{0n} m + 2b_{0n}\bar{\gamma} g_{MPSK}(2b_{0n} m + \Omega_n) \qquad \text{Eq. (59)}$$

Equations Eq. (57) is the probability of errors that could exist in the received signal at the receiving node when the used modulation is MPSK, and when the average received SNR per symbol is$\bar{\gamma}$, knowing that the shadowing variance in the communication channel between the two nodes is $\sigma_{X_{dB}}^2$ and the average Rician factor isK_r.

NUMERICAL AND SIMULATION RESULTS

The models discussed in the previous sections predict fade distribution for the signals within the channel between any two nodes in the UAV network and include the effects of both the shadowing and the multipath Rician small scale fading. System engineers need to know the fade distributions in order to make a reliable UAV network system. The dynamics of propagation will affect such system specifications such as packet length, coding, best route and others.

In this section, we study the variation of the SER in the wireless link between two neighbors in UAV networks using ideal coherent MPSK with the variation of three parameters: the average SNR per bit, the shadowing standard deviation, and the average Rician factor. Table 1 contains the parameter values that had been measured by Loo.[44] These parameters had been measured in a typical rural environment for average shadowing effect which corresponds to the case of the channel between two UAV network nodes. The corresponding estimated parameters are included. Figure 3 illustrates the variation of the SER with the average SNR per Symbol for some MPSK modulation orders using the parameters of Table 1.

Theoretical graphs for the non-shadowed channel (only the Rician effect) are added to the figure; these graphs are added for comparison. Simulation results are also shown in Figure 3, where MATLAB is used to build a shadowed Rician channel simulator depending on the model described above. We can notice how simulation results are too close to those from numerical calculations.

Table 1. *Parameters Values for A Rural Environment With Average Shadowing.*[44]

μ	–0.115	Ω	0.8368	$\sigma_{X_{dB}}$	1.3984
b_0	0.126	m	10.14		
$\sqrt{d_0}$	0.161	K_r[dB]	5.2048		

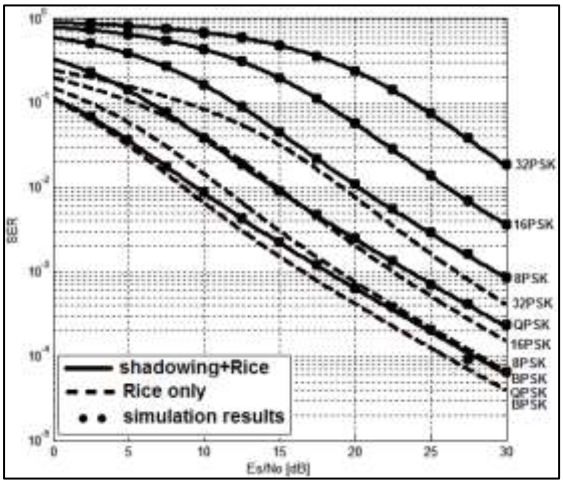

Fig. 3. *Variation of the SER with the Average SNR per Symbol for Different MPSK Modulation Orders Using Parameters of Table 1.*

It is clear in Figure 3 that for different values of the average SNR per symbol, and for different modulation orders, the shadowing effect is very important, especially when we have moderate to high SNR per symbol values, where it begins to be more significant. Thus, in UAV networks it is mandatory be consider both effects (Rician fading and shadowing) during the process of judging the channel performance.

Actually, the aim of finding the SER is at judging the link performance between a node and its neighbors; this will be used in finding the best link between different redundant links. As in most UAV networks applications the distance between nodes is almost the same, we are generally interested with the effect of shadowing and small scale fading on the SER in order to choose the best link.

Figure 4 shows the variation of the SER with the shadowing standard deviation for different values of the Rician factor when Es/No=10dB. Simulation results are included in Figure 4. We can see that simulation results are too close to numerical calculations. It is clear from Figure 4 that both the shadowing and the Rician fading have a great effect on the channel performance. Within an environment with high Rician factor values, which is the situation of UAV networks, we can notice that the SER changes with the shadowing standard deviation from the order of 10^{-5} to the order of 10^{-2} with low modulation orders, and from the order of 10^{-3} to the order of 10^{-1} with high modulation orders.

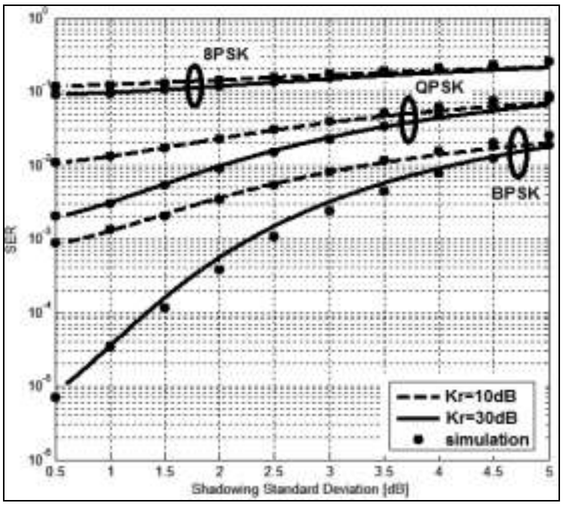

Fig. 4. *SER Variation With the Shadowing Standard Deviation for Different Values of the Rician factor and When Es/No=10dB.*

In highly shadowed environments, the performance degrades a lot, even with high Rician factor values. This can be seen for different modulation orders. This means that we will face poor performance in highly shadowed areas even if we choose low modulation orders and even if we have strong LOS component between the two communicating nodes. However, we can notice that, for different modulation orders and in highly shadowed environments, changing the Rician factor value has little effects on the system performance, while it becomes too important within environments with low and moderate shadowing standard deviation values. This means that changing the network topology in order to have stronger LOS component between adjacent nodes will be useless if the environment is in high shadowing conditions, while it may enhance the performance when the environment is in low shadowing conditions.

CONCLUSION

A statistical model for fading in UAV networks communications channels has been presented. In this model, the small scale multipath fading is considered together with the LOS lognormal shadowing. Additionally, the parameterization of this model in terms of the parameters we can estimate in real time operation will provide useful criteria in establishing the routing metric used to judge the link quality between any node and its neighbors in the network. In order to find a closed form formula for the SER, a given acceptable approximation is used. Results show that we cannot neglect any of the channel effects in real situations, neither the small scale fading effect, nor the shadowing effect.

Further work is underway to enable each node to estimate unknown or changing communication environment parameters such as the path loss exponent, the shadowing standard deviation, the Rician factor, and the noise density using online network measurements. These values can be then updated in the SER equation to calculate the communication cost dynamically.

Future work will include finding a general form of the wireless link communication cost function; this function should take all the channel parameters into consideration. This transmission quality function can be used in order to build the routing table at each node within the network. Adaptive transmission quality factor is to be concluded upon the possible approximations of the channel PDF.

Appendix I:

The PDF of Ψ_{dB} in LOO Model.

Using the Eq.: $\ln(\mathrm{x}) = (\ln(10))\log(\mathrm{x})$, we can rewrite Eq. (30) as follows:

$$f_A(a) = \frac{1}{a\sqrt{2\pi d_0}} \exp\left(-\frac{\left((\ln 10)\log a - \mu\right)^2}{2d_0}\right)$$

$$f_A(a) = \frac{1}{a\sqrt{2\pi d_0}} \exp\left(-\frac{\left(20\log a - \frac{20\mu}{\ln 10}\right)^2}{2\left(\frac{20}{\ln 10}\right)^2 d_0}\right)$$

$$f_A(a) = \frac{2\zeta}{2\zeta a\sqrt{2\pi d_0}} \exp\left(-\frac{(20\log a - 2\zeta\mu)^2}{2\times 4\zeta^2 d_0}\right)$$

where □=10/ln(10). Finally:

$$f_A(a) = \frac{2\zeta}{a\sqrt{2\pi(4\zeta^2 d_0)}} \exp\left(-\frac{\left(20\log a - (2\zeta\mu)\right)^2}{2(4\zeta^2 d_0)}\right)$$

Taking $s_a = g(a) = a^2$, we have $a = g^{-1}(s_a) = \sqrt{s_a}$. So $\left|\frac{dg^{-1}(s_a)}{ds_a}\right| = \frac{1}{2\sqrt{s_a}}$

Depending on the relation

$f_{S_a}(s_a) = f_A\left(g^{-1}(s_a)\right)\left|\frac{dg^{-1}(s_a)}{ds_a}\right|$,

Eq. (13) can be rewritten as follows:

$$f_{S_a}(s_a) = \frac{1}{2\sqrt{s_a}}\frac{2\zeta}{\sqrt{s_a}\sqrt{2\pi(4\zeta^2 d_0)}}\exp\left(-\frac{\left(20\log\sqrt{s_a}-(2\zeta\mu)\right)^2}{2(4\zeta^2 d_0)}\right)$$

$$f_{S_a}(s_a) = \frac{\zeta}{s_a\sqrt{2\pi(4\zeta^2 d_0)}}\exp\left(-\frac{\left(10\log s_a-(2\zeta\mu)\right)^2}{2(4\zeta^2 d_0)}\right)$$

As $\Psi_{dB} = 10\log\frac{P_t}{s_a}$, then $\Psi_{dB} = \frac{10}{\ln 10}\ln\frac{P_t}{s_a}$, and so $\left|\frac{ds_a}{d\Psi_{dB}}\right| = \frac{s_a}{\zeta}$.

Knowing that $10\log s_a = 10\log P_t - \Psi_{dB}$, we can find the PDF of Ψ_{dB} from the PDF of s_a as follows:

$$f_{\Psi_{dB}}(\Psi_{dB}) = \frac{s_a}{\zeta}\frac{\zeta}{s_a\sqrt{2\pi(4\zeta^2 d_0)}}\exp\left(-\frac{\left(10\log P_t-\Psi_{dB}-(2\zeta\mu)\right)^2}{2(4\zeta^2 d_0)}\right)$$

or,

$$f_{\Psi_{dB}}(\Psi_{dB}) = \frac{1}{\sqrt{2\pi(4\zeta^2 d_0)}}\exp\left(-\frac{\left(\Psi_{dB}-(10\log P_t-2\zeta\mu)\right)^2}{2(4\zeta^2 d_0)}\right)$$

Which is a normal distribution PDF with $\mu_{\Psi_{dB}} = 10\log P_t - 2\zeta\mu$ and $\sigma^2_{X_{dB}} = 4\zeta^2 d_0$.

Appendix II:

Statistical Properties of a_n.

Applying the change of variable ($a_n = a/\sqrt{\bar{S}}$) to the PDF of (13) we find:

$$f_{A_n}(a_n) = \sqrt{\bar{S}}\frac{1}{\sqrt{\bar{S}}a_n\sqrt{2\pi d_0}}\exp\left[-\frac{\left(\ln(\sqrt{\bar{S}}a_n)-\mu\right)^2}{2d_0}\right]$$

$$f_{A_n}(a_n) = \frac{1}{a_n\sqrt{2\pi d_0}}\exp\left[-\frac{\left(\ln a_n+\ln\sqrt{\bar{S}}-\mu\right)^2}{2d_0}\right]$$

$$\mu - \ln\sqrt{\bar{S}} = \frac{1}{2}\ln\left(\mu_{S_a}\right) - d_0 - \frac{1}{2}\ln(\bar{S})$$

$$\mu - \ln\sqrt{\bar{S}} = \frac{1}{2}\ln\left(\frac{\mu_{S_a}}{\bar{S}}\right) - d_0 = \mu_n \quad \text{Eq. (40)}$$

$$f_{A_n}(a_n) = \frac{1}{a_n\sqrt{2\pi d_0}}\exp\left[-\frac{\left(\ln a_n-\mu_n\right)^2}{2d_0}\right]$$

Then A_n is a lognormal distributed random variable, $\mu_n = E[\ln a_n]$, and $d_0 = Var[\ln a_n]$. Thus, we can deduce that:

$$\ln(E[A_n^k]) = \mu_n k + \frac{d_0}{2}k^2$$

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