An Efficient Approach of Improving Path Loss Models for Future Mobile Networks in Enclosed Indoor Environments

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ABSTRACT Path loss is the primary factor that determines the overall coverage of networks. Designing reliable wireless communication systems requires accurate path loss prediction models. Future wireless mobile systems will rely mainly on the super-high frequency (SHF) and the millimeter-wave (mmWave) frequency bands due to the massive available bandwidths that will meet projected users’ demand, such as the needs of the fifth-generation (5G) wireless systems and other high-speed multimedia services. However, these bands are more sensitive and exhibit a different propagation behavior compared to the frequency bands below 6 GHz. Hence, improving the existing models and developing new models are vital for characterizing the wireless communication channel in both indoor and outdoor environments for future SHF and mmWave services. This paper proposes an efficient improvement of the well-known close-in (CI) free space reference distance model and the floating-intercept (FI) model. Real measured data was taken for both line-of-sight (LOS) and non-line-of-sight (NLOS) communication scenarios in a typical indoor corridor environment at three selected frequencies within the SHF band, namely 14 GHz, 18 GHz, and 22 GHz. The research finding of this work reveals that the proposed models have better performance in terms of their accuracy of fitting real measured data collected from measurement campaigns. In addition, this work studies the impact of the angle of arrival and the antenna heights on the current and improved CI and FI models. The results show that the improved models provide better stability and sensitivity to the change of these parameters. Furthermore, the mean square error between the models and their improved versions were presented. Finally, this paper shows that shadow fading’s standard deviation can have a notable reduction in both the LOS and NLOS scenarios (especially in the NLOS), which means higher precision in predicting the path loss.

I. INTRODUCTION Era after era, the demand for higher mobile data traffic is exponentially increasing due to the tremendous revolution in technologies relying totally on mobile networks and their services. In 2019, Cisco reported that by 2022 the number of networked connections and devices would grow up to 28.5 billion, mobile-ready applications will reach up to 12.3 billion of them [1], [2]. Also, it was expected that by 2022 the overall mobile data traffic would be increased to approximately 77 exabytes per month, which is a seven-fold increase over the year of 2017 [2]. Another vital issue that will lead to more data needs is the current circumstances that the world faces nowadays, such as the Coronavirus pandemic that makes most of studying and work online, which leads to enormous use of the internet connection. Of course, this requires a massive amount of bandwidth [3]–[6].

Previously, the congestion of the spectrum below 6 GHz was enough to meet the existing systems’ requirements. On the contrary, these bands will not meet the necessities of the fifth-generation (5G) cellular networks and many other applications due to their relative shortage in the bandwidth required [7]–[11]. Because of that, research has been done to adopt the frequency regime above 6 GHz as a promising solution to accomplish high peak data transmission rates up to multi gigabits per second with the contribution of complex
In this study, we adopted measurement-based (semi-)measurement campaigns in propagation’s real environments [24]. The best understanding of the wireless channels’ can be done based on measurement campaigns in propagation [24]. The knowledge of the wireless channels’ is important because of the suitability, such as the close-in (CI) free space reference distance, floating-intercept (FI), and/or alpha-beta-gamma (ABG) model [25]–[45]. The improvement of these models in the literature was based on a consideration of some factors like cross-polarization discrimination (XPD), taking into account the mismatching of the antennas’ polarization and the ABGX model, which are an improvement of the CI and ABG models, respectively [23], [24]. Another improvement of the CI model is by presenting the path loss exponent (PLE) term as a frequency-dependent factor, as in the CIF model [23], [39], [46]–[48]. The last two factors (frequency-dependent PLE and XPD) were considered in one model called the CIFX model [23]. In [49] and [50], a dual-slope CI path loss model was presented. This model provides higher precision in predicting the path loss than the standard CI model. Note that all these improvements can be implemented easily on the FI and ABG models. Other improved models based on other different concepts can be found in [20], [27], [47], [51]–[53]. However, the question that has motivated this research is, how can we improve the accuracy and reduce the standard deviation of the shadow fading of these standard path loss models without adding parameters that depend on something else like antennas’ height or the XPD?

This question is answered through a fundamental principle: any linear equation is a polynomial equation with zero coefficients in higher orders. It is well-known that the standard path loss models (such as the CI and FI models) are a linear equation of the path loss as a function of the logarithmic scale of the separation distance between the transmitting and the receiving antennas. We incorporate an additional parameter to make these models a function of the transmitter-receiver (Tx-Rx) separation distance’s squared logarithm. This adopted improvement is simple (in the improved models’ equations, the proposed additional parameter that improves the standard models does not depend on anything like frequency and antenna height, etc.) and provides more precision in predicting the path loss, as will be proved in Section IV.

Many comparative studies between the existing path loss prediction models show the CI and FI models’ preference over other models like the ABG model [23], [39], [54], [55]. The CI and FI models offer a precise estimation of the path loss, as will be proved in Section IV.

In general, the path loss can be modeled deterministically (theoretically), empirically (statistically), or stochastically [24]. The best understanding of the wireless channels’ propagation characteristics can be done based on measurement campaigns in propagation’s real environments [24]. In this study, we adopted measurement-based (semi-)deterministic models to predict the path loss taking into account the propagation mechanisms such as reflections and diffractions and the wave-guiding effect that occurs mainly in enclosed indoor environments such as corridors.

Recently, most research aimed to characterize and model the wireless channel has focused on specific path loss models because of their suitability, such as the close-in (CI) free space reference distance, floating-intercept (FI), and/or alpha-beta-gamma (ABG) model [25]–[45]. The improvement of these models in the literature was based on a consideration of some factors like cross-polarization discrimination (XPD), taking into account the mismatching of the antennas’ polarization as in the models named CIX and ABGX models, which are an improvement of the CI and ABG models, respectively [23], [24]. Another improvement of the CI model is by presenting the path loss exponent (PLE) term as a frequency-dependent factor, as in the CIF model [23], [39], [46]–[48]. The last two factors (frequency-dependent PLE and XPD) were considered in one model called the CIFX model [23]. In [49] and [50], a dual-slope CI path loss model was presented. This model provides higher precision in predicting the path loss than the standard CI model. Note that all these improvements can be implemented easily on the FI and ABG models. Other improved models based on other different concepts can be found in [20], [27], [47], [51]–[53]. However, the question that has motivated this research is, how can we improve the accuracy and reduce the standard deviation of the shadow fading of these standard path loss models without adding parameters that depend on something else like antennas’ height or the XPD?

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have reliable semi-deterministic channel models. Measurement campaigns in typical indoor and outdoor environments are conducted to cover all frequency bands by conducting measurement campaigns. It is clear from the figure that the attenuation of the air does not follow a specific behavior. For example, Fig. 1 represents the attenuation in the air at different frequency bands in GHz. The air's attenuation at different frequency bands [35]. The rest of this paper is organized as follows. In section II, a detailed derivation of the adopted path loss prediction models and their improvements are introduced and discussed. The measurement setup and environment are described in section III. The results and discussions of this research work are presented in section IV. Finally, section V draws the main conclusions and future aspects of this research.

II. LARGE-SCALE PATH LOSS PREDICTION MODELS

Generally, all path loss prediction models can be derived from Friis’s equation [54], [55]:

$$FSPL(f, d) = \left(\frac{4\pi df}{c}\right)^2,$$  (1)

where $d$ is the Tx–Rx separation distance (in meters), $f$ is the frequency of the propagated signal (in Hz), and $c$ is the speed of light in the free space, which approximately equals to $3 \times 10^8$ m/s. This simple equation in the linear scale (absolute numbers) shows that the path loss between two isotropic antennas aligned on boresight toward each other is mainly a function of the operating frequency and the Tx-Rx separation distance. As presented in Eq. (1), the path loss is distance- and frequency-dependent; the increase in the frequency or the distance will produce higher path loss values. However, this is true when the wireless channel is in free space. In reality, the wireless channel’s problems such as attenuation, interference, distortion, and noise in the communication schemes have random behavior. For example, Fig. 1 represents the attenuation in the air at different frequency bands in GHz. It is clear from the figure that the attenuation of the air does not follow a specific behavior. This means that some low frequencies have large path loss values in outdoor environments because of air attenuation and atmospheric absorption. This issue and many other problems have accelerated the research to cover all frequency bands by conducting measurement campaigns in typical indoor and outdoor environments to have reliable semi-deterministic channel models.

It is more convenient to present the path loss equations in the logarithmic scale. Hence, Eq. (1) can be written as follows:

$$FSPL(f, d)[dB] = 32.4 + 20\log_{10}(f) + 20\log_{10}(d).$$  (2)

The value 32.4 comes from $10\log_{10}(\frac{4\pi \times 10^9}{c})^2$, and the value $10^9$ is to have values of frequencies directly in GHz (i.e., $f$ in Eq. (2) is the operating frequency in GHz). The variable $d$ in the previous equation represents the Tx-Rx separation distance in meters.

The existing path loss models can be categorized as single-frequency (like the CI and FI models) or multi-frequency (like the ABG model). For single-frequency models, the term $20\log_{10}(f)$ is constant and can be added to the first term of Eq. (2). The result is a constant term that depends on the value of the frequency (single-frequency path loss models have a pure dependence on the frequency presented as a parameter). The representation of this parameter differs from one model to another. Let us name this parameter $k_1$. The term $20\log_{10}(d)$ is basically 2 times the distance in the logarithmic scale, where the value 2 is the free space path loss exponent (FSPLE), which indicates that the path loss changes with the square of the Tx-Rx distance in the free space. However, this value will change significantly, depending mainly on the medium’s nature between the Tx and Rx. In general, it will be easier to denote it as $k_2$. Hence, Eq. (2) can be simplified as:

$$PL(d)[dB] = k_1 + k_2 \times 10 \log_{10}(d),$$  (3)

where the coefficient $k_1$ is measured in dB, and $k_2$ is unitless. It is clear from the previous equation that the power of the propagated signal decreases by $\frac{1}{d^2}$. This means that higher values of $k_2$ will lead to stronger dependency of the path loss on the separation distance between the Tx and Rx. Depending on the techniques used to evaluate the values of these coefficients, different path loss models exist. This paper adopted from those several models in the literature two well-known path loss models, the CI and FI models, and our improvement on these models. The parameters of these semi-deterministic models are based on the real measured values of the received signal levels collected from measurement campaigns. The received signal power at the Rx side mainly depends on the strength of the transmitted signal ($P_t$), the path loss of the propagated signal ($PL$), and the gain of the transmitting and the receiving antennas ($G_t$ and $G_r$), as presented in Eq. (4):

$$P_r(d)[dBm] = P_t - PL(d) + G_t + G_r.$$  (4)

In the previous equation, $P_r(d)$ and $P_t$ are in dBm, $G_t$ and $G_r$ are in dBi, and $PL(d)$ is in dB.

A. THE CLOSE-IN (CI) FREE SPACE REFERENCE DISTANCE PATH LOSS PREDICTION MODEL

The CI model can be written from Eq. (3) by replacing $k_1$ by the value of the free space path loss at the operating frequency.
(f) and the reference distance \(d_0\), and replacing \(k_2\) by the PLE \((n)\) as described in the following equation:

\[
PL^{CI}(d)[dB] = FSPL(f , d_0) + 10n\log_{10}(d) + X^{CI} \sigma, \tag{5}
\]

where \(X^{CI}\) is a Gaussian random variable with zero mean and a standard deviation \(\sigma\) in dB [6]. This term represents the shadow fading (SF), representing the large-scale fluctuations of the path loss values because of obstructions and other random propagation effects [56]. Having fewer values of the SF standard deviation means that the path loss models are more accurate. The SF’s importance for researchers and engineers lies in the fact that it can establish standards that include large-scale fading statistical models without detailed knowledge of the characteristics of a site-specific environment [6].

In this work, we adopted the physically-based reference distance to be 1 m for the reason that the wireless signals at the frequency bands above 6 GHz exhibit significant path loss values in the first meter of the propagation away from the transmitting antenna [29]. Also, it will be easier to compare our work with other works as most of the researches in the communication scenario (LOS or NLOS, etc.) will lead to a notable change in the values of \(n_1\) and \(n_2\). To have the closed-form of these parameters, let us assume that \(A = FSPL(f , d_0)\), \(B = PL^{Imp. CI}(d)\), \(D = 10\log_{10}(d)\), and \(E = 10(\log_{10}(d))^2\), then, the SF of Eq. (7) can be expressed as:

\[
X^{Imp. CI} \sigma = B - A - n_1D - n_2E. \tag{8}
\]

The SF standard deviation \((\sigma^{Imp. CI})\) can be determined from the experimental data using:

\[
\sigma^{Imp. CI} = \sqrt{\frac{\sum(X^{Imp. CI})^2}{N}}, \tag{9}
\]

where \(N\) is the number of the Tx-Rx separation distances (i.e., the total number of the average path loss samples recorded). Now, we have to differentiate the numerator of Eq. (9) with respect to both \(n_1\) and \(n_2\) and equate the result to zero to have the optimum value of these parameters that will lead to the minimum value of the standard deviation as follows:

\[
\frac{\partial}{\partial n_1}(\sum(B - A - n_1D - n_2E)^2) = 0, \tag{10}
\]

\[
\frac{\partial}{\partial n_2}(\sum(B - A - n_1D - n_2E)^2) = 0. \tag{11}
\]

After the differentiation and simplification of the previous two equations, we have two linear equations which can be expressed as:

\[
\begin{align*}
\sum D^2n_1 + \sum (DE)n_2 = \sum (BD) - A \sum D, \tag{12} \\
\sum (DE)n_1 + \sum E^2n_2 + = \sum (BE) - A \sum E. \tag{13}
\end{align*}
\]

The matrix form of the equations (12) and (13) can be written easily as:

\[
\begin{bmatrix}
\sum D^2 & \sum (DE) \\
\sum (DE) & \sum E^2
\end{bmatrix}
\begin{bmatrix}
n_1 \\
n_2
\end{bmatrix}
= \begin{bmatrix}
\sum (BD) - A \sum D \\
\sum (BE) - A \sum E
\end{bmatrix}. \tag{14}
\]

Finally, the closed-form of \(n_1\) and \(n_2\) can be found from the previous matrix.

B. IMPROVED CI PATH LOSS PREDICTION MODEL

To predict the path loss with more accuracy and sensitivity to the small changes of the propagation environments, we add an independent parameter to the CI model’s equation. The improved model has two terms that depend on the 3D Tx-Rx separation distance. This means that the path loss exponent principle exists in two parameters \((n_1\) and \(n_2\)), as presented in the following equation:

\[
PL^{Imp. CI}(d)[dB] = FSPL(f , d_0) + 10n_1\log_{10}(d) + 10n_2(\log_{10}(d))^2 + X^{Imp. CI} \sigma, \quad d > 1m, \tag{7}
\]

where \(n_1\) and \(n_2\) are the first order and second order of the PLE, respectively. This improvement of the CI will increase the opportunity to fit the real measured data collected from measurement campaigns and present more details in characterizing the wireless channel. Changing the environment where the signal can propagate, or the propagation’s communication scenario (LOS or NLOS, etc.) will lead to a notable change in the values of \(n_1\) and \(n_2\). To have the closed-form of these parameters, let us assume that \(A = FSPL(f , d_0)\), \(B = PL^{Imp. CI}(d)\), \(D = 10\log_{10}(d)\), and \(E = 10(\log_{10}(d))^2\), then, the SF of Eq. (7) can be expressed as:

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After the differentiation and simplification of the previous two equations, we have two linear equations which can be expressed as:

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\sum D^2n_1 + \sum (DE)n_2 = \sum (BD) - A \sum D, \tag{12} \\
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The matrix form of the equations (12) and (13) can be written easily as:

\[
\begin{bmatrix}
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\sum (DE) & \sum E^2
\end{bmatrix}
\begin{bmatrix}
n_1 \\
n_2
\end{bmatrix}
= \begin{bmatrix}
\sum (BD) - A \sum D \\
\sum (BE) - A \sum E
\end{bmatrix}. \tag{14}
\]

Finally, the closed-form of \(n_1\) and \(n_2\) can be found from the previous matrix.

C. THE FLOATING-INTERCEPT (FI) PATH LOSS PREDICTION MODEL

The FI model has been widely used in 3GPP and WINNER II standards [5], [23], [24], [48], [56]. It does not depend on the physical anchor point constraint that catches the path loss near the transmitting antenna. However, it depends on the mathematical curve that fits the measured path loss values. As a linear equation, the FI model has two parameters, which are the intercept (denoted by \(a\)) and slope (indicated by \(b\)) of the path loss line as presented in the following equation:

\[
PL^{FI}(d)[dB] = a + 10b \log_{10}(d) + X^{FI} \sigma, \quad d > 1m, \tag{15}
\]
where $PL_{FI}(d)$ is the path loss in $dB$, and $X_{\sigma}^{FI}$ is a Gaussian random variable with zero mean and a standard deviation $\sigma_{FI}$. In the previous expression, both $X_{\alpha}^{FI}$ and $\sigma_{FI}$ are in $dB$.

It is worth noting that the FI model’s parameters are unlike the CI model ($\alpha$ is unlike FSPL, and $\beta$ is unlike the PLE). However, the models have comparable overall performance in predicting the path loss with a preference of one over the other depending on the operating frequency as well as the environment and communication scenario of the wireless communication system [10], [57], [58].

### D. IMPROVED FI PATH LOSS PREDICTION MODEL

In this model, we follow the same principle as we used for the improved CI model, which is adding an independent parameter that will be the coefficient of the square of the logarithm of the 3D Tx-Rx separation distance as presented in the following equation:

$$PL_{Imp, FI}(d)[dB] = \alpha + 10\beta_1 \log_{10}(d) + 10\beta_2 (\log_{10}(d))^2 + X_{\alpha}^{Imp, FI}, \ d > 1m,$$

(16)

As seen from Eq. (16), this model has three parameters to be known ($\alpha$, $\beta_1$, and $\beta_2$). Using the MMSE approach and following the same derivation we used for the improved CI model, the solution matrix of these parameters can be expressed as:

$$\begin{bmatrix} N \\ \sum D \\ \sum D^2 \\ \sum E \\ \sum (DE) \end{bmatrix} \begin{bmatrix} \alpha \\ \beta_1 \\ \beta_2 \end{bmatrix} = \begin{bmatrix} \sum B \\ \sum (BD) \\ \sum (BE) \end{bmatrix},$$

(17)

where $B = PL_{Imp, FI}(d)$, $D = 10 \log_{10}(d)$, and $E = 10(\log_{10}(d))^2$. The closed-forms of the parameters are found in the previous matrix. To validate the proposed models given in equations (7) and (16), we used real measured data of the path loss in a typical indoor corridor environment, as explained in the next section.

### III. MEASUREMENT SETUP AND DATA COLLECTION METHOD

A detailed description of radio frequency (RF) propagation measurement campaigns conducted in a typical enclosed corridor environment is provided in this section. The corridor exists on the 5th floor of the Discipline of Electrical, Electronic, and Computer Engineering, University of KwaZulu-Natal, Howard College Campus, Durban 4001, South Africa.

Before beginning the measurement campaigns, we ensured that no other transmissions on the same experimental radio frequency bands existed. Also, the measurement system was carefully calibrated, and the measurements were repeated and averaged to ensure high-quality data collection.

The wireless propagation channel is a corridor environment with dimensions of 30, 1.4, 2.63 meters as a length, width, and height. Both sides of the corridor are made of bricks and dry concrete with wooden doors to offices on one side and an elevator and a staircase on the other side. It is worth noting that these indoor corridors can be approximated as a rectangular air-filled waveguide with dimensions immense compared to signals’ wavelength. This environment is crucial and commonly used for many indoor applications.

The antennas used in this experiment are vertically-polarized with directional radiation patterns. The Tx antenna’s height was 160 and 230 centimeters above the floor level, while the Rx height was 160 centimeters; which are the average antenna heights for these indoor environments that are adopted by many researchers [29], [59]–[61]. When the Tx antenna height was 230 centimeters above the floor level, we down tilted the Tx antenna to ensure that both antennas are aligned on boresight for all the Tx-Rx measurement places in the LOS communication scenario. Three frequencies in the SHF band were considered in this work: 14, 18, and 22 GHz. Both antennas were pyramidal horn antennas with half-power beamwidth values between 13 and 19.2 degrees and a directional gain ranging between 19.5 and 22.1 $dB$. At the operating frequencies. Throughout the campaigns, the intent was to place the Tx at one end of the corridor and moving the Rx away from the Tx, having a Tx-Rx separation distance of $2\sim24$ meters with an incremental step of 2 meters a time. The reference Tx-Rx distance was 1 meter, as is recommended by most research experts in this field [62]–[66]. Note that to satisfy the far-field requirements, the distance from the Tx should be much greater than the wavelength of the lowest operational frequency, which already exists since the wavelength of the SHF signals is in the range of millimeters.

The measurements were performed under the conditions of LOS and NLOS communication scenarios. In the LOS scenario, both antennas were aligned on boresight, and there were no obstacles in the direct propagation path between them. In contrast, the Rx in the NLOS depends mainly on diffractions, reflections, and waveguiding mechanisms in the corridor environment since both antennas had no alignment on boresight. Throughout the measurements, the transmit power was fixed at 10 $dBm$. However, the received power level range was between $-41.33$ and $-19.05$ $dBm$. The angle of departure (AoD) was set at 0 $degree$, while the angle of arrival (AoA) was in the range of $0\sim360$ $degrees$ with an incremental step of 10 $degrees$ a time.

A Rohde and Schwarz SMF 100A signal generator working in continuous-wave (CW) mode was applied to feed the transmitting antenna. The measured results are collected by means of a Rohde and Schwarz FSIQ 40 Signal Analyzer. This receiving equipment records 500 data sets of received signal strength (RSS) per each AoA and Tx-Rx separation distance. The RSS data were averaged to ensure accurate detection of the CW signals. Both signal generator and signal analyzer were directly connected to the antennas through coaxial cables. Since the path loss is the difference value between the Tx and Rx power, taking into account the antennas’ gain and the coaxial cables’ loss, the measured path loss $PL_m$ is calculated by:

$$PL_m[dB] = P_t - P_r + G_t + G_r - L_{cable},$$

(18)
where $L_{cable}$ is the total coaxial cable loss of the measurement system in dB. Fig. 2 represents the 3D floor plan of the indoor corridor environment. The parameters of the measurement setup used in this work are summarized in Table 1.

IV. RESULTS AND DISCUSSIONS

This section presents and discusses the main results obtained from this research work. It is presented in two subsections, each one compares a model with its improved version at the three frequencies (14, 18, and 22 GHz) for both the LOS and NLOS scenarios. Also, each subsection investigates the behavior of the models’ parameters with the AoA and the antenna’s height.

A. RESULTS AND DISCUSSIONS OF COMPARING THE CI WITH IMPROVED-CI MODELS

Fig. 3 depicts the real measured path loss, the CI model, and the Improved-CI model together for the LOS communication scenario at the three frequencies. It is clear from the figure that both models fit the measured path loss adequately and both have a comparable performance with a slight preference of the improved model. This also can be noted from Table 2 that presents the values of the models’ parameters.

Our proposed model minimizes the shadow fading’s standard deviation at the three frequencies by 2.3%, 5.2%, and 10.7% at 14, 18, and 22 GHz, respectively. We note that the reduction of the standard deviation becomes higher as we go for high frequency bands. This is because the higher frequency bands suffer from many propagation effects and have higher path loss values than lower bands. From Table 2, for the CI model,
the path loss exponent is directly proportional to the operating frequency. This leads to the general fact that higher frequency bands have higher path loss values. All the PLE’s values are under the value of the FSPL. The reason behind that is the constructive interference between the multipath signals which makes the PLE lower than 2. For the improved-CI model, as discussed previously, the concept of the PLE has split into two parameters (i.e., $n_1$ and $n_2$) as shown in Table 2. This technique gives the model more relaxation to accurately fit the measured data. It is clear that the values of $n_1$ are higher than the values of the CI model’s PLE. However, all the values of $n_2$ are negative, which will compensate the increase of $n_1$ values and make the model following the measured path loss and counts all the possible signal effect. Fig. 4 offers a graphical view of both models (CI and improved-CI) together at 14, 18, and 22 GHz for the LOS communication scenario. We plotted the MSE curves between the CI and improved CI models with respect to the separation distance between the Tx and Rx for the LOS scenario as depicted in Fig. 5. It is worth noting that all the MSE values are in the range of $10^{-4}$ to $10^{-2}$ with lower values around 14 to 16 meters (near the breakpoint of the corridor) of the Tx-Rx separation distance.

In the NLOS communication scenario, as it is known, the receiving antenna relies mainly on reflection, diffraction and the effect of waveguiding in this enclosed environment for capturing the signals from the Tx. The CI model’s PLE values here are 2.07, 2.38, and 2.26 at 14, 18, and 22 GHz, respectively. Note that because there is no direct dominant path from the transmitting to the receiving antennas, the values became notably high compared to the LOS results. However, they are still low compared to the communications in outdoor environments where the fluctuations of the propagated signals is much stronger. We find that in enclosed indoor environments such as corridors, the PLE values will not go much higher than the values of the FSPL since the maximum percentage jump is in 18 GHz band by 16%. This frequency band (i.e., 18 GHz) has a higher sensitivity to the wireless channel effects than the others for the frequencies studied. The SF standard deviation of the CI model is seen to rise to more than the double in the NLOS scenario as shown in Table 3. This means that there is less precision in predicting the path loss in NLOS scenarios than the LOS ones. Nevertheless, the proposed model provides an attractive reduction of the standard deviation since it produces a minimum reduction of 3.24 dB (54.2% less) as can be seen in Table 3. This improvement is simple and highly efficient since almost all the communication methods for indoor environments are NLOS. The reason behind this improvement is the fact that the current statistical NLOS models cannot properly model the propagation mechanisms such as reflections and diffractions effects, which are captured better by the new parameter in our improved model. Again, all the values of the parameter $n_2$ are negative and $n_1$ values are larger than the PLE value for the NLOS scenario as the LOS one. Fig. 6 displays both models at the three selected frequency bands. From this figure, it is clear that the path loss curves of the improved CI model are away from the CI model’s curves. The MSE between the CI and improved CI models are outlined in Fig. 7 for the NLOS scenario. The figure shows the increase in the MSE values compared to the LOS scenario since for the NLOS, the MSE values are in the range of $10^{-2}$ to $10^0$.

The behavior of the CI and Improved-CI models’ parameters with the AoA at 14, 18, and 22 GHz is presented in detail in Table 4, Table 5, and Table 6, respectively. From the Tables, it is clear that the PLE’s minimum values occur when

TABLE 2. A comparison between the CI and Improved-CI models’ parameters in the LOS scenario.

| Frequency (GHz) | PLE ($n_1$) | $\sigma_{CI_{min}}$ (dB) | $n_1$ | $n_2$ | $\sigma_{CI_{min}}$ (dB) |
|----------------|------------|--------------------------|------|------|--------------------------|
| 14             | 1.37       | 2.19                     | 1.61 | -0.20| 2.14                     |
| 18             | 1.58       | 1.53                     | 1.87 | -0.24| 1.45                     |
| 22             | 1.66       | 1.31                     | 1.99 | -0.28| 1.17                     |

TABLE 3. A comparison between the CI and Improved-CI models’ parameters in the NLOS scenario.

| Frequency (GHz) | PLE ($n_1$) | $\sigma_{CI_{min}}$ (dB) | $n_1$ | $n_2$ | $\sigma_{CI_{min}}$ (dB) |
|----------------|------------|--------------------------|------|------|--------------------------|
| 14             | 2.07       | 5.98                     | 5.09 | -2.57| 2.74                     |
| 18             | 2.38       | 6.87                     | 5.86 | -2.97| 3.08                     |
| 22             | 2.26       | 6.86                     | 5.69 | -2.92| 3.23                     |
the AoA equals 30 and 330 degrees. The reason behind that is that at these AoA values, the Rx antenna is still aligned near the LOS path, and with the help of the propagation mechanisms discussed above, the PLE's value is minimized. The maximum PLE values occur at 150 and 210 degrees of the AoA. This shows that around these angles when the Rx is in the opposite direction of the Tx, the propagated signal will suffer from maximum path loss values before reaching the Rx antenna. Note that when the AoA is exactly 180 degrees, the PLE values are within a good range compared to other AoA because of the back loops of the Rx antenna’s radiation pattern as can be seen from Fig. 8. These findings give an insight into what will happen in reality when the Tx or Rx orientations might not be known and how the wireless signals will be affected according to this issue in such enclosed indoor corridor environments. When we compare the three frequencies together, we observe that the fluctuations of the PLE values are 6.8%, 10.4%, and 3.1% at 14, 18, and 22 GHz, respectively. This means that the 22 GHz frequency band has an attractive behavior in terms of its stability to the AoA, which leads to accurate modeling of the wireless propagation channel in the NLOS communication scenario. For the SF’s standard deviation values, the difference between the maximum and minimum values are 2.04, 3.1, and 1.3 dB. It is clear that the worst performance between the three frequencies is at 18 GHz. For our proposed model, since the concept of the PLE is divided into two parameters, it is clear from the Tables that it outperforms the CI regarding the sensitivity and stability of the model’s parameters with the AoA.

Fig. 9 depicts the CI and improved-CI models’ parameters at two different practical antenna heights (i.e., 1.6 and 2.3 m) for both the LOS and NLOS communication scenarios. Generally, the figure shows the increase of the parameters’ values when the Tx antenna height is 2.3 m compared to 1.6 Tx antenna height because of the mismatching of the antennas’ heights. Moreover, it can be seen from the figure that our proposed model provides more sensitivity to the antenna height and capture more accurately the wireless
propagation characteristics caused by the mismatching of the Tx and Rx antenna heights. Furthermore, it reveals that the antenna height’s impact is minimum at 22 GHz and maximum at 14 GHz for both the CI model and our proposed model. However, when we look at the SF’s standard deviation values, we observe that the proposed model outperforms the standard CI model depending on the antennas’ heights. It is worth noting that the antenna height might not be an essential factor in the specific investigations presented in this work. However, the antenna locations, patterns, and relative orientation are significant factors, especially at high frequencies, mmWave and above. These performance studies will help engineers in designing reliable communication systems in such scenarios and have an accurate understanding and modeling of the wireless channel’s behavior.

**B. RESULTS AND DISCUSSIONS OF COMPARING THE FI WITH IMPROVED-FI MODELS**

Fig. 10 shows the curves of the real measured data, the FI model, and the improved FI model for the LOS results at 14, 18, and 22 GHz.
communication scenario at the three frequency bands adopted for this work. The figure shows that both models accurately fit the real measured data with the minimum possible MSE between the models and the data. As a comparison between the three frequencies, the best fit occurs at the 22 GHz frequency band. It must be emphasized that any path loss model will always depend on the operating frequency, no matter how they are derived. Maybe simplifications could come from the fact that the exact carrier frequency is not needed, and only the knowledge of the band (e.g., 14 GHz, 18 GHz, and 22 GHz) is enough. The models’ parameters are represented in Table 7. It is observed that our proposed model slightly better than the standard FI model in terms of the performance since it reduces the standard deviation values by 3.2%, 13.7%, and 1.8% at 14, 18, and 22 GHz. Note that the best improvement applies at 18 GHz, contrary to what happened between the CI and improved-CI models. Also, note that the values of the parameter $\alpha$ are not far between both models. A notable improvement can be observed from Table 8 since the percentage decrease goes up to 44% in the NLOS communication scenario. Upon comparing the four models, it is noted that the best model that fits the real measured data is the improved-FI model. Fig. 11 presents both FI and improved-FI models together at the three frequencies selected. The curves of the two models in the figure are almost the same, as also confirmed from the values in Table 7. We have plotted the MSE between both models to show how these models behave when the Tx-Rx separation distance increases. It is noted that from Fig. 12, the correlation between the models is high since the values of the MSE are in the range of $10^{-6}$ and $10^{-2}$ with minimum values around the breakpoint. Nevertheless, Fig. 13 and Fig. 14 show a highly notable difference between both models in terms of their performance in the NLOS scenario since the models’ curves are far away from each other in Fig. 13, and have MSE values higher than the ones we got from Fig. 12.

Fig. 15 represents the FI and improved-FI models’ parameters versus the AoA of the receiving antenna at 14, 18, and 22 GHz for the NLOS communication scenario. This figure shows that while both models provide a valuable stability to the change of the AoA, our proposed model shows slight advantage. This advantage is seen clearly from Tables 9, 10, and 11, where the models’ parameters are presented. The impact of the antenna heights on the models’
FIGURE 15. The behavior of the FI and improved FI models’ parameters with the AoA.

FIGURE 16. The parameters of the FI and improved-FI models at two different Tx antenna heights.

TABLE 8. A comparison between the FI and Improved-FI models’ parameters in the NLOS scenario.

| Parameter          | 14 GHz | 18 GHz | 22 GHz |
|--------------------|--------|--------|--------|
| \(\alpha_{FI} [dB]\) | 67.272 | 71.021 | 73.242 |
| \(\beta_{FI}\)     | 1.010  | 1.172  | 1.014  |
| \(\sigma^2_{FI} [dB]\) | 3.69   | 4.32   | 4.07   |
| \(\alpha_{imp,FI} [dB]\) | 61.097 | 63.767 | 66.476 |
| \(\beta_{imp,FI}\) | 3.772  | 4.430  | 4.039  |
| \(\sigma^2_{imp,FI} [dB]\) | -1.881 | -2.218 | -2.061 |

From the previous analysis, we observed that it is possible to provide valuable improvements to the existing wireless channel models without a notable increase in the models’ complexity. In fact, with the demand for more and more data traffic, we will always need to go for higher frequency bands to meet future requirements. These higher frequency bands have smaller wavelengths, they then suffer more from the wireless propagation channel. Hence, improving the existing change in the models’ parameters, and the worst behavior is seen to occur when there is a mismatch in the antenna’s heights. However, the performance of our proposed model is better than the performance of the standard FI model.
models and developing new models that accurately describe the wireless propagation channel will always be needed.

V. CONCLUSION

In this paper, a simple and efficient improvement of two well-known path loss prediction models, namely the CI and FI models, was presented and discussed in detail. The validation of the models’ performance was given by applying the CI and FI models and their improvement to fit real measured data. The data was collected in a typical indoor corridor environment at three frequencies in the SHF band, which are 14, 18, and 22 GHz. Both the LOS and NLOS communication scenarios were considered in this research. The main findings of this work are that our proposed models generally outperform the existing standard models in terms of several factors such as the accuracy of predicting the path loss with the lowest possible value of the MSE, minimizing the SF’s standard deviation for both LOS and NLOS conditions (with better improvements in the NLOS scenario), and providing better sensitivity and stability of the models’ parameters with the change of the AoA and antenna height. The improvement of the models was effected through a simple and valuable approach. There is no notable increase in the models’ complexity to be used by the planning engineers for wireless systems’ deployment and calculations of the link budget. Finally, this work shows that the proposed models can be trusted as accurate and reliable models for predicting the path loss at frequency bands above 6 GHz in enclosed indoor environments such as corridors since they provide better accuracy, sensitivity, and stability than well-known standard path loss prediction models such as the CI and FI models. Further studies and investigations need to be conducted to achieve greater accuracy in predicting the path loss since it is the dominant component that determines the networks’ overall coverage.

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