Postprint of: Laskowski M., Ambroziak S., Correia L. M., Świder K., Performance Evaluation of GAM in Off-Body Path Loss Modelling for Body Area Networks (2021), The 2021 Annual IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (IEEE PIMRC 2021), 13–16 September 2021, https://pimrc2021.ieee-pimrc.org/program/technical-sessions/track-2-rf-technologies-antennas-and-propagation/

Performance Evaluation of GAM in Off-Body Path Loss Modelling for Body Area Networks

Michał Laskowski
Gdańsk Univ. of Techn., WETI
Gdańsk, Poland
ORCID ID: 0000-0002-3862-3348

Sławomir J. Ambroziak
Gdańsk Univ. of Techn., WETI
Gdańsk, Poland
ORCID ID: 0000-0003-4446-853X

Luis M. Correia
Univ. of Lisbon, IST/INESC-ID
Lisbon, Portugal
ORCID ID: 0000-0002-7765-9896

Krzysztof Świder
Formerly with Gdańsk Univ. of Techn., WETI
Gdańsk, Poland
ORCID ID: 0000-0003-3222-0035

***Abstract*—This paper addresses the performance evaluation of an off-body path loss model, based on measurements at 2.45 GHz, which has been developed with the use of the Generalised Additive Model, allowing to model a non-linear dependence on different predictor variables. The model formulates path loss as a function of distance, antennas' heights, antenna orientation angle and polarisation, results showing that performance is very sensitive to the orientation angle and to the polarisation of the transmitting and receiving antennas. Considering the model's global performance, the obtained overall value of the adjusted coefficient of determination equals 0.60, while the mean error and the root mean square error equal 0 dB and 5.6 dB, respectively, which can be considered quite good for such a large diversity of addressed scenarios. One can then conclude that, regardless of the low performance of the method for some particular cases, the overall model accuracy may be considered good.**

***Index Terms*—Generalised Additive Model, Path Loss, Body Area Networks, Off-Body Channel, Model Evaluation.**

I. Introduction

In the process of designing any kind of wireless system, there is the need to deeply understand the properties of the radio channel that is going to be used for signal transmission. A similar demand also exists in Body Area Networks (BANs), which refer to body centric wireless communications where at least one of the communication devices is attached to the human body [1]. In this paper, an off-body case of BANs is considered, in which the radio link is established between an on-body (wearable) device and an off-body (external) access point [2].

Since the knowledge about the radio channel is crucial for calculating the radio link budget, one of the most commonly analysed and modelled channel components is the path loss, namely its mean value (MPL - Mean Path Loss), besides small- and large-scales fading [3]. Most of the research on MPL models takes a perspective based on the use of linear regression (LR) or more complex Multivariate Linear Regression (MLR), both with the Least Square Method (LSM) approach, e.g., [3], [4], [5], [6].

Recently, more sophisticated perspectives for radio channel modelling can also be found in the literature, e.g. different machine learning methods [7], deep learning techniques [8], neural network approaches [9], or even fuzzy-logic viewpoints [10]. Moreover, although path loss presents a linear dependence on many parameters (e.g., frequency and distance), other non-linear variations need to be considered (e.g., angular ones), which implies that modelling perspectives should take this into account.

The Generalised Additive Model (GAM) is a statistical learning method that uses smooth functions of predictor variables. This approach allows to analyse the contributions of each of the features towards the composite model and to model non-linear behaviours [12]. It is commonly used for elaborating statistical models in a wide scope of applications, e.g., gas usage [13], hospital admissions [14], high-speed railways management [15], or even for spatio-temporal criminal incidents [16]. To the best of the authors knowledge, the MPL modelling of the off-body channel proposed in [11] seems to be the first use of GAM for the development of models in BANs or any other kind of wireless system, which is the novelty of the present research.

The aim of this paper is to evaluate the performance of GAM in off-body MPL modelling for particular cases in BANs regarding several parameters related to the scenario geometry and antennas characteristics, i.e., the distance between the user and the off-body access point, the absolute difference between antennas' heights, the on-body antenna orientation angle with respect to the off-body antenna, and the polarisation of both the transmitting (Tx) and receiving (Rx) antennas. The influence of users with their different body constitutions has also been taken into account.

The rest of the paper is structured as follows. Section II consists of a brief description of the off-body measurements taken for model development and of the evaluation criteria used for model assessment. In Section III, a short description of the model itself is done. Section IV consists of the analysis of the model evaluation results, while Section V summarises this evaluation and analyses the model's usage possibilities. Section VI concludes the paper.

II. Measurements and Evaluation Criteria

In order to evaluate the performance of the off-body MPL model, the empirical data gathered during previously conducted research have been used. These measurements were performed for a narrow-band channel operating at 2.45 GHz in an indoor (office) environment with the use of the measurement set-up presented in [17], and in accordance with the methodology for off- and body-to-body radio channels with different diversity schemes proposed in [18]. Only the key information from the viewpoint of this paper is provided.

Path loss values have been measured for 6 different distances between Tx and Rx antennas, from 1 m to 6 m, with a 1 m step. At each point, a full body rotation was performed with a 45° counter-clockwise increment. Four users have been considered, whose characteristics are detailed in Tab. I, jointly with 3 antenna locations: torso's front side (TO_F), head's left side (HE_L), and right arm bottom part, at the wrist (AB_R). Depending on the user and antenna's placement, the height of the Tx linearly polarised antenna, h_{Tx}, took different values, while the height of the dual linearly polarised Rx antenna at the access point, h_{Rx}, was fixed at 1.4 m.

TABLE I
Heights of the Tx Antenna.

User (gender, height, weight)	h_{Tx} [m]		
	HE_L	TO_F	AB_R
U1 (male, 1.93 m, 65 kg)	1.77	1.40	0.87
U2 (male, 1.82 m, 74 kg)	1.64	1.30	0.89
U3 (male, 1.76 m, 88 kg)	1.65	1.30	0.93
U4 (female, 1.60 m, 50 kg)	-	1.30	-

For each distance and rotation, measurements were performed with 50 samples, and a median value of the path loss was calculated. Globally, 33 600 instantaneous and 672 median path loss values have been collected during measurements. The sample size (number of measurements) for each value of a particular factor influencing the path loss is summarised in Tab. II, where:

- d - distance between user and off-body access point;
- $\Delta_h = |h_{Tx} - h_{Rx}|$ - absolute difference between Tx and Rx antennas' heights;
- φ - on-body antenna orientation angle, i.e., the angle between the main directions of the on-body (Tx) and the off-body (Rx) antennas (counter clockwise);
- P - polarisation factor with two possible values, for co-polarised (CP) and cross-polarised (XP) channels, i.e., the polarisation of Tx and Rx antennas being the same or orthogonal to each other.

For the evaluation of model's performance, the commonly used statistical metrics have been applied: the mean error, μ_e, indicating the average difference between the measured path loss and the one predicted by the model [11], [19], and the root mean square error, $\sqrt{\bar{\varepsilon_e^2}}$, measuring the dispersion of the empirical data around the model (the standard deviation can be easily calculated from the previous two), hence, describing how well the model matches experimental data [19].

TABLE II
Sample Size for Particular Factors.

Factor	Value	Sample size
User	U1, U2	7 200 (per each user)
	U3	14 400
	U4	4 800
d [m]	1, 2, 3, 4, 5, 6	5 600 (per each d)
Δ_h [m]	0.00, 0.37	2 400 (per each Δ_h)
	0.10	12 000
	0.25	7 200
	0.47, 0.52	4 800 (per each Δ_h)
φ [°]	0, 90, 180, 270	6 000 (per each φ)
	45, 135, 225, 315	2 400 (per each φ)
P	CP, XP	16 800

The coefficient of determination, R^2, is also used in its adjusted formulation, i.e., R^2_{adj}, which is defined in [20], [21]. One should keep in mind that R^2_{adj}, being in the range of [0,1], gives the percentage of the variance in the dependent variable that can be explained by the independent variables used in the model. When $R^2_{adj} = 1$, the model perfectly fits the measurement data, and when $R^2_{adj} = 0$, the model does not explain any variation.

III. Description of the GAM Off-Body MPL Model

The off-body MPL model under evaluation was developed with the use of GAM, since this method allows for replacing linear components used in LR approaches by non-linear functions, which reflect real-life scenarios in a more realistic way, as described in [11].

The final off-body MPL model (with parameters defined in Section II) is formulated as follows:

$$L_{p[\mathrm{dB}]} = 48.94 + 12.69 \log\left(\frac{d_{[\mathrm{m}]}}{d_{0[\mathrm{m}]}}\right) - 3.99\Delta_{h[\mathrm{m}]} + \\ + 12.57 \sin\left(\frac{\varphi_{[°]}}{2}\right) + P_{[\mathrm{dB}]}, \quad (1)$$

where d_0 is a reference distance, i.e., 1 m, and the polarisation factor is expressed by [11]:

$$P_{[\mathrm{dB}]} = \begin{cases} 0.00 & \text{for} \quad \text{CP}, \\ 7.75 & \text{for} \quad \text{XP}. \end{cases} \quad (2)$$

The model's component related to the path length is a log-linear function of the distance, with an average power decay below 2, i.e., 1.269, which is expected in an indoor environment, given the high multipath behaviour of the signal in this type of environments. The heights difference component, via Δ_h, is characterised by a negative slope, which means that a higher difference will imply a lower path loss, which can be explained by some influence of the scenario geometry overall. The non-linearity of the model can be seen in the component related to the antenna orientation angle, where the obstruction by the body is clearly taken into account. Regarding the polarisation component, basically it expresses the two extreme cases of polarisation matching between Tx and Rx antennas, between co-polar and cross-polar, encompassing the cases of non-light-of-sight (e.g., by body obstructions) where the reflections in the surrounding environment are important.

In [11], it has been shown that the model fits well to the empirical data, all estimated MPL values being within the prediction interval. Nevertheless, there is the need to analyse its performance in narrower scenarios, in order to deepen the awareness on its possible advantages and drawbacks.

IV. Performance Evaluation of the Model

This section includes the evaluation of results and the analysis of performance of the MPL model for particular cases, including all considered factors influencing the attenuation, based on the metrics described in Section II.

The model performance for the worst cases of each independent variable can be seen in the scatter plots in Figs. 1-5, where the abscissa axis contains the measured MPL and the ordinate axis the one predicted by the model. The exact match between predictions and measurements is represented by the dotted blue line, with a slope equal to 1, while the solid black line shows the best linear fitting with a slope equal to R^2 [11]. One can clearly see the variety of measured situations by the spread of points for a given value of a measured path loss.

A. Influence of the User

The dependence of path loss on users has definitely a random nature, in the sense that each person is different and behaves in a different way. On the other hand, we all repeat certain gestures and movements, which tend to be rather cyclic and similar. The results regarding the comparison among users are gathered in Tab. III.

TABLE III
Results of the Evaluation for Different Users.

User	μ_e [dB]	$\sqrt{\bar{\varepsilon_e^2}}$ [dB]	R^2_{adj}
U1	0.63	5.44	0.61
U2	0.46	5.73	0.59
U3	-0.42	5.46	0.60
U4	-0.40	5.92	0.56

The mean error, μ_e, ranges in [-0.42, 0.63] dB, and the root mean square error, $\sqrt{\bar{\varepsilon_e^2}}$, belongs to the range [5.44, 5.92] dB, while the adjusted coefficient of determination, R^2_{adj}, varies around 0.6, in the range of [0.56, 0.61], hence, the extension of the variation not being large; the ranges of variation of μ_e and $\sqrt{\bar{\varepsilon_e^2}}$ are quite small (the intervals lengths are 1.05 dB and 0.48 dB, respectively), implying that user dependence is not that important for the measured scenarios, i.e., the impact of user's height or weight on model's performance ends up not being very important, as expected. Globally, these results show that the model performs well. The worst behaviour (in relative terms) is observed for User 4, which may be caused by the fact that, for this particular case, measurements have been performed only for one position of the on-body antenna, the TO_F one, which is the most difficult to predict for antenna orientation angles in the range of [135°, 225°], due to the higher influence of the body shadowing phenomenon in relation to the two other cases, i.e., HE_L or AB_R.

The scatter plot for User 4 is presented in Fig. 1, where one can observe that the two lines (the dotted blue for the exact

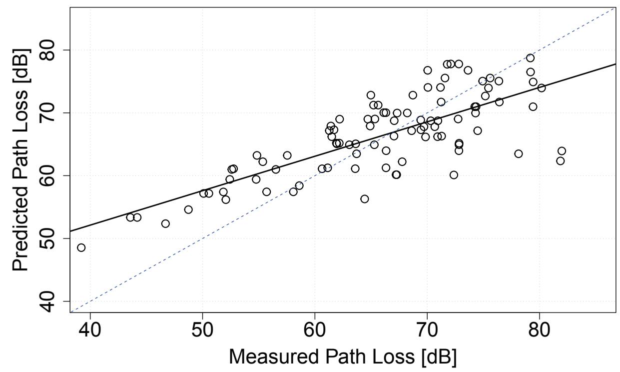

Fig. 1. Measured vs. predicted path loss for user 4 ($R^2_{adj} = 0.56$).

match and the solid black for the best linear fitting) cross at 66.8 dB; it should be noted that below this crossing point, on average, the model is overestimating path loss, while above it there is an underestimation. Furthermore, for the observed measurements, the model presents an overestimation below roughly 62 dB, while there is a consistent underestimation above roughly 75 dB. The range of variation of the measured path loss is over 40 dB, meaning that the deployment of antennas on the body does lead to significant changes in the radio channel; on the other hand, consistently with the previous observations, the predicted path loss extends over an interval of only 30 dB, i.e., the model tends to concentrate predictions around a certain value, not properly reaching the ”extreme” measured values, which somehow can be expected, i.e., these ”extreme instantaneous” values are usually captured by the modelling of slow fading and not of MPL.

B. Influence of the Distance

The general dependence of path loss on distance is well known, the logarithmic variation being a commonly accepted approximation, which is followed by this MPL model as well. Hence, the results obtained for this parameter, presented in Tab. IV can be considered expected ones. The intervals lengths for the ranges of variation of μ_e and $\sqrt{\bar{\varepsilon_e^2}}$ continue to be small, i.e., 1.01 dB and 1.58 dB, respectively, although the latter is no longer that negligible. The value of μ_e continues to vary roughly around 0 dB, while for $\sqrt{\bar{\varepsilon_e^2}}$ it is around roughly 5.6 dB, which is quite similar to the user dependence case. In the case of R^2_{adj}, it varies now in [0.41, 0.66], which is an interval wider than the previous one for user dependence. Again, the model performs well, but, clearly, distance variability has a larger impact on path loss that the user one.

There is a trend that R^2_{adj} decreases with distance, i.e., the model is giving better predictions for smaller distances. Given that the measurements were taken in a room, where multipath can play a significant role, this trend can be easily explained, in the sense that for lower distances multipath tends to be less important (reflected rays end up being smaller compared to direct ones), hence, leading to a better average behaviour of the logarithmic dependence with distance.

TABLE IV
RESULTS OF THE EVALUATION FOR DIFFERENT PATH LENGTHS.

d [m]	μ_e [dB]	$\sqrt{\bar{\varepsilon_e^2}}$ [dB]	R^2_{adj}
1	-0.26	6.39	0.57
2	0.27	5.07	0.66
3	0.56	5.97	0.52
4	-0.36	5.19	0.52
5	-0.45	4.81	0.50
6	0.24	5.90	0.41

TABLE V
RESULTS OF THE EVALUATION FOR DIFFERENT Δ_h VALUES.

Δ_h [m]	μ_e [dB]	$\sqrt{\bar{\varepsilon_e^2}}$ [dB]	R^2_{adj}
0.00	0.90	5.69	0.57
0.10	-0.27	5.56	0.62
0.25	0.02	6.04	0.56
0.37	0.34	4.65	0.74
0.47	-0.21	5.28	0.57
0.52	0.21	5.60	0.52

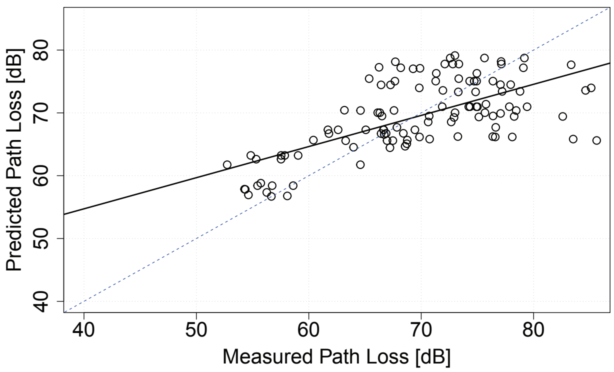

Fig. 2. Measured vs. predicted path loss for $d = 6$ m ($R^2_{adj} = 0.41$).

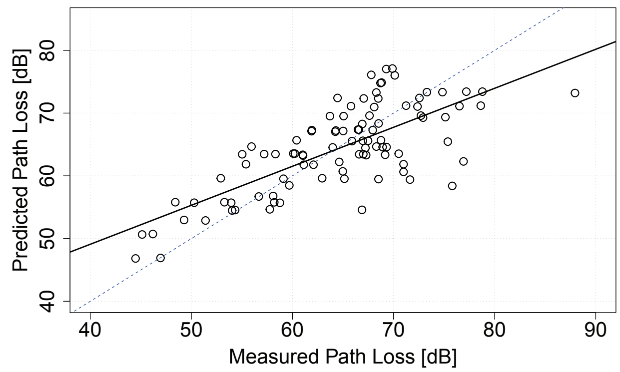

Fig. 3. Measured vs. predicted path loss for $\Delta_h = 0.52$ m ($R^2_{adj} = 0.52$).

The correlation between measured and predicted path loss values for the worst performing case ($d = 6$ m) is shown in Fig. 2. The two lines cross now at 69.2 dB, which is very similar to the previous user dependence case. For the measured points, the model presents an overestimation below roughly 63 dB, while there is a consistent underestimation above roughly 78 dB, thus, not being much different from the previous case as well. However, the range of variation of measured the path loss is reduced to around 30 dB, meaning that distance dependence can be more controlled than user one, in terms of dependence of path loss on their changes; the predicted path loss extends now for around 23 dB.

C. Influence of the Heights

In general terms, one can expect that the difference in heights between the user located antenna and the one on the external access point will have quite an impact on path loss, due to mobility, obstructions and user behaviour, among others, hence, this is an important parameter. In this case, the absolute difference between Tx and Rx antennas' heights depends not only on the location of the user's antenna, but also on the user type (see Tab. I), in the sense that User 4 had just one location.

From Tab. V, one can observe that there is no particular trend in the model accuracy for different Δ_h values. The value of μ_e varies in [-0.27, 0.90] dB while $\sqrt{\bar{\varepsilon_e^2}}$ does so in [4.65, 6.04], therefore, with interval lengths similar to the previous case (1.17 dB and 1.39 dB, respectively). Also, R^2_{adj} continues to be in the similar range of acceptable values, in [0.52, 0.74], although slightly higher.

The scatter plot for the worst case in Fig. 3 shows the two lines crossing at 64.0 dB, continuing to be quite similar to the previous cases. Regarding measured points, the model overestimation is below roughly 58 dB and the underestimation above roughly 70 dB, still in line with the previous cases as well. There is an outlier near 90 dB, but all the other measured points stay within an interval around 35 dB below 80 dB. The range of variation of the measured path loss is around 44 dB, while the predicted one is less than 21 dB.

D. Influence of the Antenna Orientation Angle

The on-body antenna orientation angle is the factor whose influence on the path loss is modelled by a non-linear component, and this non-linearity may be also observed in the accuracy of the model, Tab. VI. The best performance with the highest values of R^2_{adj} (in [0.75, 0.80]) has been obtained for the angles for which the Line-of-Sight (LoS) conditions occurs, i.e., for $\varphi \in \{315°, 0°, 45°\}$, even within the half power beamwidth of the Tx antenna. On the other hand the lowest values of R^2_{adj} (in [0.11, 0.28]) are observed for the Non-LoS cases, i.e., for $\varphi \in \{135°, 180°, 225°\}$; for these situations, there is no direct component, and the received signal consists of the components reflected and scattered from the surrounding environment, where typical office furniture (like computer desk or filing cabinet) were present.

The length for the range of variation for μ_e is also much higher, 4.17 dB, as is the one for $\sqrt{\bar{\varepsilon_e^2}}$, 2.07 dB, although globally the centre values do not change that much. These results confirm that simple MPL models are not sufficient for more complex scenarios and additionally large- and small-scale fading components should be taken into account. This may be confirmed by the scatter plot for the worst performing case ($\varphi = 225°$), presented in Fig. 4, where a very low correlation between measured and predicted path loss values

TABLE VI
RESULTS OF THE EVALUATION FOR DIFFERENT ORIENTATION ANGLES.

φ [°]	μ_e [dB]	$\sqrt{\bar{\varepsilon_e^2}}$ [dB]	R^2_{adj}
0	0.82	6.67	0.75
45	-3.03	5.61	0.78
90	0.12	4.97	0.46
135	1.14	4.60	0.28
180	0.96	6.08	0.13
225	0.88	5.79	0.11
270	-0.74	4.94	0.44
315	-1.90	4.90	0.80

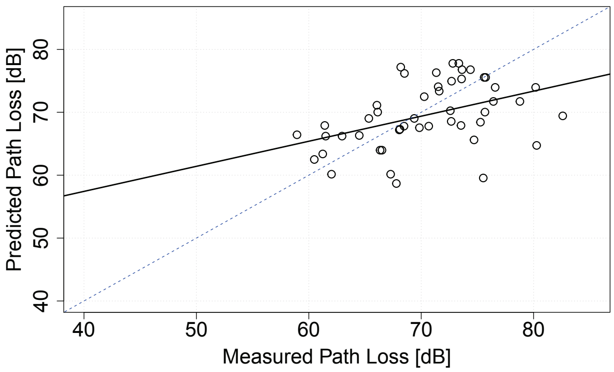

Fig. 4. Measured vs. predicted path loss for $\varphi = 225°$ ($R^2_{adj} = 0.11$).

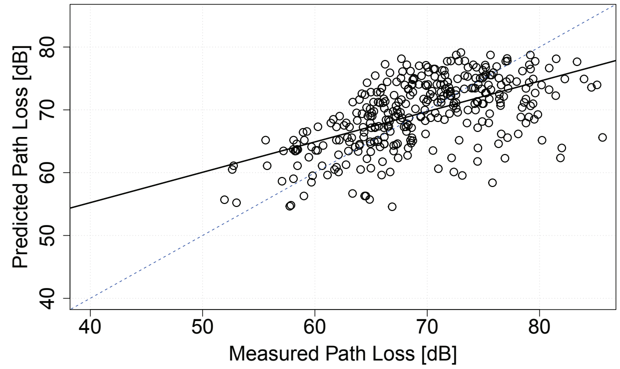

Fig. 5. Measured vs. predicted path loss for XP ($R^2_{adj} = 0.31$).

can be observed, which may be caused by the presence of the office furniture in this direction. For this case, the two lines cross at 69.0 dB, and the overestimation/underestimation behaviour continues to be observed. Interestingly, the range of variation of the measured path loss is down to 24 dB, while the predicted one is 20 dB, this being the case where both ranges are closer to each other.

One can conclude that the model's accuracy is very sensitive to the orientation angle and the immediate surroundings.

E. Influence of Polarisation

Considering the results for mutual orientation of Tx and Rx antennas, Tab. VII, the obtained root mean square error is comparable, being 5.53 dB and 5.63 dB for CP and XP, respectively, with the zero mean error for both. Nevertheless, one can observe a significant difference in R^2_{adj}, which equals 0.70 for CP and 0.31 for XP case, which shows that, for the case when Tx and Rx antennas are orthogonally polarised, there is some part of the variance in the path loss that cannot be explained by the independent variables used in the model.

TABLE VII
RESULTS OF THE EVALUATION FOR DIFFERENT POLARISATION FACTORS.

P	μ_e [dB]	$\sqrt{\bar{\varepsilon_e^2}}$ [dB]	R^2_{adj}
CP	0	5.53	0.70
XP	0	5.63	0.31

In this case, the crossing of the two lines occurs at 69.5 dB, and the overestimation/underestimation behavior continues to be observed, but in a much smaller number of cases, while the ranges of variation of measured and predicted path losses are 36 dB and 25 dB.

A comment deserves to be stated on the polarisation dependence. Opposite to all previous ones (except users), which are somehow continuous, in this case a binary approach has been taken, which is a clear simplification of reality, i.e., the polarisation mismatch between Tx and Rx antennas is indeed a continuous parameter and, regardless of the polarisation of the Tx antenna, propagation in the environment does change polarisation, due to reflection, diffraction and scattering. Still, these effects are more likely to be accounted for in fading rather than in MPL.

V. MODEL USAGE

The MPL model may be used for designing narrow-band BANs of the off-body type, operating in office indoor environments at 2.45 GHz. It is applicable for distances within [1, 6] m, the absolute difference of Tx and Rx antennas' heights up to 52 cm, and the full range of on-body antenna's orientation angles, as well as for both co- and cross-polarised Tx and Rx antenna configurations. Since the model has been developed based on users with different body constitutions, one can add that it is limited to users with a height within [1.60, 1.93] m and a weight in [50, 88] kg, but it can also be stated that this is a too strict limitation.

Considering the overall performance of the model on the whole data set, one should analyse the taken metrics, i.e., the mean error, the root mean square error, and the coefficient of determination. The global values are $\mu_e = 0$ dB, $\sqrt{\bar{\varepsilon_e^2}} = 5.6$ dB, and $R^2_{adj} = 0.60$, which allows to state that, despite the lower accuracy for some particularly difficult cases, the global application of the model presents a quite good accuracy for the goal at stake.

The representation of the averages of μ_e and $\sqrt{\bar{\varepsilon_e^2}}$ over the multiple 10^{th} percentiles of the measured data is presented in Fig. 6 and Fig. 7.

Globally speaking, regarding μ_e, the model overestimates MPL for values under the median and underestimates otherwise. From a network designer's viewpoint, while overestimation can be considered acceptable to some extent, underestimation may lead to an incorrect operation of the network due to failure to ensure an adequate communication range; if one takes out the upper and lower 10^{th} percentiles, then, μ_e has

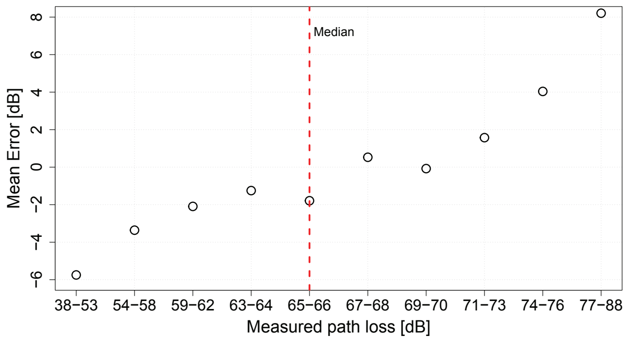

Fig. 6. Mean error for a given range of measured path loss.

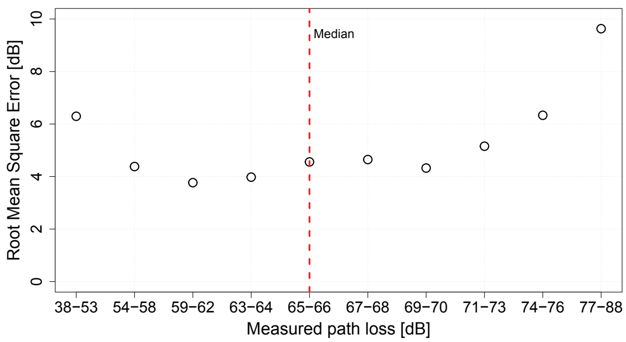

Fig. 7. Root mean square error for a given range of measured path loss.

a maximum absolute value of 4 dB, which can be considered acceptable. Furthermore, concerning $\sqrt{\bar{\varepsilon_e^2}}$, it is basically below 6 dB for nearly every measured path loss, except for the 10$^{\text{th}}$ upper percentile, which, again, can be taken as a good result for the purpose of the model. In conclusion, the analysed model's performance shows that it is at a fairly good level, being a good approach for the estimation of MPL.

VI. Conclusions

In this paper, the evaluation of an off-body mean path loss model's performance based on the Generalised Additive Model is performed, for several cases, from fitting measure data at 2.45 GHz, allowing to take a non-linear dependence on different predictor variables. The evaluation has been based on the commonly used statistical parameters, i.e., mean error, root mean square error and adjusted coefficient of determination. The parameters taken for the model are the distance between the user and the off-body access point, the absolute difference between antennas' heights, the on-body antenna orientation angle with respect to the off-body antenna and the polarisation of both Tx and Rx antennas.

The model's evaluation shows that it is very sensitive to the orientation angle and to the mutual polarisation of Tx and Rx antennas, especially for the cases with the cross-polarised antennas or the cases with the orientation angles around 180°, where the coefficient of determination is very low. However, for all analysed cases the absolute mean error is lower than roughly 3 dB and the root mean squared error is below 7 dB. Considering the overall performance of the model, an acceptable value for R^2_{adj} has been obtained, 0.60, and the mean error and the root mean square error equal 0 dB and 5.6 dB, respectively. In conclusion, the Generalised Additive Model can be used to model mean path loss from measured data, with a good performance.

References

[1] H.-B. Li, K.Y. Yazdandoost and B. Zhen, *Wireless Body Area Networks*, River Publishers, 2010.

[2] M. Mackowiak, *Modelling MIMO systems in body area networks in outdoors*, Ph.D. Dissertation, IST-University of Lisbon, Lisbon, Portugal, 2013.

[3] S.J. Ambroziak, K. Turbic and L.M. Correia, "An approach to mean path loss model estimation for off-body channels," in *Proc. of 11th Int. Symp. on Medical Information and Communication Technology (ISMICT)*, Lisbon, Portugal, Feb. 2017.

[4] R. Chávez-Santiago et al., "Experimental path loss models for in-body communications within 2.36-2.5 GHz," *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 3, pp. 930–937, May 2015.

[5] P. Cui et al., "Measurement and Modeling of Wireless Off-Body Propagation Characteristics Under Hospital Environment at 6–8.5 GHz," *IEEE Access*, vol. 5, pp. 10915–10923, May 2017.

[6] K.K. Cwalina, S.J. Ambroziak and P. Rajchowski, "An off-body narrowband and ultra-wide band channel model for body area networks in a ferryboat environment," *Applied Sciences*, vol. 8, no. 6, June 2018.

[7] J. Wen, Y. Zhang, G. Yang, Z. He and W. Zhang, "Path loss prediction based on machine learning methods for aircraft cabin environments," *IEEE Access*, vol. 7, pp. 159251-159261, Oct. 2019.

[8] J. Thrane, D. Zibar and H.L. Christiansen, "Model-aided deep learning method for path loss prediction in mobile communication systems at 2.6 GHz," *IEEE Access*, vol. 8, pp. 7925-7936, Jan. 2020.

[9] T.A. Benmus, R. Abboud and M.K. Shatter, "Neural network approach to model the propagation path loss for great tripoli area at 900 1800 and 2100 MHz bands," in *Proc. 16th Int. Conf. Sci. Techn. Autom. Control Comput. Eng. (STA)*, Monastir, Tunisia, Dec. 2015.

[10] O.O. Shoewu et al., "Fuzzy-logic based path loss models for metropolitan environment," *Proc. IEEE Int. Workshop Signal Process. Syst. (SiPS)*, Cape Town, South Africa, Oct. 2018.

[11] M. Laskowski, S.J. Ambroziak, L.M. Correia and K. Świder, "On the Usefulness of the Generalised Additive Model for Mean Path Loss Estimation in Body Area Networks," *IEEE Access*, vol. 8, pp. 176873-176882, Sep. 2020.

[12] A. Swider, H. Langseth and E. Pedersen, "Application of data-driven models in the analysis of marine power systems," *Applied Ocean Research*, vol. 92, Nov. 2019.

[13] N. Pathak, A. Ba, J. Ploennigs and N. Roy, "Forecasting gas usage for big buildings using generalized additive models and deep learning," in *IEEE Int. Conf. Smart Comput. (SMARTCOMP)*, Taormina, Italy, June 2018.

[14] L. An et al., "Generalized additive models of hospital admissions with respiratory disease and meteorology," in *Proc. IEEE 3rd Int. Conf. Cloud Comput. Intell. Syst.*, Shenzhen, China, Nov. 2014.

[15] Z. Chi, L. Yang, J. Lin and S. Huang, "Prognostics of polygonalization of high-speed railway train wheels using a generalized additive model smoothed by spline-backfitted kernel," in *Proc. IEEE Int. Conf. Prognostics Health Manage. (ICPHM)*, San Francisco, CA, USA, June 2019.

[16] X. Wang and D. E. Brown, "The spatio-temporal generalized additive model for criminal incidents," in *Proc. IEEE Int. Conf. Intell. Secur. Informat.*, Beijing, China, July 2011.

[17] S.J. Ambroziak, L.M. Correia, R.J. Katulski, M. Mackowiak, C. Oliveira, J. Sadowski and K. Turbic, "An off-body channel model for body area networks in indoor environments," *IEEE Transactions on Antennas and Propagation*, vol. 64, no. 9, pp. 4022–4035, Sep. 2016.

[18] S.J. Ambroziak, "Measurement stand and methodology for research of the off-body and body-to-body radio channels in WBANs with different diversity schemes," *International Journal of Antennas and Propagation*, vol. 2019, Article ID 3837190, pp. 1–16, Apr. 2019.

[19] J. Bendat and A. Piersol, *Random Data: Analysis and Measurement Procedures*, 4th Edition, John Wiley & Sons, 2010.

[20] M. Sarstedt and E. Mooi, *Regression Analysis. In: A Concise Guide to Market Research*, Springer, 2014.

[21] R.A. Johnson and D.W. Wichern, *Applied Multivariate Statistical Analysis*, Prentice-Hall, 1988.