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Application of Particle Filter in Path-Loss Modelling

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ABSTRACT

The article presents the dynamic estimation method of the path loss exponent parameter in the function of the distance based on the conducted measurements. A specific feature of this solution is its suitability for distance estimation on devices which are characterised by a small amount of resources. The presented method allows to provide an acceptable precision of distance estimation while using a relatively small measurement set. For this purpose, real RSSI (Received Signal Strength Indicator) measurements were used and estimation of the path-loss exponent was performed with the use of a Bayesian particle filter. The article, apart from a detailed demonstration of the algorithms, presents the results of the sensitivity analysis of this method to change the number of inserted particles and of the repetitions of calculations needed to estimate the path loss exponent. Additionally, the results of the model stability study on the size change of the experimental dataset RSSI are presented. The properties and accuracy of the proposed method are verified based on a set of actual measurement data. All the obtained results indicate the utility of the Bayesian filtering method for effective estimation of the path loss exponent and confirm the possibility of using the described method in systems with a limited amount of computing resources.

Keywords: path-loss exponent, particle filter, Bayesian filtering, received signal strength.

INTRODUCTION

Wireless sensor networks (WSN) have been the foundation for the development of a wide range of systems and services for many years. Their characteristic feature is the use of many spatially dispersed sensors [1]. In most cases, the knowledge of their relative position and distance is the key information for the correct implementation of the functionality assigned to a given WSN [2]. A summary of the issues related to the location and distance measurement (but also other key parameters) for the most popular applications of wireless, mobile and WSN networks is briefly presented in the review article [3]. Due to the wide and still growing area of WSN applications, the issue of estimating the distance among network nodes has been the subject of intensive research. Among the many solutions proposed in recent years, by far the most popular are those based on the measurement of the Received Signal Strength Indicator (RSSI) [1, 4]. Other solutions are based on indicators such as LQI (Link Quality Indicator) or time difference between sending and receiving a radio signal known as ToA (Time of Arrival) [5, 6]. Such frequent use of the RSSI results mainly from the relatively simple implementation of the measurement of this signal, which does not require the use of additional hardware resources. The methods using RSSI measurement do not interfere with the communication overhead, which is promising in WSN systems with limited resources, e.g. power [7, 8]. The RSSI values measured are used in models which bind the attenuation of the transmitted signal to the distance travelled by the signal. In other words, the process of estimating a specific distance between two antennas requires the use of an appropriate attenuation model on the signal transmission path (path loss model). However, this simple concept of solving the distance estimation problem is really challenging. Two factors are responsible for this situation. RSSI measured values are very strongly related to the conditions under which the measurement was carried out, which results from the specificity of the radio signal. On the other hand, it is extremely difficult to determine suitable values of parameters in the path-loss model that will be optimal under different conditions of the distance estimation process [9, 10]. The most popular models based on the propagation of radio signals using RSSI include: the free-space model, the 2-ray ground model and the log-normal shadow model (LNSM) [2, 11]. The LNSM model is the most universal of the three and its usefulness has been confirmed for both indoor and outdoor environments [8, 10]. In addition, it gives promising results in changing weather or environmental conditions [12-14]. Our research provides a specific look at path loss modelling. In most practical system solutions for WSN, the number of hardware resources are a key limitation. At the same time, the amount of data obtained from measurements is also subject to significant limitations. For this reason, we focused on the possibility of using an optimized method of distance estimation on devices which are characterised by a small amount of resources. We also propose a method of defining a relatively small measurement set, which can ensure an acceptable precision of distance estimation. Such an approach to the discussed issues is relatively rare in the literature. A few examples of analysis of a similar type are presented in [15]. In the aforementioned work, the authors propose to estimate the parameter of the road loss exponent depending on the distance, based on the performed measurements. The issue of distance estimation based on path loss models and RSSI signal measurements has been the subject of intensive research for many years. One of the reasons for the need for an in-depth analysis of this topic is that the values of the RSSI signal depend on the measurements conditions (influence of interference such as: additive noise, multi-path fading, shadowing etc.) as well as the parameters and hardware configuration. Extensive experimental research on the impact of changes in the environment as well as factors influencing the RSSI signal in the time domain and frequency domain are presented in detail in [16]. In turn, the importance of weather conditions, including evaluation of RSSI signal sensitivity to changes in temperature and humidity in the outdoor environment, is the subject of the experimental studies presented in [13]. Analogous research for the outdoor scenario but for the estimation of relatively large distances based on RSSI signal measurements is presented in [8]. Considering the above-mentioned environmental factors has led to the proposition of many new methods. For example, Singh et al. in [17] proposes the New Received Signal Strength Indicator (NRSSI) method. This method introduces a new way of considering noise, especially thermal noise. According to the conducted experiments, this method allows to improve the accuracy of distance estimation. Moreover, regarding the task of locating WSN nodes based on RSSI measurements, the influence of environmental parameters on the accuracy of estimates is analysed in [18]. Also, in the case of the LNSM model, the main research issue is the method of determining the value of its parameters for specific measurement conditions. In most cases, the experiments focus on improving the accuracy of the ranging and increasing the accuracy of the location. The path-loss model presented in [19] is based on two-function. Using experimental measurements, the authors determined the method of setting parameters for two kinds of distances, small and larger. A different approach is described in [20, 21]. It involves the use of the Generalised Method of Moments (GMM) to estimate the distance between sensor nodes. This statistical model of GMM was bonded with so-called RSSI-D values representing the set of offline RSSI values. As a result, they produced better positioning precision.

Some of the research works and the resulting proposals take into account the specific features of the data transmission technology used in WSN. In [22], the algorithm of estimating the location of the node in the WSN based on Bluetooth technology has been combined with determining the parameters of the path loss model using Bayesian filtering. Research regarding combination of Bayesian inference with K-means clustering to estimate indoor positioning is shown in paper [23]. In turn, for networks using ZigBee, a series of analyses of the impact of environmental conditions on the estimation of the model parameters were carried out [24, 25]. In the context of the precision of distance estimation and location of ZigBee nodes, a comparative analysis for two models, the LNSM and the Hybrid Teacher Learning Based Optimisation Algorithm technique, respectively, was presented in [26]. A separate group of research works concerns the definition of generalised methods for determining the values of the parameters of path loss models and methods of correcting their values, which would allow the use of these methods in various environmental conditions and in WSN based on various technologies. An example of this type of work is [27], which describes and experimentally verified the method of joint estimation of location coordinates and distance-power gradient for applications using the path loss model, in which the parameter values are not known a priori. The basis of this solution is the innovative use of the nonlinear least-square estimator. On the other hand, the authors of [28] conducted an in-depth analysis of statistical properties of signal propagation in WSN based on a numerical solution of the wave equation. The conclusions from this analysis, supported by the simulation results, constitute a set of important guidelines for defining the methods of determining the parameters of many path-loss models. A similar analysis of signal propagation based on parametric channel models is provided in [20].

Recent years have also brought numerous publications on the optimisation and generalisation of methods using path loss models. The research described in [29] based on the uncertainty theory, and the proposed method is the result of sensitivity analysis in relation to the properties of wireless signal propagation. In turn, [30] describes a method of optimising path loss models, which allows for a fairly accurate determination of the distance correction. The basis of this solution is an optimization algorithm known as the "firefly" algorithm and particle swarm optimization. On the other hand, in the paper [31] presents the model that allows for consideration the variety of parameters of the equipment used. This is possible due to the generalized extended interpolation method during specifying the parameters of the environment. Another attempt to implement correction of distance estimation is presented in the work [32]. In this case, the authors used the feedback filter structure, which allows for the inclusion of historical values of RSSI in the proposed correction process. Based on these and similar analyses, the authors of [33] developed methods of signal filtering in relation to the problem of predicting patterns in wave propagation and thus predicting and correcting the value of the estimated distance based on RRSI measurements and path loss models. The basis of the proposed solution is the use of non-linear regression techniques. The new path of research on the issues discussed, which uses the methods and algorithms of widely understood artificial intelligence, cannot be overlooked either. In [33] the main attention is focused on the issue of the location of nodes and in this context the path loss model parameters derived from RSSI measurements form a set of training data for a multi-layer artificial neural network (ANN). The ANN model based on the back propagation algorithm is also proposed for direct determination of the parameters of the path loss model. In this case, the basis for learning the ANN is the error model developed for the LNSM, which is described in [34]. In turn, the accuracy of the ANN methods is a subject of the comparative analysis with other classical methods in [35]. In these studies, the method based on regression analysis and polynomial approximation was chosen as a representative of the classical methods, while the ANN represented a multilayer feed-forward network. The authors showed that for the analysed cases, ANN offered greater accuracy in estimating the distance and location of network nodes. Finally, it is worth mentioning [36], in which the authors proposed a new model of distance estimation based on RSSI signal measurements, based on genetic programming. The verification of this model and its comparison with the classical LNSM model confirmed the advantage of the genetic algorithm. The main purpose of this work is to study the sensitivity of this method to change the number of inserted so-called particles and the number of repetitions of calculations needed to correct estimation of the path-loss model parameter. The model stability was tested on a reduced set of experimentally collected RSSI points. Finally, we would like to check the accuracy of our method in the case of real data. The rest of this paper is organised as follows. Section II introduces the path loss exponent estimation using Bayesian filtering. In Section III we develop a particle filtering algorithm that will make a joint estimation of the position and discrete channel parameters. Section IV confirms the advantages of the presented algorithms and the proposed models in the form of experimental results. Section V shows the test of selected system on real measurement data. Finally, Section VI concludes the paper.

PATH-LOSS EXPONENT ESTIMATION USING BAYESIAN FILTERING

It is well known that the distance between the transmitter and receiver affect the strength of the received signal. Path loss may occur due to various phenomena. The fundamental one is of course free-space path loss but reflection, diffraction, fading, shadowing or in general all the obstacles that surround or interpose between the transmitter and the receiver have influence on received signal. The RSSI signal, like any other transmitted signal, is also subject to these physical laws [1]. As stated in Section 2, one of the most popular path loss models is the log-normal shadowing model (LNSM). It allows for the description of these phenomena with the use of the formula:

$$P_r(d) = P_r(d_0) - 10n \log \frac{d}{d_0} + \xi \qquad (1)$$

where: $P_r(d)$ is the received power at distance d from the transmitter, $P_r(d_0)$ the received power measured at reference distance d_0, n is the path loss exponent, and is a zero mean Gaussian noise, which represents the random effect caused by shadowing.

The key parameter in this model is the path loss exponent (PLE). There are a large number of theoretical analyses of path loss exponent estimation but in practice, proper determination of its value is challenging task [1, 2, 10]. This path loss model parameter can be calculated by summing a perfect free-space channel. Such assumption is an oversimplification in many practical applications where extensive channel measurements are not possible. Therefore, the problem of determining the value of the PLE is the subject of a very large number of studies and experiments. The description of a generic practical analysis of PLE value estimation in three configurations, respectively: outdoor-free space environment, indoor-building space and indoor-industrial space is the subject of research presented in [37]. Among the many analysed parameters, the authors took into account the values of path loss, path loss exponent and RSSI as well as analysed the effect of log-normal shadowing, represented as standard deviation. The presented results confirmed the theoretical values provided in many previous studies. Generally, in the outdoor environment, the value of n typically varies between 1 and 3 [3, 19]. With regard to the indoor environment, a broad analysis of practical methods and the resulting precision of PLE value estimation is presented in [38]. The average PLE value shown by the authors was 4.2, which corresponds to the theoretical value range for the indoor environment, which is 4 to 6. It is worth noting, however, that in some cases, such as indoor environment with moving objects, the channel characteristics tend to change significantly over time. For this reason, allocation of transmitters and receivers is extremely important as well as the arrangement among them. These issues are discussed in detail in [39]. The authors propose a scheme of optimal node arrangement for typical path loss exponent estimation. The importance of node allocation is also investigated in [40]. The research presented in it was based on ad-hoc large-scale WSN. The distribution of nodes in this network corresponded to the homogeneous planar Poisson point process. Based on such a data transmission structure, three methods of estimating the PLE value at each node have been proposed, assessed and compared. An equally important factor, apart from those mentioned above, is the influence of weather conditions. Especially, in outdoor environment, the path loss exponent values tend to change over a long period of time because of seasonal reasons [7, 13]. It is also worth emphasising that it is not guaranteed that all anchor nodes radiate in the same manner. The elimination of this and other factors, significantly affecting the accuracy of PLE estimation, was and is a motivation for many proposals of modified and new methods [41, 42].

In our opinion, in the case of the assumptions presented in the Introduction, a Bayesian filters are the way to get good results [43-45]. This method has been widely used for several years in systems using RSSI measurements [44, 45]. We focused our research on the use of Particle Filter (PF). The research results obtained so far confirm that the use of Bayesian filtering in the context of the RSSI signal can improve the efficiency of device location [46-48]. The PF algorithm has been the subject of many extensions and modifications. In paper [44], the authors describe that the PF algorithm can improve indoor location performance based on RSSI. The authors modified the particle filtering by adding a Kalman filter to reduce the influence of signal noise and multipath reflections on the RSSI. Subsequently, the authors in [47] proposed a model fit for the rapid volatility of RSS. A signal tracking method based on a particulate filter was used. It was observed that the model describes the real experimental data quite well. In turn, authors in [45] used a particle filter algorithm to estimate the distance in a multi-antenna design. Their system consisted of a transmitter and a receiver equipped with multiple antennas. The RSSI signal values were used for the computation of important weights within the proposed algorithm. They used the log-normal model and the ground reflection model. The weighted particles were resampled to ensure proper distribution and density. The authors in [48] propose use of particle filter in a Novel Cooperative Localisation Algorithm. They argued that the real data from WSN nodes used in marine search and rescue operations was inaccurate due to the presence of the wave shadow effect. The use of particle filters allowed to reduce measurement errors.

From the point of view of the objectives of our article, interesting research is presented in [46]. This work describes the results of experiments of 3D localisation of WSN nodes from an Unmanned Aerial Vehicle (UAV) with the use of a particle filter-based algorithm. The algorithm uses the RSSI measurements collected by a node located on the UAV and was run on an on-board embedded computer. The presented analysis also covers the numerical complexity of the method, and thus the possibility of its implementation on equipment with limited resources.

PROPOSED METHOD

In recursive Bayesian estimation the probability density function of a random vector is tracked over time [49]. At each time step (t), a model describing the evolution of the random vector, as well as an observation model describing how observations are related to the state, are present. In this method a set of random samples is used. This samples are called particles [50]. The particles have an associated its weight $w_i(t)$ directly connected with likelihood $p(n_i(t)|z(t))$, where $n_i(t)$ is the state of the *i-th* particle and $z(t)$ is the observed RSSI value, at time t [43]. The state of the *i-th* particle is only related to the n parameter. The implemented particle filter (see Algorith shown in Figure 1) performs several steps: generating particles, determining particles weight, resampling and estimation desired quantities. In the prediction step, we create with a Gaussian distribution N random particles with n_i value in the range from 0 to 5. In the next steps particles change their state in a random way. The value of standard deviation δ is constant. As a process noise parameter, our particle filter used the worst deviation value taken from our measurements, e.g., δ = 8.27 m. In the update step, according to the model shown in (1) and Gaussian noise with standard deviation δ:

$$p\big(z(t)\big|n_i(t)\big) = \frac{1}{\delta\sqrt{2\pi}} e^{\left(-\frac{(z(t)-P_r(d))^2}{2\delta^2}\right)} \tag{2}$$

where: $P_r(d)$ is described by the propagation model using the appropriate n_i parameter for the *i-th* particle:

$$P_r(d) = P_r(d_0) - 10 n_i \log\frac{d}{d_0} + \xi_\delta \tag{3}$$

Next, the weights are updated and normalised:

$$w_i(t) = \overline{w_i}(t-1) p\big(z(t)\big|n_i(t)\big) \tag{4}$$

and:

$$\overline{w_i}(t) = \frac{w_i(t)}{\sum_{j=1}^{N} w_j(t)} \tag{5}$$

where stands for the normalised weights.

The resampling approach is used to avoid degeneration problems in this method when N_{eff} falls below some threshold N_T [51, 52]:

$$N_{eff} = \frac{1}{\sum_{j=1}^{N} \overline{w_j}^2(t)} \tag{6}$$

Finally, the path-loss exponent is calculated by means of a weighted sum of the state information coming from all the particles:

$$n(t) = \sum_{i=1}^{N} \overline{w_i}(t) n_i(t) \tag{7}$$

RESULTS

The real outdoor RSSI measurements $P_r(i)$ between two ZigBee nodes were performed. The measurements were carried out for various distances ranging from 1 to 100 meters. The measurement system consisted of two XBee radio modules (XB24-Z7WIT-004) with a 2mW wired antenna operating in the 2.4 GHz band. A programming platform is based on the Esp32 module. During the measurements, the distance between the modules was changed and the RSSI values were recorded for further analysis. The receiver and the transmitter were placed 1 m above the ground. The schematic diagram of the measuring system is shown in Figure 2.

For each measured distance (d), a series of 60 measurements (Ns) of RSSI value was made. The measurement system was described in detail in our previous work [12]. The results are presented in Figure 3. The measurements (shown in Figure 3) were carried out at average temperature T = 15.56^{o}C and average air humidity H = 49.93%. The value of the RSSI versus the distance decreases according to the logarithmic function.

```
input  : RSSI data read from disk for corresponding distances d
         N_s-number of experimental points,
         N_d-number of measured distances,
         N-number of added particles,
         N_T-treshold for resampling steps,
         Eq-number of repetition steps
output: An average path-loss exponent n_pf
for iq = 1 to Eq do
    for i = 1 to N_d do
        if Remove then
            Removed desired number of experimental points
        end
        for k = 1 to N do
            Generate N random particles according to propagation model
             (3) within n range [0,5]
        end
        for j = 1 to N_s do
            for k = 1 to N do
                Calculate N samples from (2) using (3) and corresponding
                 weights w_k from (4)
            end
            Calculate total weight: w_s = \sum_{i=1}^{N} w_k^j
            for k = 1 to N do
                Normalise weights: w_k = w_k / w_s
            end
            Calculate N_eff using (6)
            if N_eff > N_T then                          // Resampling step
                for k = 1 to N do
                    Replacement particles according to the weight w_k
                end
            end
            Estimate mean path-loss exponent based on propagation model
             (3) and equation (7)
        end
        Estimate mean path-loss exponent and its standard deviation for
         all measurement distances d
    end
    Collect necessary averages and standard deviations
end
```

Figure 1. Algorithm 1 – the path-loss exponent estimation algorithm

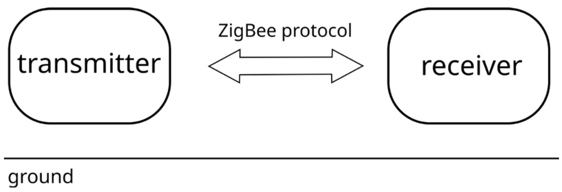

Figure 2. Model of the measuring XBee system

The value of $n_{a\chi} = 1.472$ was obtained by approximating the experimental data using a logarithmic function. The Scilab package was used. As noted in the introduction, the main goal of this work is to denoise the recorded RSSI data and estimate the path loss exponent n_{pf} using a particle filtering algorithm. Next, we want to study the sensitivity of this algorithm to change in the number of so-called particles N and the number of repetition steps needed to calculate the path loss exponent.

The obtained path loss exponent n_{pf} was compared to the path loss exponent obtained as a result of approximation n_{ax}. Comparing the difference $n_d = |n_{ax} - n_{pf}|$ has no practical meaning, so we decide to convert n_d into the corresponding distance errors *d(i)* calculated at 3, 20, and 90 meters. We calculate an absolute distance estimation error (ADEE) from the following expressions:

$$d(i) = \left|d_{ax} - d_{pf}\right| = \left|10^{\lambda(i)} - 10^{\beta(i)}\right| \quad (8)$$

and

$$\lambda(i) = \frac{P_r(d_0) - P_r(i)}{10 n_{ax}} \quad (9)$$

$$\beta(i) = \frac{P_r(d_0) - P_r(i)}{10 n_{pf}} \quad (10)$$

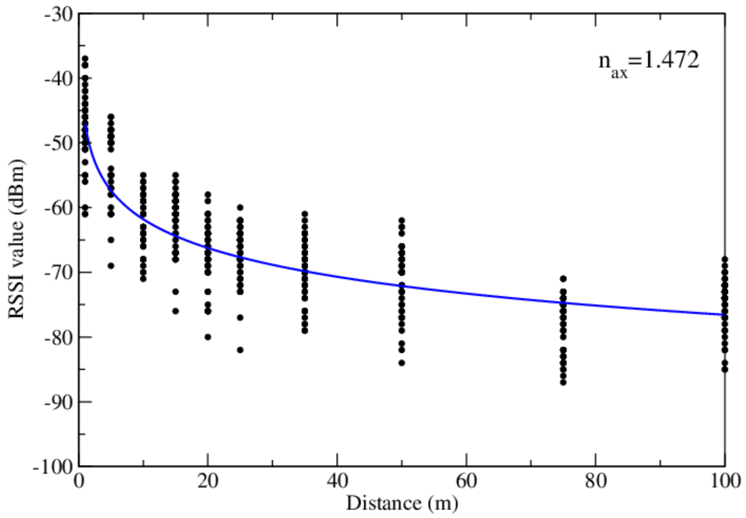

Figure 3. The results of RSSI measurements and calculated path-loss model for different distances

where: $P_r(d_0)$ – corresponds to reference RSSI value at distance d_0 = 1 m, P_r (i) – corresponds to RSSI average values taken from Figure 4 for distances 3, 20, and 90 meters for approximated path loss model with n_{ax} = 1.472, and n_{pf} are taken from particle filter optimisation process. Figure 4 explains how the ADEE has been calculated. For small distances, this error is relatively small, but grows rapidly with increasing distance.

The results of calculating the standard deviation of ADEE for 90 m and for different N and repetitions are presented in Figure 4. They show that the best statistical results are provided by filters with the number of particles higher than 10. In addition, multiple repetition of calculations (equilibration) allows the use of filters even for a very low number of inserted particles. For further tests we decided to choose three systems: (N = 25, Eq = 10), (N = 50, Eq = 10), (N = 100, Eq = 10) called as: M1, M2, M3. They are characterised by a relatively low computational cost and small statistical error associated with the algorithm (see Table 1). Next, to compare these three systems with a system with better statistics but with significantly more time-consuming calculations, the M4 system was chosen (N = 100 and Eq = 1000). Those results show that the averaged ADEE in relation to the approximated model does not exceed 7 meters for a distance of 90 m, one meter for a distance of 20 m, and 0.06 m for 3 m. The computational cost associated with experimental points N_s is $O(N{\cdot}N_d{\cdot}E_q)$. The final number of iteration steps necessary to evaluate the average path loss exponent, n_{pf}, increases with increasing of N, N_s, N_d and E_q, and for considered systems M1, M2,

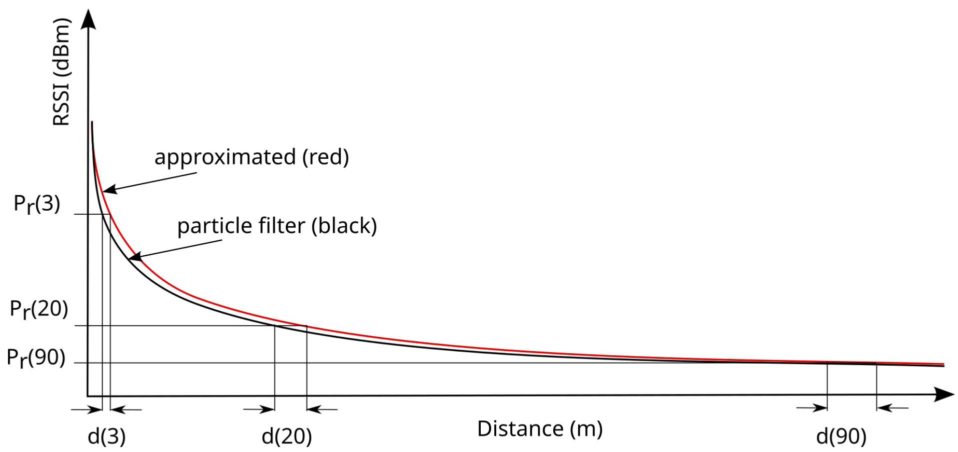

Figure 4. Graphical explanation of distance error calculating

M3 and M4 are equal to 250, 2500, 5000, 10 000 and 1 000 000 steps, respectively. The average times of running presented in Table 1, have shown that the average CPU time is not proportional to the number of iterations used during tests. The optimisation program was written in the Matlab environment. Code analysis showed that the run-time environment automatically optimises the operation of the program. Therefore, the start-up times are not reliable. In next step of our calculation, the models considered were subjected to the second tests. This was done by examining the sensitivity of those systems to depletion of the input data, i.e. experimental data. It was done by randomly decreasing the number of measurements, N_s, from the initial 60 to 15, independently for each distance. Figure 6 shows the dependence of the average absolute distance estimation error for the respective systems depending on the number of experimental points.

All results were characterised by one relationship. Reducing the size of the input data involve

Table 1. An average ADEE and its standard deviation for selected systems

No.	N	E_q $\cdot 10^2$	n_{pf}	*d*(3) [cm]	std. dev. [cm]	*d*(20) [cm]	std. dev. [cm]	*d*(90) [m]	std. dev. [m]	comp. cost $\cdot 10^4$	cpu time [s]
M1	25	0.1	1.452	5.0	0.21	89.4	3.61	6.087	0.2498	0.25	0.90
M2	50	0.1	1.451	5.0	0.20	88.6	3.77	6.038	0.2578	0.50	0.96
M3	100	0.1	1.450	5.1	0.13	91.3	1.90	6.219	0.1318	1.00	1.22
M4	100	10.0	1.450	5.3	0.01	93.9	0.26	6.399	0.0190	100.0	40.46

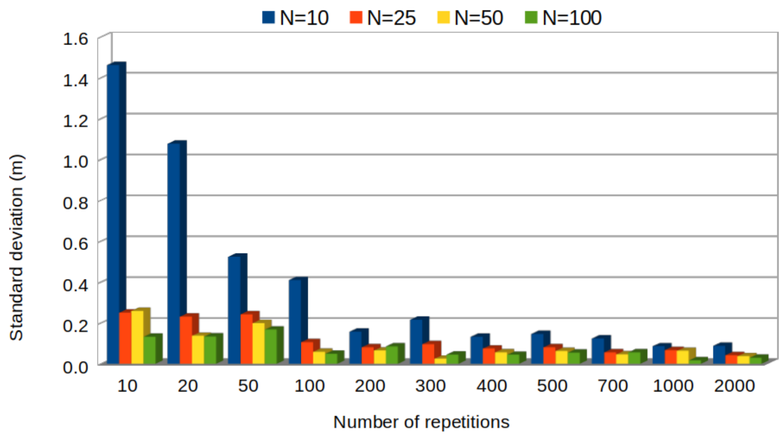

Figure 5. The standard deviation of ADEE for *d*(*90*) for different number of particles and different number of repetitions steps

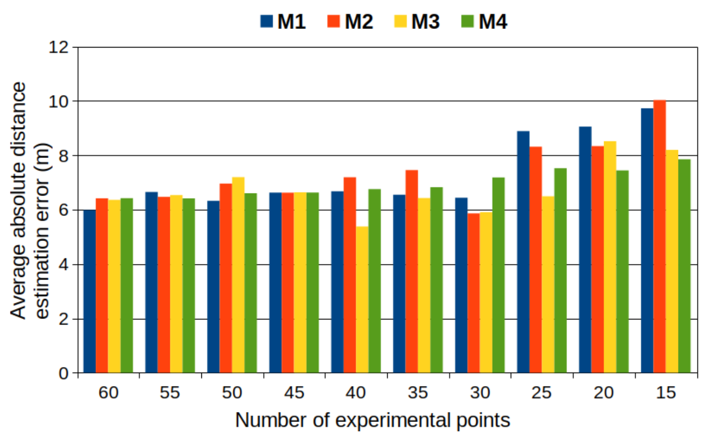

Figure 6. Average ADEE at *d*(*90*) for M1, M2, M3 and M4 for different number of measurements points remaining after depletion process

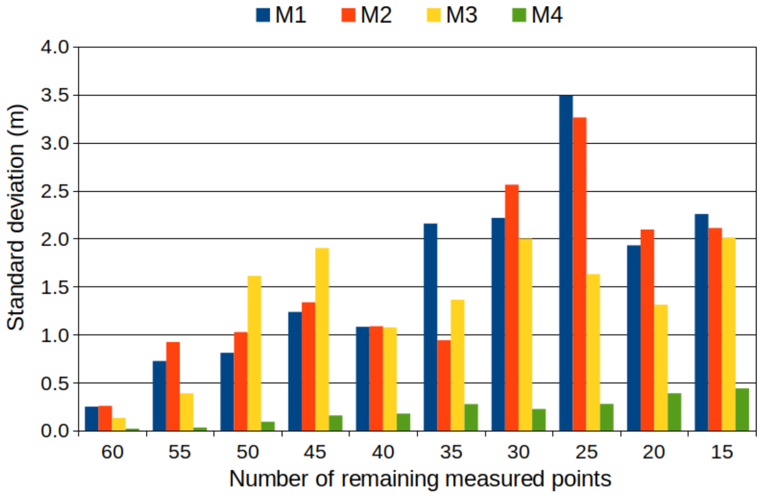

Figure 7. The standard deviation of ADEE for *d*(*90*) after decreasing the experimental data

overestimation of the distance measurement. Initially, the fluctuation of distance is not too high, the differences become more visible when the number of removed measurement points exceeds 50%. Above this value, a better quality of the M4 system is visible. Moreover, it seems that the chosen system (M4) gave a good distance estimation even if from of 60 measuring points per distance measurement remains only 15 remain. The results calculated based on original number of measurements were characterised by average distance estimation error equal to ≈6.4 m and small statistical error, not exceeding 0.26 m for all systems (see Table 1).

Unfortunately, the situation is completely different in the case of progressive reduction of the number of experimental points, especially for the M1, M2, M3 systems. Figure 7 presents the standard deviation of ADEE for *d*(*90*) after decreasing of experimental data. The results show that a small reduction in the number of measurement points results in a significant increase in the standard deviation of ADEE. Increasing the value of standard deviation is caused by too little randomness in removing measurement points. To keep the standard deviation low, it became necessary to increase the number of equilibrium steps for each distance (compare systems M3 and M4 systems). These results confirm that increasing the number of repetitions allows a significant reduction of statistical error more than increasing the number of particles. It should be added that this error is related only to the quality of the pseudo-random number generator and using a generator with a better distribution of generated numbers should reduce this error.

Based on the results shown in Figures 6 and 7, we can estimate the maximum distance measurement error. From Figure 6 the maximum absolute distance estimation error is 10 m for $N_s = 15$ and the highest standard deviation from Figure 7 is 3.5 m for $N_s = 25$. Hence, the estimated maximum measurement error is 10 m ± 3.5 m depends on the input data and the entire optimisation procedure. In summary, the M3 and M4 systems allow to similar distance estimation. They are distinguished by their computational complexity and statistical error. Increasing the number of iterations in the M3 system reduces the statistical error and converts it to the M4. Given the above, in our opinion system M3 is not very sensitive to reducing the amount of input data. It works with optimal speed and in a small way overstates the distance measurement.

In Figure 8 the path loss exponents curves for the M3 system and originally approximated from the experimental data are compared. One can see that the difference between the RSSI data for a distance of 100 m does not exceed 0.6 dBm (see inset). The distance measurement error is less than 10% for such large distances.

TESTS WITH REAL DATA

A series of measurements were performed to evaluate the usefulness of the M3 system ($N = 100$, $Eq = 10$, $n_{pf} = 1.450$). During the collection of the experimental data presented in Figure 2, the data necessary to prepare the test were also saved. Thus, the measuring conditions were the

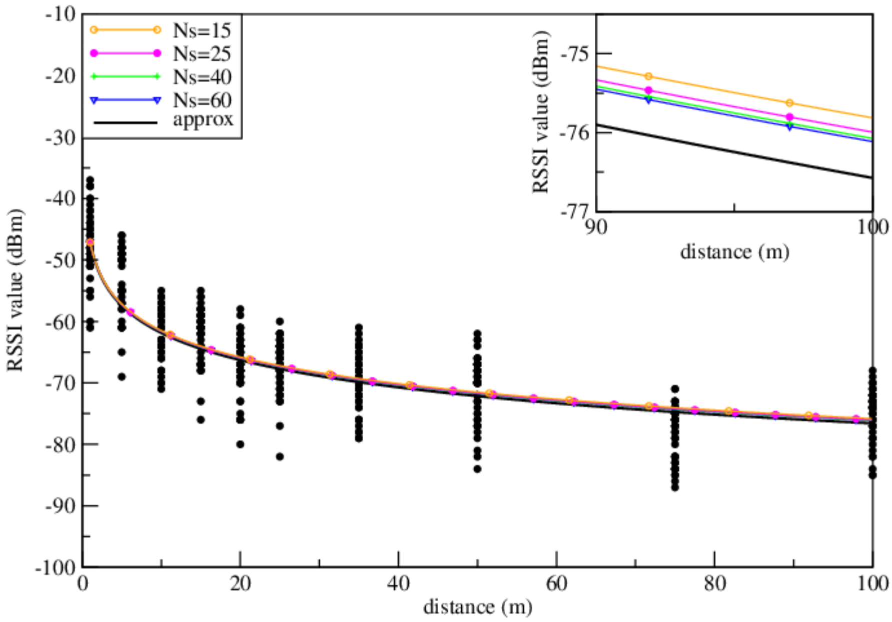

Figure 8. Approximated path-loss model and M3 model for different distances. Model M3 was calculated for remained number of measured points (*Ns*) equal to: 60, 40, 25 and 15, respectively. The inset shows zoomed last point of presented results

same. The test data have not previously been used previously for model estimation. Measurements were made for a known distance d equals to 3 m, 20 m, and 70 m between the devices. The different number of RSSI samples, ranged from 10 to 60, were collected for each distance. The average distance d_{est} was calculated directly from the following expressions:

$$\langle d_{est} \rangle = 10^{\beta(i)} \quad (11)$$

and

$$\beta(i) = \frac{P_r(d_0) - \langle P_r(i) \rangle}{10 n_{pf}} \quad (12)$$

and

$$\langle P_r(i) \rangle = \frac{\sum_{i=1}^{N_s} P_r(i)}{N_s} \quad (13)$$

Where $P_r(d_0)$ corresponds to reference RSSI value at distance $d_0 = 1$ m, $P_r(i)$ corresponds to average RSSI values taken from measurements $P_r(i)$ for distances 3, 20, and 70 m, *Ns* is the number of measured experimental points, and $n_{pf} = 1.450$ are taken from particle filter optimisation process for the M3 system. The results are shown in Table 2.

The obtained results show that the standard deviation of distance estimation increases with the increase of measured distances. Moreover, as the number of measured points decreases, the standard deviation also increases. It should be noted that the determined path loss parameter makes it possible to estimate the distance quite accurately. On the other hand, this estimate is burdened with a fairly large statistical error (compare Table 1 for M3 with Table 2). The measurement error is influenced by both the error related

Table 2. Estimated distances and their standard deviations for the n_{pf} = 1.45 for different number measurement points Ns

N_s	$\langle d_{est} \rangle$	std. dev.	$\langle d_{est} \rangle$	std. dev.	$\langle d_{est} \rangle$	std. dev.
	[m]	[m]	[m]	[m]	[m]	[m]
60*	2.88	0.97	18.20	6.17	66.51	22.73
60	2.93	1.01	19.05	6.56	70.88	24.63
40	2.97	1.14	19.12	6.66	67.50	24.32
20	3.06	1.31	19.32	6.88	72.21	25.58
10	2.89	1.74	21.09	7.12	73.95	27.29

Note: *data obtained for approximated model $n_{ax} = 1.472 n_{ax}$

to the operation of the device itself and the environmental conditions in which the measurement was carried out. Moreover, while the standard deviation of the RSSI measurements is relatively small, the already calculated distance is characterised by very large values of the standard deviation (see Table 2). Table 2 also shows estimated distances obtained for the approximated path loss exponent parameter. The use of the approximated parameter n_{ax} to estimate the distances resulted in the underestimation of the obtained distance values. The lower values of the standard deviation for the same data result directly from the higher value of the path loss parameter.

CONCLUSIONS

The channel model parameters variation and noise will result in inaccurate distance measurement, and consequently, incorrect positioning. Many authors use various approaches to model the PLE. Linear regression with the Least Square Method [15, 53], Generalized Additive Model [54], Multivariate Linear Regression [55], a non-linear regression [56] or machine learning combined with clustering algorithm [57] are widely used. The statistical approaches are also used to estimate PLE [58]. The presented methods have more or less computational complexity. The authors in [15] proposed a simplified low complexity RSS based location estimator for unknown path loss model. They linearised the non-linear path loss equations using linear least square (LLS) solution. This method allows to improve the inaccurate distance measurement and estimate the optimal position and its computational complexity is low. Moreover, LLS reduces the effect of Gaussian noise very well. However, if the environment is noisy (the signal is blocked or multipath exist), the measured RSSI values are far away from the expected values and LLS may not yield a good solution in such an environment. In this case, using the dynamic estimation of the path loss exponent parameter based on Bayesian filtering method gave good results.

In conclusion, the use of a Bayesian particle filter to dynamically estimate the path loss exponent for experimental measurements was successful. Examination of the sensitivity of the chosen systems to depletion of the input data, i.e., experimental data was done. In addition, we perform a test that uses the estimated path loss exponent parameter to estimate distances based on the measured RSSI values for selected distances. The method is easy to implement and resistant to a small number of collected measurement points. The most important results from this study include the following. The particle filter can be successfully used to predict path loss exponent. Increasing the number of particles improves the convergence of results but results in an increase of computational complexity. Optimising the way generation of pseudo-random numbers and limiting their use in the filter would speed up the determination of n_{pf} and reduce the statistical error of the method. Filter optimisation based on reducing the amount of input data, while maintaining a constant number of particles, causes a dramatic increase in error. Therefore, it became necessary to increase the number of particles. The performed tests confirmed the necessity to increase the number of collected measuring points to reduce the error of the distance estimation.

REFERENCES

1. Rappaport T.S. Wireless Communications: principles and practice. 2nd edition. Prentice Hall; 2002.
2. Dargie W., Poellabauer C. Fundamentals of Wireless Sensor Networks Theory and Practice. John Wiley & Sons Ltd; 2010.
3. Hightower J., Borriello G. Location Systems for Ubiquitous Computing. IEEE Computer Magazine 2001; 34(8): 57-66.
4. Xu J., Liu W., Lang F., Zhang Y., Wang C. Distance measurement model based on RSSI in WSN. Wireless Sensor Network 2010; 2: 606-611.
5. Chen K., Xu Z., Gong L. Research of the Distance Calculation Algorithm Based on RSSI. Advanced Materials Research 2012; 499: 464-468.
6. Botta M., Simek M., Adaptive Distance Estimation Based on RSSI in 802.15.4 Network, Radioengineering 2013; 22: 1162-1168.
7. Martinez K., Hart J.K., Ong, R. Environmental sensor networks, Computer 2004; 37(8): 50-56.
8. Hartung S., Brosenne H., Hogrefe D. Practical RSSI long distance measurement evaluation in Wireless Sensor Networks. In: Proc. of IEEE Conference on Wireless Sensor, Kuching, Malaysia 2013, 1-6.
9. Fang Z., Zhao Z., Guo P., Zhang Y.-G. Analysis of distance measurement based on RSSI. Chinese Journal of Sensors and Actuators 2007; 20(11): 2526-2530.
10. Kurt S., Tavli B. Path-Loss Modeling for Wireless Sensor Networks: A review of models and

comparative evaluations. IEEE Antennas and Propagation Magazine 2017; 59(1): 18-37.

11. Malajner M., Benkic K., Planinsic P., Cucej Z. The Accuracy of Propagation Models for Distance Measurement between WSN Nodes. In: Proc. of 16th International Conference on Systems, Signals and Image Processing, Chalkida, Greece 2009, 1-4.
12. Wojcicki P., Zientarski T., Charytanowicz M., Lukasik E. Estimation of the Path-Loss Exponent by Bayesian Filtering Method. Sensors 2021; 21: 1934-1945.
13. Czerwinski D., Przylucki S., Wojcicki P., Sitkiewicz J. Path loss model for a wireless sensor network in different weather conditions. In: Proc. of 24th International Conference on Computer Networks, Lądek Zdrój, Poland 2017, 106-117.
14. Egi Y. and Otero C. E. Machine-Learning and 3D Point-Cloud Based Signal Power Path Loss Model for the Deployment of Wireless Communication Systems, IEEE Access 2019, 7: 42507-42517.
15. Salman N., Kemp A.H., Ghogho M. Low Complexity Joint Estimation of Location and Path-Loss Exponent. IEEE Wireless Communications Letters 2012; 1(4): 364-367.
16. Wu R.H., Lee Y.H., Tseng H.W., Jan Y.G, Chuang M.H. Study of characteristics of RSSI signal. In: Proc. of IEEE International Conference on Industrial Technology, Chengdu, China 2008, 1-3.
17. Singh A., Singh D., Kumar S. NRSSI: New proposed RSSI method for the distance measurement in WSNs. In: Proc. of 1st International Conference on Next Generation Computing Technologies, Dehradun, India 2015, 296-300.
18. Zheng J., Wu C., Chu H., Xu Y. An Improved RSSI Measurement in Wireless Sensor Networks. Procedia Engineering. 2011; 15: 876-880.
19. Bose A., Foh C.H. A Practical Path Loss Model for Indoor WiFi Positioning Enhancement. In: Proc. of 6th International Conference on Information, Communications & Signal Processing, Singapore 2007, 1-5.
20. Tarrio P., Bernardos A.M., Casar J.R. An RSS Localization Method Based on Parametric Channel Models. In: Proc. of International Conference on Sensor Technologies and Applications, Valencia, Spain 2007, 265-270.
21. Li X., Chen L., Wang J., Chu Z., Liu B. A Novel Method to Improve the Accuracy of the RSSI Techniques Based on RSSI-D. Journal of Networks 2014; 9: 3400-3406.
22. Rodas J., Escudero C.J. Joint Estimation of Position and Channel Propagation Model Parameters in a Bluetooth Network. In: Proc. of IEEE International Conference on Communications Workshops, Dresden, Germany 2009, 1-5.
23. Pinto B., Barreto R., Souto E. and Oliveira H. (2021). Robust RSSI-Based Indoor Positioning System Using K-Means Clustering and Bayesian Estimation, IEEE Sensors Journal 2021, 21(21): 24462-24470.
24. Jianwu Z., Lu Z. Research on Distance Measurement Based on RSSI of ZigBee. In: Proc, of ISECS International Colloquium on Computing, Communication, Control, and Management, Sanya, China 2009, 210-212.
25. Mohammed S.L., Techniques E.E. Distance Estimation Based on RSSI and Log-Normal Shadowing Models for ZigBee Wireless Sensor Network. Engineering and Technology Journal 2016; 34(15) Part (A): 2950-2959.
26. Kaundal V., Sharma P., Prateek M. Wireless Sensor Node Localization based on LNSM and Hybrid TLBO- Unilateral technique for Outdoor Location. International Journal of Electronics and Telecommunications 2017; 63(4): 289-397.
27. Li X. RSS-based Location Estimation with Unknown Pathloss Model. IEEE Transactions on Wireless Communications 2006; 5(12): 3626-3633.
28. Kelner J.M., Kryk M., Lopatka J., Gajewski P. A Statistical Calibration Method of Propagation Prediction Model Based on Measurement Results. International Journal of Electronics and Telecommunications 2020; 66(1): 11-16.
29. Yan X., Zhou P., Luo Q., Wang C., Ding J., Hu C. UAM-RDE: an uncertainty analysis method for RSSI-based distance estimation in wireless sensor networks. Neural Computing and Applications 2020; 32: 13701–13714.
30. Liu Y., Li N., Wang D., Guan T., Wang W., Li J., Li N. Optimization Algorithm of RSSI Transmission Model for Distance Error Correction. Advances in Intelligent Information Hiding and Multimedia Signal Processing 2020: 27-36.
31. Shang J., Cheng T., Sheng L., Shi H., Yue K. Application of generalized extended interpolation method in distance measurement based on RSSI. Chinese Journal of Sensors and Actuators 2016; 29: 1768-1772.
32. Houssaini D.E., Mohamed Z., Khriji S., Besbes K., Kanoun O. Distance measurement correction based on feedback Filter for RSSI localisation technique in WSNs. International Journal of Space-Based and Situated Computing 2018; 8(3): 160-168.
33. Ordonez D., Avalos D.H., Gomez E. High degree complete orthogonal polynomials to improve distance prediction based on RSSI. RISTI - Revista Iberica de Sistemas e Tecnologias de Informacao 2019: 584-594.
34. Krupanek B., Bogacz R. Localization technique of IoT Nodes Using Arti_cial Neural Networks (ANN). International Journal of Electronics and Telecommunications 2020; 66(4): 769-774.

35. Yang F.E.I., Qingzhi D.U. RSSI ranging method based on BP neural network model. Chinese Journal of Radio Science 2018; 33: 195-201.
36. Gadhgadhi A., Hachaichi Y., Zairi H. Distance Estimation using Polynomial Approximation and Neural Network Based on RSSI technique. In: Proc. of 19th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering, Sousse, Tunisia 2019, 24-29.
37. Gualda D., Urena J., Garcia J.C., Garcia E., Ruiz D. RSSI distance estimation based on Genetic Programming. In: Proc. of International Conference on Indoor Positioning and Indoor Navigation, Montbeliard, France 2013, 1-8.
38. Miranda J., Abrishambaf R., Gomes T., Goncalves P., Cabral J., Tavares A., Monteiro J. Path loss exponent analysis in Wireless Sensor Networks: Experimental evaluation. In: Proc. of 11th IEEE International Conference on Industrial Informatics, Bochum, Germany 2013, 54-58.
39. Dharmadhikari V., Pusalkar N., Ghare P. Path Loss Exponent Estimation for Wireless Sensor Node Positioning: Practical Approach. In: Proc. of IEEE International Conference on Advanced Networks and Telecommunications Systems, Indore, India 2018, 1-4.
40. Pu C.C., Lim S.Y., Ooi P.C. Measurement arrangement for the estimation of path loss exponent in wireless sensor network. In: Proc. of 7th International Conference on Computing and Convergence Technology, Seoul, Korea (South) 2012, 807-812.
41. Srinivasa S., Haenggi M. Path loss exponent estimation in large wireless networks. In: Proc. of Information Theory and Applications Workshop, San Diego, CA, USA 2009, 124-129.
42. Zaarour N., Kandil N., Affes S., Hakem N. Path loss exponent estimation using connectivity information in wireless sensor network. In: Proc. of IEEE International Symposium on Antennas and Propagation, Fajardo, PR, USA 2016, 2069-2070.
43. Chan F., Chan Y.T., Inkol R. Path loss exponent estimation and RSS localization using the linearizing variable constraint. In: Proc. of IEEE Military Communications Conference, Baltimore, MD, USA 2016, 225-229.
44. Doucet A., Godsill S., Andrieu C. On sequential Monte Carlo sampling methods for Bayesian Filtering. Statistics and Computing 2000; 10: 197-208.
45. Zafari F., Papapanagiotou I., Hacker T.J. A novel Bayesian Filtering based algorithm for RSSI-based indoor localization. In: Proc. of IEEE International Conference on Communications, Kansas City, MO, USA 2018, 1-7.
46. Svecko J., Malajner M., Gleich D. Distance estimation using RSSI and particle Filter. ISA Transactions 2015; 55: 275-285.
47. Cuesta F., Cordero M., Diaz L., Viguria A., Ollero A. A particle Filter-based method for ground-based WSN localization using an Aerial Robot. Computational Intelligence, 2015; 604: 143-158.
48. Wang Z., Liu H., Xu S., Bu X., An J. A diffraction measurement model and particle filter tracking method for RSS-based DFL. IEEE Journal on Selected Areas in Communications 2015; 33(11): 2391-2403.
49. Wu H., Mei X., Chen X., Li J., Wang J., Mohapatra P. A novel cooperative localization algorithm using enhanced particle filter technique in maritime search and rescue wireless sensor network. ISA Transactions 2018; 78: 39-46.
50. Zhang X., Zhao L., Zhong W., Gu F. Performance Analysis of Resampling Algorithms of Parallel/Distributed Particle Filters, IEEE Access 2021; 9: 4711-4725.
51. Kirkpatrick S., Stoll E. A Very Fast Shift-Register Sequence Random Number Generator. Journal of Computational Physics 1981; 40(21): 517-526.
52. Hol J.D., Schon T.B., Gustafsson F. On Resampling Algorithms for Particle Filters. In: Proc. of IEEE Nonlinear Statistical Signal Processing Workshop, Cambridge, UK 2006, 79-82.
53. Barembruch S., Garivier A., Moulines E. On optimal sampling for particle Filtering in digital communication. In: Proc. of IEEE 9th Workshop on Signal Processing Advances in Wireless Communications, Recife, Brazil 2008, 634-638.
54. Kim M., Liang J., Lee J., Park J., Park B. Path loss measurements and modelling for indoor office scenario at 28 and 38 GHz. In: Proc. of the International Symposium on Antennas and Propagation, Okinawa, Japan 2016, 24-28.
55. Ambroziak S.J., Katulski R.J. An empirical propagation model for mobile radio links in container terminal environment. IEEE Trans. Veh. Technol. 2013; 62: 4276-4287.
56. Laskowski M., Ambroziak S.J., Correia L.M., Swider K. On the Usefulness of the Generalised Additive Model for Mean Path Loss Estimation in Body Area Networks. IEEE Access 2020; 8: 176873-176882.
57. Mahasukhon P., Sharif H., Hempel M., Zhou T., Wang W., Ma T. Propagation path loss estimation using nonlinear multiregression approach. In: Proc. of the IEEE International Conference on Communications, Cape Town, South Africa 2019, 23-27.
58. Nurminen H., Talvitie J., Ali-Loytty S., Muller P., Lohan E.S., Piche R., Renfors M. Statistical path loss parameter estimation and positioning using RSS measurements. In: Proc. of the Ubiquitous Positioning, Indoor Navigation, and Location Based Service, Helsinki, Finland 2012, 1-8.