Comparison of Path Loss Prediction Models for UAV and IoT Air-to-Ground Communication System in Rural Precision Farming Environment

Sarun Duangsuwan[1] and Myo Myint Maw[2]
[1] Information Engineering, King Mongkut's Institute of Technology Ladkrabang, Prince of Chumphon Campus, 17/1 Chumcoo District, Pathio, Chumphon, Thailand
[2] Department of Computer Engineering and Information Technology (CEIT), Mandalay Technological University (MTU), Patheingyi Township, Mandalay, Myanmar
Email: sarun.du@kmitl.ac.th; myomyintmawphdit5@gmail.com

Abstract —The comparison of path loss model for the unmanned aerial vehicle (UAV) and Internet of Things (IoT) air-to-ground communication system was proposed for rural precision farming. Due to the uncertainty of propagation channel in rural precision farming environment, the comparison of path loss prediction was investigated by the conventional particle swarm optimization (PSO) algorithms: PSO (exponential or Exp), PSO (polynomial or Poly) and the machine learning algorithms: *k*-nearest neighbor (*k*-NN), and random forest, are exploited to accurate the path loss models on the basic of the measured dataset. Meanwhile, the empirical model in the rural precision farming was considered. By using the machine learning-based algorithms, the coefficient of determination (R-squared: R^2) and root mean squared error (RMSE) were evaluated as highly accuracy and precision more than the conventional PSO algorithms. According to the results, the random forest method was able to perform more than other methods. It has the smallest prediction errors.

Index Terms—UAV, IoT, air-to-ground communication, path loss, machine learning methods, rural precision farming environment

I. Introduction

Significantly, the usage of UAV called the drone has been increasing in recent years, and it can be useful for commercial applications. Most commercial drones are usually as quadcopter with a structure different from that of airplanes. With various advantage, there are more and more attractive applications for UAV, such as low altitude surveying and monitoring, the emergency rescue, the forest fire detection, the cargo transport, and so on [1], [2]. Moreover, the UAV is emerging of important role for fifth-generation (5G) wireless communication, providing to air-to-ground connecting with the multiple IoT or the user equipment (UE) or ground sensing, and potential relaying mobile base station.

In rural communications, the UAV-based air-to-ground or ground-to-air communication is more attractive in the agricultural area. The UAV can be applied as the hotspot mobility network, due to the low power energy of the IoT devices (WiFi), herein, it did not provide the low power wide area network (LPWAN) [3]. WiFi coverage is limited to 100 meters, where the general UAV cannot fly exceeding 100 meters and distance (<1 km). However, the propagation environment of UAV-based communication is uncertainty. Although the link is line-of-sight (LOS) but it is different with the terrestrial wireless communications [4]. The smart antenna must be used for the 5G-UAV communications, it is similar to UAV-based machine learning method (UAV-MLM). Beamforming technique is very important to detect the highly data streaming accuracy of UE or IoT ground sensors [5]. In addition, the channel estimation method is used for adaptive signal processing and equalization to the noise and interference as the successive cancellation [6].

Due to the uncertainty of propagation channel of UAV and IoT air-to-ground communication model in the rural precision farming environment, we summarize the major contributions and novelties of this paper as follows:

(1) The measured dataset of path loss is predicted by using machine learning algorithms and compared with the conventional PSO methods.
(2) The prediction error results such as R-squared (R^2), and RMSE are considered by comparing of between machine learning algorithms and PSO algorithms.

The remainder of this paper is organized as follows. The related works describe in Section II. Section III presents the conventional of PSO methods and machine learning methods. Section IV describes the measurement data and evaluation the path loss results, R^2, RMSE, and discussion. Finally, conclusions are drawn in Section V.

II. Related Works

In [7], the comprehensive work on air-to-ground channel characterization as the point of view of such as channel measurement campaigns, the large and small-scale fading channel models, their limitation, and future research, were presented. The challenging of air-to-ground communication has to evaluate the propagation scenario in several environments, channel sounding, link

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Corresponding author email: sarun.du@kmitl.ac.th.
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distance or the path loss between the transmitter and the receiver, elevation angles, antenna positioning on the UAV, and the channel statistics are discussed.

The study of air-to-ground channel characterization was firstly proposed in [8]-[11]. The proposed air-to-ground channel scenario such as the measurement results and models for hilly and mountainous terrain were addressed suburban and near-urban environments respectively, [9], [10]. The parameters of path loss and delay spread at L-band and C-band were tested for the unmanned aircraft system (UAS). In addition, airframe shadowing channel model was introduced in [11]. These works are relevant to the investigation of propagation channel for UAV-based communication systems.

The radio frequency energy transfer (RFET) was presented to play a key role for recharging of field nodes in smart farming by S. Suman [12]. The accuracy of path loss models was formulated to the experiment in both suburban and agriculture areas. The path loss with two group scenarios for different elevation angles and the plant height for LOS and non-line-of sight (NLOS) were researched. The results showed the mean path loss, variance and elevation angles of UAV-assisted RFET in agriculture fields.

The measurement-based characterization of LOS and NLOS drone-to-ground channel was presented for drone-based advanced communication, especially for wideband beamforming systems [13]. The concept aims to develop the drone-based machine learning where deploys a software defined radio (SDR) platform as the drone-based beamforming systems. In field of LOS scenario, at three drone altitudes (10 m, 20 m and 30 m), the results were analyzed at transmitter-receiver separation distance from 10 to 100 m. The beamforming method can be gained. The higher drone from 60 m to 100m, the more decreases the link performance. On the other hand, in field of NLOS, the beamforming at 50 m and 20 m drone altitude provides a gain of up 86.9 % in the rural environment. Then, MIMO-based beamforming called UABeam was presented in [14]. The prototype is based on SDR platform to mount on the drone, the performance of bit error rate (BER) is initially reduced by increasing the distance as well as the path loss. At 900 MHz, 1800 MHz, and 5 GHz respectively, throughput of the single-input-single-output (SISO) channel without beamforming is decreased up to average 39%. On the other hand, with the proposed drone-based beamforming, the throughput is improved to 89.3% (at 900 MHz), 76.5% (at 1800 MHz), and 21.1% (at 5 GHz).

Most of these aforementioned works are emphasized on the air-to-ground channel and communications. An alternative application approach of UAV is used as the mobile station of the communication, i.e., smart farming. There are few related papers for providing the air-to-ground channel model in the farm scenario. As M. Bacco *et al* claimed [15] that the IEEE 802.15.4-based communication between the UAV and fixed ground sensors were researched. The empirical model of path loss based on two-ray channel model was discussed the performance of packet loss in smart farming scenario. To discuss the study, the authors have suggested considering; the path loss accuracy, the error recovery method, power allocation technique, the optimization trajectory method, as well as the learning-based channel estimation method. Then, the accuracy of empirical path loss model was presented in [16]. The path loss model was formulated by using the PSO algorithm where two functions were used as exponential (Exp) and polynomial (Poly) to predict the path loss accuracy. PSO is one of the heuristic algorithms [17] that can be used to present a solution for optimization problems.

Actually, the path loss modeling is a supervised regression problem and can be solved by using machine learning algorithms. By G. Yang [18], machine learning-based prediction methods for path loss and delay spread in air-to-ground scenario millimeter-wave channels were presented. The machine learning models were compared with Okumura-Hata and COST-231 Hata model. It can be seen that the accuracy of random forest-based method is the highest for path loss prediction and *k*-NN performs better than other models for delay spread prediction. However, these scenarios are simulated for urban areas which are not realistic rural environment.

To realize satisfactory prediction performance of these machine learning algorithms, random forest and *k*-NN, the measured dataset in rural empirical models for the air-to-ground communication are studied. In this paper, the path loss predictions between machine learning algorithms are compared with PSO algorithms in terms of R^2 and RMSE.

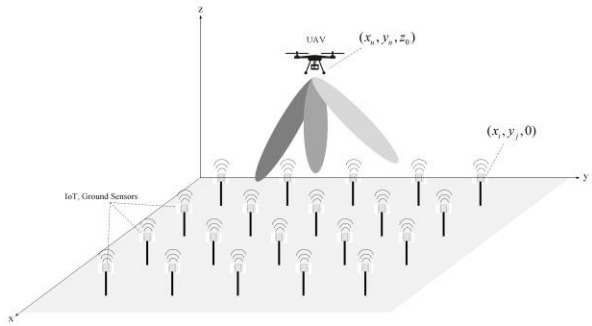

Fig. 1. The air-to-ground communication with trajectory model.

III. Path Loss Prediction Methodologies

In Fig. 1, the communication system of air-to-ground channel model is proposed for precision farming, where a rotary-wing UAV-based beamforming with flight altitude in z_0 -axis and positioning at (x_u, y_u, z_0) communicates with the multiple IoT or ground sensors at $(x_i, y_j, 0)$. The prediction of channel model between the UAV and IoT is defined, in [19]

$$\mathbf{h}_c = \sqrt{\frac{P_L d_c^{-\alpha_L} K}{1+K}}\mathbf{h}_{c,LOS} + \sqrt{\frac{P_N d_c^{-\alpha_N}}{1+K}}\mathbf{h}_{c,NLOS} \quad (1)$$

where K is the Rician K-factor of the wireless channel model. P_L and P_N are the path loss factors of the LOS and NLOS, respectively. α_L and α_N are the path loss components of the LOS and NLOS, respectively. d_c is the separation distance between the UAV and IoT. $\mathbf{h}_{c,L}$ and $\mathbf{h}_{c,N}$ are in terms of LOS and NLOS channel.

For UAV channel measurement, the log-distance path loss modeling can be expressed in [20], and is given by

$$P_L(d_c) = P_L(d_{c,0}) + 10n\log\left(\frac{d_c}{d_{c,0}}\right) + X_\sigma(K) \quad (2)$$

where $d_{c,0}$ denotes the reference distance. $X_\sigma(K)$ is the small-scale fading following Rician distribution with different K-factor. The values of n depend on path loss exponents.

A. Conventional of Paticle Swarm Optimization (PSO) Methods

Considering to the received signal strength indicator (RSSI), the equations in term of exponential (Exp) and polynomial (Poly) are given by [16]

$$RSSI_{\exp}(dBm) = a \cdot e^{\{b(d_c)\}} + c \cdot e^{\{d(d_c)\}} \quad (3)$$

$$RSSI_{\text{poly}}(dBm) = p_1 d_c^3 + p_2 d_c^2 - p_3 d_c - p_4 \quad (4)$$

where a, b, c, and d are the four coefficients of exponential (exp). p_1, p_2, p_3, and p_4 are the four polynomial (poly) functions, which represented the constants used in functions as the PSO method.

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The PSO is one of the Meta-heuristic algorithm [17], which is depended on particles to obtain the best position ($pbest$) and the global best ($gbest$). The first key is the best solution, which is represented by $pbest_j = \left(pbest_{j1}, pbest_{j2}, pbest_{j3}, \ldots, pbest_{jM}\right)$; the second one is the best practice of global best, where $gbest_j = \left(gbest_{j1}, gbest_{j2}, gbest_{j3}, \ldots, gbest_{jM}\right)$. Each particle maintains the $pbest$ and $gbest$ values until to the $pbest_{jM}$ and $gbest_{jM}$ in its memory. While the update each position of j-th swarm is denoted by $x_j = \left(x_{j1}, x_{j2}, x_{j3}, \ldots, x_{jM}\right)$, and the velocity of this swarm is $u_j = \left(u_{j1}, u_{j2}, u_{j3}, \ldots, u_{jM}\right)$, the function update is defined by

$$\begin{aligned} y_{jM}^{n+1} &= w \cdot y_{jM}^{n} + c_1 rand1\left(pbest_{jM} - x_{jM}\right) \\ &\quad + c_2 rand2\left(gbest_{jM} - x_{jM}\right) \end{aligned} \quad (5)$$

$$x_{jM}^{n+1} = x_{jM} + u_{jM}^{n+1} \quad (6)$$

where n is the iteration number; u_{jM}^{n} is the velocity of the j-th particle in the M-dimension of the n-th iteration; c_1 and c_2 are cognitive and social acceleration coefficients, respectively; $rand1$ and $rand1$ are random numbers in the range of 0-1.

B. Proposed Machine Learning Methods

Machine learning algorithms can provide to learn the measurement dataset for path loss prediction. In this paper, the path loss is predicted by using two machine learning methods; random forest and *k*-NN.

1) Random forest algorithm; is based on the decision tree-based data processing, proposed by S. P. Sotiroudis [21]. The random forest comprises of a root node, few internal nodes, and leaf nodes such as each node split consists of a subset of randomly selected features. The procedure of random forest algorithm consists of three main parts as:

Input: Sample training set $x = \left[\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\right]$ with responses $y = \left\{PL_1, PL_2, \ldots, PL_N\right\}$, where the dataset $\mathbf{x}_i = \left(d_{ci}, h_i, I_i, \theta_i\right)$, $i = 1, \ldots, N$. Note that the dataset in $\mathbf{x}_i$ are such as distance between UAV and IoT d_{ci}, the altitude h_i, the path visibility LOS and NLOS I_i, and the elevation angle θ_i between UAV and IoT.

Training Process:

For *t = 1 to T*

(1) Take a bootstrap sample $\left[x_t, y_t\right]$ of size N from $\left[x, y\right]$.

(2) Use $\left[x_t, y_t\right]$ as the training data to train the t-th decision nodes by using binary recursive function.

(3) Repeat the following steps recursively for each unsplit node until the stopping criterion is met:

i. Calculate the square error for each possible splitting point of each feature, and fine the best binary split among all binary splits on the features.

ii. Split the node into two descendant nodes using the best split.

Prediction:

Given a new $\mathbf{x}_i = \left(d_{ci}, h_i, I_i, \theta_i\right)$, the predicted path loss value is obtained by

$$\hat{P}_L^r(d_c,\theta)=\frac{1}{T}\sum_{t=1}^{T}\hat{p}_t(\mathbf{x}_i) \tag{7}$$

where T denotes the number of decision tree nodes and $\hat{p}_t(\mathbf{x}_i)$ represents the predicted path loss values of the t-th decision tree nodes, and $\mathbf{x}_i$ denotes the feature dataset.

2) k-NN algorithm; the *k*-nearest neighbor (*k*-NN) was used extensively in pattern analysis application [22]. It is a classical machine learning algorithm that is often used to solve classification problems. The component of *k*-NN is to find the closest sample to be predicted based on a distance metric and the information of these k neighbors. It is also suitable for regression tasks by averaging the values of k neighbors to estimate the path loss prediction result. Generally, the *k*-NN is based on the distance between two training objects and testing using Euclidean distance formula.

$$\hat{P}_L^{knn}(d_c,\theta)=\sum_{i=1}^{k}\left(P_L^i(d_c,\theta)-\hat{P}_L^i(d_c,\theta)\right)^2 \tag{8}$$

Training process:

For i = 1 to k

(1) Determine k nearest neighbor and N set of training dataset.

Prediction:

(2) Calculate distance from $\hat{P}_L^{knn}(d_c,\theta)$

(3) Select the k closest training dataset.

(4) Use majority voting to classify the prediction path loss.

(5) Finished the data processing.

The data flow of system consists of *k*-NN; firstly, k parameter is determined as shown in Table I. The train dataset is presented. Finally, the prediction process of the proposed system is calculated and classified based on Euclidian distance.

TABLE I: SIMULATION SETUP PARAMETERS

Description	Value
Dataset ($\mathbf{x}_i$)	50
Decision tree node (T)	20
k-nearest	50
$c_1 = c_2$	1.494 [16]
w	0.500 [16]

IV. EXPERIMENT AND EVALUATION

The experiment was conducted in a farm field for rural scenario; Ruzi grass farm, where the farm size is shown as in Fig. 2. Note that the measurement location was in the Tropical Animal Research Institute, Ramkhamhaeng University, in Thailand. The work was to monitor the soil moisture in daytime for the automatic water control.

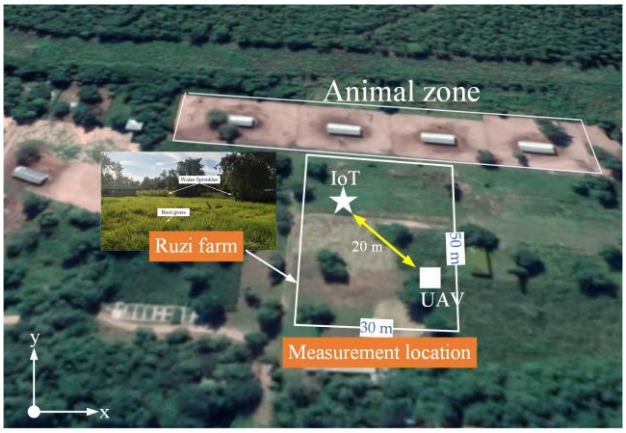


Fig. 2. The measurement location in the Ruzi farm.

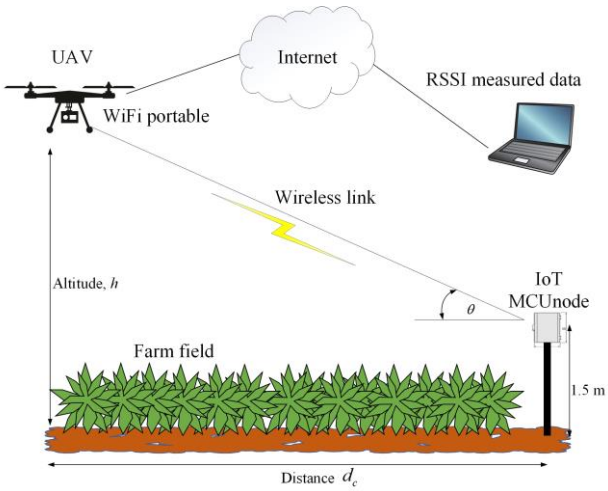
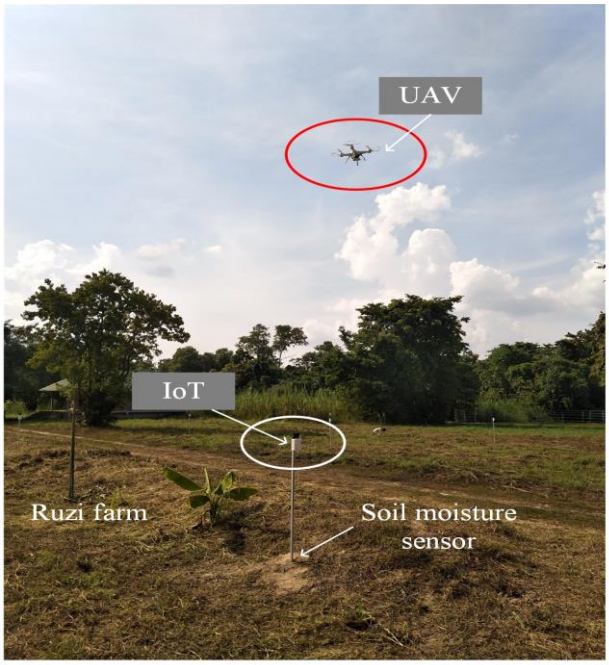


Fig. 3. The experimental setup model in the farm field.

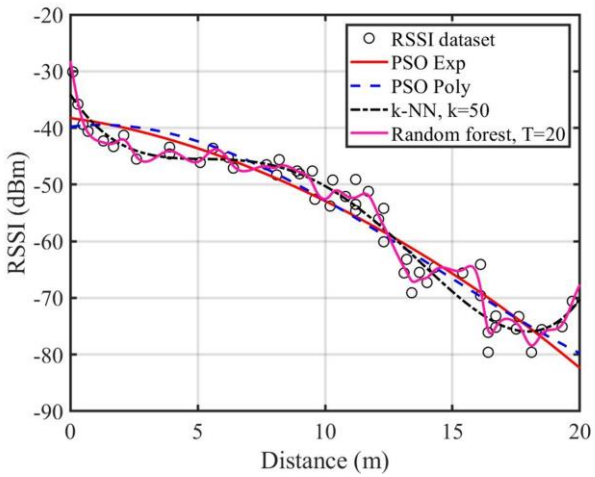
TABLE II: EXPERIMENTAL PARAMETERS SETUP

Description	Value
Environment	Rural
Carrier frequency	2.400 – 2.480 GHz
Bandwidth	20 MHz
Transmit power	20 dBm
UAV altitude	5 m
Number of IoT	15
Distance	1 – 20 m
UAV flight time	20 min.
Tx antenna gain (UAV)	5.1 dBi
Rx antenna gain (IoT)	3 dBi
Elevation angle	~55 degree

In this experiment, the UAV and the IoT ground sensor are connected by using WiFi portable and links to microcontroller unit (MCU) node for IEEE802.11b. The IoT was designed as the soil moisture sensor kit and installed in the Ruzi farm field to 15 sensors, where the power is supplied by using a solar cell 5 volts and 3 watts. Fig. 3 shows the experiment setup where the RSSI can measure via internet in the application program interface (API) software. In addition, the experimental parameters setup is shown in Table II.



(a) The measurement test in farm.



(b) RSSI versus distance test.

Fig. 4. Result of RSSI measured and prediced at 5 m UAV altitude.

To evaluate the accuracy of the part loss prediction, two statistical properties, R^2 and RMSE, are parameters as metrics. The predicted path loss can be calculated by comparing the dataset in the test as equation (9)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(P_L^i(d_c,\theta) - \hat{P}_L^{method}(d_c,\theta)\right)^2} \quad (9)$$

where N is the total number of test samples, $P_L(d_c,\theta)$ is the path loss value of the i-th sample in the test set, and $\hat{P}_L(d_c,\theta)$ is the prediction value.

The RSSI measured data at IoT positioning (x_i, y_j, z) where $(x_1, y_3, 5)$ is the coordinate sensor position of Ruzi13 in Ruzi farm, while the measurement test is shown in Fig. 4 (a). The altitude distance between UAV and IoT was fixed at 5 m in z-plane. While the samples RSSI values (N = 50) were averaged for evaluation of the reliability of distance and RSSI values, as shown in Fig. 4 (b). It can be observed that the RSSI at 1 m to 10 m, the measured data was -30 dBm to -50 dBm and decreased to -77 dBm when distance is increased. By using MATLAB program, the coefficient of PSO Exp is a = -5.625, b = -0.1637, c = -32.64, and d = 0.04616. For PSO Poly, the coefficient of p_1 = 0.005697, p_2 = -0.2416, p_3 = 0.5532, and p_4 = -39.79, respectively. As the results, the experiential performance comparison of RSSI is shown in Table III, where the best prediction model is random forest algorithm with the lowest RMSE as 2.367.

TABLE III: PERFORMANCE COMPARISON OF RSSI PREDICTION

Prediction models	R^2	RMSE
PSO Exp [16]	0.9061	4.145
PSO Poly [16]	0.9112	4.031
k-NN	0.9524	2.983
Random forest	0.9892	2.367

After establishing exact relationship between RSSI value and distance, the evaluation of path loss prediction between PSO algorithms and machine learning was performed for the proposed system.

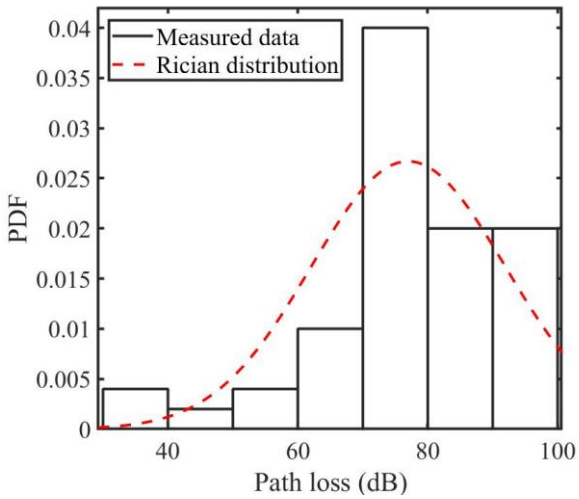


Fig. 5. Comparison of measured data with Rician distribution.

The probability of density function (PDF) of path loss measured data versus the Rician distribution model is shown in Fig. 5. From the results, the range of path loss measurement data is 58 dB to 100 dB. This characterization is caused by the uncertainty of channel in farm, and the standard deviation is more than 40 dB.

The comparison of the path loss prediction in decibels (dB) by using the PSO algorithms and the machine learning algorithms is shown in Fig. 6. At the red line is the PSO Exp, the estimated data is similar to the path loss dataset, but it still be varied in the higher order statistical. The blue line is the PSO Poly. It can optimize less than the PSO Exp as smoothly curve. To compare the machine learning algorithms, the *k*-NN is approached to the PSO Exp while the random forest method in the pink line is absolutely optimized as the closest to the path loss dataset more than the other methods. Herein, the values of k = 50,

and T = 20 are used for *k*-NN and random forest. After simulating, these values are optimized for this scenario model.

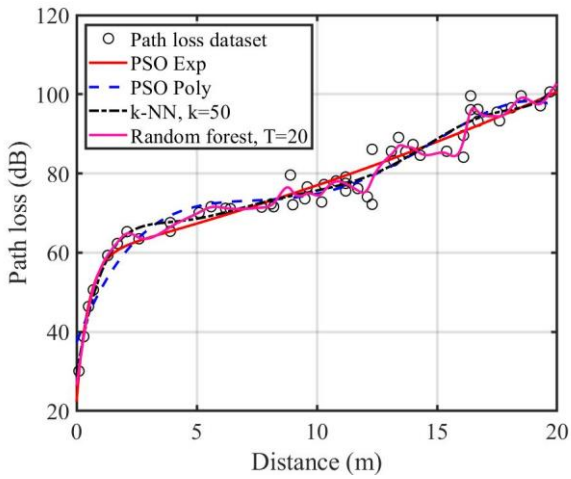


Fig. 6. Plot of path loss vs distance for the proposed system.

The performance comparison between the PSO algorithms and machine learning algorithms is provided in Table IV. The prediction error both R^2 and RMSE are similar to the optimal performance. However, the best performance is random forest that verifies RMSE as 3.032.

TABLE IV: PERFORMANCE COMPARISON OF PATH LOSS PREDICTION

Prodiction Models	R^2	RMSE
PSO Exp [16]	0.9545	3.374
PSO Poly [16]	0.9447	3.764
k-NN	0.9605	3.289
random forest	0.9755	3.032

V. CONCLUSION

Deployment of UAV and IoT communications for precision farming has become a challenge due to the large-scale agricultural area and dense plants, which contribute toward high uncertainly path loss. The path loss caused packet loss when the data are transmitted from the IoT sensors to UAV base station in the farm.

In this paper, the comparison of path loss prediction models for UAV and IoT air-to-ground communication system has been presented between the conventional PSO algorithms and the proposed machine learning algorithms to highly accurate the predicted path loss in the rural precision farming environment. It has been demonstrated that the random forest is the best path loss prediction performance in the experimental scenario because the prediction error such as RMSE is the lowest. The comparison of the path loss prediction by using the machine learning algorithms can absolutely optimize the uncertainty of the propagation channel characterization in the rural precision farming environment.

The machine learning-based models like the artificial neural network (ANN) and support vector regression (SVR) will be studied.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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Sarun Duangsuwan received the B.Eng. and M. Eng. degrees in Information Engineering from the King Mongkut's Institute of Technology Ladkrabang (KMITL), Thailand, in 2008, 2010, respectively, and the D.Eng. degree in Electrical Engineering in 2015 from KMITL, Thailand. Since 2016, he has worked with Information Engineering, KMITL, Prince of Chumphon Campus, Thailand. He is an assistant professor with Information Engineering, Department of Engineering, KMITL, Prince of Chumphon Campus. His research interests include IoT, UAV communication systems, machine learning methods, wireless communications, massive MIMO, 5G communication systems, and advanced signal processing.

Myo Myint Maw received the B.Eng. and M. Eng. degrees in Information Technology from Department of Information Technology, Mandalay Technological University (MTU), Myanmar, in 2005 and 2007, respectively, and the D.Eng. degree in Electrical Engineering from the King Mongkut's Institute of Technology Ladkrabang, (KMITL), Thailand, in 2015. Since 2007, she has worked with the Department of Computer Engineering, and Information Technology, where she is currently a professor in Department of Computer Engineering, and Information Technology, MTU, Mandalay, Myanmar. Her research interests include ICT, IoT, UAV, channel modeling and propagations, machine learning algorithms and wireless communications.