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Machine Learning-Based Field Data Analysis and Modeling for Drone Communications

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ABSTRACT In recent years, unmanned aerial vehicle (UAV), also called a drone, is getting more and more important in many emerging technology areas. For communication area, the drone also takes an important role in lots of significant topics like emergency communications, device-to-device (D2D) communications, and the Internet of Things (IoT). One of the important drone applications is to collect and share data among drones and other aircraft, which is useful for drone control so that dangerous conditions can be avoided. In particular, the drone control and safety guarantees are difficult to attain, especially, when drones fly beyond the line of sight (BLOS). For this reason, we develop a drone location information sharing system using the 920-MHz band. We use this system to do a long distance propagation field experiment for model establishment. Unfortunately, the current data collection for model establishment work needs a great effort and time to do experiments to collect a huge number of data for data analysis so that a suitable model can be established. Therefore, in this paper, we propose a novel method, which is based on machine learning approach, to data analysis and model establishment for drone communications, so that the effort and cost for establishing model can be reduced and a model, which captures more details about the drone communications, can be obtained. The results of this paper validate that the proposed method can indeed establish a more complicated model with less effort. Specifically, from the distribution of the training error, it can be known that there are over 80% training errors with intensity less than 5, which ensures the error performance of the proposed method.

INDEX TERMS Unmanned aerial vehicle (UAV), drone communication, machine learning, Internet of Things (IoT).

I. INTRODUCTION

In recent years, unmanned aerial vehicle (UAV), which is also called drone, is very popular in new technology area. For wireless communications, drone related communication topics are also popular in many emerging areas, like emergency communications, device-to-device (D2D) communications, Internet of Things (IoT) etc. Because of the flying characteristic of drones, the drones can be used to construct a communication network in a very flexible and fast way regardless of the environment and terrain. Therefore, drone communication is very suitable for emergency communications which need flexible and fast recovery of communication after disaster happens, or for IoT and D2D communications which needs an useful way to carry out the wireless connection everywhere.

For drone communications, recently there are many research groups are focusing on different topics in related areas [1]–[11]. For example, in [1] a game theory based method is proposed to solve the channel assignment (CA) problem in UAV and D2D based network. In [2] the non-orthogonal multiple access (NOMA) method is applied to improve sum rate performance for drone communications. In [3] the probability of using drone for D2D communication is addressed and the performance is investigated. In [4] a dynamic route control method is proposed for drone communications to improve the throughput and delay performance. In [5] mobile edge computing is realized by using drone communication network.

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In drone application area, it is important to guarantee the safety for the flying vehicles when drones are flying and doing their tasks. If there are number of deployed drones over an area is drastically increasing, drones information is becoming essential to avoid collision and interference. Besides, if there is any manned aircraft nearby like helicopter, it might be very dangerous for the manned aircraft because the pilot might miss viewing the drones. Therefore the drone communication among flying vehicles for better drone control is very important, and establishing this kind of model can provide significant help for this topic. Besides, to enhance and promote the application of drone communications, we develop a drone location information sharing system using 920MHz band. We use this system to do field experiment for data collection and model establishment.

Currently realizing this kind of drone application needs huge number of field measurements to collect enough information for establishing a useful model, which requires great effort if the area under measurement is large. Besides, in field experiments, there may be situations, where unpredictable things happen, which results in data missing. In this kind of situations, a good model establishment approach which can recover missing data is important to avoid re-doing the field measurements. Although there have been some methods like compressive sensing [12] which can recover data from a set of undersampled data, there are still some limitations, e.g. some statistical characteristics are needed, to realize the method. Therefore, it would be very helpful if there is smarter way to establish this kind of model by using more intelligent approaches, like artificial intelligence (AI) or machine learning based methods.

Due to the fast development of computer science in recent years, AI and machine learning areas are growing significantly. In the past, there are many difficult problems which are hard to be solved but now can be solved by machine learning based method. In communication area, machine learning based method is also applied in many important topics [13]–[19]. For example, in [13] the possible applications and challenges of adopting machine learning are addressed for next generation communications. In [14] a method using genetic algorithm based feature selection and machine learning based data detection for detecting covert cyber deception assaults in smart grid communication is proposed. In [15] the modulation recognition problem for cognitive radio (CR) communications is solved by machine learning based method. In [16] a method using unsupervised machine learning method to cluster low power nodes and decide fog nodes is proposed. In [17], machine learning based method to collect images from surveillance cameras for recognizing blockage locations is proposed. In [18], the machine learning based method is used to solve precoding problem in massive multiple-input-multiple-output (MIMO) systems. However, AI or machine learning based methods are still seldom used to solve problems in drone communication area. Therefore, in this paper, we want to adopt machine learning based method to establish received signal strength indication (RSSI) model for drone communications.

The contributions of this paper are summarized as follows.

- In this paper, we propose a machine learning based method for drone applications. Specifically, we use proposed method to do data analysis and modeling for the data recorded in drone field experiment. Due to the limitations of experimental equipment and environment, there may be data missing or data with complicated trend after field experiment. In the past, dealing with these problems needs great effort to re-process the field experiment or analyze data to do modeling from the recorded data. However, with the proposed machine learning based method, the recovery of missing data or model establishment can be done with much less effort and good performance.
- In the proposed machine learning based method, we consider the location information, speed of the aircraft, and direction angle to help do the modeling of RSSI data. From the results, it can be seen that, the proposed method can do good modeling work with much better mean square error (MSE) performance than the traditional linear regression method. In addition, from the result of fitting missing field data, it can be seen that the recovery part matches the sensitivity of the experimental equipment, which validates the performance and effectiveness of the proposed method.
- Although there are already some research groups applied machine learning based approaches on wireless channel estimation related issues, such as OFDM channel estimation for signal detection [24], massive MIMO channel estimation [25], fading channel estimation [26], etc., there is nearly no application on drone communications. Therefore, in this paper, we apply machine learning based approach on drone related experimental data to show examples about how machine learning based approached can help the drone communication related issues. In this paper, we reveal a preliminary work for applying machine learning based approach on drone communications and show its capabilities and probabilities. In the future, we may use machine learning based approach on other drone related topics which are difficult to be solved.

The rest of this paper is organized as follows. The system overview is described in Sec. II. The proposed method is introduced in Sec. III. Simulations are conducted to validate the proposed method in Sec. IV. Finally, some conclusion remarks are given in Sec. V.

II. SYSTEM OVERVIEW

In this study, we develop a drone information management system to record, manage, and share collected data. We provide an overview of this system in Fig. 1, and we call this system as drone communication system in the following paragraphs. The drone communication system shown in Fig. 1

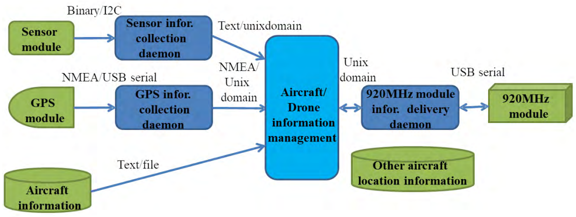

FIGURE 1. Overview of the drone communication system, a prototype of drone location and ID information sharing system.

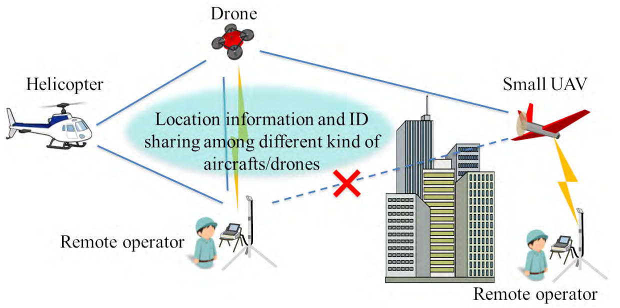

FIGURE 2. Concept of drone location and ID information sharing system.

can provide low cost broadcast based location information sharing between drones and the operators, and also the information sharing between drones and manned aircrafts flying in surrounding airspace to provide safe operation for flying vehicles. The drone communication system we developed includes the following features.

- The drone communication system is based on simple D2D broadcasting protocol without the need of infrastructure, such as base station (BS) or access point (AP).
- The system uses license-free 920MHz band for telemetry, telecommand and data transmission radio equipment via Association of Radio Industries and Businesses (ARIB) standard [20].
- The system covers BLOS drone communications with multi-hop relay communication which contains up to two hops.
- The system shares location and ID information among drones and helicopters within 10km distance by one hop.
- The system is a remote information sharing system via network by sending drone information to internet services or unmanned aircraft system traffic management (UTM) using integrated satellite telecommunications.

The data collected and shared by aircrafts would be managed by the system mentioned above. From Fig. 1, it can be seen that, there are three types of data to be collected, which are environment data measured by sensors, location data obtained by global positioning system (GPS), and aircraft information. The three types of data are stored in aircraft/drone information management system and can be exchanged among the tablet on helicopter, drone, and ground monitoring station via license-free 920MHz band. In Fig. 2, we show the concept of designing the drone location and ID information sharing system.

TABLE 1. Data format in the drone communication system.

Item	Range
Time (UTC)	0~86400(sec)
Latitude	ddmm.mmmm
Longitude	dddmm.mmmm
Altitude	-32767~+32767
Speed	0~1023(km/h)
Direction	0~720(Decimal/2) degree

TABLE 2. Radio parameters of the drone communication system.

Item	Specification
Modulation Method	LoRa
Frequency Band	Selectable in 920.5~928.1MHz
Transmission Power	Maximum 20mW
Wireless Channel Bandwidth	125 kHz
Modulation and Data Rate	Chirp Spread Spectrum (CSS), 20kbps
Reception Sensitivity	CSS: -117dBm (BER 0.001)
Antenna Gain	1.0dBi
Antenna Directivity	Vertical Polarized Monopole Antenna

We list the data format used in drone communication system in TABLE 1, and list the specification of the 920MHz radio module used in the prototype of drone communication system in TABLE 2. According to the number of the accommodated units listed in TABLE 2, we can calculate the bit rate of the current system. With data size 400 bits per drone communication unit, the data rate is 20kbps.

There are many other research groups also spend their effort on developing similar systems [21]–[23]. For example in the US, the Federal Aviation Administration (FAA), National Aeronautics and Space Administration (NASA), other federal agencies, and industry partners, have developed unmanned aircraft system (UAS) traffic management for autonomously controlled operations, and some laws and regulations have been issued for the future drone use. In Japan, the Japan Unmanned System Traffic and Radio Management Consortium was established in 2016 for the social and safe implementation of drone technology. The Japan consortium also works on radio management for drone deployment in Japan. These types of groups are working on the development of the related technology and addressing any possible future problem for drone, such as collision avoidance, route planning, airspace design, and weather condition response. However, to enable the simultaneous use of multiple drones flying at low altitudes, there are still many technical barriers need to be overcome. In particular, location awareness is one of the most important technologies for properly controlling drones, especially in BLOS environment.

We use the drone communication system to share location information of flying vehicles (drone, helicopter, etc.) and the collected data will be used to establish model for drone communications. In traditional method, the model establishment is usually completed with some conventional statistical approach, like linear regression. However, this kind of approach can only investigate linear relationships among parameters, but in real case there is usually non-linear complicated relationships existing in the model. Therefore, in the

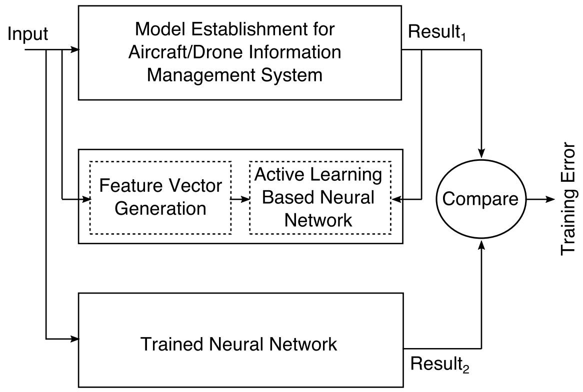

FIGURE 3. Structure of the proposed machine learning based method.

following section, a novel method of model establishment, which is based on machine learning and targets to build a more complicated model, is proposed.

III. PROPOSED METHOD

In this paper, we want to solve the problem mentioned in Sec. II by adopting machine learning based method. The structure of the proposed machine learning based method is addressed as follows.

Firstly, a general model of the proposed method is presented in Fig. 3. In the structure of the proposed method, the related information like RSSI, GPS information, environment parameters etc. would be input to the aircraft/drone conventional wireless communication system generates a result, which is denoted as Result$_1$ in Fig. 3. The trained neural network which can be operated independently also generates a result, which is denoted as Result$_2$ in Fig. 3. The trained neural network block is supported by machine learning based block, which operates feature vector generation and active learning based neural network and can use input data and Result$_1$ to capture the features of the system under modeling.

Finally Result$_1$ and Result$_2$ are compared to generate training error. In this study, we use the mean square training error as the cost function, which should be minimized as much as possible, and can be expressed as

$$e = \left|\left|\hat{y} - y\right|\right|^2, \tag{1}$$

where y is the Result$_1$, $\hat{y}$ is the Result$_2$, and e is the training error in Fig. 3, respectively. The $\hat{y}$ is calculated by machine learning and can be expressed as

$$\hat{y} = f_\theta(\boldsymbol{x}), \tag{2}$$

where f_θ means the data model we want to train, θ denotes the parameter set we want to find for the trained model, and $\boldsymbol{x}$ is input data vector which contains location information, speed, and direction in this study. Therefore, the whole problem actually is to find a suitable parameter set θ_{op} for the data model f and can be further mathematically written as

$$\theta_{\mathrm{op}} = \arg\min_{\theta} \left|\left|f_\theta(\boldsymbol{x}) - y\right|\right|^2. \tag{3}$$

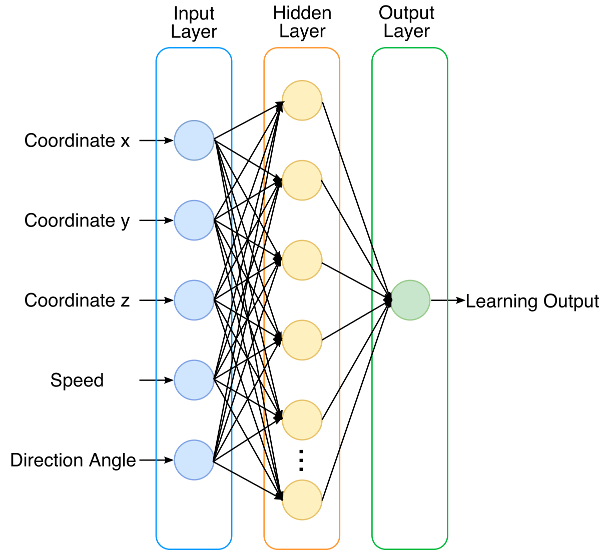

FIGURE 4. Concept of the neural network adopted in the proposed method.

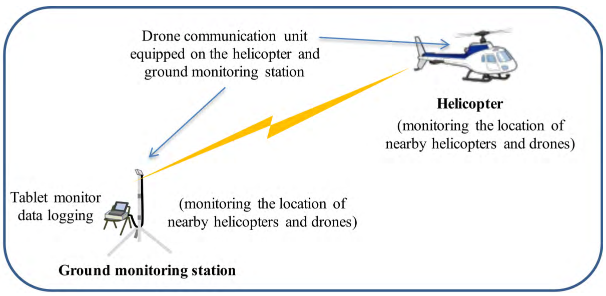

FIGURE 5. Basic setting for the field experiment with helicopter and ground monitoring station.

In this paper, in the upper block of model establishment in Fig. 3 we adopt linear regression model to do the task. In the lower block of model training in Fig. 3 we use a three-layer neural network to train the communication model. The three-layer neural network includes one input layer, one output layer, and one hidden layer. The input layer includes 5 input nodes which are location information (x, y, and z coordinate information), speed of the aircraft, and direction angle. The hidden layer includes 20 neurons to process the learning algorithm so that the result can be generated and obtained at the output node in output layer. The concept of the three-layer neural network is summarized in Fig. 4.

IV. FIELD DATA ANALYSIS RESULTS AND DISCUSSIONS

A. FIELD EXPERIMENT SETTINGS

To validate the proposed model establishment method for drone communications, we set up a field experiment to collect drone transmission data. The drone communication experiment settings are illustrated as follows.

In this field experiment, there are two basic constitute components, which are shown in Fig. 5 and introduced as follows. In Fig. 5, there is a manned control helicopter, and ground monitoring station. There are two sets of drone

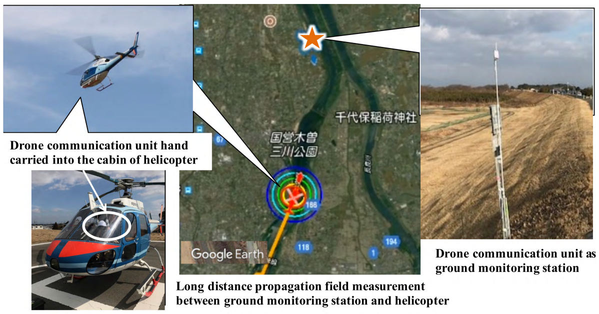

FIGURE 6. An example of the field experiment settings.

communication unit and data logging tablet are equipped on helicopter and responsible for monitoring the location and parameters near flying vehicles, while there is another set of drone communication unit as ground monitoring station. Each drone communication unit module contains transceiver function to communicate with each other. There are two reasons why we put two sets of drone communication unit on the helicopter. The first reason is using two sets of drone communication unit to avoid the risk of the equipment breakdown in the field experiment. If one set gets breakdown, we still have one set to continue the experiment. The second reason is that using two sets can increase the amount of the recorded data, which helps the model establishment by machine learning. We give an example picture to show the practice operation when doing field experiment in Fig. 6.

The helicopter and ground monitoring station can process communications with each other via license-free 920MHz band. The transmission is using on IEEE802.15.8 based protocol. The data logging tablet and the ground monitoring station keep logging data whenever system operates to collect data.

The experiment area is in part of Kiso River in Aichi Prefecture, Japan. The helicopter was flying alone the river for a long distance propagation field measurement. The flying route of helicopter is shown in Fig. 7. From the flying route, it can be seen that, the helicopter took off from the south point beside the river, were flying northward along the river, took a U-turn at the north point on the river, and went back to the start point. The flying speed is kept at 40km/h and the distance between the starting point and U-turn point is about 9km. During the whole flying period, the location information, speed, direction angle, RSSI between each pair of transmitter and receiver, are recorded in the information management system mentioned in Fig. 1 in Sec. II.

Besides, from our measurement, we can know that the helicopter body shielding causes radio attenuation to be maximum 25 dBm difference between the front side and the back side of the helicopter [27]. Because of this attenuation difference, when the helicopter leaves more than 2 km, the ground monitor station almost cannot receive the location information from helicopter in the forward route. Then, when the helicopter head direction turns around to the ground monitor station at 9 km away in the backward route, the ground

FIGURE 7. The flying route of the helicopter.

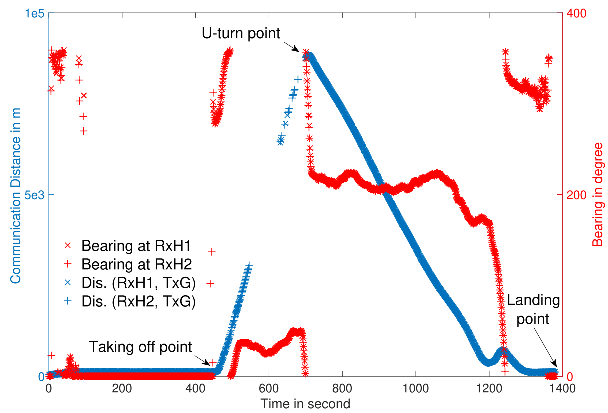

FIGURE 8. Drone communication unit log data of distance between ground monitoring station and helicopter, and the data of helicopter head direction. G: Ground monitoring station; H1: Drone communication unit 1 on helicopter.

monitor station can receive the location information from helicopter. Therefore the slopes of the regression lines are different.

B. RESULTS

In the following results, we denote TxH1, TxH2, and TxG as the transmitters of the drone communication unit 1 and 2 on helicopter, and on ground monitoring station, respectively. Similarly, we denote RxH1, RxH2, and RxG as the receivers on drone communication unit 1 and 2 on helicopter, and on ground monitoring station, respectively. In this paper, we choose RSSI as the target to establish model. We processed the data collected and shared in two aspects, which are addressed as follows. The drone communication unit log data of the distance between the ground monitoring station and helicopter, and the data of helicopter head direction, are shown in Fig, 8. Because the data from drone communication unit 1 and 2 are similar, for the sake of simplicity, in the following paragraphs we only show the results of drone communication unit 1 on helicopter.

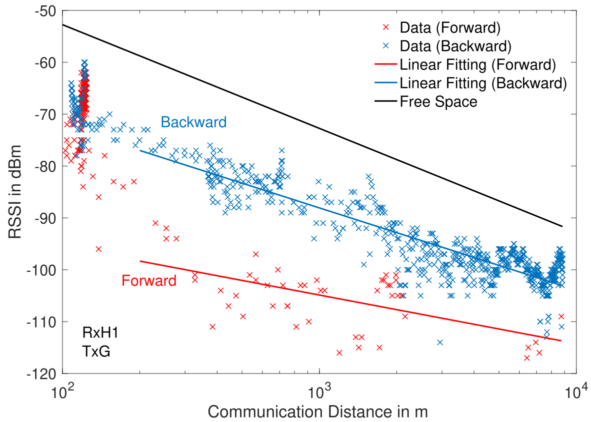

FIGURE 9. Regression results for RSSI versus distance between drone communication unit 1 on helicopter and ground monitoring station.

1) MODEL ESTABLISHMENT

The first aspect we want to illustrate about the proposed method is the ability of model establishment. The data of RSSI versus distance between the helicopter and ground monitoring station is considered. The data collected and shared for both drone communication unit on helicopter and the results obtained by linear regression are shown in Fig. 9. In addition, for more careful data processing, the recorded data are separated into forward route and backward route according to the data collecting time before or after the U-turn happens. Besides, as a reference, we also put the curve of free space path loss in Fig. 9 which is obtained by

$$\frac{P_{\mathrm{r}}}{P_{\mathrm{t}}} = G_{\mathrm{TX}} G_{\mathrm{RX}} \left(\frac{\lambda}{4\pi d} \right)^2, \tag{4}$$

where P_{r} is received signal power, P_{r} is transmission power, G_{TX} is the transmission antenna gain, G_{RX} is the receiving antenna gain, λ is wavelength, and d is the distance between transmitter and receiver.

From the data points in Fig. 9, it can be seen that, the whole data cannot be fit by linear regression well. More specifically, due to that the reception sensitivities of the drone communication units are limited by -117 dBm for BER equal to 0.001, it is impossible to record the data with RSSI below -117 dBm. For the case of the smaller RSSI caused by the larger distance communications (more than 10^3 meter as an example in Fig. 9) and the same route (forward or backward), the absolute value of slope using linear regression therefore should be small and close to zero. Therefore, to establish model with linear regression, we have to carefully process the recorded data according to some additional information such as the information in Fig. 8, so that we can extract suitable data segments and obtain a good regression results as in Fig. 9.

On the other hand, the results obtained by the proposed method is shown in Fig. 10. By using the proposed machine learning method, it is not necessary to separate data according to additional information, and just to feed all data into the proposed machine learning based method to establish a

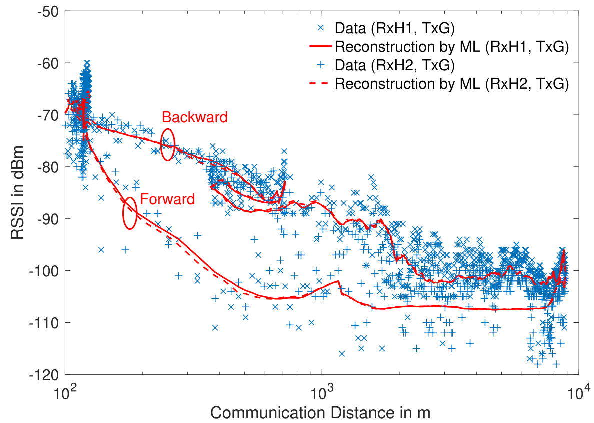

FIGURE 10. The model established by the proposed method for RSSI versus distance between helicopter (drone communication unit H1 and H2) and ground monitoring station (G).

TABLE 3. MSE of the proposed machine learning based method and linear regression method.

Method	MSE
Proposed machine learning based	15.2%
Linear regression	32.8%

model, which reduce the effort needed for model establishment. From the result shown in the figure, it can be seen that, although we did not separate data according to the flying routes before model establishment, the result fits the data quite well, which validates the effectiveness of the proposed method.

Moreover, Fig. 10 shows that, for the case of communication distance below 10^3 meter, although the recorded RSSI of backward route (upper lines) is higher than the one of forward route (lower lines) caused by the helicopter body shielding. The fitted curves by the proposed machine learning method have the similar slopes that means the varying of RSSI in both routes are following the same attenuation rule. Furthermore, the figure also indicated that, for the case of communication distance above 10^3 meter, in particularly on the forward route, the RSSI data are approximately fitted by a line with a small (or zero) slope. This fact confirms the existing of reception sensitivity and points out limitations of using conventional linear regression in the present study.

To validate the performance of the proposed machine learning based method and linear regression method, we compare the MSE of both methods and list the results in TABLE 3. Without loss of fairness, the MSEs of both methods are calculated by all field data. From the MSE results in TABLE 3, it can be seen that, the MSE of the proposed machine learning method is much better than that of linear regression method, and the data processing effort by using proposed machine learning method is much less than the linear regression method.

2) FITTING MISSING DATA

Besides, from the experiment, there is another aspect which can be helped by the proposed machine learning

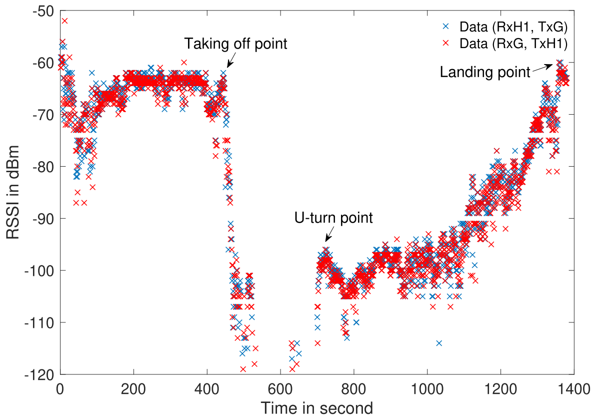

FIGURE 11. RSSI versus time between drone communication unit 1 on helicopter (H1) and ground monitoring station (G).

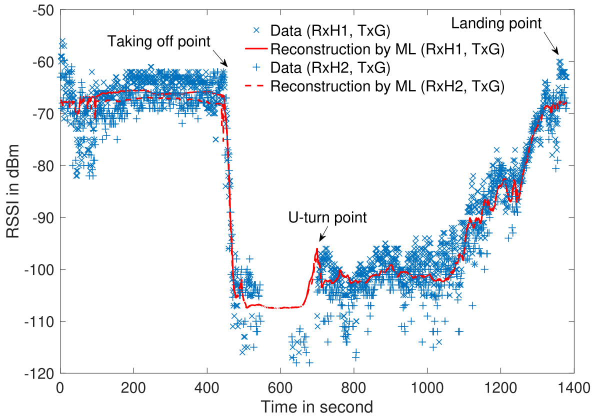

FIGURE 12. Results obtained by the proposed machine learning (ML) method for RSSI versus time.

based method. We use the data of RSSI versus time as an example. The original recorded RSSI data versus time between drone communication unit on helicopter and ground monitoring station is shown in Fig. 11. From the result in Fig. 11, it can be seen that, for the drone communication unit on helicopter, the RSSIs are changed dramatically at almost the same time. It is because there was an obstacle appeared between the helicopter and ground monitoring station near this time so that the receiving condition became very bad. From Fig. 11, it can be also seen that, there is a part of data missed near the time when the obstacle appeared. For finding the missing data, it is cost consuming if we do the experiment again, and the better way is constructing a good model to find the missing data by fitting the data already collected. However, it can be known easily that, the recorded data can not be fit well by linear model.

Therefore, it motivates our idea to using the proposed machine learning based method. By using proposed method, a new fitting model of RSSI versus time can be obtained and shown in Fig. 12. It can be seen from the result in Fig. 12 that, by using proposed method, the resultant model fits the collected data very well, and the missing part of the collected data can be found by the fit result.

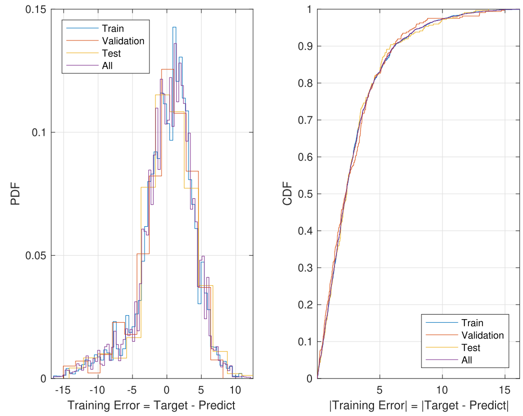

FIGURE 13. The model establishment error distribution.

C. DISCUSSIONS

From the results shown in Sec. IV-B, there are some points worthy to be addressed in more detailed way. Firstly, For the results of fitting missing data, although there is a period of data missed in the collected data shown in Fig. 11, it can be seen that the proposed method can indeed recover it well via machine learning based approach. From the original data shown in Fig. 11, the trend of the recorded data is far away from linear type, and it can be foreseen that, the performance would not be good if conventional linear method is applied, and the resultant data should be far away from its local trend. In this case, the field experiment may need to be operated again to collect data, which needs lots of additional effort and cost. However, by using the proposed method, the data of the missing part can be recovered by machine learning based approach with the trend well matching the data nearby, as the result shown in Fig. 12.

In another example about model establishment, for conventional linear regression method, it needs some effort before data regression, because the data distribution is not linear due to that the surrounding environment during data collecting is varying. Comparing with the results in Fig. 9 and 10, it can be known that, the effort cost for establishing model by conventional linear approach and the effort for doing the same thing by the proposed machine learning based method are totally different. When using conventional approach like linear regression method, it is important to separate or categorize data by some proper attributes, so that the resultant model could fit the collected data well. However, in real cases, the real distribution or real model of the case under investigation usually cannot be analyzed well by a simple linear approach, and the resultant model could not be very useful if the data categorization is not done well. For the proposed machine learning based method, all the collected data can be processed without being categorized, and the resultant model still fits data well as the result shown in Fig. 10. In addition, from the result in Fig. 10, the resultant model reveals that, the characteristics of the drone communication, like flying route, can be captured by the proposed machine learning based method, without the effort of categorizing data before data processing.

Finally, to validate the performance of the proposed method, the training error produced in the process of machine learning is calculated and its distribution is shown in Fig. 13. In Fig. 13, the left-hand-side is the probability distribution function (PDF) and the right-hand-side is cumulative distribution function (CDF) of the training error. From the results in Fig. 13, it can be seen that, as what shown in PDF, the intensity of the training error is mostly around 0. From the CDF, it can also be known that, there are over 80% training errors are with intensity less than 5, which ensures the error performance of the proposed method.

V. CONCLUSION

In this paper, we proposed a novel method to establish the model for drone applications. The proposed model establishment method can capture more detailed characteristics about drone communications with less effort. To validate the proposed method, we set up a field experiment to collect real data of drone communications, and use the collected data to process the traditional and proposed methods. Comparing the results of the two methods, it can be seen that, the proposed method can indeed establish a better model which includes more information. The model obtained by the proposed method can be used to help improve drone communications for better drone control. Furthermore, the proposed method can be easily extended for the communication of multiple drones, which is left as future topic.

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