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Mission-Based Energy Consumption Prediction of Multirotor UAV

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ABSTRACT Unmanned aerial vehicle (UAV) is lately one of many popular research topics. High variety of its usage makes it attentive to be studied on its construction or the control. However, without knowing the energy that will be consumed in each mission, the available flight duration will be unknown and the usages of this vehicle will be limited. A mission-based black box modeling of UAV's energy consumption prediction was proposed in this paper. The setup consists of ArduPilot with Mission Planner Firmware installed to a custom built hexarotor. The method consists of three consecutive steps: data collection, data preprocessing, and regression. To collect the required data, flight patterns that contained several types of movements were defined, where the flight data log that contained missions, GPS, and battery, was collected. The preprocessing included the movement separation and also included the acceleration and the deceleration of horizontal movement. Finally, the regression was done using the Elastic Net Regression from Sklearn. The model was then tested on two flight patterns to simulate a surveillance application of a UAV and could predict with 98.773% mean of energy accuracy of the missions that started from the takeoff and ended with the return to launch command.

INDEX TERMS Hexarotor, energy consumption, multirotor, regression, UAV.

I. INTRODUCTION

Unmanned Aerial Vehicle (UAV) in the form of multirotor is one out of many popular research topics. The capability of doing various maneuver in the air opens abundance opportunities to create some applications such as surveillance systems, package delivery, video recording, or other military usage. However, the success rate of those applications depend on the flight duration which is related to the energy consumption and battery capacity.

There were several methods that had been proposed in the previous researches to estimate the energy consumption of an UAV [1]. Most of their methods can be classified into the white box method and the black box method.

The white box method is a modeling method that requires physical parameters which will be estimated and then calculated in a theoretical model. Liu *et al.* [1] were one of the researchers who used an aero-mechanic modeling of a Helicopter to be a reference to make a energy consumption model of a Quadcopter but not including the transition between the movement and was stated to be one of the drawback of their model. Furthermore, this method also relied on 8 parameters that needed some specific methods to estimate the value and were hard to get. This made the model could not be easily implemented in any UAV. Bezzo *et al.* [2] did a white box modeling and put the transition of the movements into the model. They predicted the consumed energy in an interpolation function but directly used it for the control purpose without explaining and giving enough experiment result about the accuracy of the model. Abdilla *et al.* [3] also did a white box method by modeling the battery characteristic then directly predict the flight duration that the UAV could do. This method put a very detail explanation and experiment on the battery of the UAV but would not be easily implemented to other UAV with different type of battery.

The black box method is a modeling method that does not require any physical parameters nor any theoretical model. This model will only rely on the input that we choose and the

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output that we want in a regression process. Valenti *et al.* [4] used a black box modeling method to model the flight duration of the UAV from the collective stick position of the remote controller. They only design the model of the hovering in a form of flight duration and did not cover any other movement that required more energy than hover such as vertical movement or horizontal movement. Maekawa *et al.* [5] created a black box modeling only for a constant horizontal movement with flight speed and weight as the input. Tseng *et al.* [6] tried to model a more complete energy consumption of vertical, horizontal, and hover move with adding wind and weight effect into the calculation. Dietrich *et al.* [7] also did a black box modeling by simplifying the movement into flight angle variation where horizontal movement equal to 0° flight angle and vertical movement equal to ±90° flight angle. Abeywickrama *et al.* [8] did an even more complete modeling of the UAV energy consumption of the idle mode, arm mode, horizontal movement, hover movement, vertical upward movement, vertical downward movement, payload effect, and wind effect with a black box regression and claimed that it could be easily implemented.

Unfortunately, Tseng *et al.* [6] did not explain explicitly how they separate each movement which was needed in the training or the predicting part while Abeywickrama *et al.* [8] used a fix time to explain the separation. The fix time, however, indeed was useful for a well defined duration movement such as hover, but not to a horizontal or vertical movement where the duration depended on the distance and the speed and therefore became uneasy to implement it. Separating each movement was believed to be easily achieved by reading the mission command which were done in [7], but the movement transition of each movement was again neglected in their research even though had been stated in [1] to be necessary.

To eliminate the aforementioned drawbacks, an analysis and a model of the transition part was proposed in this paper by including the acceleration and deceleration of horizontal movement into the model. Furthermore, a systematic method from taking the flight data with automatic data fetching of the vertical, horizontal, and hover movements to energy consumption regression of a UAV are also explained. After the parameter of the trained model was achieved, the testing by defining 2 flight patterns to simulate a surveillance application of an UAV were designed and the consumed energy were predicted only by the mission list and the speed parameter of the UAV. This project was supported by Industrial Technology Research Institute of Taiwan (ITRI) and implemented to the winning R&D 100 2018 Conference Awards project called APUPS (Automatic Police UAV Patrol System) [9]. The UAV was captured in Fig. 1.

The paper were organized as follow. Section 2 was Mission Based Energy Consumption Prediction Method. That section would explain the process from the flight patterns, data preprocessing, and regression. Section 3 was the Experimental Testing that would explain about the missions and flight patterns to evaluate the prediction. Section 4 was the Result and Discussion that would explain about the evaluation method

FIGURE 1. APUPS (Automatic Police UAV Patrol System) from ITRI.

and comparisons with previous researches. Section 5 was Conclusion that would also explain about the contribution and future works.

II. MISSION BASED ENERGY CONSUMPTION PREDICTION METHOD

The first problem of defining and training a black box model was defining a reliable method of the data collection. After the needed amount of data were achieved, the data had to be preprocessed before then fed into the regression process.

The Method was done in 3 major steps which were data collecting, data preprocessing, and regression. The data collection was done with 1 flight pattern that would cover 3 main movements of the UAV which were hover, vertical, and horizontal movement. The log file then would be processed in the data preprocessing by sectioning the flight and generating label of each movement. Finally the preprocessed data were then fed into each of the related regression to get the parameter of the regression model. Those steps were explained in Fig. 2.

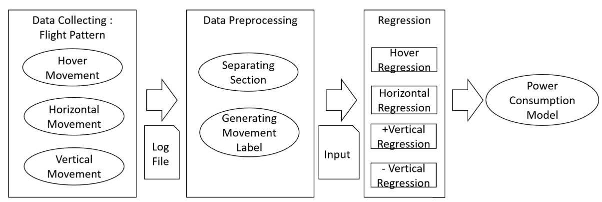

FIGURE 2. Training power model of UAV.

A. DATA COLLECTION

This method were designed and implemented in ArduCopter Firmware [10] and Mission Planner [11]. From this firmware, the log file which would include GPS, altitude data, mission status, and battery status could be downloaded easily. To solve the asynchronous sampling time of the log file, where the GPS sampling time was 0.2s and the rest of the data were 0.1s, the python package Pandas [12] was used to merge the data to the nearest time of the GPS time log. In the end, the battery status would be used to compare the accuracy of our model to the real consumed energy.

There were 6 Horizontal Movements covered in the training flight pattern with the speed varied from 1 m/s to 8.5 m/s

N_k	Command	Hover Duration (s)	Altitude (m)	Horizontal Distance(m)
1	TAKEOFF	-	50	0
2	LOITER_TIME	10	50	0
3	WAYPOINT	-	50	50
4	LOITER_TIME	5	50	0
5	WAYPOINT	-	100	0
6	LOITER_TIME	5	100	0
7	LAND	-	100	0

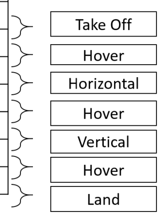

FIGURE 3. Commands to do horizontal or vertical movement flight pattern and process of generating movement label.

and distance from 30m to 350m. The first one was to move in 34.83m with horizontal speed equal to 1 m/s. The second one was to move in 307.10m with horizontal speed equal to 6.25 m/s. The third one was to move in 157.77m with horizontal speed equal to 4.3 m/s. The fourth one was to move in 347.16m with horizontal speed equal to 8.5 m/s. The fifth one was to move in 77.83m with horizontal speed equal to 3 m/s. The last one was to move in 86.55m with horizontal speed equal to 2.8 m/s. The LOITER_TIME command, which was a command to do hover movement, was needed to be put in between of each of other movement to easily separate the acceleration and deceleration part where then will be processed in the regression part. The concept of this pattern was summarized in Fig. 3 where the k in N_k was the sequence of the mission.

The vertical movement was similar with horizontal movement pattern but the WAYPOINT command only used to move vertically upward and vertically downward with 5 variation of speed from 0.5 m/s to 2 m/s. The first one was to move 20m vertically upward with vertical upward speed equal to 0.5 m/s. The second one was to move 60m vertically upward with vertical upward speed equal to 2 m/s. The third one was to move 30m vertically downward with vertical downward speed equal to 0.5 m/s. The fourth one was to move 50m vertically downward with vertical downward speed equal to 2 m/s. The fifth one was to move 50m vertically upward with vertical upward speed equal to 1.5 m/s. The sixth one was to move 70m vertically downward with vertical downward speed equal to 1.5 m/s. The seventh one was to move 50m vertically upward with vertical upward speed equal to 1.8 m/s. The last one was to move 40m vertically downward with vertical downward speed equal to 1.8 m/s. The LOITER_TIME command also put in between of each movement to easily separate the movement.

Finally the Hover Movement was covered with 3 different duration from 20s to 40s. All the LOITER_TIME command in between other movement were also used to be fed into the hovering movement regression.

The detail of the training mission was explained in Table 1. The Prm1 and Prm2 in the table were missions input parameter in the Mission Planner. In the LOITER_TIME command, the Prm1 was the hover duration. Furthermore, in the DO_CHANGE_SPEED command, the combination values

TABLE 1. Mission lists of training pattern.

N_k	Command	Prm1	Prm2	Altitude (m)	Horizontal Distance (m)
1	TAKEOFF	0	0	50	0
2	LOITER_TIME	30	0	50	0
3	DO_CHANGE_SPEED	0	1	50	0
4	WAYPOINT	0	0	50	34.83
5	LOITER_TIME	2	0	50	0
6	DO_CHANGE_SPEED	2	0.5	50	0
7	WAYPOINT	0	0	70	0
8	LOITER_TIME	2	0	70	0
9	DO_CHANGE_SPEED	0	6.25	70	0
10	WAYPOINT	0	0	70	307.10
11	LOITER_TIME	2	0	70	0
12	DO_CHANGE_SPEED	2	2	70	0
13	WAYPOINT	0	0	130	0
14	LOITER_TIME	2	0	130	0
15	DO_CHANGE_SPEED	0	4.3	130	0
16	WAYPOINT	0	0	130	157.77
17	LOITER_TIME	2	0	130	0
18	DO_CHANGE_SPEED	3	0.5	130	0
19	WAYPOINT	0	0	100	0
20	LOITER_TIME	2	0	100	0
21	DO_CHANGE_SPEED	0	8.5	100	0
22	WAYPOINT	0	0	100	347.16
23	LOITER_TIME	2	0	100	0
24	DO_CHANGE_SPEED	3	2	100	0
25	WAYPOINT	0	0	50	0
26	LOITER_TIME	2	0	50	0
27	DO_CHANGE_SPEED	0	3	50	0
28	WAYPOINT	0	0	50	77.83
29	LOITER_TIME	2	0	50	0
30	DO_CHANGE_SPEED	2	1.5	50	0
31	WAYPOINT	0	0	100	0
32	LOITER_TIME	2	0	100	0
33	DO_CHANGE_SPEED	0	2.8	100	0
34	WAYPOINT	0	0	100	86.55
35	LOITER_TIME	2	0	100	0
36	DO_CHANGE_SPEED	3	1.5	100	0
37	WAYPOINT	0	0	30	0
38	LOITER_TIME	2	0	30	0
39	DO_CHANGE_SPEED	2	1.8	30	0
40	WAYPOINT	0	0	80	0
41	LOITER_TIME	20	0	80	0
42	DO_CHANGE_SPEED	3	1.8	80	0
43	WAYPOINT	0	0	40	0
44	LOITER_TIME	40	0	40	0
45	LAND	0	0	40	0

of Prm1 and Prm2 were needed to explain which speed that was wanted to be changed. The Prm1 equal to 0 was for the horizontal speed where the Prm2 would be read as the desired horizontal speed in m/s. The Prm1 equal to 2 was for the vertical upward speed where the Prm2 would be read as the desired vertical upward speed in m/s. The Prm1 equal to 3 was for the vertical downward speed where the Prm2 would be read as the desired vertical downward speed in m/s.

B. DATA PREPROCESSING

The preprocessing of the data included 2 part. Those part were separating the flight section and generating the movement label. The flight section separation was needed to define each section of the flight from the log file of 1 training flight data. The movement label was needed to then differentiate each movement. While generating the movement label in the training data, the horizontal movement with acceleration and deceleration part and the landing with high and low speed part were also defined. The acceleration and deceleration part was needed to be defined to solve the problem that was stated in [1]. The landing movement in ArduCopter was divided into high and low landing with different speed and therefore would have different duration and consumed energy. Later these 2 preprocessing could not be done in the testing part where a regression would be used to predict these values.

A flight section was defined as a complete data from the take off command to the landing command in auto mode. The log file of the Mission Planner would start recording the flight once the battery was connected and would stop when it was disconnected which in turn would put some patterns to be combined in a long flight record log file. To do a mission, the UAV need to be armed with RC and arming it could not be done in auto mode. Therefore a method to separate each flight section was necessary to later easily differentiate each movement in the second part of the preprocessing. The separation was done by reading not just the CId of the CMD data, but also the mode from the MODE data. Then the string value "auto" in the MODE data could be used to identify and separate the section.

To generate the movement label, the CMD was read from the log file. The Movement was assumed to be done once the next mission was executed and it was explained in the Fig. 3. Then the consumed energy for one movement would be taken from the BAT data from the log with the related start and stop time of the mission.

The acceleration and deceleration part of horizontal movement were defined by reading the horizontal speed with the start and stop time of the mission. The start time was the time when the acceleration part began and the stop time was when the deceleration part finished. The end of the acceleration and the start of deceleration were defined to be the first and the last time the speed of the UAV was in 98%-102% of the desired speed and was depicted in Fig. 4.

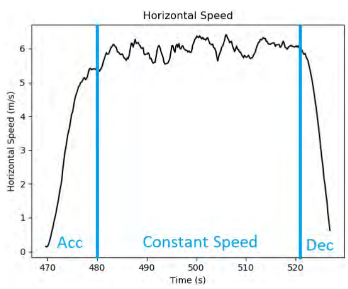

FIGURE 4. Defining acceleration (Acc) and deceleration (Dec) part from horizontal movement.

Based on the ArduCopter documentation, the UAV will move in low speed when the landing process reach the altitude equal to 10m. Therefore it was possible to define the separation between the high speed and low speed landing by reading the altitude data and the process was depicted in Fig. 5.

After all the movements has been labeled with the start and stop time, the inputs of the regression that related to those movement were extracted and explained in the Table 2. The consumed energy was defined to be the total power during the related mission and was described in (1), where E was the consumed energy in Wh, P was the Power in W, and t was the time in s where 1 hour was equal to 3600 seconds.

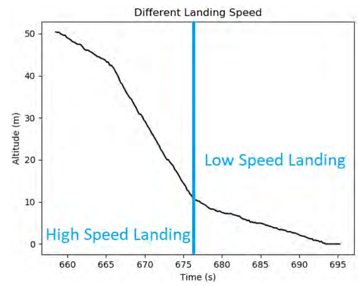

FIGURE 5. Defining high speed landing and low speed landing from landing movement.

TABLE 2. List of regressions inputs.

Name	Explanation	Regression
x_1	Upward Vertical Speed (m/s)	-Upward Vertical Duration -Upward Vertical Power Consumption
x_2	Upward Vertical Distance (m)	-Upward Vertical Duration -Upward Vertical Power Consumption
x_3	Downward Vertical Speed (m/s)	-Downward Vertical Duration -Downward Vertical Power Consumption
x_4	Downward Vertical Distance (m)	-Downward Vertical Duration -Downward Vertical Power Consumption
x_5	Horizontal Distance (m)	-Acceleration Duration -Deceleration Duration -Horizontal Power Consumption
x_6	Horizontal Speed (m/s)	-Acceleration Duration -Deceleration Duration -Horizontal Power Consumption
x_7	Hover Duration (s)	-Hover Power Consumption

$$E = \frac{1}{3600} \int_{t_{start}}^{t_{stop}} P dt \tag{1}$$

Other then separating the data, polynomial features also extracted from the vertical speed and vertical distance to improve the upward vertical and downward vertical duration with (2), where x_1 was the upward vertical speed and x_2 was the upward vertical distance. The order of the polynomial features were tuned manually to be 3 in the training process to prevent over-fitting.

$$Pol(x_1, x_2) = [1, x_1, x_2, x_1^2, x_1x_2, x_2^2, x_1^3, x_1^2x_2, x_1x_2^2, x_2^3] \tag{2}$$

C. REGRESSION

After all the preprocessing part, the regression was done by feeding the related data into the related regressor. There were 8 regressor that needed to be trained which were acceleration duration, deceleration duration, upward vertical duration, downward vertical duration, hover energy consumption, horizontal movement energy consumption, upward vertical movement energy consumption, and downward vertical movement energy consumption.

$$\hat{y} = w_0 + x_1 w_1 + \ldots + x_p w_p. \quad (3)$$

Given a linear regression model in (3) where $\hat{y}$ was the estimation of the true y and x_i with $i = 1, 2, \ldots, p$ were the observable variable and w_j with $j = 0, 1, \ldots, p$ were the weight. One of the methods that have been widely used to update the weight value in the training process was Elastic Net regularization method [13] with Sklearn package [14] and was described in (4).

$$min \frac{1}{2p} ||\hat{y} - y||_2^2 + \alpha\rho ||w||_1 + \frac{\alpha(1-\rho)}{2} ||w||_2^2 \quad (4)$$

In (4), it was showed that it was similar to least square with α and ρ as the parameters that were needed to be tuned. Those parameter would give trade-off between Lasso and Ridge Regression which was the advantage of this method. In the training process, we did K-Fold Cross Validation with 5 number of Folds while tuning the best value of α and ρ for each of regressions.

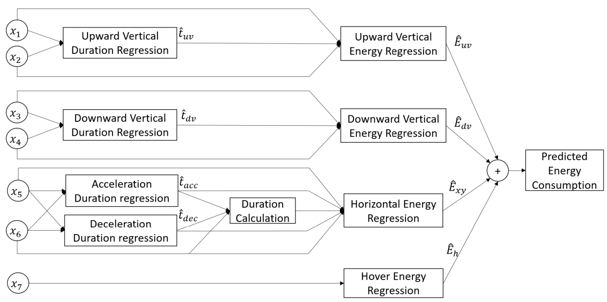

FIGURE 6. Prediction process scheme.

TABLE 3. List of regressions outputs.

Name	Explanation
$\hat{t}_{uv}$	Upward Vertical Duration (s)
$\hat{t}_{dv}$	Downward Vertical Duration (s)
$\hat{t}_{acc}$	Horizontal Acceleration Duration (s)
$\hat{t}_{dec}$	Horizontal Deceleration Duration (s)
$\hat{E}_{uv}$	Upward Vertical Energy Consumption (Wh)
$\hat{E}_{dv}$	Downward Vertical Energy Consumption (Wh)
$\hat{E}_{xy}$	Horizontal Energy Consumption (Wh)
$\hat{E}_h$	Hover Energy Consumption (Wh)

The trained model could be used in prediction by putting the related input to each of them and explained in the Figure 6. The output of all the regressions were listed in the Table 3. The output of duration regressions would be used again as one of the inputs of the energy regressions. However, the estimated acceleration and deceleration duration would also be used to estimate the distance in (5) and (6). The estimated distance would be used in the duration calculation in (7). In (5), (6), and (7), $\hat{s}_{acc}$ was the distance that has been through during the acceleration in m and $\hat{s}_{dec}$ during the deceleration in m. The output of the calculation was $\hat{t}_{cs}$ in second which was the estimated horizontal movement in constant speed.

$$\hat{s}_{acc} = \frac{1}{2} x_6 \hat{t}_{acc} \quad (5)$$

$$\hat{s}_{dec} = \frac{1}{2} x_6 \hat{t}_{dec} \quad (6)$$

$$\hat{t}_{cs} = \frac{x_5 - \hat{s}_{acc} - \hat{s}_{dec}}{x_6} \quad (7)$$

In the end of predicting process, all the estimated energy consumption from the missions then could be integrated which then would be the estimated total consumed energy for those missions.

III. EXPERIMENTAL TESTING

The testing was done by predicting the energy consumption of 2 lists of surveillance system missions. There were 2 patterns that were used as the test set. The first pattern was to simulate a surveillance of building windows which required more vertical movement. The second pattern was to simulate a surveillance of a wider area which required more horizontal movement. Both of the patterns were done in the ITRI Head Quarter, Taiwan. The mission lists of the first pattern was explained in Table 4 and the second pattern in Table 5. The picture of the first pattern was showed in Fig. 7 and the second pattern was in Fig. 8. The horizontal speed in the testing patterns was 2.8 m/s, upward vertical speed was 1.5 m/s, and downward vertical speed was 1.5 m/s for all the patterns.

TABLE 4. Mission lists of building surveillance flight pattern.

N_k	Command	Hover Duration (s)	Altitude (m)	Horizontal Distance (m)
1	TAKEOFF	-	50	0
2	LOITER_TIME	30	50	0
3	WAYPOINT	-	50	28.41
4	WAYPOINT	-	50	55.28
5	LOITER_TIME	30	50	0
6	WAYPOINT	-	80	0
7	LOITER_TIME	60	80	0
8	RETURN_TO_LAUNCH	-	80	62.25

There were 3 sections of the first pattern and 1 section of the second pattern. The testing data were not as complete as the training data and needed a cascaded regression system to predict the duration of acceleration, deceleration, and constant speed that has been described in Fig 6. The Return to Launch command was also predicted by defining it as a horizontal movement then followed then a landing command. Defining Return to Launch command was useful to make the future mission planning become more flexible. The consumed power in Watt for the Building Surveillance Flight Pattern was showed in Fig. 9. In Fig. 9, N_k was labeled with the information in Table 4.

The Return to Launch Command was labeled in number 8 and contained 2 movements. Those movements were horizontal movement to the home latitude and longitude

TABLE 5. Mission lists of area surveillance flight pattern.

N_k	Command	Hover Duration (s)	Altitude (m)	Horizontal Distance (m)
1	TAKEOFF	-	130	0
2	LOITER_TIME	10	130	0
3	WAYPOINT	-	130	220.71
4	LOITER_TIME	15	130	0
5	WAYPOINT	-	130	93.39
6	LOITER_TIME	15	130	0
7	WAYPOINT	-	130	718.62
8	LOITER_TIME	15	130	0
9	WAYPOINT	-	130	71.03
10	LOITER_TIME	15	130	0
11	WAYPOINT	-	130	713.09
12	LOITER_TIME	15	130	0
13	WAYPOINT	-	130	125.17
14	WAYPOINT	-	130	724.69
15	WAYPOINT	-	130	73.41
16	WAYPOINT	-	130	487.80
17	RETURN_TO_LAUNCH	-	130	140.14

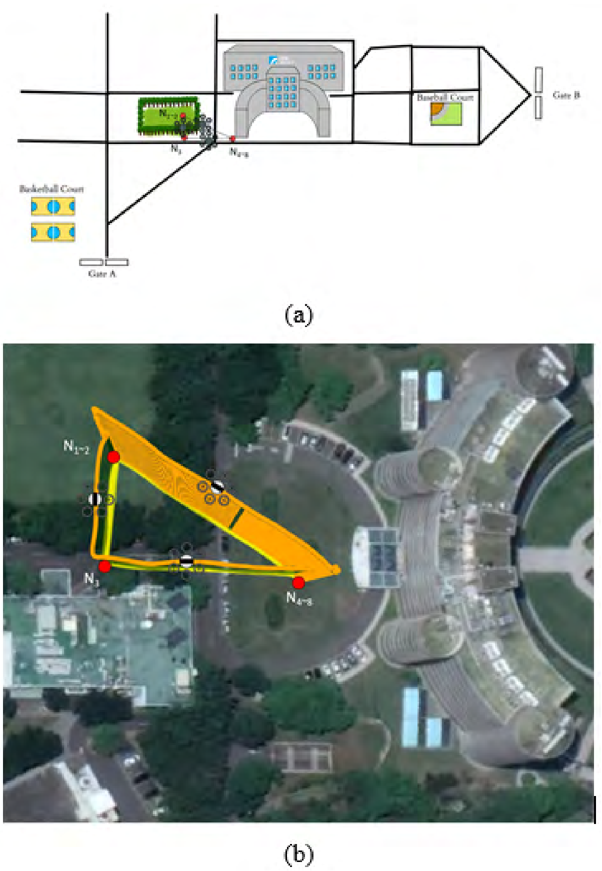

FIGURE 7. (a) Building surveillance flight pattern for testing; (b) satellite image.

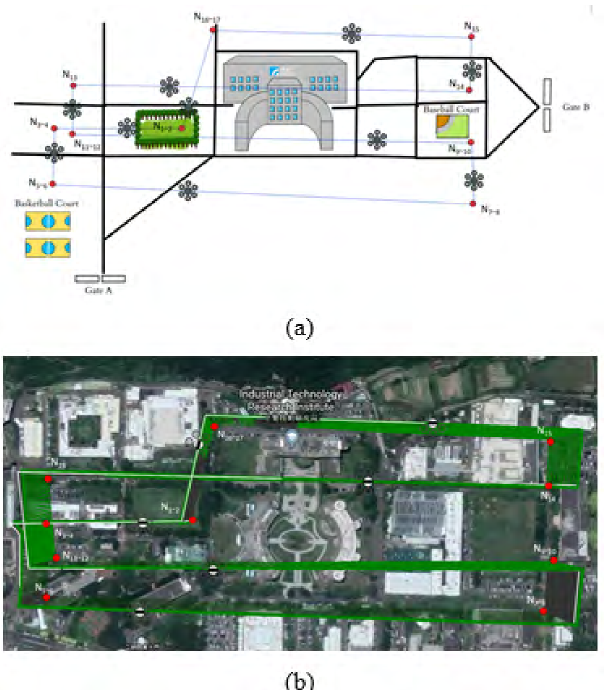

FIGURE 8. (a) Area surveillance flight pattern for testing; (b) satellite image.

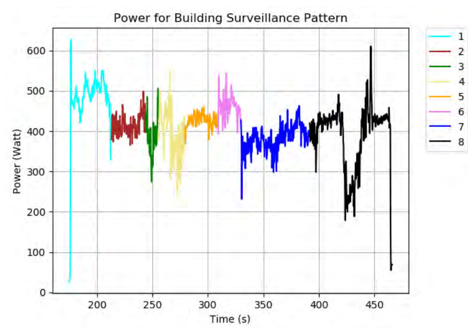

FIGURE 9. Consumed power for building surveillance flight pattern.

and landing. However, the landing movement contained high speed landing and low speed landing where the difference could be seen clearly in Fig. 10. In Fig. 10, the separation between the horizontal movement and landing could also be seen clearly. The horizontal movement also contained the acceleration and the deceleration part. The effect of those parts to the consumed power could also be seen clearly to the power plot with the related time. The high speed landing would consume less power compare to horizontal movement and the low speed landing because to obtain a higher landing speed, the rotation speed of the motor were decreased. The comparison of the true consumed energy and the estimated consumed energy would be discussed in the next section.

IV. RESULT AND DISCUSSION

To evaluate the regression results, the absolute error that was described in (8) and the accuracy in percent that was described in (9) were used. The evaluation of the results using these equations was described in Table 6.

$$|e| = \left|E - \hat{E}\right| \tag{8}$$

$$Accuracy = 100\% \times \left(1 - \left|\frac{E - \hat{E}}{E}\right|\right) \tag{9}$$

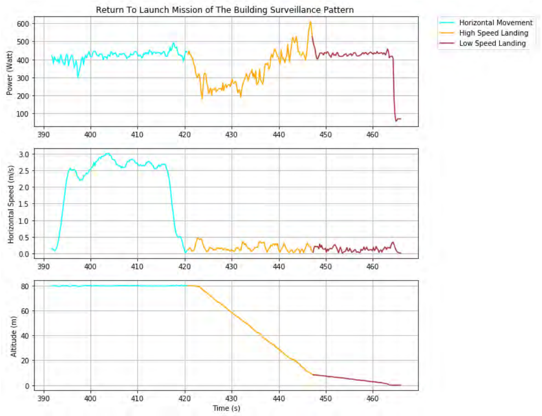

FIGURE 10. Return to launch mission.

TABLE 6. Results and evaluations.

Pattern	Section	True Consumed Energy (Wh)	Estimated Consumed Energy (Wh)	Absolute Error (Wh)	Accuracy
I	1	33.2313	32.6787	0.5525	98.3372%
	2	32.7783	32.6787	0.0996	99.6961%
	3	33.5082	32.6787	0.8294	97.5246%
II	1	165.7813	165.0108	0.7705	99.5352%

Table 6 showed the mean of the absolute error was 0.5630 Wh and the mean of Accuracy is 98.773%. The biggest absolute error from our evaluation was 0.8294 Wh from the second pattern while the smallest error we could get was 0.0996 Wh from the section 2 of the first pattern. True consumed energies of the first pattern were different in those 3 sections although missions were the same. This could happen because of real wind conditions. Besides, estimated consumed energies were the same because the missions' parameters were the same.

The comparison with previous works in [5], [7], and [8] had been done by replicating the method and feeding the training data from Table 1. Then the replicated methods were used to predict only horizontal movement from a flight pattern that was described in Table 7 with horizontal speed equal to 7 m/s. The corresponding performance comparisons were summarized in Table 8, in which predicted accuracies were calculated according to (9). Because, Liu *et al.* [1] used several physical parameters that could not be easily achieved from APUPS or any other UAV, the corresponding accuracy in Table 8 was the horizontal flight accuracy showed in [1].

TABLE 7. Mission lists of horizontal flights.

N_k	Command	Hover Duration (s)	Altitude (m)	Horizontal Distance (m)
1	WAYPOINT	-	50	162.497
2	WAYPOINT	-	50	147.421
3	WAYPOINT	-	50	202.514
4	WAYPOINT	-	50	167.012

Moreover, only the power was predicted in [5], and the flight duration estimation was not included in [8]. To solve these problems, the flight duration estimation proposed by Dietrich *et al.* [7], which was defined by dividing the distance with the speed, was implemented to predict the consumed energy via replicated methods in [5] and [8].

TABLE 8. Performance comparison.

Previous Research	Physical Parameter	Vertical	Transition	Horizontal Speed Variation	Horizontal Flight Accuracy
[1]	8	✓	-	-	83.673%
[5]	0	-	-	-	75.742%
[7]	0	✓	-	-	85.210%
[8]	0	✓	-	-	72.317%
Proposed Method	0	✓	✓	✓	95.512%

In Table 8, it is obvious that only the proposed method includes the transition of horizontal movement, and the variation of horizontal speed. This advantage gives the impact to the accuracy comparison, which was more than 10% greater than other methods for this scenario. This could be achieved because the value of 7 m/s was considered to be a high speed, and the acceleration and deceleration would take more time than the constant speed part in those distances. Considering the transition movement (acceleration and deceleration) into account would give more detail prediction and predict with a better accuracy.

The other issue of the energy consumption prediction of a UAV was the effect of the wind. Like the references that were cited in this paper, this paper also assumed that the UAV would fly only in negligible wind condition. This limitation was analyzed by doing a prediction test of a horizontal movement in head and tail wind conditions. The tail wind was when the UAV flew in the same direction as the wind while the head wind was the opposite direction. The illustration of consumed power during head and tail at class 2 Wind Power (Wind Speed $\leq$ 5.1 m/s in 10m) flight was given in Fig. 11. Total true consumed energy of head wind horizontal flight was 6.962 Wh while the tail wind was 5.832h Wh. The prediction was 6.246 Wh which was the same for both condition because the proposed method did not take wind conditions into account. However, it could be seen that the

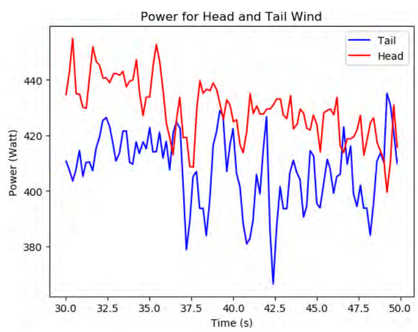

FIGURE 11. Power consumption in head and tail wind flight.

prediction could still achieve 92.91% accuracy for tail wind and 89.71% for head wind.

Another issue was the aggressiveness of the UAV, which was depended on a control profile. The proposed method belongs to be a data driven approach, where the control profile of the testing data was required to be the same as the training data. Therefore, a new training process was necessary once the control profile of the auto mode has been changed.

To solve the wind and the aggressiveness problem, a better method from time-series Machine Learning method like Long-Short Term Memory by Hochreiter and Schmidhuber [15] was believed to be needed. An UAV with a fast online communication of the UAV position and orientation synchronized with the missions was a promising method to achieved a more accurate and more flexible model to various type of maneuvers, even for a manually controlled flight.

Based on those discussion, the contribution of this paper were:

1) An analysis and a model of the transition part including the acceleration and deceleration of horizontal movement into the model.
2) A systematic method from taking the flight data with automatic data fetching of the vertical, horizontal, and hover movement to energy consumption regression of a UAV
3) A designed reference of 2 flight patterns to simulate a surveillance application of an UAV
4) Defining a complete model of an UAV energy consumption with the prediction only using the mission lists and the speed parameter to make mission planning process easier.

V. CONCLUSION

Knowing the consumed energy of UAV's each mission was essential for the mission planning. The black box method is believed to be the easiest method to implement the energy consumption modeling. The transition of each movement which includes the acceleration and deceleration part are necessary to predict the duration of the mission easier and therefore increase the accuracy of the estimated energy consumption.

A mission-based black box modeling of UAV's energy consumption prediction was proposed in this paper. The setup consist ArduPilot with Mission Planner Firmware installed to a custom build hexarotor. The method consist of 3 consecutive steps: data collection, data preprocessing, and regression. To collect the required data, a flight pattern that contained several type of movements were defined where then the flight data log that contained missions, GPS, and battery were collected. The preprocessing included the movement separation and also included the acceleration and deceleration of horizontal movement. Finally the regression was done using Elastic Net Regression from Sklearn. The model then was tested on 2 flight pattern to simulate a surveillance application of an UAV and could predict with 98.773% mean of energy accuracy of the missions which started from the take off and ended with the return to launch command. Moreover, a comparison of the proposed method with replicated methods from the references showed that the proposed method could have more than 10% greater accuracy in predicting energy consumed of horizontal flights by considering transition and speed variation into account.

The future works of this topics can be about using time-series Machine Learning method like Long-Short Term Memory to do the Energy consumption modeling of the UAV. This method will open more possibilities of modeling various movement.

REFERENCES

[1] Z. Liu, R. Sengupta, and A. Kurzhanskiy, "A power consumption model for multi-rotor small unmanned aircraft systems," in *Proc. Int. Conf. Unmanned Aircr. Syst. (ICUAS)*, Jun. 2017, pp. 310–315.
[2] N. Bezzo, K. Mohta, C. Nowzari, I. Lee, V. Kumar, and G. Pappas, "Online planning for energy-efficient and disturbance-aware UAV operations," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Oct. 2016, pp. 5027–5033.
[3] A. Abdilla, A. Richards, and S. Burrow, "Power and endurance modelling of battery-powered rotorcraft," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Sep./Oct. 2015, pp. 675–680.
[4] M. Valenti, B. Bethke, J. P. How, D. P. de Farias, and J. Vian, "Embedding health management into mission tasking for UAV teams," in *Proc. Amer. Control Conf. (ACC)*, Jul. 2007, pp. 5777–5783.
[5] K. Maekawa, S. Negoro, I. Taniguchi, and H. Tomiyama, "Power measurement and modeling of quadcopters on horizontal flight," in *Proc. 5th Int. Symp. Comput. Netw. (CANDAR)*, Nov. 2017, pp. 326–329.
[6] C.-M. Tseng, C.-K. Chau, K. Elbassioni, and M. Khonji. (2017). "Autonomous recharging and flight mission planning for battery-operated autonomous drones." [Online]. Available: https://arxiv.org/abs/1703.10049
[7] T. Dietrich, S. Krug, and A. Zimmermann, "An empirical study on generic multicopter energy consumption profiles," in *Proc. Annu. IEEE Int. Syst. Conf. (SysCon)*, Apr. 2017, pp. 1–6.
[8] H. V. Abeywickrama, B. A. Jayawickrama, Y. He, and E. Dutkiewicz, "Comprehensive energy consumption model for unmanned aerial vehicles, based on empirical studies of battery performance," *IEEE Access*, vol. 6, pp. 58383–58394, 2018.
[9] *R. 1. Conference, Award Winners & Finalists*. Accessed: Nov. 20, 2018. [Online]. Available: https://www.rd100conference.com/awards/winners-finalists/year/2018/
[10] ArduPilot Dev Team. *Ardu Copter, Copter Home*. Accessed: Oct. 29, 2018. [Online]. Available: http://ardupilot.org/copter/
[11] ArduPilot Dev Team. *Mission Planner, Mission Planner Home*. Accessed: Oct. 29, 2018. [Online]. Available: http://ardupilot.org/planner/index.html
[12] W. McKinney, "Data structures for statistical computing in python," in *Proc. 9th Python Sci. Conf.*, S. van der Walt and J. Millman, Eds., 2010, pp. 51–56.
[13] H. Zou and T. Hastie, "Regularization and variable selection via the elastic net," *J. Roy. Statist. Soc., B (Statistical Methodology)*, vol. 67, no. 2, pp. 301–320, 2005.
[14] F. Pedregosa *et al.*, "Scikit-learn: Machine learning in Python," *J. Mach. Learn. Res.*, vol. 12, pp. 2825–2830, Oct. 2011.
[15] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997.

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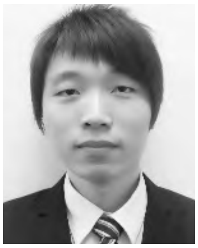

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