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ABSTRACT

Accurate and economic estimation of aircraft fuel consumption is fundamental for optimizing aviation opera- tions, including emission reduction, flight route planning, and fuel management. Numerous literature presented mathematical models to estimate aircraft fuel consumption but often neglected the challenges of applying those methods in aviation operations. This paper explores a novel strategy to estimate aircraft fuel consumption by modeling flight data from onboard flight data recorder (FDR) and automatic dependent surveillance – broadcast (ADS-B). The Classification and Regression Tree (CART) and Neural Networks (NNs) are adopted for modeling. CART and NN models are developed using FDR data; ADS-B data are used to assess the model performance. The result indicates that the CART model performs better when inputs contain errors and missing values, and the ADS-B data could be used to estimate aircraft fuel consumption as a less-expensive and more convenient strategy compared to the FDR data.

Introduction

Air transport carried over 35 percent of all good by value and sup- ported 3.5 percent of global GDP as reported by the most recent data in 2019 (International Civil Aviation Organization [ICAO], 2019a). Estimation of aircraft fuel consumption is crucial for a variety of aspects in aviation operations, such as aviation emission reduction, economic flight route planning, and optimal fuel management for aviation operators. While air transport is tremendously facilitating the growth of economy and convenience of social life, sustainable development has been pursued by aviation authorities and a variety of stakeholders considering the remarkable environmental impact from aviation activities. The Committee on Aviation Environment Protection (CAEP) of the International Civil Aviation Organization (ICAO) is an example of initiatives to assist the council for the development of policies and Standards and Recommended Practices (SARPs) related to aviation environmental impact mitigation (ICAO, n.d.). In addition, the Inter- national Air Transport Association (IATA), the Federal Aviation Administration (FAA), EUROCONTROL, the U.S. Environmental Protection Agency (EPA), and many aviation industry stakeholders also exercised a variety of programs to alleviate the environmental impact created by aviation activities (International Air Transport Association [IATA], n.d.; Federal Aviation Administration [FAA], 2020a; European Union, 2009; U.S. Environmental Protection Agency, 2020). The four-pillar strategy to mitigate aviation carbon emissions by developing advanced technology, improving aircraft operation efficiency, upgrading existing infrastructure, and adopting economic measures was pro- posed and implemented by different stakeholders (IATA, 2020; Lufthansa Group, 2020). The ICAO is also pursuing a variety of supplementary measures to achieve the global goals on emission reduction and sustainable growth of international aviation, including aircraft technology improvement, operational improvement, alternative aircraft fuel, and market-based measures (ICAO, 2019b). To measure the progress and effectiveness of different aviation emission mitigation strategies, the Emission and Dispersion Modelling System (EDMS) was developed in mid-1980s and upgraded to a more advanced solution – the Aviation Environment Design Tool, Version 3c (AEDT, V.3c) as of March 6, 2020 (FAA, 2020b). The AEDT 3c is required to be used for all FAA aviation noise, fuel burn, and emissions modeling actions in the U.S. (FAA, 2020b). The ICAO's Fuel Savings Estimation Tool (IFSET) also provides another option for countries that do not have available detailed measurement or modeling of fuel savings (ICAO, 2016). Other examples of strategies, including the Advanced Emissions Model (AEM), Open-ALAQS, and IMPACT, are developed by European agencies for estimation and analysis of aircraft fuel consumption and emissions (EUROCONTROL, n.d.).

Among different aircraft fuel consumption and emission assessment approaches, the phases of flight, durations of each phase of flight, fuel flow rate, and aircraft engine emission index of exhausted emissions are widely used for estimating the total fuel consumption or volume of exhaust emissions by the phases of flight, as shown in Eq. (1) (ICAO, 2017).

$$Q_{,j} = \Sigma\ (EI_{i,j} * FFR_i * DUR_i) \qquad (1)$$

where $Q_{,j}$ is the total volume of emission j (kg), Σ is the sum of phases of flight during a time period, $EI_{i,j}$ is the aircraft engine emission index for a specific pollutant j in the phase of flight i (kg-exhaust chemical/kg-fuel burned), FFR_i is the average fuel flow rate in the phase of flight i (kg- fuel/s), i is a certain phase of flight, and DUR_i is the duration of the phase of flight i (s).

In current practice, the information of fuel flow rate could be obtained from a variety of channels, for example, many on-board flight data recording devices log aircraft fuel flow rate and the total fuel consumption information; some advanced aircraft powerplant management systems also track and monitor fuel consumption. However, those strategies not only require an expensive investment in advanced flight data recording and analytics technologies, but also involve latency and inconvenience as most flight data become available only when flights are completed. Moreover, relying on advanced flight data recorder (FDR) or powerplant management system excludes a large number of general aviation (GA) aircraft which are usually not equipped or compatible with existing technologies for direct fuel consumption monitoring and recording. Therefore, the development of an inexpensive and effective strategy to estimate aircraft fuel consumption is necessary for all aviation operators.

As one of the critical elements in aircraft fuel consumption estimation, the fuel flow rate can be derived from the statistical relationship with other aircraft operational parameters. In 2012, Khadilkar and Balakrishnan modeled commercial aircraft fuel consumption while taxiing using flight data recorder information (Khadilkar and Balakrishnan, 2012). Baklacioglu et al. published studies on aircraft fuel flow rate modeling for phases of flight using different modeling strategies (Baklacioglu, 2015, 2016, 2021; Oruc and Baklacioglu, 2020). The fuel flow rate during the airborne phases of flight was modeled using flight data recorder data from turbofan aircraft (Chati and Balakrishnan, 2016). Considering the operational and performance difference of GA aircraft, Huang et al. modeled the fuel flow rate of reciprocating-engine GA aircraft using aircraft operational data (Huang et al., 2017). Instead of adopting the LTO cycle, Pagoni and Psaraki-Kalouptsidi proposed a flight path profile based method to calculate aircraft fuel consumption focusing on the Climb-Cruise-Descent (CCD) cycle (Pagoni and Psaraki-Kalouptsidi, 2017). Because the actual performance of a flight is usually affected by a variety of unforeseeable factors, such as weather, delay, and detour, flight trajectory simulation-based models were recently developed for more accurate fuel burn computation (Yanto and Liem, 2018; Seymour et al., 2020). Aforementioned studies developed mathematical foundations for fuel consumption estimation from different perspectives.

However, most published studies focused on modeling aircraft fuel consumption using FDR data without discussing the difficulties and cost of obtaining such data, therefore, how to practically and widely use those theoretical models remains unsolved. From a practical perspective, this paper presents a strategy of estimating aircraft fuel consumption by leveraging the advantages of existing avionics systems equipped by most aircraft and statistical modeling of historical aircraft fuel consumption data. FDR data with fuel consumption information were used for statistical modeling, and Automatic

Dependent Surveillance – Broadcast (ADS-B) data were used for the assessment of model performance.

Use of avionics in fuel consumption estimation

This section introduces a novel use of avionics systems for ground- based real-time fuel consumption estimation in the process of flight operations. The avionics systems investigated in this study include on- board FDR from Garmin G1000 system and ADS-B. The integrative use of these two avionics systems and selection of modeling variables are explained respectively.

Integrative use of avionics

Among different types of aviation data, flight operational data are widely used for a variety of purposes because of the increasing capacity and capability of flight data recording devices; flight safety improvement, aircraft system health monitoring, fuel management, and aircraft accident and incident investigation are typical examples of applications. The modern FDRs are able to capture over hundreds of flight parameters, such as parameters of aircraft attitude, position, and fuel consumption. However, retrieving the fuel consumption information directly from onboard FDR does not address many operational issues, such as the high cost for routine data collection, latency of information, and exclusion of many aged GA aircraft. The required equipage of ADS-B Out in air traffic surveillance provides a potential advantageous channel to obtain flight data over onboard FDR. ADS-B is a precise Global Positioning System (GPS) based surveillance system. ADS-B Out peri- odically broadcasts aircraft's location, speed, altitude and other data utilizing the GPS information. All aircraft operating in designated airspace in the United States are required to be ADS-B Out capable by the FAA, which provides a versatile data collection channel for both commercial and GA aircraft (14 C.F.R. § 91.225, 2011; 14 C.F.R. § 91.227, 2014). The unique feature that FDR and ADS-B share the same data sources of GPS and aircraft sensors for certain flight parameters makes it possible to derive fuel consumption information from ADS-B data adopting statistical models developed from FDR data.

In this study, a strategy of estimating aircraft fuel consumption using ADS-B data is proposed, as shown in Fig. 1. This strategy consists of two steps: 1) statistical models are developed between selected explanatory variables and aircraft fuel flow rate using historical flight operational data from onboard FDR; 2) the same explanatory variables obtained from ADS-B are used as inputs for the developed statistical models to output the estimation of fuel flow rate. The total fuel consumption can be estimated by multiplying fuel flow rate and duration. This novel use of avionics systems and statistical modeling methods provides an advantageous solution to estimate aircraft fuel consumption by:

1. Reducing the cost of flight operational data collection;
2. Providing ground-based operators with real-time fuel consumption information;
3. Serving most commercial and GA aircraft;
4. Extending the use of existing aviation technologies without requiring additional equipment.

In this study, the Garmin G1000 system was used as the onboard FDR to collect flight operational data for modeling. The G1000 system shares the same technical features with most onboard flight data recording devices as described above. The G1000 Attitude and Heading Reference System (AHRS) utilizes GPS information to determine aircraft parameters, such as aircraft position, attitude, heading, ground speed, and vertical speed (Garmin, 2011). The G1000 system used in this study records 64 aircraft parameters every 1 s on average, such as time- stamped 3-dimensional aircraft location, ground speed, vertical speed, fuel flow rate, and aircraft engine revolution per minute. ADS-B was used to provide real-time flight operational data containing explanatory variables for fuel consumption estimation. The standard message broadcasted by ADS-B Out contains fewer aircraft parameters, which primarily consists of aircraft identity, timestamped 3-dimensional aircraft location, ground speed, vertical speed, and other indicators of data quality measured by the GPS (ICAO, 2008). However, these two systems share the same data sources for flight operational parameters of 4-dimensional aircraft location, ground speed, and vertical speed.

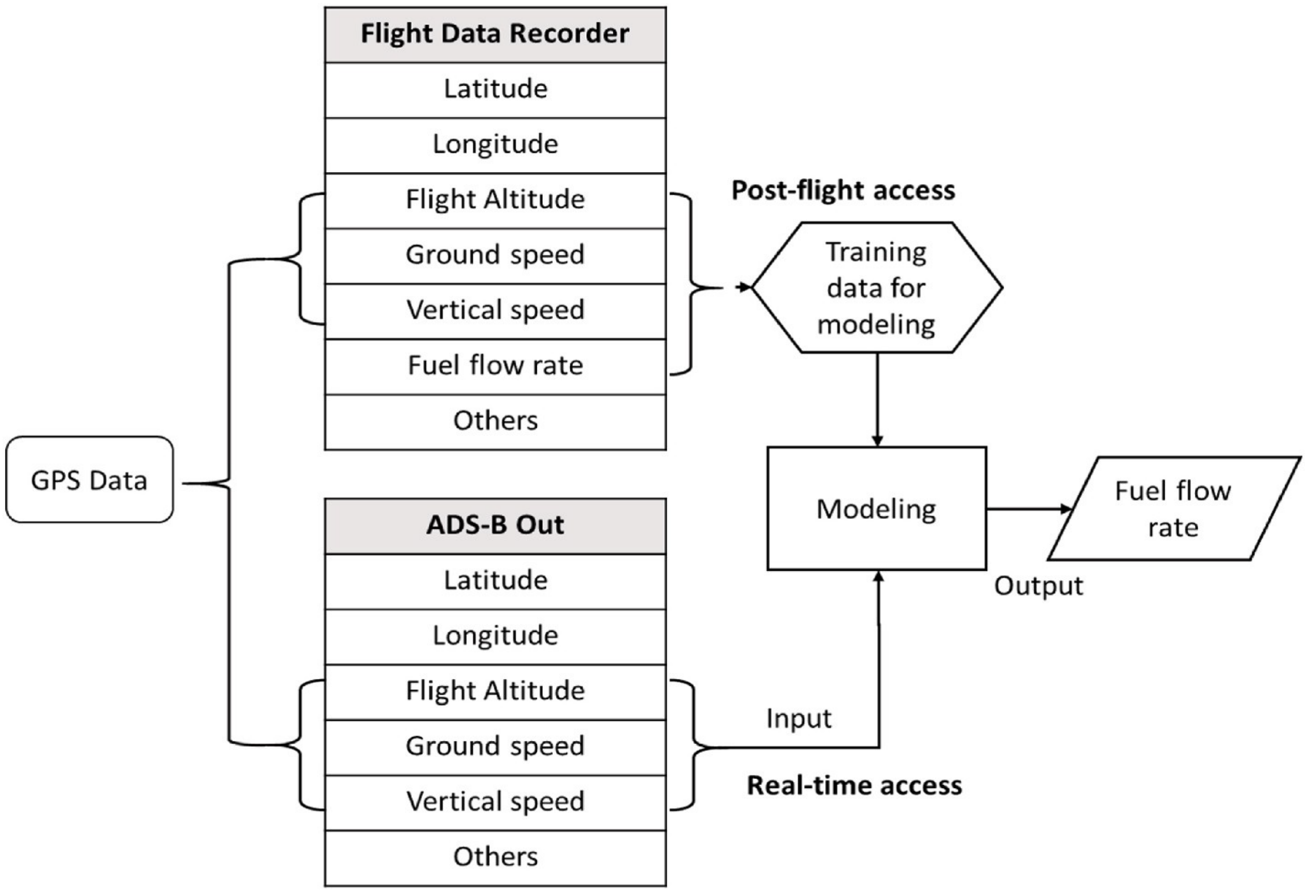


Fig. 1. Estimation of fuel consumption from ADS-B data.

Selection of variables

The number of aircraft operational parameters logged by onboard FDR varies by the models of aircraft and FDRs, and many operational parameters could be selected for the modeling of fuel consumption. However, various factors could affect aircraft fuel consumption; there- fore, no universal standard is published on the selection of explanatory variables for fuel consumption estimation. According to the findings of previous studies and principle of aircraft powerplant operations, the fuel consumption is primarily determined by the engine parameters, speed, the total mass of aircraft, the ambient atmospheric density, extra thrust for changing of flight altitude, wing reference area, etc., and many factors are likely to be correlated to each other (Collins, 1982). For example, the ambient atmospheric density could be related to the flight altitude, the extra thrust for changing of flight attitude could be deter- mined by the vertical speed and durations of descent or ascent, and the change of aircraft mass in the process of flight is related to fuel consumption. In addition, almost all FDRs log timestamped 3-dimensional aircraft location information, ground speed, vertical speed, which are also broadcasted by ADS-B Out, as shown in Fig. 1. In order to develop a transferrable model which could be used with ADS-B data, aircraft ground speed, flight altitude, and vertical speed are selected as explanatory variables to estimate the fuel flow rate for model development. Previous study conducted by the authors also demonstrated a good fit of those three selected variables in explaining the fuel flow rate of piston-engine aircraft operations (Huang et al., 2017).

Model preparation

This section describes the model preparation for fuel flow rate estimation using flight operational data collected from the onboard FDR. This study adopted the Classification and Regression Tree (CART) and Neural Network (NN) as modeling methods.

Data collection

In this study, flight operational data from the FDR of G1000 system and ADS-B Out were used in statistical modeling based on the following observations and assumptions:

1. GA piston-engine aircraft are more technologically limited compared to other advanced high-end aircraft and are often ignored by previous studies; the strategy presented in this study applies to most manned aircraft from all sectors of aviation;
2. GA aircraft operate more irregularly compared to scheduled commercial flights in terms of flight schedule and flight profile, thus the flight operational data contain more diverse patterns;
3. Commercial flight operational data logged by onboard recording

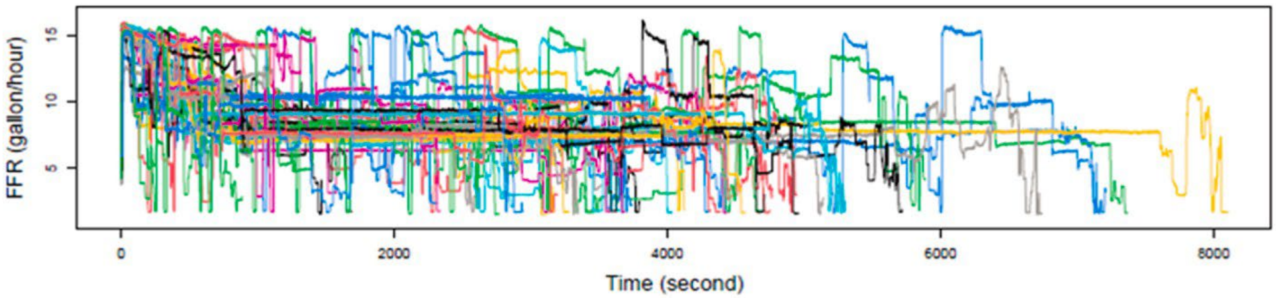
devices are usually considered as sensitive information for airlines and is, therefore, not disclosed to researchers publicly;

4. This method is expected to be transferrable to other types of aircraft given available flight operational data.

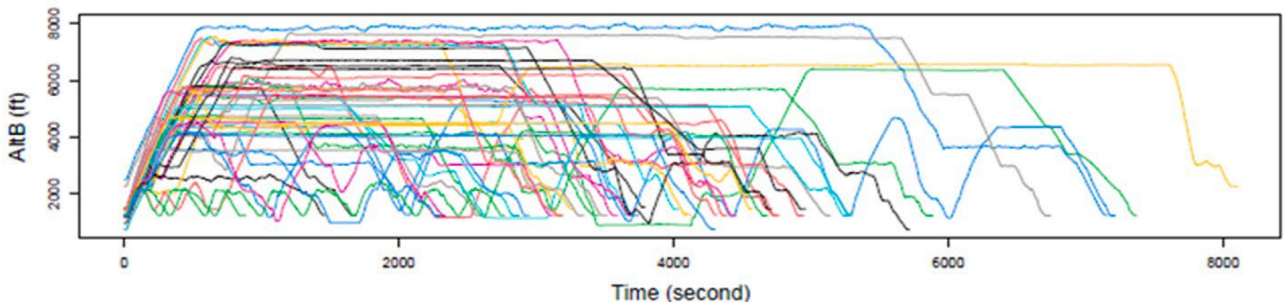
Flight operational data were collected from the Cessna Skyhawk 172 aircraft, which is equipped with Garmin G1000 system and ADS-B Out transponder. Because the aircraft was in mixed-use for flight training and other missions, the flight phase of taxi was excluded in this study to avoid the big variance of fuel consumption in ground operations. A total of 44 sets of G1000 data and 21 sets of ADS-B Out data was selected from 44 flights with 184,376 observations for each parameter in the dataset. Aircraft used for data collection is based at a GA airport in the Midwest of U.S.

Modeling methods

A variety of methods could be used to model aircraft fuel consumption (Khadilkar and Balakrishnan, 2012; Baklacioglu, 2015, 2016, 2021; Chati; Balakrishnan, 2016; Huang et al., 2017; Oruc and Baklacioglu, 2020). Because aircraft engine performance usually changes in different phases of flight and is more frequently adjusted by pilots in GA operations due to rapid and frequent change of speed and altitude, as shown in Fig. 2, generic regression methods are generally not ideal for modeling the fuel consumption in different phases of flight. In addition, the response variable of fuel flow rate is collectively affected by the three explanatory variables; and the simple linear correlation cannot describe the relationship between explanatory variables and response variable, as shown in Fig. 3. The observed outliers, which are likely caused by system errors, turbulence, or sensor misreading, also exclude the use of generic regression methods in this study.



(a)



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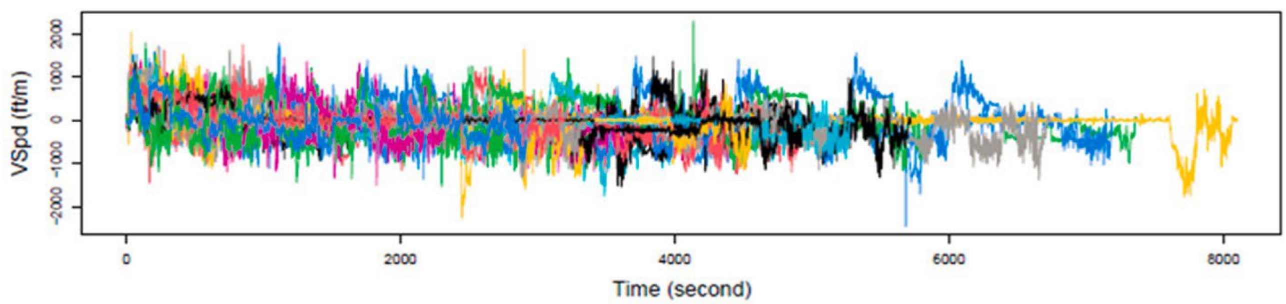

(c)

Fig. 2. (a) Plot of aircraft engine performance by fuel flow rate of 44 flights (gallon per hour), (b) Plot of flight altitude of 44 flights (feet above the mean sea level), (c) Plot of the vertical speed of 44 flights (feet per minute).

As a variation of decision tree algorithms, CART is commonly used in classification and regression problems, for the high adaptability to data type and quality, and the high self-interpretability to users without analytical background. The tree methods aim to divide the sample space into multiple sub-spaces, such that the impurity of the response variable in each sub-space can be minimized. CART adopts the recursive binary splitting algorithm that greedily searches all possible split points of all predictor variables and selects the best split point, which can maximize the difference of the prediction error for regression (e.g., mean squared error), or the difference of impurity for classification (e.g., cross-entropy), before and after the split (Breiman et al., 1984). The splitting procedure can be visualized by a tree graph. All the observations start at the root node, then they are split into two branches by the first splitting rule, searched by the algorithm. The child node can be split deeper into grandchild nodes, and so forth. Theoretically, a node cannot be split when the predictor variables of all the observations in the node are the same, and then the tree stops growing. A fully grown tree will lead to the overfitting problem, so the decision tree algorithm usually takes two ways to prevent overfitting, tree pruning or stopping criteria, both of which shrink the tree size. The tree pruning approach cuts the redundant branches by adding the tree size penalty to the loss function. The stopping criteria, such as the size of the child nodes, are commonly used by software to stop splitting at an early stage. To make prediction, a new observation is placed at the root node, then follows the splitting rules to enter a sequence of internal nodes, and finally reaches a terminal node (also called leaf node), which already contains a set of observations from the original data. The summary of the original observations in the terminal node, i.e., mean for regression and majority category for classification, will be used as the predicted value of the new observation.

Neural networks, also called artificial neural networks (ANNs), is a class of predictive learning methods that adopt the biological concept of neurons to build connections between the independent and dependent variables (Friedman et al., 2001; Goodfellow et al., 2016). The method can be used for both regression and classification problems. In a neural network, the explanatory variables are treated as nodes or neurons in the input layer, while the response variable as the node in the output layer. A sequence of hidden layers connects the input and output layers and each hidden layer can have a set of nodes. Each node in the hidden layer and output layer are linked by the edges from all nodes in the previous layer, so the node value can be determined by the weighted linear combination of the node values from the previous layer with a pre-determined activation function. The weights between nodes are commonly trained by the backpropagation method to minimize the loss function of fitted values (mean squared error for the data in this study). In this study, the resilient backpropagation (Riedmiller and Braun, 1993) was used for weight calculation. The activation function projects the node values to a different scale for better learning the complex nonlinear patterns from the data. The architecture and hyper-parameters of the neural networks are usually selected by cross validation or validation set approach. When a neural network model is specified, values from new observations will be processed through the network, from the input layer to hidden layers, and eventually to the output layer with predicted values. The neural networks can be visualized as a graphical model with nodes and directed edges labelled by weights, as shown in Fig. 5.

Considering different advantages of various mathematical models, the features of flight operational data, the convenience of practice in aircraft daily operations, and the results of exploratory analysis using different machine learning techniques, this study adopted the CART and NN approaches in modeling the fuel flow rate for total fuel consumption estimation for the following advantages:

1. Both CART and NN modeling approaches are adaptive for nonlinear relationship among variables;
2. Both CART and NN methods learn the complex relationship from multivariate data and generate nonparametric models for selected variables;
3. These two methods are robust to outliers;
4. The modeling outcomes are easy to interpret and use in daily flight operations.

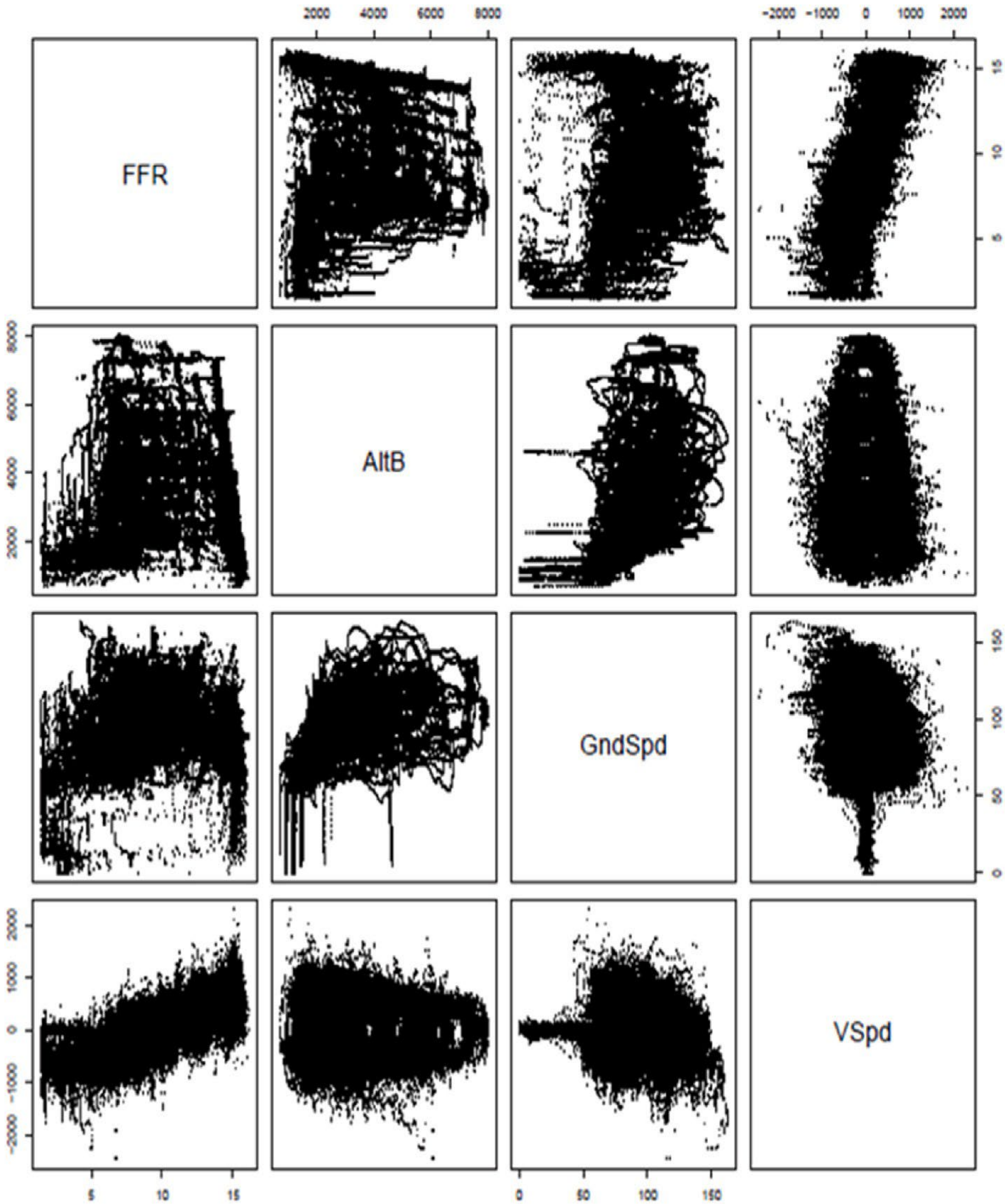

Fig. 3. Scatter plot matrix of the relationship between response variable and three explanatory variables.

Results of modeling

Two evaluation metrics, the mean absolute error (MAE), shown as Eq. (2), and the root mean square error (RMSE), shown as Eq. (3), were used for model comparison and selection. MAE measures the average magnitude of the errors in the set of predicted fuel flow rates, whilst RMSE measures the average square of the errors, which gives more penalty on bad predictions that are far from the actual values.

$$MAE = \frac{SEA}{N} = \frac{\sum_{i=1}^{N} |x_i - \hat{x}_i|}{N} \qquad (2)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{x}_i - x_i)^2} \qquad (3)$$

where x_i is the observed fuel flow rate in time series, x_i is the predicted fuel flow rate, N is the number of time points, and *SAE* is the sum of the absolute errors.

Model validation was conducted in two approaches: 50-50 split for training and test sets, and 5-fold cross validation. 50-50 split is a vali- dation set approach for estimating the model's performance on a new data sample from the same population. The k-fold cross-validation is commonly used for model selection and parameter tuning (Kohavi, 1995; Gareth et al., 2013). For the 50-50 split, 92,385 (50.1%) of the data observations from 22 flights were used as the training set, and 91, 991 (49.9%) of the data from the other 22 flights were used as the test set. For the 5-fold cross validation, the 44 flights were grouped into 5 folds, with 9, 9, 9, 9, and 8 flights respectively. The percentage of observations in each fold ranges from 18.9% to 21.1%.

Results of the CART modeling

The tuned regression tree received an MAE of 1.376 gallon/hour (RMSE of 1.875 gallon/hour) on the test set and 1.359 gallon/hour (RMSE of 1.881 gallon/hour) from the 5-fold cross validation. The final CART regression tree created on the entire data was shown in Fig. 4. The regression tree describes the predicted value of fuel flow rate collectively determined by the conditions of three explanatory variables. The performance of CART in fuel consumption estimation will be described in the section of Assessment of Fuel Consumption

Estimation.

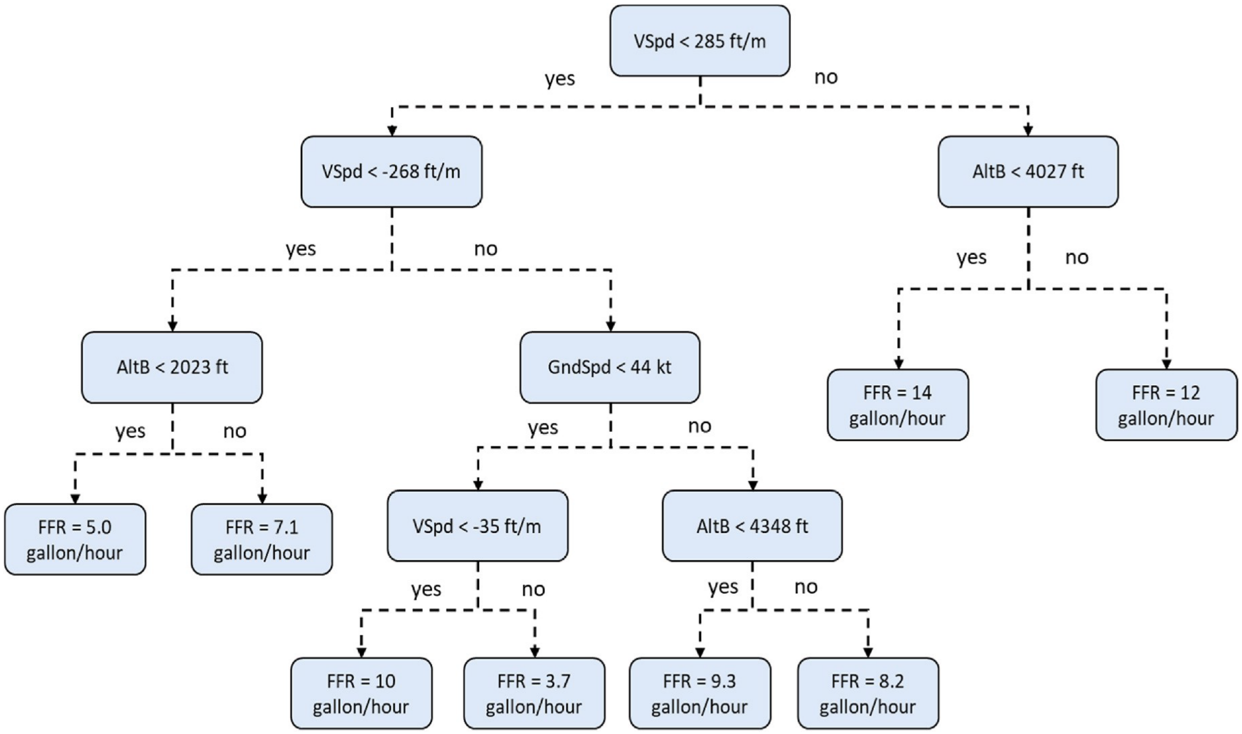

Fig. 4. The CART regression tree for fuel flow rate prediction of Cessna Skyhawk-172 aircraft. *VSpd*: aircraft vertical speed by feet per minute; *AltB*: aircraft barometric altitude by foot; *GndSpd*: aircraft ground speed; *FFR*: aircraft fuel flow rate.

Results of the neural networks modeling

In addition to CART, the NN algorithm appears to be another better method among all tested candidate methods. The selected NN model has two hidden layers with 3 and 2 nodes respectively. It obtains the lowest MAE of 1.329 gallon/hour (RMSE of 1.792 gallon/hour) on the test set and 1.210 gallon/hour (RMSE of 1.651 gallon/hour) by the cross vali- dation. The final NN model using the entire dataset for fuel flow rate prediction can be visualized as shown in Fig. 5.

The diagram in Fig. 5 consists of circles and segments with arrows. Each circle represents a node. The three nodes in the left column indicate the input layer with values from the three explanatory variables: *AltB*, *GndSpd*, and *VSpd*. The three nodes on the second column are the variables generated from the first hidden layer. The two nodes on the third column are the second hidden layer. The node at the right side is the output layer for fuel flow rate (*FFR*). The blue circles on the top represent the intercepts in each linear combination. Numbers on the arrows are the weights of the nodes. For instance, the top node in the first hidden layer, is given by

$$f(-31.3732 - 1.34462\ AltB - 24.82655\ GndSpd - 79.972774\ VSpd)$$

where f is the activation function (logistic function in this model), and *AltB*, *GndSpd*, *VSpd* are the feature values after the min-max scaling. The output *FFR* value is also on the 0–1 scale, hence it will be transformed back to the regular scale.

Assessment of fuel consumption estimation

Theoretically, the ADS-B Out equipped aircraft transmits its position and velocity at least once per second while airborne or while moving on the airport surface, and transmits its position at least once every 5 s while stationary on the airport surface (14 C.F.R. § 91.227, 2014, p. 743). However, the reception rate of ADS-B data by ADS-B In capable devices is determined by many factors, such as the performance of ADS- B equipment and blockage of signal. Dropout, missing payload, data jump, and other anomalies were detected from ADS-B messages (Tabassum and Semke, 2018). As a result, the update rate of ADS-B data is usually lower than FDR data. Similar issues were observed in this study as well, for instance, for each flight parameter obtained from the same flight, the received ADS-B data contain less observations compared to the FDR data recorded by the onboard G1000. Fig. 6 presents an example of flight profile comparison by barometric altitude for the same flight. The red markers represent the ADS-B data observations, and the smooth black line is the recreation of flight profile using G1000 recorded flight data. Lower update rate of ADS-B data can be observed from the recreation of flight profile comparison.

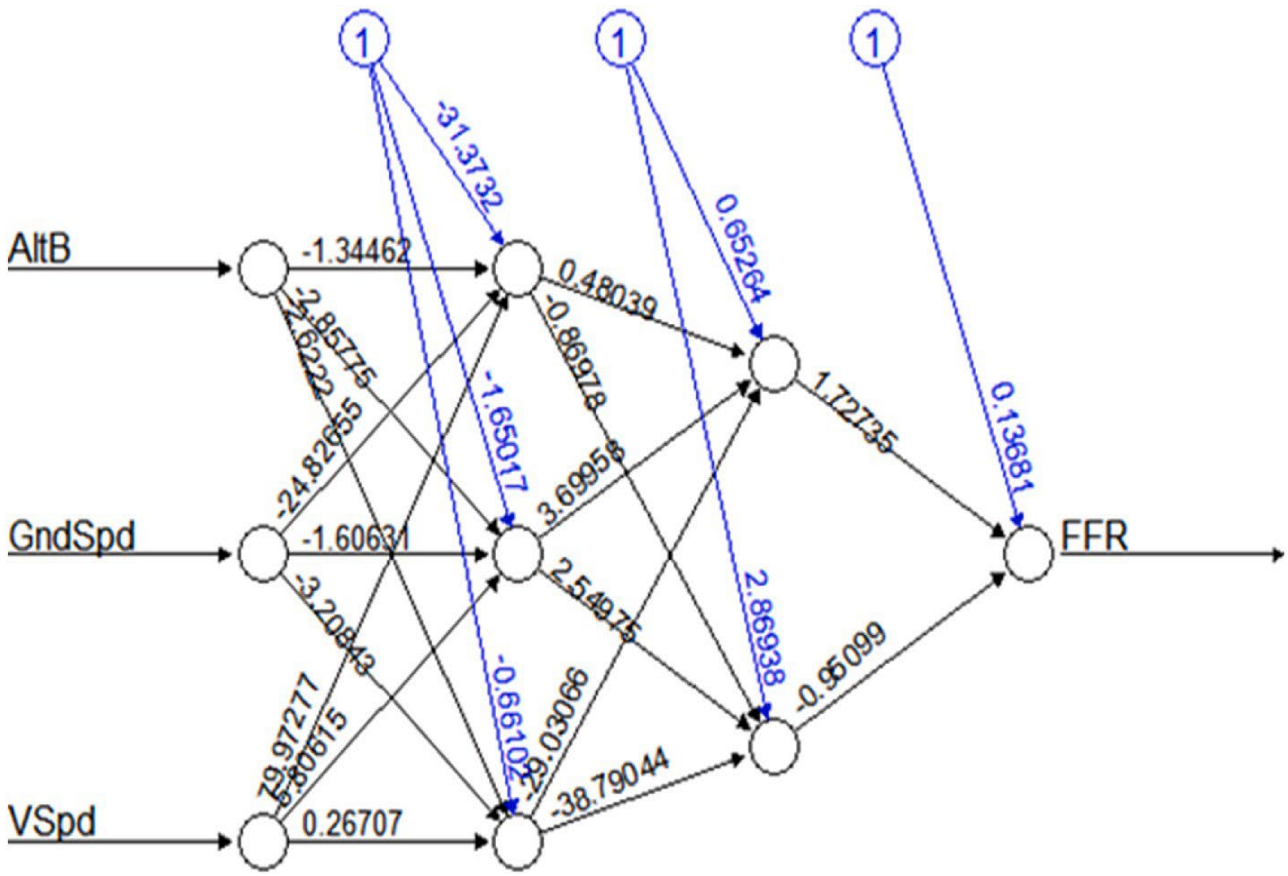

Fig. 5. Neural network model for fuel flow rate prediction.

As introduced in the second section, this study introduces a fuel consumption estimation strategy by developing and applying transfer- able statistical models from FDR data to ADS-B data. This section presents the performance assessment of the developed models using ADS-B data as inputs. The estimated fuel consumptions were compared with the actual fuel consumptions recorded by the G1000 onboard fuel management system. Because the quality of ADS-B data was affected by many factors, in total, 21 flights with better ADS-B data quality were selected for the assessment. However, to eliminate the impact of poor ADS-B data quality, the ADS-B data used for assessment were trimmed and only include the segments of flight when the ADS-B data were stably recorded with intervals of no more than 30 s between adjacent data points. The total fuel consumption was estimated by multiplying the instantaneous fuel flow rate and the duration. The impact of potential aircraft performance change within the interval of data observations was simplified in this study by linearly connecting adjacent data observations.

The assessment followed the procedure shown in Fig. 7. For each flight, the three explanatory variables from ADS-B data were used as inputs for models to predict the instantaneous fuel flow rate, which was used to estimate the total fuel consumption. For the same flight, the actual fuel consumption was acquired from the onboard G1000 system. Since the duration varies from flight to flight, the mean absolute per- centage error (MAPE) was used to measure the accuracy of total fuel consumption estimation for each flight, as shown as Eq. (4).

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{x_i - \hat{x}_i}{x_i}\right| \qquad (4)$$

where $\hat{x}_i$ is the predicted value time series, x_i is the observed time series, and N is the number of observations.

In GA operations, flight profiles show different characteristics be- tween cross-country flights and local traffic pattern practice. Four examples of predicted instantaneous fuel flow rate were presented in Fig. 8 for cross-country flights and local traffic pattern practice. In general, the predictions of the CART model better reflect the changes and values of actual fuel flow rates than the NN model, regardless of the type of flight operation. The logic of the CART model appears to be more robust to the errors in ADS-B data, although the NN model shows lower MAE when using FDR data with less data input errors. Because of a variety of un- avoidable system errors occurred in ADS-B data transmission between the aircraft and ground receiving station, the ADS-B data do not perfectly match the FDR data by timestamp even though they share the same GPS data source for selected aircraft parameters. From this perspective, the vertical speed (*VSpd*) is the primary variable among the three selected explanatory variables showing significant difference be- tween FDR data and ADS-B data. For the same flight at the same time- stamp, the values of *VSpd* observed from ADS-B are systematically lower than the corresponding values of *VSpd* from the G1000 system by an average of 64%. The average percentage differences between G1000 and ADS-B data for the barometric altitude (*AltB*) and ground speed (*GndSpd*) are 6% and 0% respectively. This observation suggests that further studies should be focused on addressing the impact of ADS-B data errors on vertical speed. In addition, the CART model appears to better perform with the cross-country flight data than the local traffic pattern practice data. Many reasons could result in this different performance of the CART model. For instance, the low flight altitude and rapid change of aircraft status in local traffic pattern practice require a higher update rate of ADS-B data to record the changes of aircraft status, therefore, the CART model would output more continuous values of predicted fuel flow rates.

Table 1 presents the assessment results of 21 flights, the MAPE shows that the CART model performs better with smaller average MAPE of 6.3% compared to the NN model with bigger average MAPE of 14.14%. From the perspective of the average estimated fuel consumption error by gallon, the average estimation error of 0.007 gallon seems to be an acceptable estimation accuracy for these 21 flights, but the big variance in estimation has to be further investigated before this strategy can be used by industry. To further compare the performance between two models considering the impact of variances, descriptive analyses and *t*- tests of the means of estimated fuel consumption errors and absolute percentage errors generated the result as shown in Table 2 and Table 3. The results of descriptive analyses and *t*-tests also indicate that the CART estimation performs better than the NN model by total gallons of consumption for 21 flights, however, by percentage, the CART model shows an average of 6.3% of estimation error while the NN model has 14.1% of estimation error. The estimation errors by percentage of both models are likely too high for industry applications. Potential reasons could be the data used in this study are from GA aircraft which are used for a variety of purposes, the irregular flight pattern from flight training requires a higher update rate of ADS-B data to record the changes of aircraft performance; linear interpolation of ADS-B missing values could also increase the error of final estimation. Consequently, the quality of ADS-B data used in this study is very likely an influencing factor for the accuracy of fuel consumption estimation.

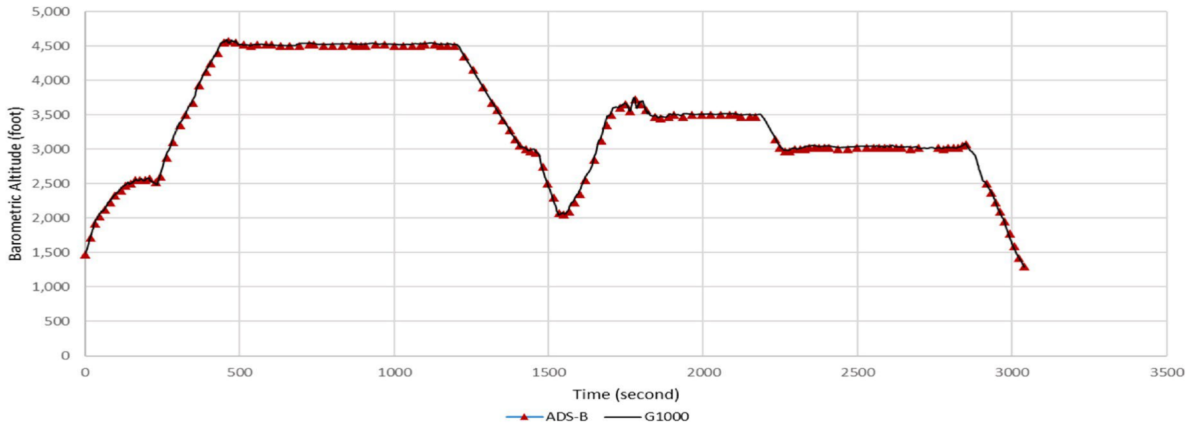

Fig. 6. Recreation of flight profile by barometric altitude.

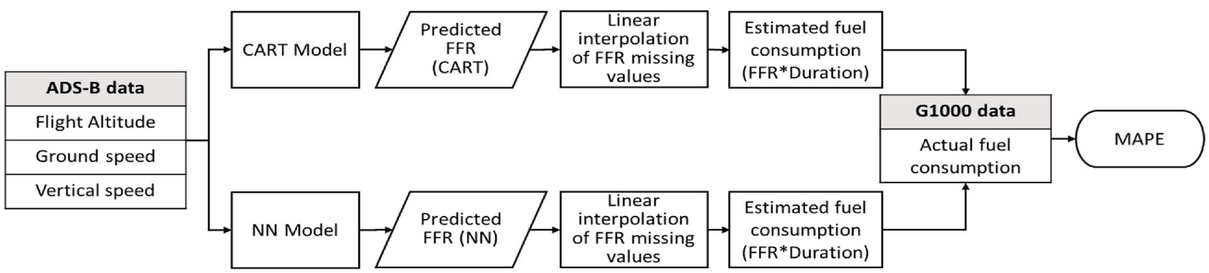

Fig. 7. Accuracy assessment of fuel consumption estimation.

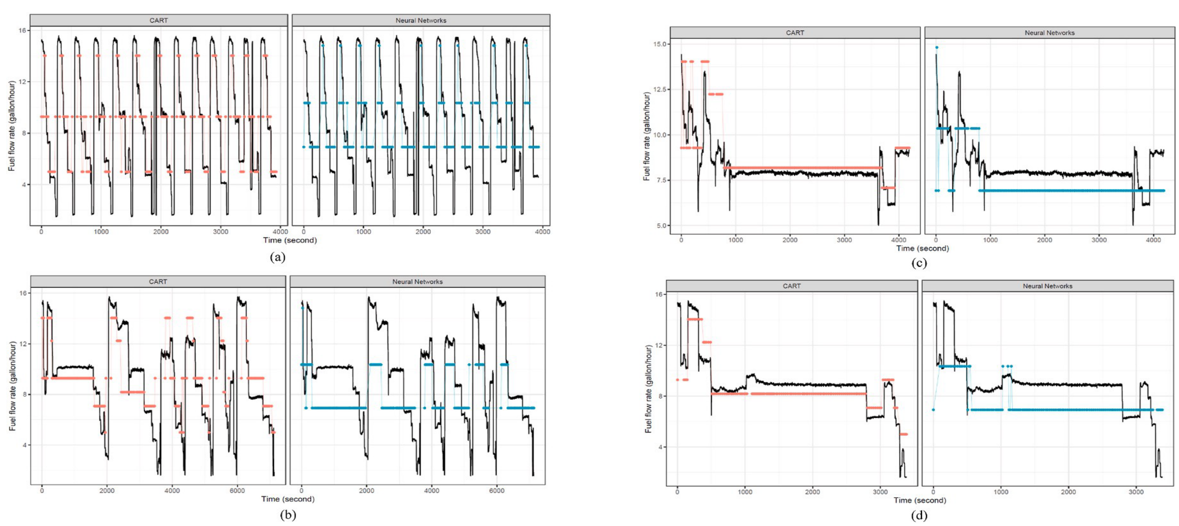

Fig. 8. The examples of predicted fuel flow rate using ADS-B data. Note, (a) (b) two flights of local traffic pattern practice, (c) (d) two flights of cross-country operations, red and blue dots represent predicted fuel flow rate using ADS-B data, black line represents actual fuel flow rate logged by flight data recorder. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Conclusions

This study explores a novel strategy to estimate aircraft fuel consumption by leveraging the advantages of modern avionics systems and statistical modeling techniques. This strategy was developed based on the shared technical features that onboard flight data recording devices and ADS-B have the same data sources for certain aircraft operational parameters. The near real-time data transmission of ADS-B Out makes the data acquisition less expensive, more convenient, and with less latency for most aircraft. Machine learning techniques more accurately develop the statistical relationship between multiple explanatory variables and the response variable. In addition, the mandatory requirement of ADS-B Out in the U.S. and the growing number of aircraft becoming ADS-B Out capable worldwide facilitate the adoption of this presented strategy by different sectors of aircraft operations.

The CART and NN approaches were adopted for statistical modeling in this study using the data logged by FDR. The NN model shows better performance than the CART model on predicting the fuel flow rate using MAE and RMSE as comparison metrics. However, in the assessment of total fuel consumption estimation using ADS-B data as inputs. It is interesting to observe that the CART model performs better than the NN model. Both the CART model and the NN model generated better results for cross-country flight operations compared to local traffic pattern operations. The assessment results of fuel consumption estimation are believed to be reasonable from the standpoint of flight operations. Possible reasons for the difference of model performance in the assessment could be: (1) a variety of system errors existing in ADS-B data result in variance and lower update rate of ADS-B data; (2) NN model might be more sensitive to the noise and poor quality of ADS-B data; (3) the samples size used in modeling and assessment is very limited.

Table 1

Assessment result of total aircraft fuel consumption estimation.

Flight	Actual fuel consumption (gallon)	Estimated fuel consumption error			
		CART* (gallon	MAPE (%)	NN* (gallon)	MAPE (%)
1	9.3738	1.5580	16.62	2.9478	31.45
2	7.8617	0.0321	0.41	1.1904	15.14
3	8.4054	0.3057	3.64	1.3302	15.83
4	8.1074	-0.6194	7.64	0.5567	6.87
5	6.2849	-0.0399	0.63	1.0166	16.18
6	18.5022	-0.0280	0.15	2.9942	16.18
7	6.7209	-0.8908	13.25	0.6833	10.17
8	10.7829	-0.3686	3.42	1.2229	11.34
9	9.6095	-0.6849	7.13	0.9140	9.51
10	7.6182	-0.4255	5.59	0.6989	9.17
11	6.9023	0.2215	3.21	0.6347	9.20
12	9.6243	-0.2147	2.23	0.4159	04.32
13	12.2352	1.2189	9.96	3.5997	29.42
14	13.0666	1.1542	8.83	2.8918	22.13
15	6.5991	0.6754	10.23	1.5566	23.59
16	9.5934	-1.2753	13.29	1.2227	12.75
17	11.1274	0.4654	04.18	1.6374	14.72
18	11.7095	0.3602	3.08	2.2630	19.33
19	1.8466	-0.0685	3.71	-0.0214	1.16
20	7.3496	-0.0927	1.26	1.0784	14.67
21	10.3707	-1.4350	13.84	0.4055	3.91
Average		-0.007	6.30	1.392	14.14

*A positive number indicates that the predicted fuel consumption is more than actual consumption; a negative number presents that the predicted fuel consumption is less than actual consumption.

In general, the fuel estimation strategy explored in this study appears to be promising with a few important advantages over the existing methods, including cost-effectiveness, convenience, and less latency for most aircraft. The poor quality of ADS-B data due to low update rate and errors of aircraft vertical speed is likely a major factor affecting the accuracy of fuel estimation using ADS-B data. Focuses of further studies could be the evaluation and validation of this presented method using improved ADS-B data with larger sample size and improvement of model accuracy. However, with the continuous improvement of ADS-B data receiving equipment, the proposed approach is expected to yield more accurate estimation of aircraft fuel consumption. Given the advantages as aforementioned, this fuel estimation approach could potentially benefit a variety of air transport operational and managerial practice, for example, accurate estimation of jet fuel consumption ensures more reliable assessment and practical policy making of aircraft exhaust emission reduction (Owen et al., 2010), the proposed approach is capable of fuel consumption estimation by the phase of flight and thus helps more reliable economic flight trajectory planning (Murrieta-- Mendoza et al., 2015), in addition, accurate and dynamic prediction of aircraft fuel consumption by the presented method provides critical information that facilitates better decision making for optimal fuel management, procurement, and hedging programs in air transport operations (Brueckner and Abreu, 2017; Merkert and Swidan, 2019).

Table 2

Descriptive analysis and t-test of estimated fuel consumption error by gallon.

	Mean (μ)	**Standard Deviation**	**Standard Error**	**P-value for t-test (H_0 : μ = 0)**
CART	-0.007	0.771	0.17	0.966
NN	1.392	0.993	0.22	0.000*

*significant at α = 0.05.

Table 3

Descriptive analysis and t-test of estimated fuel consumption error by percentage.

	Mean (μ)	**Standard Deviation**	**Standard Error**	**P-value for t-test (H_0 : μ = 0)**
CART	0.0630	0.0496	0.011	0.000*
NN	0.1414	0.0789	0.017	0.000*

*significant at α = 0.05.

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References

Automatic Dependent Surveillance-Broadcast (ADS-B) Out Equipment and Use, 14 C.F.R. §, 91, 225,2011.

Automatic Dependent Surveillance-Broadcast (ADS-B) Out Equipment Performance Requirements, 14 C.F.R. §, 91, 227, 2014.

Brueckner, J.K., Abreu, C., 2017. Airline fuel usage and carbon emissions: determining factors. J. Air Transport. 62, 10–17. https://doi.org/10.1016/j. jairtraman.2017.01.004.

Baklacioglu, T., 2015. Fuel flow rate modelling of transport aircraft for the climb flight using genetic algorithms. Aeronaut. J. 119 (1212), 173–183.

Baklacioglu, T., 2016. Modeling the fuel flow rate of transport aircraft during flight phases using genetic algorithm-optimized neural networks. Aero. Sci. Technol. 49, 52–62.

Baklacioglu, T., 2021. Predicting the fuel flow rate of commercial aircraft via multilayer perceptron, radial basis function and ANFIS artificial neural networks. Aeronaut. J. 125 (1285), 453–471.

Breiman, L., Friedman, J., Stone, C.J., Olshen, R.A., 1984. Classification and Regression Trees. CRC Press.

Chati S., Y., Balakrishnan, H., 2016. Aircraft Engine Performance Study Using Flight Data Recorder Archives. 30th Congress of the International Council of the Aeronautical Science. http://www.icas.org/ICAS_ARCHIVE/ICAS2016/data/papers/2016_0619_paper.pdf.

Collin, B.P., 1982. Estimation of aircraft fuel consumption. J. Aircraft 19 (11), 969–975.

EUROCONTROL, n.d.. Environment: noise and local air quality modelling tools. Online. https://www.eurocontrol.int/environment. (Accessed 10 December 2020).

European Union, 2009. Directive 2008/101/EC of the European parliament and of the council. Official Journal of the European Union. Online. https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2009:008:0003:0021:EN:PDF. (Accessed 10 December 2020).

Federal Aviation Administration, 2020a. Environmental policy. Online. https://www.faa.gov/regulations_policies/policy_guidance/envir_policy/ (Accessed 10 December 2020).

Federal Aviation Administration, 2020b. Aviation environmental design tool version 3c. Online. https://aedt.faa.gov/3c_information.aspx. (Accessed 10 December 2020).

Friedman, J., Hastie, T., Tibshirani, R., 2001. The Elements of Statistical Learning. Springer series in statistics, New York.

Garmin, 2011. Garmin G1000 pilot's guide for Cessna Nav III. Online. https://static. garmincdn.com/pumac/190-00498-07_0A_Web.pdf. (Accessed 10 December 2020).

Gareth, J., Daniela, W., Trevor, H., Robert, T., 2013. An Introduction to Statistical Learning: with Applications in R. Spinger.

Goodfellow, I., Bengio, Y., Courville, A., 2016. Deep Learning. MIT Press, Cambridge, MA.

Huang, C., Xu, Y., Johnson, M.E., 2017. Statistical modeling of the fuel flow rate of GA piston engine aircraft using flight operational data. Transport. Res. Transport Environ. 53, 50–62. https://doi.org/10.1016/j.trd.2017.03.023.pdf. (Accessed 10 December 2020).

International Civil Aviation Organization, 2019b. 2019 Environmental report: aviation and environment. Online. https://www.icao.int/environmental-

protection/Documents/EnvironmentalReports/2019/ENVReport2019_pg111-115.pdf. (Accessed 10 December 2020).
International Civil Aviation Organization, 2017. Environmental Protection – Aircraft Engine Emissions (Annex 16, Volume II, fourth ed. (Montreal, Canada: Author).
International Civil Aviation Organization, 2016. ICAO fuel savings estimation tool (IFSET Version 2.1). Online. https://www.icao.int/environmental-protection/Download%20IFSET%20Application/IFSET%20User%20Guide%20v2.1.pdf. (Accessed 10 December 2020).
International Civil Aviation Organization, 2008. Technical Provisions for Mode S Services and Extended Squitter (Doc 9871) (Montreal, Canada: Author).
International Civil Aviation Organization, n.d.. Committee on aviation environmental protection. Online. https://www.icao.int/environmental-protection/pages/caep. aspx. (Accessed 10 December 2020).
International Air Transport Association, 2020. Working towards ambitious targets. Online. https://www.iata.org/en/programs/environment/climate-change/. (Accessed 10 December 2020).
International Air Transport Association, n.d.. Our actions for the environment. Online. https://www.iata.org/en/programs/environment/. (Accessed 10 December 2020).
Khadilkar, H., Balakrishnan, H., 2012. Estimation of aircraft taxi fuel burn using flight data recorder archives. Transport. Res. Transport Environ. 17 (7), 532–537. https:// doi.org/10.1016/j.trd.2012.06.005.
Kohavi, R., 1995. A study of cross-validation and bootstrap for accuracy estimation and model selection. In Ijcai 14 (2), 1137–1145.

Lufthansa Group, 2020. Four pillars for climate protection. Online. https://www.luftha nsagroup.com/en/responsibility/climate-environment/fuel-consumption-and-emissi ons/four-pillars-for-climate-protection.html. (Accessed 10 December 2020).

Merkert, R., Swidan, H.M., 2019. Flying with(out) a safety net: financial hedging in the airline industry. Transport Res E-Log 127, 206–219. https://doi.org/10.1016/j. tre.2019.05.012.

Murrieta-Mendoza, A., Botez, R.M., Patro´n, R.S.F., 2015. Flight Altitude Optimization Using Genetic Algorithms Considering Climb and Descent Costs in Cruise with Flight Plan Information (No. 2015-01-2542). SAE Technical Paper. https://doi.org/ 10.4271/2015-01-2542.

Oruc, R., Baklacioglu, T., 2020. Modeling of fuel flow rate of commercial aircraft for the climbing flight using cuckoo search algorithm. Aircraft Eng. Aero. Technol. 92 (3), 453–471.

Owen, B., Lee, D.S., Lim, L., 2010. Flying into the future: aviation emissions scenarios to 2050. Environ. Sci. Technol. 44 (7), 2255–2260. https://doi.org/10.1021/ es902530z.

Pagoni, I., Psaraki-Kalouptsidi, V., 2017. Calculation of aircraft fuel consumption and CO2 emissions based on path profile estimation by clustering and registration. Transport. Res. Transport Environ. 54, 172–190. https://doi.org/10.1016/j. trd.2017.05.006.

Riedmiller, M., Braun, H., 1993. A direct adaptive method for faster backpropagation learning: the RPROP algorithm. In: IEEE International Conference on Neural Networks, San Francisco, 1993, pp. 586–591.

Seymour, K., Held, M., Georges, G., Boulouchos, K., 2020. Fuel estimation in air transportation: modeling global fuel consumption for commercial aviation. Transport. Res. Transport Environ. 88 https://doi.org/10.1016/j.trd.2020.102528.

Tabassum, A., Semke, W., 2018. UAT ADS-B data anomalies and the effect of flight parameters on dropout occurrences. Data 3 (2).

U.S. Environmental Protection Agency, 2020. Regulations for greenhouse gas emissions from aircraft. Online. https://www.epa.gov/regulations-emissions-vehicles-and-engines/regulations-greenhouse-gas-emissions-aircraft#regulations. (Accessed 10 December 2020).

Yanto, J., Liem, R.P., 2018. Aircraft fuel burn performance study: a data-enhanced modeling approach. Transport. Res. Transport Environ. 65, 574–595. https://doi.org/10.1016/j.trd.2018.09.014.