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TOWARDS AN ONLINE PREDICTIVE MODEL OF AIRCRAFT ENERGY STATE USING SUPERVISED MACHINE LEARNING

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Abstract

In recent years, due to the increased availability of data and improvements in computing power, the application of machine learning techniques to aviation safety problems has gained momentum. Data-driven techniques are used for identifying, isolating, and reducing risk in aviation operations through proactive and predictive approaches. Data collected from on-board recorders in commercial aircraft may contain thousands of parameters recorded in the form of multivariate time-series (continuous, discrete, categorical, etc.), which are used by machine learning models for safety analysis purposes. While these retrospective insights are valuable, they offer limited utility for real-time risk identification. The performance and trajectory of an aircraft during its approach phase is a strong indicator of its landing performance which, in turn, is typically indicative of incident or accident probability such as runway excursions or hard landings. Energy state awareness and energy management are critical concepts in the characterization, detection, and prevention of safety-critical conditions, particularly in the approach and landing phases. Hence, the management of an aircraft's energy state is considered critical to ensure a safe landing. In this work, a methodology for building a novel prediction model of aircraft's future energy state is developed using flight data from the approach phase. The method builds on the collection of aircraft sensor data between different altitude thresholds and the development of machine learning models for predicting the kinetic and potential energy at future altitude gates. This information can provide a direct insight into the landing performance of the aircraft given its current state and flight history, and enable to proactive prevention of unsafe situations. The proposed methodology is demonstrated using publicly available flight data from NASA (National Aeronautics and Space Administration) that contains thousands of flight records from commercial airline operations. The results indicate that the deep learning model is able to predict the potential and kinetic energy of future aircraft trajectory within 5–10% relative error and is thus a tool that can be used in an early-warning system for alerting the flight crew of abnormal energy situations developing in the future.

Keywords: Safety, Energy State, Machine Learning, Predictive Modeling, Risk

1. Introduction

Over the last two decades, there has been a steady increase in the volume and frequency of air traffic worldwide. Despite the COVID-19 pandemic, air traffic is expected to continue to grow over the next few decades. The safety record of aviation has also improved due to advancements in technology, focused efforts of government, manufacturers, and operators through various programs, and increased awareness [1]. The aviation industry has been shifting from a *reactive* to a *proactive* and *predictive* approach where potential unsafe events and precursors are identified beforehand and mitigation strategies are implemented to prevent loss of life. Modern commercial aircraft are equipped with sensors that record thousands of parameters at a high frequency throughout the duration of the flight. This recording capability coupled with the high volume of operations results in an explosion of data available to airliners and operators for safety analysis purposes.

Traditional techniques of safety analysis have focused on a continuous cycle of data collection from on-board recorders, retrospective analysis of flight-data records, identification of operational safety exceedances, design and implementation of corrective measures, and monitoring to assess their effectiveness. While qualitative techniques for safety enhancement are of value when limited information is available, they can fall short of providing a tangible course of action in a real-time setting. Data-driven machine learning techniques seek to bridge this gap by providing additional insights that are not easily attainable from qualitative techniques. Despite numerous applications of machine learning in aviation safety in unsupervised and semi-supervised contexts [2, 3, 4, 5, 6], applications in a supervised learning context remain scarce due to a lack of straightforward labels [7, 8]. However, rapid advances have been made in supervised learning (particularly deep learning) in domains other than aviation [9]. Therefore, it is of interest to explore the possibility of leveraging the strengths of supervised learning models in the analysis of flight data to provide meaningful insights into safety and risk.

Assessing the probability of encountering risky situations is valuable for any online condition monitoring system. It is of particular importance and relevance to flight crews during the approach phase of flight as shown by the high number of accidents and incidents that have historically occurred in this phase. During the approach phase, the pilots' workload is typically high and they have to be aware of several factors including Air Traffic Control (ATC) constraints, weather conditions, aircraft state, etc. One of the tenets of a safe approach and landing is a 'stabilized approach', defined by the FAA (Federal Aviation Administration) as: "[...] characterized by a constant-angle, constant-rate of descent approach profile ending near the touchdown point, where the landing maneuver begins" [10]. Stabilized approach is an active area of research and there have been recent efforts by the FAA to revisit some of the definitions of the stabilized approach thresholds [11]. Nevertheless, a stabilized approach is viewed as one of the key features of safe approaches and landings in air carrier operations. As seen from its definition, proper energy management is one of the main cornerstones of a stabilized approach.

Energy state awareness and energy management are critical concepts in the characterization, detection, and prevention of safety-critical conditions [12]. Previous studies have shown that improper or poor energy management and loss of energy state awareness (LESA) are among the top contributors to Loss of Control (LOC) and Controlled Flight into Terrain (CFIT) accidents [13]. Therefore, in this work, a methodology for building a model to predict the aircraft energy state at a future instant (such as the touchdown point) is developed using flight data from the approach phase. This information can provide direct insight into the landing performance of the aircraft given the current state and history of the flight, and provide some insight into the risk of continuing on the approach trajectory.

As such, the main objective and contributions of the proposed research are as follows:

1. Provide a novel predictive model of aircraft future energy state and landing performance using data collected on-board an aircraft during the approach phase
2. Provide one of the first implementations of a supervised learning risk identification methodology for large-scale flight data problems using sequence-to-sequence models

2. Background and Literature Review

Improving energy state awareness is of critical concern for flight safety. The International Air Transport Association (IATA) identified poor energy management as contributing factors to the most frequent and severe accidents between the years 2016 and 2020 [14]. According to this report, poor energy management combined with unstable approach and other human factors may lead to undesired aircraft states. As a method of resolving poor energy management, tools are developed to help pilots evaluate the excess energy that the aircraft need to bleed off. The excess energy is frequently measured based on required landing distance as it can lead to runway overruns or similar incidents. An example of such tool is the Runway Overrun Awareness and Alerting System also known as ROAAS [15]. Tools like ROAAS combine pilots feedback on the runway condition with effectiveness of braking devices to estimate the minimum and maximum required landing distances [27, 28]. Efforts are also made by airport operators to install indicators that can help pilots identify their relative position to the ideal path [29].

The emphasis on energy management is because the amount of energy that an aircraft can drain during ground roll is limited. As such, the aircraft total energy needs to be reduced or managed prior to touchdown for a safe and efficient landing. The FAA has released an advisory circular regarding the effectiveness of various braking devices and the amount of energy they can drain from touchdown [16]. The amount of energy that the aircraft braking devices need to drain is significantly impacted by the final approach, flare, and external conditions. A pilot may end up performing a long landing on purpose to ensure that sufficient energy is bled off before touchdown. In the case of a contaminated runway, the pilot may perform a hard landing at touchdown to ensure full contact between the landing gear and the runway so the braking performance is maximized. To assist pilots' decision making during the approach phase, the following recommendations were made by various aviation organizations [17].

1. Wings level at 500 ft or 300 ft above touchdown for visual and circling approaches.
2. Aircraft speed within $V_{app}+20$ kts .
3. Sink rate below 1000 ft/min.
4. Stable by 1000 ft (Instrument Meteorological Conditions) or 500 ft (Visual Meteorological Conditons).

Where V_{app} is the approach velocity.
These recommendations make use of “decision gates" (for e.g. 1000 ft, 500 ft, 300 ft, etc.). Decision gates are various altitude points above touchdown where a list of flight conditions need to be met in order for the aircraft to be stable or on track for a safe landing. A study by Campbell et al. [11] evaluated the lowest altitude gate at which pilots are capable of making corrections for deviations in approach from the ideal path. The study showed that below the 300 ft decision gate, it is difficult for the pilots to make corrections in the approach path. Aircraft altitude and speed are two of the many factors considered in this study. These metrics are related to energy management through potential and kinetic energy. The specific variant of these energy metrics are identified by Puranik et al. [12] to obtain the specific total energy. The equations for specific total (TE), potential (PE) and kinetic (KE) energy are shown below.

$$TE = PE + KE \tag{1a}$$
$$PE = h - href \tag{1b}$$
$$KE = \frac{V^2}{2g} \tag{1c}$$

Where h is the altitude, h_{ref} is the runway altitude, V is the true airspeed, and g is the gravitational acceleration. The significance of energy management for evaluating aircraft safety during the approach and landing phases emphasizes the need for a model to predict aircraft energy states. A survey by Trujillo [18] found that predictive tools need to consider identifying flight parameter trends and threshold exceedances. Therefore a tool that can predict aircraft energy states may be of value to pilots during flight. Multiple studies in the aviation industry focus on predicting aircraft speed near touchdown. The predicted speed values may be combined with Equation 1 to predict the aircraft energy near touchdown and evaluate the stability of the aircraft. Many of these speed prediction methods use machine learning models such as neural networks, random forest, linear regression, support vector machines, and decision trees [19, 20, 21, 23, 30]. Long short-term memory (LSTM) neural networks are frequently used in these studies due to their ability to handle exploding or diminishing feedback errors when modeling a dynamic system. This helps improve the convergence of the model to a local minimum. The studies by Puranik et al. [19] and Lee et al. [23] also emphasized the importance of predictive range and attempted to predict ground speed near touchdown from flight data obtained 300 ft above touchdown. Machine learning models were also used to predict hard landing based on predicted vertical acceleration [31, 32, 33]. These studies show the potential for machine learning models to predict various metrics.The focus of this study is to build on the two aforementioned studies by the authors and predict aircraft total energy during final approach. This study also represents an attempt at evaluating the predictability of total energy with neural network models. The following section will further introduce the methodology developed as part of this study.

3. Methodology

The methodology and steps followed in this paper are outlined in Figure 1. The elements of the methodology follow those of a general machine learning pipeline. The main difference in this work is that the processed features generated from flight data are used in a supervised learning context to predict future energy states. The following sections provide further details on each of the individual steps of this methodology.

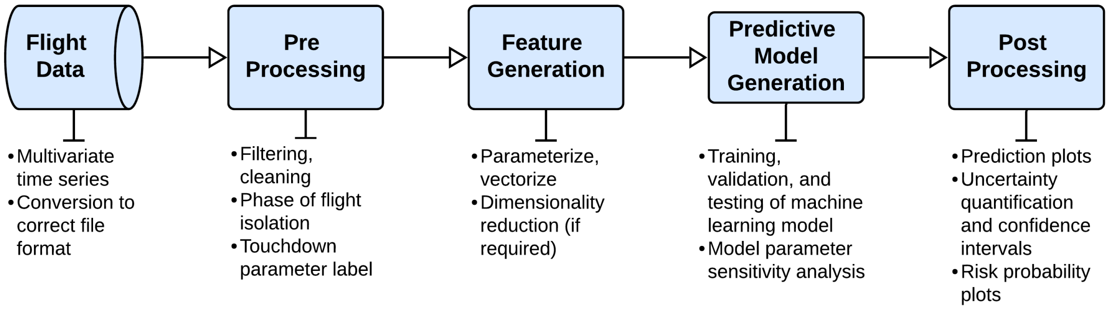

Figure 1 – Flow of data and steps in the prediction model generation framework

3.1 Data Processing

The main source of flight data used in this study is the Flight Operational Quality Assurance (FOQA) data. The initial goal for the FOQA program is to identify aggregate flight trends by mapping flight parameters to accident precursors through threshold exceedance criteria [24]. The FOQA data is a recording of all the flight and ground sensors between 0.25 and 16 Hz frequency. They are hierarchically arranged with atmosphere, aircraft state, GPS (Global Positioning System), engine, control, and fuel system data at the top level. At the lower level are the sensor recordings from each system in various units. For this complex data to be used to model aircraft kinetic and potential energy, the data must be rearranged so that the data length from each flight is equal. This is because most machine learning algorithms require the input from each sample to be equal. The data used in this research is publicly available from NASA[1] and consists of thousands of commercial aviation flight data records.
For the purpose of this research, only the flight data corresponding to the final approach is considered due to its significance with respect to touchdown condition. The time stamps for the final approach phase when the aircraft crosses the 1000 ft and 300 ft gates are identified, for each flight. Then 35 data points between these two gates, that are equal distance apart, are extracted. The two altitude gates are determined based on the stability requirement, at 1000 ft above touchdown, and the minimum altitude that the pilots need to respond to deviations from ideal approach path, at 300 ft above touchdown. The 35 data points are selected based on the fact that a few ground speed prediction models from earlier studies indexed the input data at 20 ft intervals. Following the same logic, the prediction target data between altitudes 300 ft and 40 ft above touchdown are selected but this time with 13 equally distanced data points. The reason for not extending predictions to touchdown (0 ft) is due to the presence of significant noise in sensor readings at, or close to, touchdown. Based on ground speed and altitude data, the potential and kinetic energy at each point are calculated using Equation 1. The data is reshaped so that every column is a flight parameter at each time stamp and every row is a flight. The data is then normalized for each parameter using the following equation.

$$y = \frac{x - min_i}{max_i - min_i} \tag{2}$$

Where y is the normalized value, x is the raw input value, and min_i and max_i are the minimum and maximum value for each parameter, respectively. This data is used as input to a random forest regression model to perform sequence to sequence prediction. The result from the random forest regression is used to identify the top 20 significant parameters for determining kinetic and potential energy.

[1] https://c3.nasa.gov/dashlink/resources/?page=3&sort=-created&type=28

The FOQA data is then reshaped to perform sequential prediction of energy states at each time stamp of the input window. To do so, the data is modified so each set of data represents 10 seconds of input, for generating the prediction model, and 10 seconds of output, for calculating the prediction error. Single-layer and double-layer LSTM models are used for generating the prediction model.

3.2 Model Generation

As mentioned, the goal of this study is to generate a sequential energy states prediction model that can identify risk during approach. Risk in this study is defined as the deviation of specific kinetic or potential energy from the norm. This may be illustrated by overlaying predicted specific kinetic and potential energy trajectories on top of the energy density contour. The energy density contour is generated by combining kinetic and potential energy trajectories of historical flights, during final approach. The concept of energy density contour is built on the specific energy probability density used previously by one of the authors [26], to analyze flight safety. To do so requires the model to, not only predict energy states at the decision gates, but throughout the final approach. To that end, this study uses the past 10 seconds of flight data to predict energy states 10 seconds into the future at each time step during the final approach. An illustration of this is shown in Figure 2. The

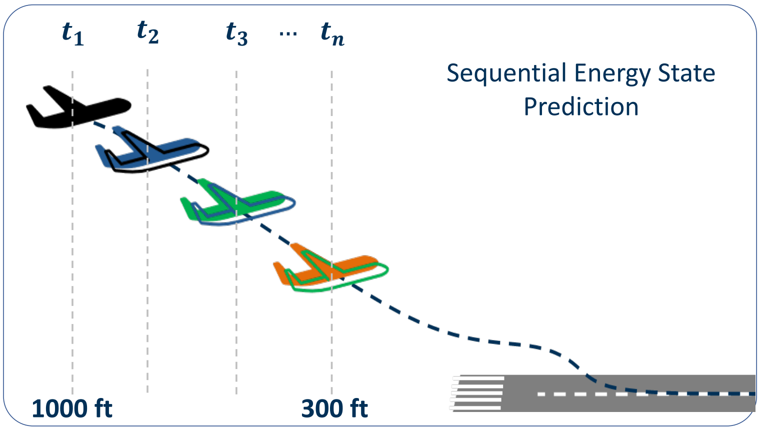

Figure 2 – Illustration of the sequential prediction model prediction process.

different colors in Figure 2 indicate different time stamps with the shaded and hollow aircraft indicating current and future energy states, respectively. The prediction model is trained at each point in the final approach based on the mean square error function of the predicted energy state trajectories.
The difficulty in training this type of prediction model resides in the fact that the model needs to consider the change in nonlinear aircraft behavior with altitude and time. Recurrent neural networks (RNN) models are capable of capturing the nonlinear system behavior, but these models lack the ability to deal with exploding or diminishing feedback errors. A LSTM neural network model is a type of RNN that deals with exploding or diminishing feedback errors through gates/activation functions (Figure 3). This is realized through the following four steps.

1. *Forget gate*, which selects the feedback errors.

$$f_t = A(W_f(h_{t-1}, x_t) + b_f)$$

2. *Input gate*, which decides how the inputs modify the states.

$$i_t = A(W_i(h_{t-1}, x_t) + b_i)$$
$$\tilde{C}_t = A(W_C(h_{t-1}, x_t) + b_C)$$

3. *State update*, based on selected feedback errors and input.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

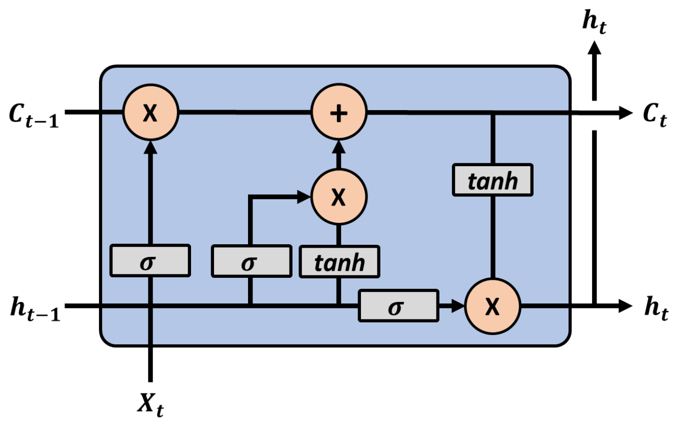

Figure 3 – Illustration of the LSTM model structure.

4. *Output gate*, where the feedback error and states are passed to the next cell.

$$O_t = A(W_O(h_{t-1}, x_t) + b_O)$$
$$h_t = O_t * A(C_t)$$

Where f is the forget gate, i is the input gate, O is the output gate, C is the updated state, h is the hidden layer state, x is the input state, W is the weight, b is the bias, and A is the activation functions. These steps are repeated for the full input sequence. The recursion and nonlinear activation functions of the LSTM model allow for the model to capture the nonlinear system behavior.
This study attempts to predict energy states by capturing the aircraft dynamics with single-layer and double-layer LSTM models. An illustration of the overall structure of these two models is provided in Figure 4. LSTM models are neural network models that utilize memory gates to limit or enhance

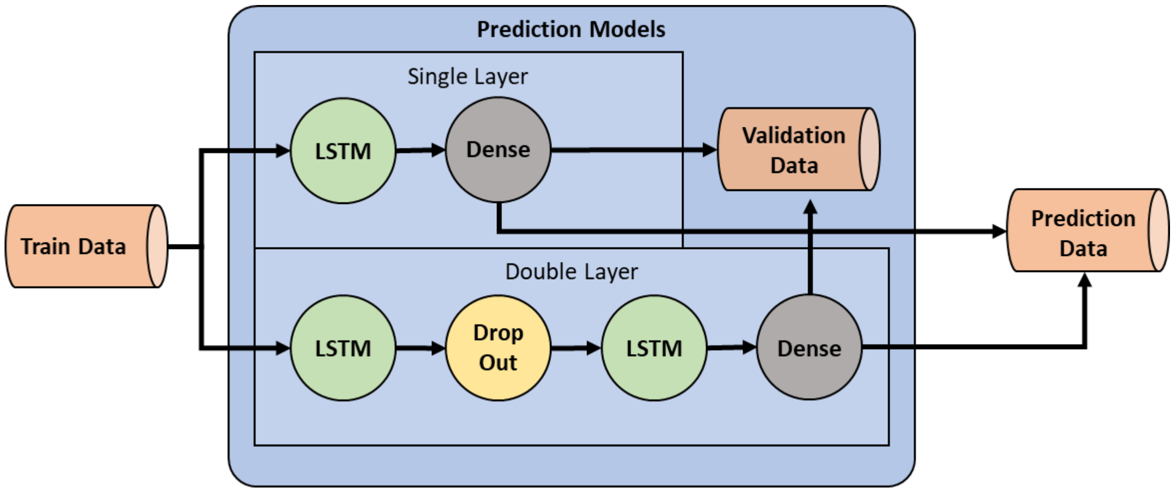

Figure 4 – Illustration of single-layer and double-layer LSTM model structures.

feedback terms. The complexity of these models come at the cost of evaluating the optimal configuration for modeling the system. A hyperparameter optimization technique called *Hyperband* is used to find the best configuration for predicting energy states with LSTM models [25]. In particular, *Hyperband* is a technique which utilizes successive halving to find the optimal configuration. This technique assigns small computational power for each configuration to filter out the poor performers early on. More resource is assigned to the configuration with slower convergence to generate the optimal model. Model hyperparameters are optimized using this technique with the hyperparameters considered for this study being the number of hidden units and model bias.

4. Results

The initial prediction model generated with random forest regression provides a base understanding of energy state prediction models. Potential energy, kinetic energy prediction errors and their relative variants are shown in Table 1.

Table 1 – Energy state prediction errors and their relative errors.

Prediction Range	280 ft	200 ft	100 ft	40 ft
$abs.\ e_{PE}$ (ft)	3.61	8.25	7.16	3.49
$abs.\ e_{KE}$ (ft)	12.72	22.95	33.15	38.37
$rel.\ e_{PE}$ (%)	1.24	3.79	6.09	8.73
$rel.\ e_{KE}$ (%)	1.38	2.51	3.80	4.70

Where abs. is absolute, rel. is relative, e is error, PE is potential energy, and KE is kinetic energy.

The relative prediction error of potential energy increases with prediction range linearly. This is an expected trend since the predictive power is expected to fall off with prediction range. This trend contradicts the absolute error in potential energy. A potential reason is that as the aircraft approaches touchdown the reference potential energy diminishes, which amplifies the relative error. Another reason for the contradiction is that with all aircraft trying to perform stable approaches, it is less likely for the aircraft to deviate from the ideal configuration closer to touchdown. Since the distribution of error is narrower as the aircraft gets closer to touchdown, the prediction error is smaller. This does not necessarily mean the model has improved performance at lower altitudes.

The kinetic energy prediction errors perform differently from potential energy prediction errors. Both absolute and relative errors increased linearly until touchdown. A potential explanation for this observation is that the aircraft ground speed does not reach zero at touchdown, unlike altitude. Consequently an exponential increase in relative error near touchdown due to the diminishing denominator term is not observed. In fact, flying a stable approach encourages a constant rate of descent and ground speed until flare. The pilots are encouraged to keep the ground speed at a set percent higher than the stall speed. This can be seen from the ground speed distribution near touchdown in Figure 5, where the mean of ground speed is between 115 and 120 kts at all altitudes. Since there is no cause for an increase in predictive power, it decreases linearly with prediction range for both absolute and relative kinetic energy prediction errors. Figure 5 shows that the standard deviation of ground speed increases with increasing altitude from touchdown. However, this change is small so it does not result in reduced kinetic energy prediction error closer to touchdown.

The prediction result with random forest regression shows that relative errors for PE and KE predictions are relatively low. Although the random forest regression model is not perfect, it is sufficient to identify significant parameters, based on feature importance, for generating the prediction model. These significant parameters, which are listed in Figure 6, are used to generate the sequential energy state prediction model. The random forest feature importance is generated based on the impurity of each feature at all the index combined. The lower the impurity the clearer the division at each of the branch generated by the algorithm. A clearer division indicates a stronger correlation between the input parameter and the predicted metric. The feature importance result is mostly expected since it includes acceleration, energy, and speed parameters, which define the specific kinetic and potential energies predicted. This means parameters such as core speed, angle of attack, pitch angle, and wind speed are expected parameters because they have direct impact on the acceleration, energy, and speed parameters. Any distance parameters such as distance to way point and pressure altitude are also expected since they represent final approach progress. The significance of aircraft state parameters, such as latitude position, longitude position, and roll angle, is unexpected as they do not have direct relationship to the kinetic or potential energy of the aircraft. Flights will have to be analyzed individually to identify potential relationship between how branches are made for these parameters and the predicted data. Nonetheless the list of important parameters generated here indicates potential metrics for defining energy management performance. They may be used by regulators and pilots for improving safety during final approach.

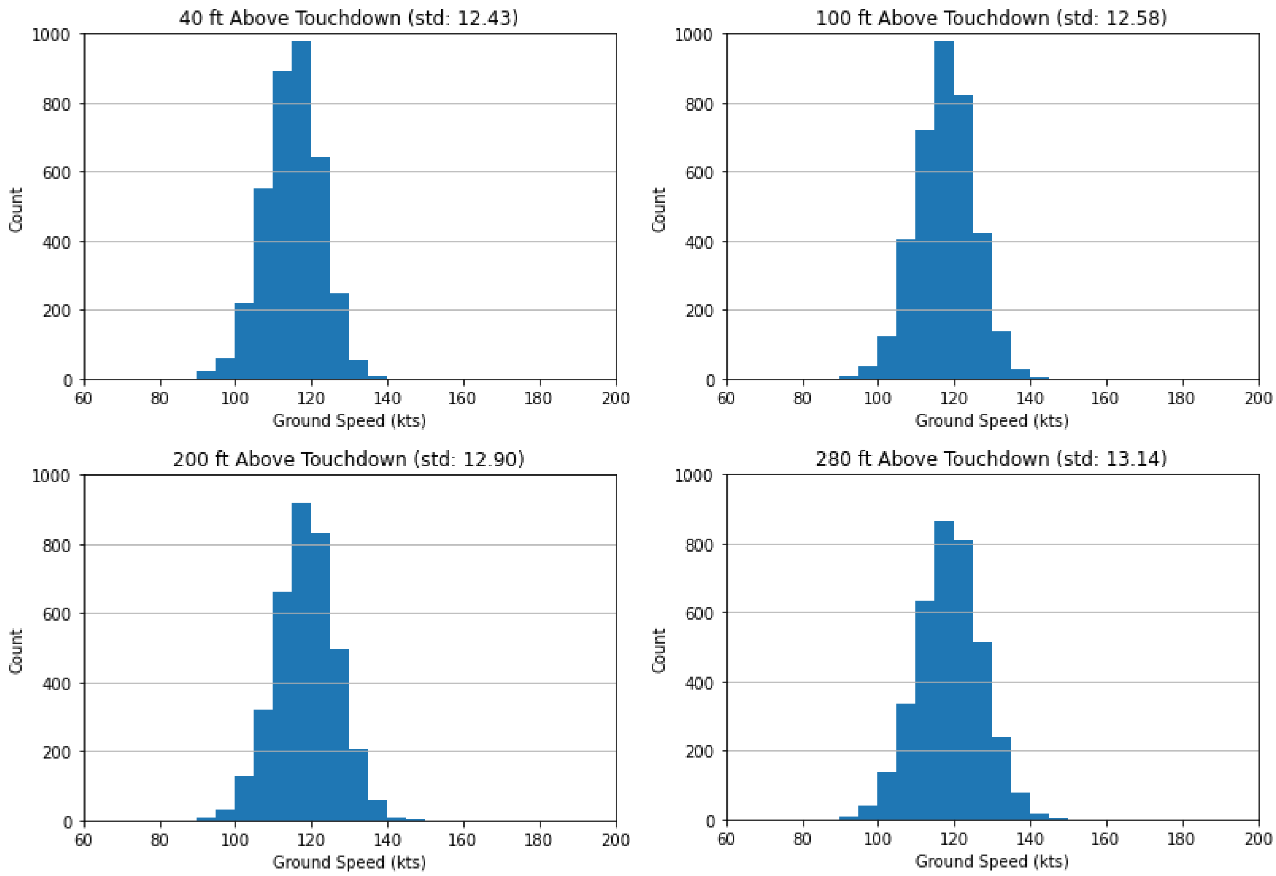

Figure 5 – Distribution of ground speed at prediction indexes.

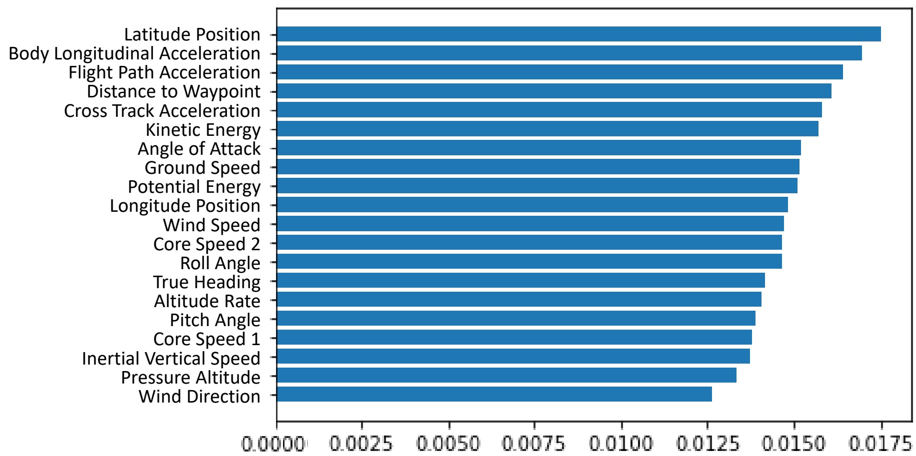

Figure 6 – Significant features for generating the energy prediction model.

4.1 Prediction Model Performance

Both single and double LSTM layer models are optimized based on mean square error of the energy state prediction trajectories. The optimized hyperparameters are 600 units for both LSTM layers with model bias turned on. Note that the maximum units for hidden units was set to 600 for this study due to the limited computational power. The model performance is evaluated based on two factors, accuracy in terms of prediction range, and accuracy at discrete altitude gates. The accuracy in terms of prediction range is calculated by finding the RMSE (Root Mean Square Error) of all the predictions made between 1 to 10 seconds into the future. The accuracy at discrete altitude gates is calculated by finding the RMSE of all the predictions made at a given altitude. These results are used to conduct a prediction sensitivity analysis in terms of target altitude and prediction range. For the remainder of this section only the result for the double LSTM layer model is introduced because it outperformed the single LSTM layer model for both accuracies. The double layer LSTM model accuracies in terms of prediction range and altitude are shown in Table 2.

Table 2 – Double layer LSTM model prediction errors in terms of altitude and prediction time.

Prediction Time (s)	**1**	**4**	**7**	**10**
e_{PE} **(ft)**	7.28	7.31	11.19	15.62
e_{KE} **(ft)**	1.59	7.09	14.15	20.53
Prediction Altitude (ft)	**900**	**700**	**500**	**300**
e_{PE} **(ft)**	11.9	11.36	10.27	9.79
e_{KE} **(ft)**	20.48	14.13	10.64	7.64

Both specific PE and KE accuracies degraded with prediction time as expected. However the model is capable of predicting KE much better than PE at shorter prediction time, while the KE accuracy degraded much faster than PE. This may be due to the aircraft altitude being highly dependent on the approach technique, while the speed is typically stabilized from the stabilization gate. This relationship is illustrated in Figure 7, where the kinetic energy distribution is fairly stable until the altitude is beyond the stabilization gate. This indicates the need for a model sensitive to the change in kinetic energy especially for generating a long range prediction model that gives enough time for pilots to respond.

The prediction error based on altitude shows the opposite trend. The prediction accuracies for potential energy and kinetic energy increase with decreasing altitude. This may initially sound not intuitive since during the approach the lower altitude point is further down the flight path. One explanation for this result is that the aircraft stabilizes closer to touchdown. So the altitude and speed distributions at these points in the approach are much narrower. Similarly, at higher altitudes, the aircraft's height and speed depend more on the type of approach. However, as the aircraft is near touchdown, all the types of approach converge to aircraft touchdown target speed. The narrower distribution makes it easier for the model to predict with smaller absolute error. This does not mean the model is ineffective but that the sensitivity and robustness of the model output to the input have to be considered for future work.

4.2 Predictions for Sample Flights

Two sample flights are selected to illustrate how energy predictions combined with energy probability density contours can be used to visualize aircraft stability. The first flight (in red) is an unstable flight where the specific kinetic energy, at a specific potential energy of 300 ft, is significantly above its peers. The specific potential energy of 300 ft is important for analysis since 300 ft above touchdown is identified as a decision gate. High specific kinetic energy at the decision gate indicates that not enough energy is drained from the start of approach. The second flight (in green) is a stable flight where the specific kinetic energy is located near the center of the distribution. The line plots represent actual flight paths and the triangle points are predicted energy states 10 seconds into the future. The two flights are visualized on a contour plot of probability density of specific kinetic and potential energy based on historical flights. The contours shaded in dark blue means higher probability density.

Few observations are made regarding Figure 7. First, the specific kinetic energy and potential energy are not linearly related during final approach. The specific kinetic energy is almost constant between touchdown and 1000 ft. Then above 1000 ft the kinetic energy increases exponentially. This behavior may be explained by the fact that most pilots do try to stabilize by the 1000 ft decision gate. Unfortunately this is not the case for flight A where the specific kinetic energy is significantly above peer for most of the final approach. The specific kinetic energy at touchdown is within the typical distribution indicating that the flight did land safely. However, flight A is a great example of how the pilot could have been notified of a potential unstable approach at 1000 ft based on the predicted values. While the figure does indicate that the aircraft touched down at a safe energy level, the flight may have been safer by reducing the risk of unstable approach.

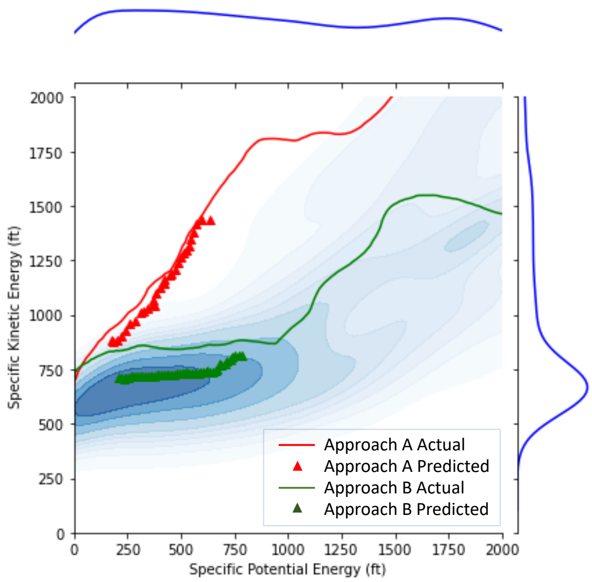

Figure 7 – Specific kinetic energy and potential energy of an unstable and a stable flight.

As introduced above, flight B is an example of a stable flight. An important observation made is the error between actual and predicted flights. For a prediction model, the error at the furthest prediction point is of most interest because the errors typically increase as the prediction window increases. Further study is required to build an optimal model that minimizes the maximum error. Overall this study does show that energy states can be predicted ten seconds into the future in a sequential manner. Additional prediction results with various energy trajectories are illustrated in Figure 8.

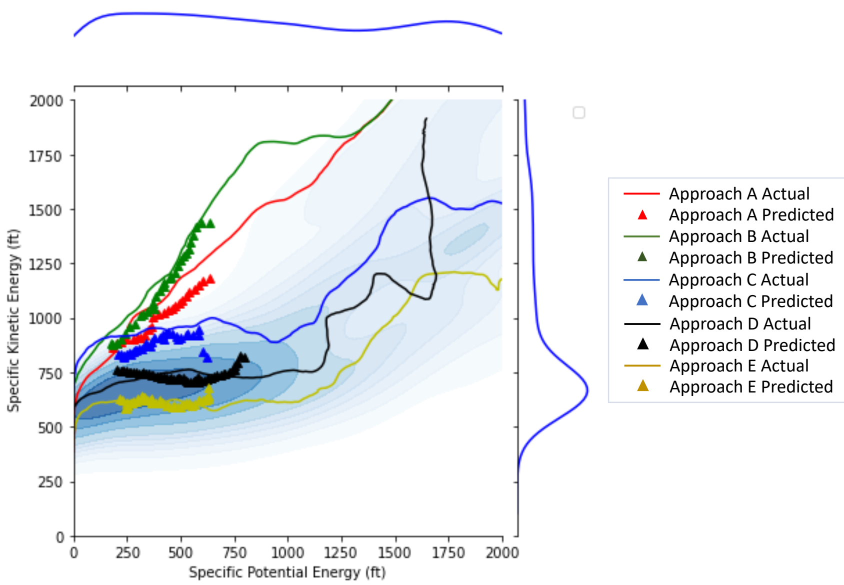

Figure 8 – Specific kinetic energy and potential energy trajectories for five sample flights.

Some flights with large errors are observed. Techniques such as model hyperparameter optimization need to be considered to improve the prediction accuracy. Nonetheless the model's ability to accurately predict energy states for high energy flights shows that the energy prediction model can be used to predict unstable approaches based on a total energy threshold exceedance criteria.

5. Concluding Remarks

This research focused on the development of a sequential predictive model of aircraft energy states to evaluate landing performance. The model was used to evaluate the predicted energy state sensitivity to prediction range and altitude during final approach. The benefit of evaluating flight performance based on energy states is the ability to visualize the performance based on specific kinetic energy and potential energy distribution from historical data. The historical data provides a reference against which to compare the energy states of a flight of interest. A threshold exceedance criteria for identifying unstable approach may also be considered based on the illustrated distribution of energy states. FOQA data was used to train the prediction model and generate the energy states distribution plot.

The results from this study showed that specific kinetic and potential energies may be predicted directly using machine learning models. The random forest regressor was capable of predicting energy states through sequence to sequence prediction. Flight data between 1000 ft and 300 ft altitude gates during approach was used to predict energy states below 300 ft. Highest and lowest specific PE and KE errors were 8.25 and 38.37 ft. They are equivalent to 3.79 and 4.70 % relative RMSE. Although not ideal, this model was used to identify the 20 most significant parameters for predicting specific PE and KE. These significant parameters were used to generate a sequential prediction model for predicting energy states up to 10 seconds into the future from 10 seconds of flight data at every second of final approach. The result showed that the errors of specific PE and KE predictions were below 15.62 and 20.53 ft in terms of prediction range. The prediction accuracy degraded almost linearly with prediction range for both specific PE and KE. However, the prediction accuracy improved with decreasing prediction altitude. This may be due to ground speed variance decreasing with altitude as pilots tend to target a specific speed near touchdown. The analysis based on sample flights showed the potential for predicting energy states to visualize the approach performance to the pilots. This can be used to visualize flight parameter trends and identify potential unstable approach based on threshold exceedance criteria.

Some avenues for future work are considered based on the study. First is the sensitivity study on prediction model accuracy vs input data frequency. As introduced earlier, FOQA flight parameters are recorded at various frequencies. Understanding the ideal frequency for generating prediction may be helpful for generating future prediction models. Second is the consideration for data indexing technique to restructure the input data to better represent flight behaviors. Third is the use of noise reduction techniques to generate smoother trajectories for the input data to improve prediction.

6. Copyright Statement

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