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Abstract

In today's competitive landscape, the effective development and utilization of machine-learning (ML) applications have become crucial across diverse economic sectors. This study presents an outline of the procedure involved in creating and implementing ML models for conceptualizing and evaluating aircraft engines. These models leverage supervised deep-learning algorithms to analyze patterns within an open-source repository containing data on both production and research conventional turbofan engines. The main areas of focus encompass crucial engine parameters like thrust-specific fuel consumption (TSFC), engine weight, engine diameter, and turbomachinery stage counts. While the creation of ML models is fundamental for their utilization, ensuring their seamless deployment holds equal significance. To address this aspect, a conversational AI chatbot that specifically focuses on propulsion has been developed. Leveraging natural language processing (NLP) techniques, this chatbot simplifies the deployment of machine learning (ML) models. The comprehensive workflow encompasses several key stages: gathering and enhancing engine data, training and cross validating the ML models, testing and evaluating their performance, and finally, deploying, monitoring, and updating the ML models. By following this systematic approach, the aim is to streamline the development and deployment process of ML models tailored for aircraft engine assessment.

Nomenclature

AI	Artificial Intelligence
API	Application Program Interface
BPR	Bypass Ratio
DNN	Deep Neural Networks
EPA	Environmental Protection Agency
FAA	Federal Aviation Administration
ICAO	International Civil Aviation Organization
LPC/HPC	Low/High Pressure Compressor
LPT/HPT/IPT	Low/High/Intermediate Pressure Turbine
OPR	Overall Pressure Ratio
TSFC	Thrust Specific Fuel Consumption

1.0 Introduction

In recent years, the accessibility of big data and the growing emphasis on data-informed decision-making have fueled a surge of interest in applying machine learning (ML) techniques across various industrial sectors. One such sector witnessing significant traction in ML adoption is the aircraft engine industry. Over time, this industry has amassed substantial datasets from diverse sources, ranging from databases housing current engine models to records from ongoing and completed development projects, as well as conceptual designs. These datasets represent a trove of valuable information that holds immense potential as a knowledge asset for shaping the future of engine development.

Designing an aircraft engine is a complex and labor-intensive process, marked by interdisciplinary considerations and significant time investments. A critical challenge faced by engine designers, particularly during the conceptual design phase, is the rapid and accurate evaluation of engine performance against mission requirements and design parameters. Given the vast array of potential engine configurations, designers often resort to system analysis and simulation techniques to estimate performance, necessitating exhaustive propulsion system studies for each configuration. This process can be exceedingly time-consuming, especially when dealing with expansive design spaces.

The advent of advanced data science techniques and ML algorithms presents a promising solution for addressing these challenges. By leveraging existing and historical engine datasets, ML models can be trained to assess new aircraft engine concepts swiftly and accurately, offering insights that may elude conventional analysis methods. These models have the capacity to discern intricate patterns and trends within the data, thereby enabling more informed decision-making and expediting the engine design process. The ability to rapidly evaluate new engine concepts not only enhances efficiency but also confers a competitive edge in the highly dynamic landscape of aircraft engine development.

However, the efficacy of ML models hinges not only on their development but also on their seamless deployment in production environments. Effective deployment strategies, such as the use of user-friendly interfaces and conversational AI platforms, are crucial to ensure practical utilization of these models in real-world scenarios.

Furthermore, the dynamic nature of data necessitates ongoing assessment and updating of deployed ML models to maintain their relevance and predictive accuracy. Regular integration of fresh engine data into the models facilitates adaptation to evolving industry trends and patterns, ensuring continued effectiveness over time.

This paper outlines the methodology for creating and deploying machine learning (ML) models to evaluate aircraft engine concepts. The process comprises two main sections: frontend and backend development. Frontend development centers around creating a conversational AI platform called *Aero-Engines Chatbot*, leveraging natural language processing (NLP). The NLP-based chatbot allows users to interact with the ML models using natural language. Users can input queries, prompts, or instructions in plain language, making the interaction more intuitive. Chatbots powered by NLP (like ChatGPT) are gaining popularity because of their impressive capability to comprehend and produce text that mimics human conversation.

Conversely, backend development entails building ML models using supervised deep-learning algorithms. These models analyze patterns in an open-source database covering both production and research conventional turbofan engines. Key engine parameters, such as thrust-specific fuel consumption (TSFC), engine weight, diameter, and turbomachinery stage counts, are primary areas of analysis. The workflow includes data collection, augmentation, and preparation; training and cross-validation of ML models; testing and evaluation; as well as continuous monitoring and updating of the models. The ML model development process, previously described by the author (Refs. 1 to 3), is summarized in this paper.

The author previously developed a user-friendly application interface designed to facilitate the deployment of pre-trained machine learning (ML) models for evaluating aircraft engine concepts. The app, detailed in Reference 1, features a simple point-and-click functionality to enhance user experience. The current study investigates an alternative deployment method by integrating established ML models into an NLP-based chatbot, named *Aero-Engines Chatbot*. Figure 1 illustrates the systematic workflow for deploying ML models using the chatbot.

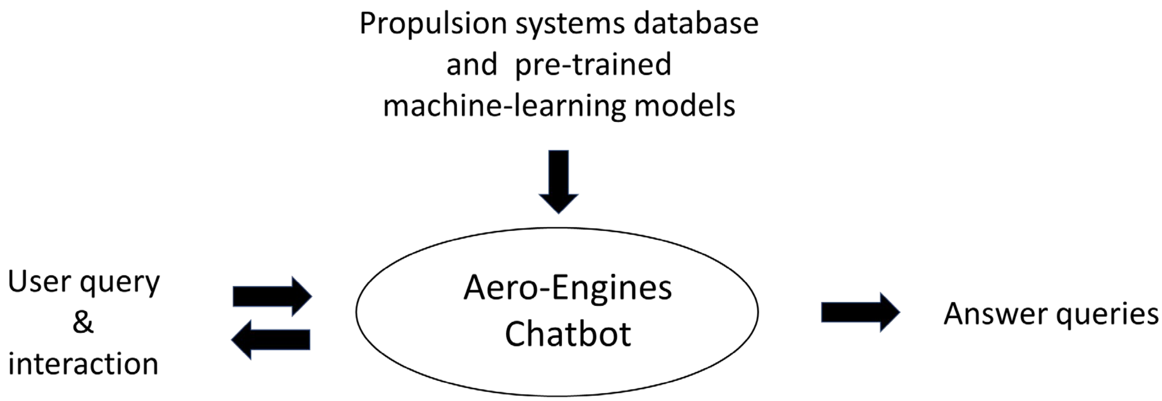

Figure 1.—Workflow process of ML models deployment via *Aero-Engines Chatbot*.

2.0 AI Chatbot Building Process

The *Aero-Engines chatbot*, an AI-driven tool, is used to deploy the ML models developed for assessing aero-engines concepts. Originally developed to enhance the sharing of aeropropulsion knowledge among department members and improve organizational efficiency, this interactive chatbot has been upgraded to facilitate ML model deployment. It mimics human conversation through text-based interactions, engaging users in the process of deploying the ML models for engine conceptual design.

Unlike generative AI, which learns from data and adapts its behaviour based on discovered patterns, this chatbot operates using explicitly programmed rules - a rule-based approach. This design choice helps save computing power and memory usage, as it does not require a GPU (graphics processing unit). The chatbot was built through natural language processing (NLP) using Python’s NLTK (Natural Language Toolkit) library (Ref. 4) and Keras (Ref. 5). NLTK is an open-source Python library for Natural Language Processing.

NLTK provides essential tools for working with human language data, while Keras offers a high-level neural networks API for building and training deep learning models. The chatbot automates conversations and interact with users through messaging platforms. Here’s an overview of the chatbot-building process:

- **Data Collection and Preprocessing**: The first step is to gather conversational data or a corpus. This corpus can be in the form of chat logs, customer service interactions, or any other text-based conversations. In this study, a JSON (JavaScript Object Notation) data file was created to catalog the tags, word or phrase patterns, and responses related to aircraft engine design input parameters that the Chatbot would address. An example of a JSON data file is shown below:

```
{"tag": "turbofan",
 "patterns": ["design a turbofan", "help me to design a turbofan"],
 "responses": ["Direct-Drive or Geared (enter '0' for 'direct-drive' or '1' for 'geared',
                    default = 'direct-drive')?"]
}
```

  Once created, the data needs preprocessing, which includes tokenization (splitting text into words or phrases), removing stop words (commonly used words like "and," "the," etc.), and stemming or lemmatization (reducing words to their root form). NLTK provides functions for these tasks.

- **Feature Extraction**: After preprocessing, the text data needs to be converted into numerical vectors that can be fed into a machine learning model. In this work, Bag-of-Words (BoW) (Ref. 5) technique was used for this purpose. The BoW model works on the principle of representing text data as a bag of words, ignoring grammar and word order while preserving the frequency of each word. The representation is based on how often each word appears. Essentially, it converts a text document into a numerical feature vector where each unique word in the text corresponds to a feature and the value represents the frequency of the word. NLTK provides functions to implement this technique.
- **Model Building**: Once the data was preprocessed and features were extracted, the next step was to build the chatbot model. In this case, Keras (Ref. 6) came into play. Keras is an open-source neural networks API written in Python. A neural networks architecture was constructed to train the chatbot.
- **Training**: With the model architecture defined, it's time to train the model using the preprocessed data. During training, the model learns to map input text sequences to appropriate responses. Keras provides easy-to-use APIs for training neural networks, with TensorFlow (Ref. 7) as the backend engine. Keras allows one to specify parameters such as the number of epochs, batch size, and optimizer choice.
- **Evaluation and Testing**: After training, it's crucial to evaluate the performance of the chatbot model. This involves testing the chatbot with unseen data or human evaluators to assess its ability to generate meaningful and contextually appropriate responses.
- **Deployment**: Once the model performs satisfactorily, it can be deployed into production as a chatbot application. This involves integrating the ML models into a chat interface where users can interact with it in real-time. Figure 2 depicts the deployment of *Aero-Engines chatbot*, showcasing an example conceptual design output for an engine.

By leveraging NLTK for text pre-processing and feature extraction and Keras for building and training the deep learning model, the *Aero-Engines chatbot* is capable of understanding and generating human-like responses based on natural language input.

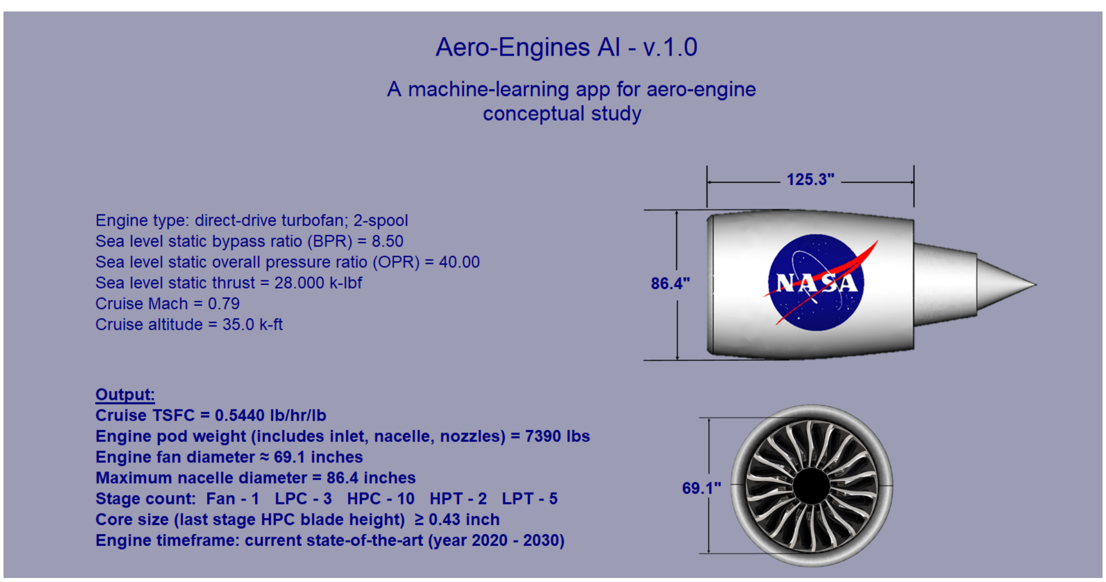

Figure 2.—An example engine design output.

3.0 ML Models Development

The current development of machine learning models focuses on axial-compressor turbofan engines, with plans for future expansions to include other engine types like turboshaft and hybrid-turbofan. The model development process consists of the following steps:

1. Engine data collection, augmentation, and preparation
2. ML models training
3. ML models testing and evaluation
4. Monitoring and updating

3.1 Engine Data Collection, Augmentation, and Preparation

3.1.1 Engine Data Collection

Our database primarily comprises 145 commercial engines (Refs. 8 to 14) and 39 engines from NASA aeronautics projects (Refs. 15 to 20). The commercial engines represent a broad spectrum of advancements and insights into engine technology over the past five decades, thereby providing a robust foundation for our machine learning models. The data on NASA engines come from aeronautics research that targets three generations of aircraft: near-term, mid-term, and far-term. Each generation, designated as 'N+1', 'N+2', and 'N+3', respectively, has specific targets for reducing noise, emissions, fuel consumption, and field length compared to current state-of-the-art aircraft. The research aims to develop new vehicle configurations that align with NASA's ambitious technology goals for the next 25 years. The database is shown in the Appendix A.

3.1.2 Data Augmentation

Data augmentation is a crucial technique employed in machine learning to enhance model performance and generalization. By augmenting existing data through various transformations and modifications, we increase the diversity and quantity of training data, thereby improving the model's adaptability and performance. In our study, we augmented the data by scaling up current engines by 10 percent, while maintaining key operating parameters such as bypass ratio, overall pressure ratio, and others, as shown below:

BPR	OPR	SLS Thrust (lbs)	Mach	Alt. (ft)	TSFC (lb/hr/lb)	Weight (lbs)
8.44	38.37	79377	0.85	35000	.5526	18949
8.44	38.37	87315	0.85	35000	.5526	20844

With data augmentation, our database expanded as follows:

Turbofan type	No. of engines
2-spool direct-drive	273
2-spool geared	89
3-spool direct-drive	50

Following data collection and augmentation, the next step involved preparing the data for training our machine learning models. This process entailed cleaning, preprocessing, normalization, and random shuffling of the dataset. The dataset was then split into training and testing sets for model training and evaluation, respectively.

3.1.3 Dataset Preparation

The next step was to prepare the data that would be used to train the ML models. It involved cleaning and preprocessing the data to remove errors or inconsistencies and organizing the data into a format that could be used for the training. The engine dataset was normalized and shuffled randomly (using pseudo-random number generator) and divided into two datasets: the training set and the testing set. The training set was used to train, cross-validate, and build predictive models. The testing set consisted of the remaining engines that were unseen by the training models and was retained for the final evaluation of the predictive analytics. The dataset preparation is described in detail in References 1 to 3.

3.2 ML Models Training

Once the data was prepared, we selected appropriate algorithms for training our machine learning models. Supervised deep-learning and K-nearest neighbor algorithms (Ref. 21) were utilized for constructing models predicting TSFC, engine weight, core size, fan diameter, and turbomachinery stage count.

These models were developed and trained using Keras, an open-source neural networks API, with TensorFlow as the backend engine. Regularization techniques such as L2 and Dropout (Refs. 22 and 23) were employed to prevent overfitting, and optimization was performed using the Adam optimization algorithm (Ref. 24). A grid-search routine was utilized for hyperparameter tuning, ensuring optimal model performance.

A total of nine ML models were trained and cross-validated for various engine parameters. The training and cross validation of these ML models are described in detail in Reference 1 to 3.

3.3 ML Models Testing

Following model training, the next step involved testing and evaluating their performance using a separate testing dataset, described in detail in References 1 to 3. The results indicated high accuracy levels across all models, as shown in Table I.

TABLE I.—ML MODELS TEST RESULTS

ML model	Mean accuracy, percent	Uncertainty 95% confidence interval (2 standard deviations)
TSFC	98	4%
Weight	95	5%
Core size	98	4%
Fan diameter	98	5%
LPC stage count	98	14% (or 1 stage)a
HPC stage count	98	8% (or 1 stage)a
HPT stage count	96	39% (or 1 stage)a
LPT stage count	98	18% (or 1 stage)a
IPT stage count	90	44% (or 1 stage)a

[a]Based on the current database. 1-stage fan is assumed for all the engines.

3.4 Monitoring and Updating

Continuous monitoring and updates are vital for ensuring the sustained performance of our machine learning models. While the commercial engine data remain static, the NASA engine data are subject to revisions over time as aeronautics research progresses. It's imperative to periodically update our models to incorporate these changes and maintain their accuracy, reliability, and effectiveness. As NASA's research evolves through different aircraft generations (labeled N+1, N+2, N+3), corresponding updates to our models will be crucial to align with evolving technological objectives and advancements.

4.0 Summary

This paper presents a comprehensive methodology for the development and deployment of machine learning (ML) models aimed at assessing aircraft engine concepts. The approach is bifurcated into two core components: the frontend and the backend.

At the frontend is the *Aero-Engines Chatbot*, an AI-driven conversational platform powered by natural language processing (NLP) techniques. Designed to emulate interactive human dialogue through text, the chatbot engages users in the practical application of ML models, thereby enhancing user experience and involvement in the engine evaluation process.

In contrast, the backend is dedicated to the construction of robust ML models utilizing supervised deep-learning algorithms. These models meticulously scrutinize data from an extensive open-source repository that encompasses a wide array of both operational and experimental turbofan engines. The analysis predominantly focuses on critical engine metrics such as thrust-specific fuel consumption (TSFC), engine weight, diameter, and turbomachinery stage counts. The comprehensive workflow encompasses data collection, augmentation, preparation, followed by the training, cross-validation, testing, and evaluation of the ML models, culminating in their ongoing refinement and enhancement.

This study shows that the integration of AI-powered chatbot to deploy ML-based predictive analytics offers a promising opportunity for the exploration of aircraft engine design concepts.

Long-term, for the aircraft engine AI tool to achieve true effectiveness, it needs integration with an aircraft database, evolving into a propulsion-airframe integration AI tool. This will allow for predictions of aircraft-level metrics like fuel burn, noise emissions, and more. Additionally, enhancing the chatbot with a large language model (LLM) would enable it to read and understand regulations from government authorities like the FAA, EPA, and ICAO. See Figure 3 for the propulsion-airframe integration AI tool schematic.

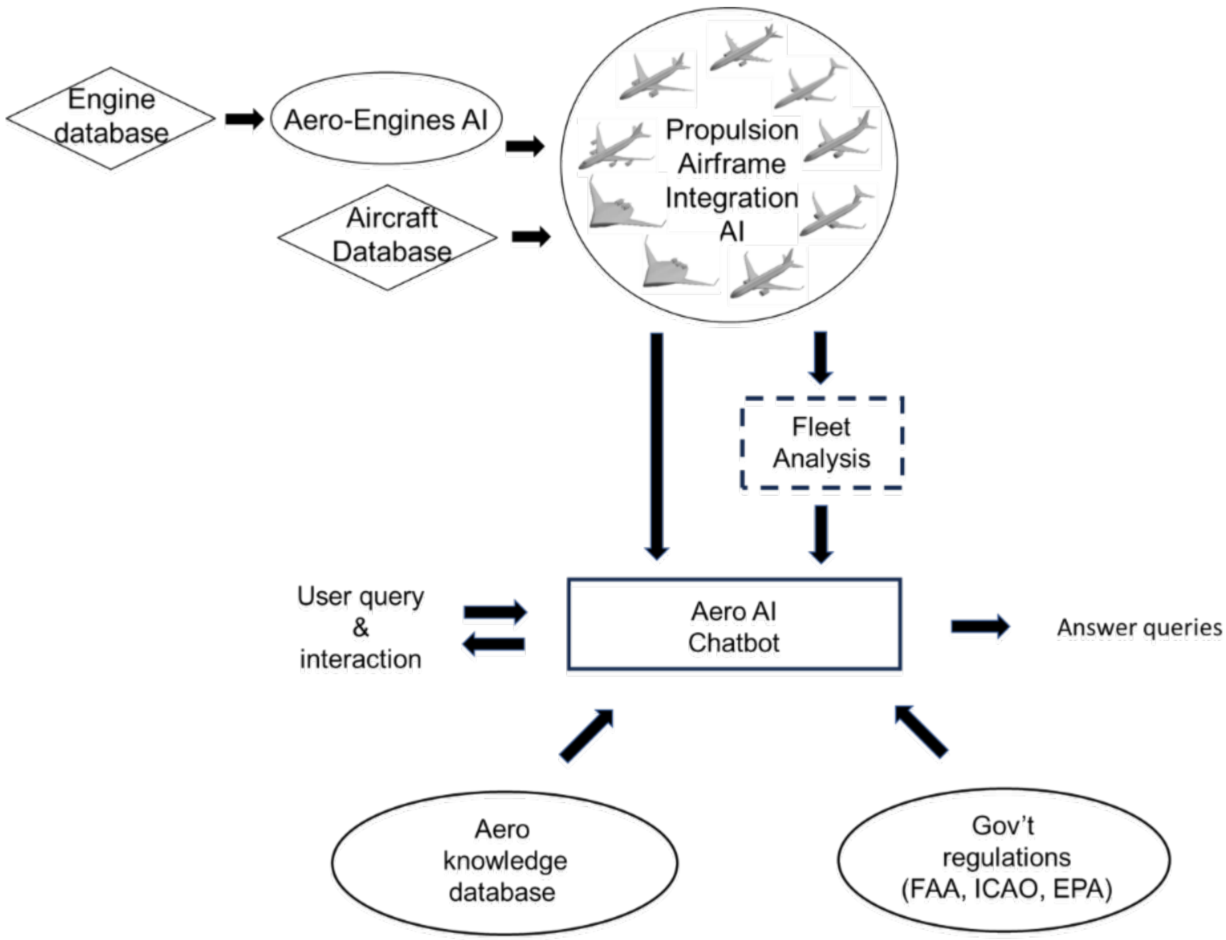

Figure 3.—Propulsion-airframe integration AI tool schematic.

Appendix A.—Engine Database

Org.	Engine Model	BPR (SLS)	OPR (SLS)	Thrust, lbs (SLS)	Cruise Mach	Cruise Alt. k ft.	Year certified	System Type	No. of Spools	Cruise TSFC lb/lbf.hr	Propulsion System Weight, lbs
CFM Int'l	CFM56-2C1	6.0	23.50	22000	0.80	35	1979	DD	2	0.651	7199
CFM Int'l	CFM56-3B1	5.1	22.40	20000	0.80	35	1984	DD	2	0.655	6389
CFM Int'l	CFM56-3B2	5.1	24.30	22000	0.80	35	1984	DD	2	0.655	6607
CFM Int'l	CFM56-3C1	5.1	25.50	23500	0.80	35	1986	DD	2	0.667	6766
CFM Int'l	CFM56-5A1	6.0	26.60	25000	0.80	35	1987	DD	2	0.596	7770
CFM Int'l	CFM56-5A3	6.0	27.90	26500	0.80	35	1990	DD	2	0.596	7850
CFM Int'l	CFM56-5A4	6.0	23.80	22000	0.80	35	1996	DD	2	0.596	7375
CFM Int'l	CFM56-5A5	6.0	25.10	23500	0.80	35	1996	DD	2	0.596	7534
CFM Int'l	CFM56-5B1	5.7	30.20	30000	0.80	35	1994	DD	2	0.600	8366
CFM Int'l	CFM56-5B2	5.6	31.30	31000	0.80	35	1993	DD	2	0.600	8479
CFM Int'l	CFM56-5B3	5.4	32.60	33300	0.80	35	1997	DD	2	0.600	8734
CFM Int'l	CFM56-5B4	5.9	27.10	27000	0.80	35	1994	DD	2	0.600	8036
CFM Int'l	CFM56-5B5/P	5.9	23.33	22000	0.80	35	1996	DD	2	0.600	7509
CFM Int'l	CFM56-5B6/P	6.0	24.64	23500	0.80	35	1995	DD	2	0.600	7659
CFM Int'l	CFM56-5C2	6.8	28.80	31200	0.80	35	1991	DD	2	0.545	8796
CFM Int'l	CFM56-5C3	6.7	29.90	32500	0.80	35	1994	DD	2	0.567	9122
CFM Int'l	CFM56-5C4	6.6	31.15	34000	0.80	35	1994	DD	2	0.567	9285
CFM Int'l	CFM56-7B20	5.4	22.61	20600	0.80	35	1996	DD	2	0.603	6963
CFM Int'l	CFM56-7B22	5.3	24.41	22700	0.80	35	1996	DD	2	0.603	7194
CFM Int'l	CFM56-7B24	5.2	25.78	24200	0.80	35	1996	DD	2	0.603	7360
CFM Int'l	CFM56-7B26	5.1	27.61	26300	0.80	35	1996	DD	2	0.603	7602
CFM Int'l	CFM56-7B27	5.0	28.63	27300	0.80	35	1996	DD	2	0.603	7872
CFM Int'l	LEAP-1A26	11.1	33.40	27112	0.78	35	2015	DD	2	0.536	8840
CFM Int'l	LEAP-1A35	10.7	38.60	32170	0.78	35	2015	DD	2	0.536	9401
CFM Int'l	LEAP-1B25	8.4	38.40	26797	0.79	35	2016	DD	2	0.536	7778
CFM Int'l	LEAP-1B27	8.5	39.90	28034	0.79	35	2016	DD	2	0.536	7898
CFM Int'l	LEAP-1B28	8.6	41.50	29315	0.79	35	2016	DD	2	0.536	8024
GE	CF6-6D	5.9	24.70	40000	0.85	35	1970	DD	2	0.646	11749
GE	CF6-6D1	5.9	24.70	41500	0.85	35	1971	DD	2	0.646	11895
GE	CF6-6D1A	5.9	25.40	41500	0.85	35	1971	DD	2	0.646	11895
GE	CF6-45A2	4.3	25.90	46500	0.85	35	1973	DD	2	0.630	12927
GE	CF6-50C	4.3	28.80	51000	0.85	35	1975	DD	2	0.657	13323
GE	CF6-50C1	4.3	29.80	52500	0.85	35	1975	DD	2	0.657	13467
GE	CF6-50C2	4.3	28.44	52500	0.85	35	1978	DD	2	0.630	13467
GE	CF6-50C2B	4.3	29.06	54000	0.85	35	1979	DD	2	0.630	13611
GE	CF6-50E	4.3	28.44	52500	0.85	35	1973	DD	2	0.657	13505
GE	CF6-50E2	4.3	29.80	52500	0.85	35	1973	DD	2	0.630	13505
GE	CF6-80A	5.0	29.00	48000	0.80	35	1981	DD	2	0.623	12883
GE	CF6-80A2	5.0	30.10	50000	0.80	35	1981	DD	2	0.623	13076
GE	CF6-80A3	5.0	30.10	50000	0.80	35	1981	DD	2	0.623	13069
GE	CF6-80C2A1	5.1	30.96	59000	0.80	35	1985	DD	2	0.576	14782
GE	CF6-80C2A2	5.1	28.00	52460	0.80	35	1986	DD	2	0.578	14034
GE	CF6-80C2A3	5.1	31.64	58950	0.80	35	1988	DD	2	0.576	14776
GE	CF6-80C2A5	5.1	31.58	60100	0.80	35	1988	DD	2	0.578	14907
GE	CF6-80C2A8	5.1	31.00	59000	0.80	35	1996	DD	2	0.602	14782
GE	CF6-80C2B1	5.1	30.08	56700	0.80	35	1987	DD	2	0.576	14529
GE	CF6-80C2B1F	5.1	30.13	57160	0.80	35	1989	DD	2	0.564	14628
GE	CF6-80C2B2	5.1	27.74	51590	0.80	35	1987	DD	2	0.576	14039
GE	CF6-80C2B4	5.1	30.36	57180	0.80	35	1987	DD	2	0.590	14575
GE	CF6-80C2B6	5.1	31.56	60070	0.80	35	1987	DD	2	0.602	14851
GE	CF6-80E1A1	5.1	32.46	67500	0.80	35	1993	DD	2	0.562	14844
GE	CF6-80E1A2	5.1	33.10	68240	0.80	35	1993	DD	2	0.562	14844
GE	CF6-80E1A3	5.1	35.70	68520	0.80	35	2001	DD	2	0.562	14844
GE	CF6-80E1A4	5.1	34.50	66870	0.80	35	1997	DD	2	0.562	14844
GE	CF34-10A	5.4	26.50	18290	0.74	37	2010	DD	2	0.650	5453
GE	CF34-10E	5.1	27.30	18820	0.74	37	2002	DD	2	0.665	5598
GE	CF34-3A	6.3	19.70	9220	0.74	37	1986	DD	2	0.704	2849
GE	CF34-8C1	5.1	23.03	12670	0.74	37	1999	DD	2	0.664	3988
GE	CF34-8C5	5.1	23.09	13358	0.74	37	2002	DD	2	0.680	3935
GE	CF34-8E5A2	5.1	24.82	14500	0.74	37	2002	DD	2	0.680	4129
GE	GE90-76B	8.6	35.45	79654	0.80	35	1995	DD	2	0.545	20930

System type: DD = direct-drive system
G = geared system

Appendix A.—Continued

Org.	Engine Model	BPR (SLS)	OPR (SLS)	Thrust, lbs (SLS)	Cruise Mach	Cruise Alt. k ft.	Year certified	System Type	No. of Spools	Cruise TSFC lb/lbf.hr	Propulsion System Weight, lbs
GE	GE90-85B	8.4	38.37	87315	0.80	35	1995	DD	2	0.553	21656
GE	GE90-90B	8.4	39.70	94000	0.80	35	1997	DD	2	0.545	22280
GE	GE90-94B	8.3	40.53	97300	0.80	35	2000	DD	2	0.545	22592
GE	GE90-115B	7.1	42.24	115529	0.80	35	2003	DD	2	0.550	25876
GE	GEnx-1B54	9.4	35.20	57394	0.85	40	2008	DD	2	0.514	16594
GE	GEnx-1B58	9.2	37.20	60991	0.85	40	2008	DD	2	0.514	16952
GE	GEnx-1B64	9.0	40.60	66993	0.85	40	2008	DD	2	0.514	17537
GE	GEnx-1B70	8.8	43.50	72299	0.85	40	2008	DD	2	0.514	18054
P&W	JT8D-7	1.1	15.82	14000	0.80	35	1966	DD	2	0.796	4508
P&W	JT8D-9	1.0	15.88	14500	0.80	35	1967	DD	2	0.807	4646
P&W	JT8D-17AR	1.0	17.28	16400	0.80	35	1982	DD	2	0.825	4910
P&W	JT8D-17R	1.0	18.24	17400	0.80	35	1976	DD	2	0.825	5009
P&W	JT8D-209	1.8	18.30	18500	0.80	35	1979	DD	2	0.724	5905
P&W	JT8D-219	1.7	20.27	21000	0.80	35	1985	DD	2	0.737	6266
P&W	JT9D-3A	5.2	21.50	44300	0.85	35	1969	DD	2	0.624	12794
P&W	JT9D-7	5.2	22.20	46300	0.85	35	1971	DD	2	0.620	13102
P&W	JT9D-7A	5.1	20.30	46950	0.85	35	1972	DD	2	0.625	13169
P&W	JT9D-7F	5.1	22.80	48000	0.85	35	1974	DD	2	0.631	13270
P&W	JT9D-7J	5.1	23.50	50000	0.85	35	1976	DD	2	0.631	13468
P&W	JT9D-7Q	4.9	24.50	53000	0.85	35	1978	DD	2	0.631	14055
P&W	JT9D-7R4D	5.0	23.40	48000	0.85	35	1978	DD	2	0.615	13553
P&W	JT9D-7R4E	5.0	24.20	50000	0.85	35	1982	DD	2	0.620	13565
P&W	JT9D-7R4G2	4.8	26.30	54750	0.85	35	1982	DD	2	0.639	14220
P&W	JT9D-7R4H1	4.8	26.70	56000	0.85	35	1982	DD	2	0.628	14340
P&W	JT9D-20	5.2	20.30	46300	0.85	35	1972	DD	2	0.624	13097
P&W	JT9D-70A	4.9	24.50	53000	0.85	35	1974	DD	2	0.631	13990
P&W	1127G	12.3	31.70	27000	0.78	35	2014	G	2	0.530	6300
P&W	1519G	11.6	32.30	19000	0.78	35	2013	G	2	0.544	4800
P&W	2037	6.0	26.90	37600	0.80	35	1983	DD	2	0.563	10607
P&W	2040	5.5	29.40	40900	0.80	35	1987	DD	2	0.563	10972
P&W	2043	5.3	31.90	42600	0.80	35	1995	DD	2	0.563	11159
P&W	4052	5.0	26.32	52200	0.85	35	1987	DD	2	0.560	14027
P&W	4056	4.7	29.30	56750	0.85	35	1986	DD	2	0.560	14490
P&W	4060	4.5	32.40	60000	0.85	35	1988	DD	2	0.560	14819
P&W	4074	6.8	32.20	74500	0.85	35	1994	DD	2	0.560	19457
P&W	4077	6.7	33.20	77000	0.85	35	1994	DD	2	0.560	19950
P&W	4084	6.4	36.20	84000	0.85	35	1994	DD	2	0.560	20549
P&W	4090	6.1	39.16	90200	0.85	35	1996	DD	2	0.560	21522
P&W	4098	5.8	41.37	95340	0.85	35	1998	DD	2	0.560	22025
P&W	4152	4.9	26.90	52200	0.85	35	1986	DD	2	0.560	14036
P&W	4156	4.7	29.30	56750	0.85	35	1986	DD	2	0.560	14490
P&W	4164	5.2	31.24	64000	0.85	35	1993	DD	2	0.560	16886
P&W	4168-1D	4.9	33.10	68600	0.85	35	2008	DD	2	0.560	17345
P&W	4460	4.7	30.68	60000	0.85	35	1988	DD	2	0.560	14802
P&W	4462	4.6	31.91	63300	0.85	35	1992	DD	2	0.560	15126
P&W	6122A	4.8	25.70	22100	0.80	35	2004	DD	2	0.540	6311
Rolls-Royce	RB211-22B	4.7	25.00	41000	0.85	35	1973	DD	3	0.655	12098
Rolls-Royce	RB211-524B	4.5	28.40	49100	0.85	35	1973	DD	3	0.633	13270
Rolls-Royce	RB211-524B4-02	4.4	29.00	50000	0.85	35	1981	DD	3	0.603	13309
Rolls-Royce	RB211-524C2	4.5	29.10	51500	0.85	35	1979	DD	3	0.656	13370
Rolls-Royce	RB211-524D4	4.3	29.70	53000	0.85	35	1983	DD	3	0.631	13606
Rolls-Royce	RB211-524G	4.3	32.10	58000	0.85	35	1989	DD	3	0.582	14040
Rolls-Royce	RB211-524H	4.2	34.00	60600	0.85	35	1989	DD	3	0.572	14186
Rolls-Royce	RB211-535C	4.5	21.50	37400	0.80	35	1981	DD	3	0.646	10338
Rolls-Royce	RB211-535E4	4.1	25.40	40100	0.80	35	1983	DD	3	0.598	10648
Rolls-Royce	AE3007A	5.2	18.08	7580	0.78	32	1997	DD	2	0.625	2332
Rolls-Royce	BR710-A1-10	4.2	24.23	14750	0.80	35	1996	DD	2	0.630	4640
Rolls-Royce	BR715-A1-30	4.7	28.98	18920	0.76	35	1998	DD	2	0.620	6155
Rolls-Royce	BR715-C1-30	4.6	32.15	21430	0.76	35	1998	DD	2	0.620	6155
Rolls-Royce	Trent 1000-A	9.5	41.00	70000	0.85	35	2007	DD	3	0.506	18056
Rolls-Royce	Trent 553-61	7.5	35.19	56620	0.82	35	2000	DD	3	0.539	14843

System type: DD = direct-drive system
G = geared system

Appendix A.—Concluded

Org.	Engine Model	BPR (SLS)	OPR (SLS)	Thrust, lbs (SLS)	Cruise Mach	Cruise Alt. k ft.	Year certified	System Type	No. of Spools	Cruise TSFC lb/lbf.hr	Propulsion System Weight, lbs
Rolls-Royce	Trent 556-61	7.5	36.70	56620	0.82	35	2000	DD	3	0.539	14843
Rolls-Royce	Trent 7000-72	9.0	45.40	73700	0.85	35	2018	DD	3	0.506	18864
Rolls-Royce	Trent 768	5.2	34.00	68400	0.82	35	1994	DD	3	0.565	16839
Rolls-Royce	Trent 772	5.0	35.80	71100	0.82	35	1994	DD	3	0.565	17105
Rolls-Royce	Trent 772B-60	4.9	36.80	72000	0.82	35	1998	DD	3	0.565	17215
Rolls-Royce	Trent 875	6.1	35.42	79100	0.83	35	1995	DD	3	0.560	19430
Rolls-Royce	Trent 877	6.0	36.30	81300	0.83	35	1995	DD	3	0.560	19650
Rolls-Royce	Trent 884	5.9	38.96	87700	0.83	35	1995	DD	3	0.560	20284
Rolls-Royce	Trent 890-17	6.2	40.70	91300	0.83	35	1995	DD	3	0.560	20602
Rolls-Royce	Trent 892	5.7	41.38	92500	0.83	35	1997	DD	3	0.560	20762
Rolls-Royce	Trent 895	5.7	41.52	92900	0.83	35	1999	DD	3	0.560	20801
Rolls-Royce	Trent 970-84	8.5	38.00	76100	0.85	35	2006	DD	3	0.518	19379
Rolls-Royce	Trent XWB-84	9.0	41.10	85200	0.85	35	2013	DD	3	0.488	21163
Rolls Royce	Trent XWB-97	8.0	48.60	98200	0.85	35	2017	DD	3	0.488	22771
IAE	V2500-A1	5.3	29.80	25000	0.80	35	1988	DD	2	0.580	7300
IAE	V2522-A5	4.9	25.70	23043	0.80	35	1996	DD	2	0.575	7500
IAE	V2524-A5	4.8	26.90	24518	0.80	35	1996	DD	2	0.575	7597
IAE	V2525-D5	4.8	27.20	25000	0.80	35	1992	DD	2	0.575	7900
IAE	V2527-A5	4.8	27.20	25000	0.80	35	1992	DD	2	0.575	7651
IAE	V2528-D5	4.7	30.00	28000	0.80	35	1992	DD	2	0.575	8140
IAE	V2530-A5	4.6	32.00	29900	0.80	35	1992	DD	2	0.575	8219
IAE	V2533-A5	4.5	33.44	31600	0.80	35	1996	DD	2	0.575	8420
NASA SFW	UHB	18.8	44.7	36833	0.80	35	2015	G	2	0.477	9300
NASA AATT	N3CC-2016	17.6	31.6	18830	0.70	35	2040	G	2	0.461	5343
NASA AATT	N3CC-2017	17.3	36.9	21515	0.78	35	2040	G	2	0.485	6012
NASA AATT	N+3	27.5	36.6	28620	0.80	35	2040	G	2	0.464	9354
NASA AATT	Small Core geared	25.5	38.8	37659	0.80	35	2040	G	2	0.460	12152
NASA AATT	N3CC-2018	21.6	36.7	21662	0.79	37.7	2040	G	2	0.479	6007
NASA ERA	Large-DD-2015	16.6	43.7	71792	0.80	35	2030	DD	2	0.480	21399
NASA ERA	Large-DD-2015-HWB-V1	14.4	48.9	67183	0.80	35	2030	DD	2	0.485	18768
NASA ERA	Large-DD-2015-HWB-V2	13.7	49.8	67233	0.80	35	2030	DD	2	0.487	18832
NASA ERA	Large-Geared-2015-HWB-V3	20.0	47.2	56172	0.80	35	2030	G	2	0.465	15591
NASA ERA	Large-Geared-2015-HWB-V2	20.0	47.1	67423	0.80	35	2030	G	2	0.464	18823
NASA ERA	Large-Geared-2015-HWB	19.3	47.2	67386	0.80	35	2030	G	2	0.466	18823
NASA ERA	Large-Geared-2015	24.7	39.9	74149	0.80	35	2030	G	2	0.458	23023
NASA ERA	Medium-Geared-2015	23.9	38.4	45829	0.80	35	2030	G	2	0.466	13631
NASA ERA	Medium-Geared-2015-V2	24.8	38.5	45799	0.80	35	2030	G	2	0.465	13668
NASA ERA	Small-DD-2015	9.9	28.7	14647	0.80	35	2030	DD	2	0.526	3815
NASA ERA	Small-DD-2015-V2	10.0	28.7	14686	0.80	35	2030	DD	2	0.525	3812
NASA ERA	Small-Geared-2015	27.0	24.6	21525	0.80	35	2030	G	2	0.485	6203
NASA ERA	Small-Geared-2015-V2	27.4	24.8	21553	0.80	35	2030	G	2	0.483	6232
NASA ERA	Large-DD-2014	16.2	47.4	80071	0.80	35	2030	DD	2	0.469	22534
NASA ERA	Large-Geared-2014	22.4	47.2	87496	0.80	35	2030	G	2	0.458	23248
NASA ERA	Medium-Geared-2014	22.4	44.7	51295	0.80	35	2030	G	2	0.467	12645
NASA ERA	Small-DD-2014	9.8	29.7	15566	0.80	35	2030	DD	2	0.519	3833
NASA ERA	Small-Geared-2014	24.7	29.2	24887	0.80	35	2030	G	2	0.486	5913
NASA SFW	SA-FPR1.4-DD-2D	18.4	33.1	23813	0.80	35	2025	DD	2	0.479	10563
NASA SFW	SA-FPR1.5-DD-2D	15.0	33.8	23370	0.80	35	2025	DD	2	0.496	7965
NASA SFW	SA-FPR1.6-DD-2D	12.7	34.4	23046	0.80	35	2025	DD	2	0.510	6592
NASA SFW	SA-FPR1.7-DD-2D	10.9	35	22734	0.80	35	2025	DD	2	0.525	6099
NASA SFW	SA-FPR1.3-GR-HW-2D	24.1	32.6	26343	0.80	35	2025	G	2	0.470	8736
NASA SFW	SA-FPR1.4-GR-HW-2D	17.5	33.8	24917	0.80	35	2025	G	2	0.486	7401
NASA SFW	SA-FPR1.5-GR-HW-2D	14.6	33.5	23369	0.80	35	2025	G	2	0.502	6626
NASA SFW	SA-FPR1.6-GR-HW-2D	12.4	34	22924	0.80	35	2025	G	2	0.517	6252
NASA SFW	SA-FPR1.3-GR-HW-2E	26.0	32.3	28358	0.80	35	2025	G	2	0.473	8550
NASA SFW	SA-FPR1.4-GR-HW-2E	18.0	33.8	26575	0.80	35	2025	G	2	0.495	7123
NASA SFW	SA-FPR1.5-GR-HW-2E	12.1	35.4	24686	0.80	35	2025	G	2	0.515	6305
NASA SFW	SA-FPR1.6-GR-HW-2E	9.9	36.3	24262	0.80	35	2025	G	2	0.534	5896
NASA SFW	SA-FPR1.7-DD-LW-2E	8.5	37.6	23889	0.80	35	2025	DD	2	0.547	5561
NASA SFW	Simulated Genx	9.2	41.4	63800	0.85	35	2008	DD	2	0.523	17198
NASA SFW	Simulated GE90-110B	7.2	42	110000	0.85	35	2003	DD	2	0.549	23728

System type: DD = direct-drive system
G = geared system

SFW—Subsonic Fixed Wing project
ERA—Environmentally Responsible Aviation project
AATT—Advanced Air Transport

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