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A MACHINE-LEARNING APPROACH TO ASSESS AIRCRAFT ENGINE SYSTEM PERFORMANCE

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ABSTRACT

Machine learning and big data have become the most disruptive technologies for organizations to improve workplace efficiency and productivity. This work explored the application of machine learning-based predictive analytics that would enable aircraft engine designers to estimate engine system performance quickly during the conceptual design stage. Supervised machine-learning algorithm was employed to study patterns in an open-source database of one-hundred-eighty-three production and research turbofan engines, and built predictive analytics for use in predicting system performance of new turbofan designs. Specifically, the author developed deep-learning analytics to predict turbofan *system weight*, using turbofan design parameters as the input. The predictive analytics were trained and deployed in Keras, an open-source neural networks API (application program interface) written in Python, with TensorFlow (an open-source Google machine learning library) serving as the backend engine. The current engine-weight prediction results, together with those for the TSFC (thrust specific fuel consumption) and core-size predictions that were studied previously by the author, show that machine learning-based predictive analytics can be an effective, time-saving tool for assessing aircraft engine system performance (TSFC, weight, and core size) during the conceptual design stage. It would enable expeditious identification of the best engine design amongst several candidates.

Keywords: aircraft engine, deep learning, Python, TensorFlow

INTRODUCTION

Due to the high-risk nature and stringent safety requirements of aviation industry, technological improvements of aircraft engines are generally made incrementally, drawing heavily from experiences and lessons learned. Engine companies have generated and collected large amounts of data over the years. These big data, from various sources such as the database of currently manufactured engines, current development projects, previously completed development

projects, and the designs that were not manufactured, are valuable resources of intelligence that can support new engine development. With advances in data science and machine-learning algorithms, employing machine learning to mine these data can provide valuable insights that could drive higher levels of efficiency in engine conceptual design.

Aircraft engine design is a time-consuming, multi-disciplinary task. During the conceptual design phase, engine designers often face a daunting challenge: how can one quickly estimate the performance of a particular engine design? When one considers aircraft mission requirements and all the engine design parameters, the set of possible engine configurations can be large. Generally, in exploring the design space, designers fall back onto system study and simulation to estimate the performance of each engine configuration. They must perform a complete propulsion system study on each possible configuration before its performance can be found, which can be time-consuming for a large design space. In this and previous work, the author fills the gap by developing machine learning-based predictive analytics that would enable the designers to estimate engine TSFC, system weight, and core size quickly during the conceptual design stage. Rapid turnaround time and reliable engine performance estimations at the conceptual design stage can be a powerful competitive advantage in aircraft engine development.

The author's previous studies [1 and 2] showed that machine learning-based analytics can be an effective tool for engine thrust specific fuel consumption (TSFC) and core-size prediction. In this work, the focus was on the application of machine-learning analytics for engine-weight prediction. Supervised machine-learning algorithms for regression were employed to find patterns in the database of one-hundred-and-eighty-three manufactured engines and engines that were studied previously in various NASA aeronautics projects. Analytics for engine-weight prediction was built. The objective was to determine if machine learning-based predictive analytics

could be an effective tool for engine-weight prediction at the conceptual design stage.

Engine weight is a key design parameter for any new aircraft engine. It affects aircraft range and is a key element in fuel burn. Weight is also considered an indicator of engine cost. Reliable engine-weight estimation at the conceptual design stage is critical to the development of new aircraft engines. It helps to identify the best engine concept amongst several candidates.

ENGINE DATABASE

The basic engine architecture in this study was an axial-compressor turbofan. The engine database consisted of 144 manufactured (commercial) engines [3 to 9] and 39 engines that were studied previously in various NASA aeronautics projects. These commercial engines span the era from the mid-1960s to late-2010s. The database captures over half-a-century of engine technology improvements and lessons-learned, which injects realism to the predictive analytics. The NASA engine data were the system-study results for various NASA aeronautics projects [10–15].

There are three different types of turbofan systems in the database:

<u>System type</u>	<u>No. of engines</u>
2-spool direct-drive	130
2-spool geared	27
3-spool direct-drive	26

NASA uses engine *system weights* for its aircraft performance assessment. However, majority of the open-source engine weight data are *dry weights* that exclude inlet, nacelle and nozzles. To account for these excluded components, the engine weights for these systems were determined by multiplying the *dry weights* by system-weight-to-dry-weight ratios. These weight ratios were estimated based on a few available commercial propulsion system weights and those of the NASA systems. They are shown in Figure 1.

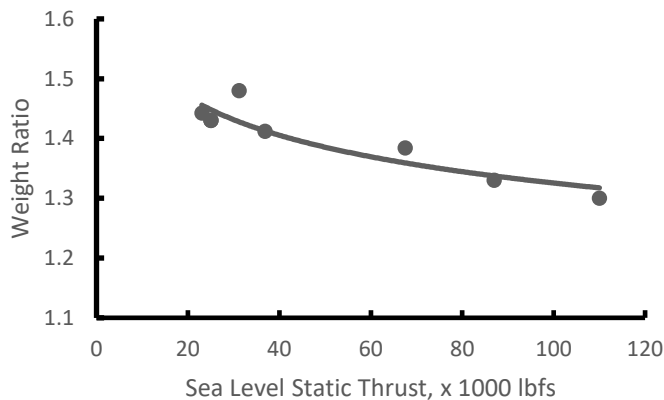


Figure 1 – Engine system-weight-to-dry-weight ratio

DEEP-LEARNING NEURAL NETWORK (DNN)

Deep learning is a subset of machine learning that uses multiple-layered artificial neural network [16] to progressively extract higher-level features from the input, and to establish correlations between the input variables and the outputs. In this work, the author developed a deep learning-based predictive analytics for engine-weight prediction.

Deep-Learning Neural Network for Engine-weight Regression

Engine-weight prediction was considered a regression problem. Due to the high degree of accuracy required for the weight prediction, its predictive analytics was developed using a deep-learning neural network (DNN) that established correlations between the input variables and engine weight. In this work, the DNN consisted of one input layer, seven hidden layers, and one output layer. Each subsequent hidden layer, consisted of six neurons, progressively extracting higher-level features from the input. These layers used backpropagation to optimize the weights of the input variables to improve the predictive power of the analytics. A scaled exponential linear unit (SELU) function [17] was used for the activation function in the hidden layers, defined as:

$$SELU(x) = scale \begin{cases} x & \text{if } x > 0 \\ \alpha e^x - \alpha & \text{if } x \leq 0 \end{cases}$$

where x = weighted sum of input variables

$\alpha \approx 1.67326$, a predefined constant to preserve the mean and variance of the inputs

$scale \approx 1.05070$, a predefined constant to preserve the mean and variance of the inputs

A grid-search routine was used to determine the regularization parameter, number of epochs, batch size, and the number of ‘neurons’ in the hidden layers that give the lowest training error. L2 regularization (or Ridge regression) technique [17] was used to avoid overfitting the training data. The number of epochs determined the number of times an entire training dataset was passed forward and backward through the DNN. Batch size referred to the number of training samples used for each iteration. The Adam optimization algorithm [18] was used for this effort. The predictive analytics was trained and deployed in Keras [17], an open-source neural networks API written in Python, with Google’s TensorFlow [19] serving as the backend engine. Keras provided the building blocks for developing the deep-learning analytics, and TensorFlow handled the tensor computations and manipulations. TensorFlow is an open-source library for numerical computation and large-scale machine learning.

PREDICTIVE ANALYTICS

With the DNN described in the previous section, the author developed a predictive analytics for engine-weight prediction. The Python programming language was used to develop the analytics.

Input engine design parameters for weight predictive analytics were:

- Bypass ratio
- Overall pressure ratio (OPR) at sea level static condition
- Sea level static thrust
- Cruise Mach number
- Cruise altitude
- System design parameter – either direct-drive or geared
- System configuration – either 2-spool or 3-spool
- Engine technology factor (engine certified year)

The sea-level flight condition for OPR and thrust was chosen for data availability; majority design data for these two parameters are publicly available at the sea-level flight condition. For the NASA engines, the engine certified years were assumed to be 2025, 2030, and 2040 respectively for the engines that were studied for entry-into-service in the N+1, N+2, and N+3 timeframes. The timeframes were directed at three generations of aircraft in the near, mid, and far terms that were studied under NASA aeronautics projects.

Training and building the predictive analytics involved machine learning algorithms and data science. The approach consisted of three steps: dataset preparation; building, training, and cross-validation of the preliminary analytics; and building, training, and evaluation of the final analytics.

- Dataset preparation

The engine dataset was 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 analytics. The testing set consisted of the remaining engines that were unseen by the predictive analytics, and was retained for the final evaluation of the predictive analytics. Table 1 depicts the training-testing dataset split.

Table 1

Training-Testing dataset split for the predictive analytics

System	Training dataset (no. of engines)	Testing dataset (no. of engines)
2-spool direct-drive	103	27
2-spool geared	22	5
3-spool direct-drive	21	5
Total	146 (80% of dataset)	37 (20% of dataset)

- Building, training, and cross-validation of the preliminary analytics

The building, training and cross-validation of the analytics were conducted using the training dataset. Within the training dataset (146 engines), a 6-fold cross-validation procedure was used to conduct a preliminary evaluation and to fine-tune the analytics. The training dataset was randomly split into 6 groups: 5 groups were used to train the analytics and 1 group was used to cross-validate the analytics. This process was repeated 6 times so that each of the 6 groups got the chance to be used for training and validation. The performance measure was then the average of the values, in terms of the means and standard deviation, computed in the iteration loop.

- Building, training, and evaluation of the final analytics

Cross-validation was no longer needed for this step, i.e., all 146 engine data were used to build and train the predictive analytics. The analytics were then used to predict the engine weights in the testing dataset (37 engines), and the results were compared with the actual data in the testing dataset.

PREDICTIVE RESULTS

Preliminary training and cross-validation results

During preliminary training and cross validation, the algorithm parameters and prediction uncertainty were determined. Using grid-search routines, the algorithms parameters that give the smallest errors for both analytics are shown in Table 2.

Table 2 – Deep neural network parameters

Parameters
Number of hidden layers = 7
Number of neurons in each hidden layer = 6
Regularization parameter = 0.00003
Learning rate = 0.00095
Epoch=10206
Batch size = 16

The prediction accuracy for engine weight measured how close the prediction was to the training data. The uncertainty was defined at 95% confidence level, i.e. two standard deviations for normal data distribution. The preliminary training and cross-validation results show that the analytics has a mean accuracy of 95.1%, with 5.3% uncertainty. They are shown in Table 3.

Table 3 – Preliminary training and cross-validation results for analytics accuracy with training data

Mean accuracy	Uncertainty 95% confidence interval (2 standard deviations)
95.1%	5.3%

Evaluation of the final predictive analytics with testing dataset

The final predictive analytics, built with the parameters determined during the preliminary training and with all 146 training data (i.e., no cross validation), were then used to predict the engine weights in the testing dataset (the 37 engines unseen by the analytics). Table 4 summarizes the evaluation results of the engine-weight predictive analytics. On average, the prediction accuracy is quite high, at 96.8%. Table 5 shows the detailed comparison of the prediction and the testing data. The prediction accuracy exceeds 90% for 36 of the 37 engines. The prediction accuracy for the one engine is 89.7%. Comparing to the TSFC and core-size predictions that were done previously using machine-learning analytics [1 and 2], the engine-weight prediction is more complex because of the geometric design variables (the number of spools, direct-drive or geared system, etc.). Further improvement of overall accuracy would require more training data, especially those for the geared and the 3-spool systems. As shown in Table 1, the current dataset has only 22 geared and 21 3-spool engines available for training.

Table 4

Evaluation results of the engine-weight predictive analytics with testing data

Accuracy (mean)	Accuracy (maximum)	Accuracy (minimum)
96.8%	99.9%	89.7%

The performance of the deep-learning model over time during training is shown in Figure 2. It shows the mean squared error decreases consistently and converges over training epochs. The DNN engine-weight analytics performs well consistently for both the training and testing datasets. An epoch is a measure of the number of times an entire dataset is passed forward and backward through the neural network.



Figure 2 – Deep-Learning Neural Network model accuracy on training and testing datasets

Table 5 - Comparison of engine-weight predictions with testing dataset

Org.	Engine model	Engine Weight (lbs)		Accuracy %		Org.	Engine model	Engine Weight (lbs)		Accuracy %
		Data	Prediction					Data	Prediction	
P&W	1127G	6300	6950	89.7	←	P&W	4462	15127	14974	99.0
P&W	JT9D-7	13102	12992	99.2		P&W	JT9D-3A	12794	12571	98.3
CFM	56-5A5	7534	7274	96.5		P&W	JT9D-7R4H1	14340	14333	99.9
P&W	JT9D-7A	13169	13264	99.3		Rolls Royce	Trent XWB-97	22771	21951	96.4
GE	CF6-80E1A4	14844	15267	97.2		GE	CF6-6D	11750	11468	97.6
NASA ERA	Small-DD-2015	3814	3850	99.1		P&W	4164	16887	15396	91.2
P&W	JT9D-7Q	14056	13994	99.6		NASA AATT	Small Core geared	12151	11168	91.9
GE	CF6-80C2A8	14783	14395	97.4		IAE	V2525-A5	7652	7313	95.6
NASA ERA	Small-DD-2015-V2	3812	3900	97.7		CFM	56-5C3	9121	9044	99.1
GE	90-115B	25876	24499	94.7		P&W	JT9D-70A	13991	13983	99.9
P&W	JT8D-209	5905	5525	93.6		P&W	4056	14491	14242	98.3
NASA ERA	Large-DD-2015-HWB-V2	18768	18869	99.5		Rolls Royce	Trent 768	16840	16398	97.4
Rolls Royce	Trent 877	19650	19324	98.3		CFM	56-5B1	8366	8376	99.9
Rolls Royce	RB211-524B4-02	13309	13168	98.9		NASA ERA	Large-Geared-2014	23247	22776	98.0
IAE	IAE V2525-D5	7900	7313	92.6		NASA ERA	Large-Geared-2015-HWB	18823	18452	98.0
GE	CF6-45A2	12927	12289	95.1		GE	CF6-80C2B2	14038	13370	95.2
Rolls Royce	RB211-524B	13270	13060	98.4		NASA SFW	SA-FPR1.5-DD-2D	7965	8076	98.6
NASA ERA	N+3	9354	8513	91.0		NASA ERA	Small-DD-2014	3832	4016	95.2
NASA SFW	SA-FPR1.6-GR-HW-2D	6252	5845	93.5						

Mean accuracy = 96.8%

← accuracy below 90%

AATT – Advanced Air Transport Technology project

ERA – Environmentally Responsible Aviation project

SFW – Subsonic Fixed Wing project

CONCLUSIONS

The author developed a deep-learning predictive analytics for engine-weight prediction. The development used the database of one-hundred-eighty-three production engines and engines that were studied previously in NASA aeronautics projects. The engine-weight predictive analytics has a mean accuracy of 96.8%, with 5.3% uncertainty. Overall, the analytics show remarkable prediction accuracy considering the limited amount of data available for the training.

To further improve the overall accuracy (and reduce the uncertainty) of engine-weight prediction, the database would need to be expanded; to have more training data for the *geared* and the *3-spool* turbofans. However, the limit availability of open-source engine data is a challenge to overcome.

The current engine-weight prediction results, together with those for the TSFC and core-size predictions that were studied previously [1 and 2], show that by bringing together sufficient (big) high quality data, robust machine-learning algorithms, and advances in data science, machine learning-based predictive analytics can be an effective, time-saving tool for assessing aircraft engine system performance (TSFC, weight, and core size) during the conceptual design stage. It would enable expeditious identification of the best engine design amongst several candidates.

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Appendix A

Engine database

<u>Org.</u>	<u>Engine Model</u>	<u>BPR (SLS)</u>	<u>OPR (SLS)</u>	<u>Thrust, lbs (SLS)</u>	<u>Cruise Mach</u>	<u>Cruise Alt. k ft.</u>	<u>Year certified</u>	<u>System Type</u>	<u>No. of Spools</u>	<u>Cruise TSFC lb/lbf.hr</u>	<u>Propulsion System Weight, lbs</u>
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 (cont'd)

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
GE	GE90-858	8.4	38.37	87315	0.80	35	1995	DD	2	0.553	21656
GE	GE90-908	8.4	39.70	94000	0.80	35	1997	DD	2	0.545	22280
GE	GE90-948	8.3	40.53	97300	0.80	35	2000	DD	2	0.545	22592
GE	GE90-1158	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-Q2	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

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Appendix (cont'd)

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