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R&D Target-Setting Difficulties Addressed through Emergent Method: Technology Forecasting Using Data Envelopment Analysis

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The aim of this study is to provide a foundation for researchers and managers to further discuss and resolve difficulties associated with R&D target-setting. While multiple studies mention the difficulty of R&D target-setting, few studies exist which compile reasons for these difficulties; nor do they address this issue in any detail. This paper provides what appears to be one of the first studies outlining reasons for R&D target-setting difficulties through a literature review; then also provides an initial set of analyses and results after applying an emerging quantitative method, Technology Forecasting Using Data Envelopment Analysis (TFDEA) addressing these difficulties, step-by-step to commercial airplanes. Results include determining the state-of-art in commercial airplane technology and technological rate-of-change variants in setting R&D targets.

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1. Introduction

A multitude of studies mention difficulties in R&D target-setting as well as make statements in support of continued research focus on this issue; yet few studies were found which compile and/or address these R&D target-setting difficulties into one review and deeper analysis. One study states that a system of technology estimation and forecasting is needed to improve R&D target-setting, but to-date, this system is "…not yet well-established." (Y.-G. Lee & Song, 2007) Other studies mention R&D target-setting difficulties faced in order to set policy targets for science and technology in Israel (Trajtenberg, 2002) and Thailand (Sabhasri & Yuthavong, 1983). Adding urgency to this research topic, a couple studies mention how the need to address R&D target-setting issues is timely and expected to increase in importance (Edler, Meyer-Krahmer, & Reger, 2002; Sungjoo Lee, Kang, Park, & Park, 2007). Lee, et al. (2007), is one of the more comprehensive frameworks found which translates technology roadmapping into operational processes, yet this study also focuses on the overall technology planning process without delving deeper into the R&D target-setting difficulties.

To address this research gap, first a list of R&D target-setting difficulties was necessary, and this is accomplished as shown below in the literature review. Secondly, an example of addressing these difficulties is shown through applying an emergent method, Technology Forecasting Using Data

Envelopment Analysis (TFDEA) to commercial airplanes. TFDEA has been mentioned as a possible method which could aid strategic R&D decision-makers (Inman, 2004).

Complex technological barriers, as well as exogenous economic, environmental, and government concerns (Ashford, 1985; Esposito, 2004; Gillett & Stekler, 1995) help form a difficult set of critical decisions in new product development and R&D target-setting facing commercial airplane manufacturers. As an earlier study indicates (A. Lamb, T. R. Anderson, & T. U. Daim, 2010), the whole host of parameters affecting these decisions has contributed to an application difficult for technology forecasting and determining strategies for R&D target-setting. Frequently, forecasters overcome these airline industry challenges by focusing on one or a subset of parameters (Brueckner & Pai, 2009; Fraser, 1985; Liu, 1993; Masson, Brown, Soban, & Luongo, 2007; Ruffles, 2003).

This paper highlights application of TFDEA to commercial airplanes to aid in overcoming some of the difficulties in technology R&D target-setting. Specifically it addresses: 1) **Methods needed which focus on measuring technology inputs and outputs as reliable yardsticks; 2) external/competitor technology monitoring**; 3) **trend analysis and forecasting needed**; and **4) human-based motivation factors**. Multiple technology rates-of-change (RoC) are utilized in order to showcase decision-making options facing managers.

2. Literature Review

Setting targets was generally included as one of the tasks in the increasingly formalized process/approach for technological innovation seen in the literature in the late 1990s/early 2000s. (Chiesa, Coughlan, & Voss, 1996; McDermott & O'Connor, 2002; Song & Montoya-Weiss, 1998; Veryzer Jr, 1998; Zhang & Doll, 2001) This literature included a heavy emphasis in making a distinction between R&D innovation processes for incremental versus new products (McDermott & O'Connor, 2002; Song & Montoya-Weiss, 1998; Veryzer Jr, 1998). Then, in addition to a couple early examples (Nightingale, 2000; Sabhasri & Yuthavong, 1983), there has been a growth in the literature since 2002 stating that R&D target-setting has been difficult from several perspectives: Specific technology application examples--with a heavy emphasis on energy technologies--(Bosetti, Carraro, Sgobbi, & Tavoni, 2009; Kosugi, Hayashi, & Tokimatsu, 2004; Sungjoo Lee et al., 2007; Y.-G. Lee &

Song, 2007; Nightingale, 2000; Zinkle, 2005); specific industry journals (Kosugi et al., 2004; Nightingale, 2000; Zinkle, 2005); national perspective papers (Bosetti et al., 2009; Sabhasri & Yuthavong, 1983; Trajtenberg, 2002); and, in addition to these industry-specific journals, a few examples have begun to appear in recent technology management and R&D research journals. (Bremser & Barsky, 2004; Edler et al., 2002; Sungjoo Lee et al., 2007; Y.-G. Lee & Song, 2007; Okuyama & Matsui, 2003). The field today does not provide a depth of understanding of the specific R&D target-setting difficulties: Four are discussed below, and then summarized in Table 1.

R&D target-setting decision-makers struggle with what aspects of a technology to measure—what are the inputs, outputs, and reliable yardsticks for assessing the technology? Methods are needed which focus on measuring technology inputs and outputs as reliable yardsticks (Kosugi et al., 2004; Sabhasri & Yuthavong, 1983; Zinkle, 2005). **(Input/output focus as reliable yardsticks)**

Also, while there appears to be general agreement on the importance of knowing external and competitor information for feeding the R&D target-setting decisions, decision-makers often find it difficult knowing how to narrow this sub-topic sufficiently in order to not become lost in all the data (Edler et al., 2002; Sungjoo Lee et al., 2007). **(External/competitor technology monitoring)**

One note of interest is that recent discussions by experts in the field centered around whether monitoring should be considered a separate, stand-alone, activity in R&D management, or a sub-process step leading to improved capability for forecasting. These experts advise monitoring should be considered as leading (in other words a sub-process step) toward improved forecasting (Roper, Cunningham, Porter, Mason, & Banks, 2011). Again, while there appears to be wide agreement that studying the historical technology development and future trends is important for setting R&D targets; robust and less limiting methods are needed for doing so, particularly with fewer restrictions on what technological aspects can be measured accurately (Edler et al., 2002; Kosugi et al., 2004; Sungjoo Lee et al., 2007; Y.-G. Lee & Song, 2007; Sabhasri & Yuthavong, 1983). **(Trend analysis and forecasting needed)**

An emerging and compelling sub-topic research area in difficulties with setting R&D targets revolves around the motivations of the managers involved in the target-setting process itself. Although "…target setting and budget goals are intended to provide motivation for employee actions" (Bremser

& Barsky, 2004), there is increasing evidence that managers set technological target goals based on what they believe is more easily achievable rather than pushing technological progress/boundaries (Bremser & Barsky, 2004; Sunghan Lee, Ahn, & Choi, 2009; Nightingale, 2000). **(Human-based motivation factors)**

Table 1: Literature Review on R&D Target-Setting Difficulties and Description

	R&D Target-Setting Difficulties	Description	References
1	**Input/output focus as reliable yardsticks**	R&D target-setting decision-makers struggle with what aspects of a technology to measure—what are the inputs, outputs, and reliable yardsticks for assessing the technology?	(Kosugi et al., 2004; Sabhasri & Yuthavong, 1983; Zinkle, 2005)
2	**External/competitor technology monitoring**	Decision-makers often find it difficult to know how to narrow this sub-topic sufficiently in order to not become lost in all the external and competitor technology data.	(Edler et al., 2002; Sungjoo Lee et al., 2007)
3	**Trend analysis and forecasting needed**	Robust and less limiting methods are needed for conducting trend and forecast analysis, particularly with fewer restrictions on what technological aspects can be measured accurately.	(Edler et al., 2002; Kosugi et al., 2004; Sungjoo Lee et al., 2007; Y.-G. Lee & Song, 2007; Sabhasri & Yuthavong, 1983)
4	**Human-based motivation factors**	There is increasing evidence that managers set technological target goals based on what they believe is more easily achievable rather than pushing technological progress/boundaries.	(Bremser & Barsky, 2004; Sunghan Lee et al., 2009; Nightingale, 2000)

Again, further discussion of the initial four R&D target-setting difficulties and their application to commercial airplanes will form the framework for deeper analysis and depth on these topics in the current study.

Anderson, et al, 2008, provided historical context for technology forecasting research and fit with TFDEA so this will also not be covered in this paper. (Anderson, Daim, & Kim, 2008) This paper was designed in mind to show managers and researchers how TFDEA can aid in strategic planning, new product project selection, and overall technology trends and paradigm shifts (Anderson et al., 2008; Scott, 1993)—but applied to commercial airplanes and specifically addressing how these sub-topics can be used in facing difficulties in R&D target-setting.

There is not one encompassing set of parameters to use for focused decision-making on airplane technology studies (Ashford, 1985; Esposito, 2004; Gillett & Stekler, 1995). A couple papers describe the use of technological and economic parameters for jet fighters (Inman, Anderson, & Harmon, 2006; Martino, 1993); and although there are some shared parameters between jetfighters and commercial aircraft such as speed and range, there are significant differences in what is important to manufacturing each with the jetfighter more focused on weaponry and non-detection and less so on passenger economics and profit – important considerations for commercial airplanes (Gillett & Stekler, 1995).

Gillett and Stekler (Gillett & Stekler, 1995) provided a detailed descriptive paper on the strategic process of introducing a new airplane. Based on their work, and augmented from additional literature sources, five critical technological performance parameters being used today by airplane manufacturers, and their customers, the airlines, are: Fuel efficiency/capacity (Gillett & Stekler, 1995; Kumar & Hefner, 2000; Masson et al., 2007; Ruffles, 2003); range (Gillett & Stekler, 1995; Kumar & Hefner, 2000); max speed and typical cruising speed (Esposito, 2004); and, number of passengers (Gillett & Stekler, 1995; Kumar & Hefner, 2000; Wall, 2006b). These five parameters will form the basis of our model for applying TFDEA in this current study.

The current commercial airplane study focuses attention on applying TFDEA to complex and costly systems similar to fighter jets, but instead illustrates a current much discussed technology and commercial industry with more market and economic constraints than the military and fighter jets.

3. Methodology

The five measures of performance are utilized in the Data Envelopment Analysis (DEA) introduced in Charnes' seminal paper in 1978 (Charnes, Cooper, & Rhodes, 1978). DEA is now a widely accepted (Cooper & Seiford, 2004) econometrics-based method for measuring relative efficiency; in particular for determining organizational, decision-making, and business process efficiencies. However, DEA requires regular time periods for comparing relative efficiency; thus, until recently, rendering the method incapable of forecasting technologies which are typically introduced at intermittent time periods. TFDEA is a recent extension of DEA to allow for technology applications.

Used concurrently with DEA, state-of-art (SoA) frontiers are conceptually combined to allow for TFDEA to become a dynamic method for technology forecasting and assessment. SoA is defined as "the state of best implemented technology as reflected by the physical and performance characteristics actually achieved during the time period in question". (Sahal, 1976)

To aid in conceptual understanding, the step-by-step operational explanation of TFDEA is provided below (Table 2) as well as explaining how these steps apply to commercial airplanes. Steps correspond to equations in Appendix 1.

Table 2: Step-by Step Operational Explanation of TFDEA applied to Commercial Airplane

Step	Commercial Airplane (k)
(1)	For each airplane (pre 2007)
(2) *	Measure that airplane relative to all previous airplanes (prior to the release date)
(3) *	Measure the plane relative to 2007 (the year chosen for setting the forecast)
(4) **	Calculate the technological rate of change
(5)	Repeat for each consecutive airplane model
(6) **	Calculate overall average rate of change (RoC) for all airplanes

* Steps 2 & 3 are derived from the mathematical formulae, Eq's (1-7), in Appendix 1.
** Results from Steps 4 & 6 are used for forecasting future airplane models.

4. Analysis and Discussion: Addressing Difficulties in R&D Target-Setting Through Results from Technology Forecasting Using Data Envelopment Analysis

As discussed in the literature review section, the primary areas of difficulties in R&D target-setting were found to be: Methods needed which focus on measuring technology inputs and outputs as reliable yardsticks; external/competitor technology monitoring; trend analysis and forecasting needed; and human-based motivation factors. These provide this study with a framework in which to analyze the results from TFDEA applied to a set of commercial airplanes.

4.1. Methods needed which focus on measuring technology inputs and outputs as reliable yardsticks

Decision-makers struggle with what aspects of a technology to measure—what are the inputs, outputs, and reliable yardsticks for assessing the technology? (Kosugi et al., 2004; Sabhasri & Yuthavong, 1983; Zinkle, 2005) While one researcher states the need for multiple indicators, the assertion continues with a recommendation to "…classify indicators into input and output indicators."

(Sabhasri & Yuthavong, 1983) Although the authors of this paper recommend combining TFDEA with additional methods; TFDEA is based on multiple input and output indicators. As described in the literature review section above, parameters chosen to measure were from technological performance output parameters which could help represent the many economic/market factors influencing technology design of commercial aircraft. There is no one standard for a researcher doing a study of this type on commercial aircraft; therefore rationale was tied with the literature review findings above to focus on the parameters below.

- First Customer Flight Year. A year of new product introduction was needed and was settled on first customer flight date because that is the first commercial use.
- Maximum Passengers. The maximum number of passengers that an airplane can transport is used as a primary payload and profit goal for a commercial plane.
- Maximum Speed. Maximum speed (Esposito, 2004) is the maximum speed at which a plane is designed to operate.
- Cruising Speed. The air speed at which an airplane model is designed to operate most efficiently. It occurs between ascent and descent phases and forms the majority of the time of the flight. (Esposito, 2004; Gillett & Stekler, 1995)
- Maximum Range at Full Payload. The long range commercial planes particularly needed the economies with pushing the passenger capacity (Gillett & Stekler, 1995; Kumar & Hefner, 2000; Wall, 2006b). Maximizing passenger load is often a tradeoff with range so that is why the three class configuration was chosen because it allows maximum range particularly for the longer overseas flights which were an important market driver. Other than in the definition section, this parameter will now be referred to simply as range for the purposes of brevity.
- Passenger Fuel Efficiency. Although frequently mentioned as a critical performance output parameter; there appears to be widely differing definitions for fuel efficiency. To provide a consistent measurement reflecting the importance of passengers as “economics”—revenue generators, this study will focus on passenger fuel efficiency (Thomas, 2005). Fuel capacity (Gillett & Stekler, 1995; Kumar & Hefner, 2000; Masson et al., 2007; Ruffles, 2003) was collected in order to derive passenger fuel efficiency as fuel efficiency has economic and technology trade-

offs such as allowing longer ranges and reduced overall weight. Passenger fuel efficiency (PFE) can be generalized as:

$$Passenger\ Fuel\ Efficiency = \frac{Passengers * Range}{Fuel\ Capacity} \quad (9)$$

The set of parameters used for this forecasting study are summarized in Table 3.

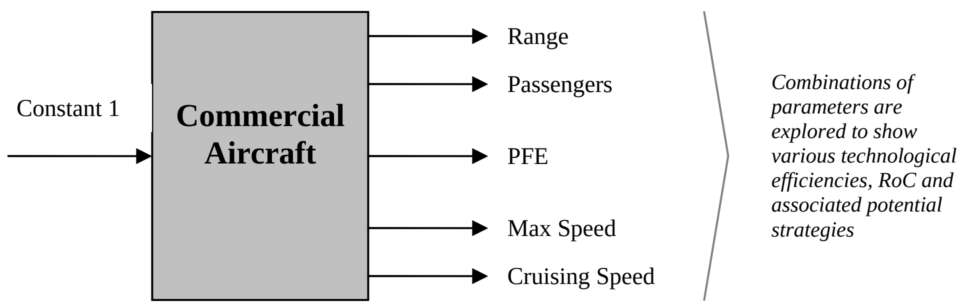
Table 3: Variable Definitions

Variable	Abbrev.	Unit	Definition
First Customer Flight Year	Year	Year of Commercialization	The date the customer (airline) first flies the model.
Maximum Passengers	Passengers	Quantity of Passengers	The maximum number of passengers expected to fly on the standard model (3-class configuration).
Cruising Speed	Cruising Speed	km/hr	The air speed at which the airplane is designed to operate with maximum efficiency.
Maximum Speed	Max Speed	km/hr	The maximum speed at which the airplane is designed to operate, typically with decreased range.
Maximum Range at Full Payload	Range	1000s km	The maximum range at which a standard model can fly carrying a full payload.
Fuel Capacity		Kiloliters	Fuel weight when all tanks are full. Not used in model except to derive passenger fuel efficiency below.
Fuel Efficiency		km/liters	Derived variable with range divided by fuel capacity.
Passenger Fuel Efficiency ($\log_{10}$PFE)	PFE	(passengers*km) /liters	Derived from the above variables: Max Passengers, Max Range at Full Payload, and Fuel Capacity.

The model with it's performance outputs is depicted in Figure 1 below. As technological strategy is built off of trade-offs in decision-making and goals, the authors will also explore various combinations of parameters to determine a variety of technological rate-of-changes. Together, this information provides a foundation of information and data for airplane manufacturers to utilize in strategic decision-making for setting R&D targets; addressing competitive and technological evolution and prediction.

Future models could consider inputs such as cost per plane, R&D cost, R&D time, annual maintenance cost, and/or required crew size.

Figure 1: Illustration - Performance Output Variables for Commercial Aircraft Model



By creating increased focus on inputs, outputs and objective design and performance data, TFDEA can enable increased reliable yardsticks in which to study technological progress.

4.2. External/competitor technology monitoring

TFDEA requires individual technology introduction start dates; and to collect this data by manufacturer aids in building the specificity needed to examine the technology for both special innovative events as well as possible competitor strategy; therefore, as a method, TFDEA focuses necessarily on both external and competitor technology monitoring. Table 4 is the list of past commercial airplane models with their associated performance output.

Table 4: Historical data set used for this study *(*Note, Fuel Capacity used only to derive PFE)*

	Aircraft	Year	Range	*Fuel Capacity	Passengers	PFE	$\log_{10}$(PFE)	Cruising Speed	Max Speed
1	DC8-55	1965	9.205	88.55	132	13.721	2.619	870	933
2	DC8-62	1966	9.620	91.89	159	16.646	2.812	870	965
3	747-100	1969	9.800	183.38	366	19.559	2.973	893	945
4	747-200	1971	12.700	199.16	366	23.339	3.150	893	945
5	DC10-30	1972	10.010	137.51	250	18.199	2.901	870	934
6	DC10-40	1973	9.265	137.51	250	16.844	2.824	870	934
7	L1011-TriStar 500	1979	10.200	120.34	234	19.834	2.987	892	955
8	747-300	1983	12.400	199.16	412	25.652	3.245	902	945
9	767-200ER	1984	12.200	90.77	181	24.327	3.192	849	913
10	767-300ER	1988	11.065	90.77	218	26.575	3.280	849	913
11	747-400	1989	13.450	216.84	416	25.803	3.251	902	977
12	MD-11	1990	12.270	146.17	293	24.595	3.203	870	934
13	A330-300	1993	10.500	97.17	295	31.877	3.462	870	913
14	A340-200	1993	15.000	155.04	261	25.252	3.229	870	913
15	A340-300	1993	13.700	147.85	295	27.335	3.308	870	913
16	MD-11ER	1996	13.408	157.53	293	24.939	3.216	870	934
17	777-200ER	1997	14.305	171.17	301	25.155	3.225	892	945
18	777-300	1998	11.120	171.16	365	23.713	3.166	892	945
19	A330-200	1998	12.500	139.10	253	22.735	3.124	870	913
20	A340-600	2002	14.600	195.88	380	28.323	3.344	881	913
21	A340-500	2003	16.700	214.81	313	24.334	3.192	881	913
22	777-300ER	2004	14.685	181.28	365	29.568	3.387	892	945
23	777-200LR	2006	17.370	181.28	301	28.841	3.362	892	945
24	A380-800	2007	15.200	323.55	525	24.664	3.205	902	945

**Note, data revised from (A.-M. Lamb, T. Anderson, & T. Daim, 2010)

The commercial airplane example includes airplanes manufactured by Boeing, Airbus, and Lockheed Martin, and McDonnell-Douglas.

It was shown in a previous study that of all the R&D activities, monitoring external technology received the lowest percentage of R&D funds (Edler et al., 2002). TFDEA could enable focus on what information to track on competitor/external technology and thereby also ease this area of difficulty for target-setting.

4.3. Trend analysis and forecasting needed.

Again, while there is some agreement that studying the historical technology development and future trends is important for setting R&D targets; quantitative and less limiting methods are needed for doing so, particularly with fewer restrictions on what technological aspects can be measured accurately (Edler et al., 2002; Kosugi et al., 2004; Sungjoo Lee et al., 2007; Sabhasri & Yuthavong, 1983).

4.3.1. Trend analysis

. For this study, two sets of parameters are used as a basis for strategic discussion in setting targets. In running the model, the authors found these two sets to represent the fastest and slowest technological rate of change (**Table 5**). The Efficiency at Time of Release column show a value of one if the product was considered efficient upon release. Several airplane models were introduced as non state-of-art (SoA). A few possibilities exist to explain these results.

First, a previous study by the same authors showed (A. Lamb et al., 2010) the complexities of exogenous (economic, social, and political) factors which are considered in the new product introduction decisions for airplane manufacturers; and while the TFDEA model likely accounts for some of the economic considerations within the passenger fuel efficiency parameter, improvements to the model could work toward accounting for a greater number of the exogenous factors where possible. One recent example is that for various political reasons, the Airbus A380 entailed far greater development costs than expected; yet various European governments financially supported development in which profit from this model is far from certain or projected to take even 20 years for Airbus to see a profit (Matlack, 2006, Oct. 10).

Secondly, the long product lifecycle of these airplane models, sometimes reaching 30 years combined with the high development costs and long design lead times could lend itself toward high risk product introductions for the manufacturers as a different manufacturer may be first entrant to a market, leading toward a potential increase in non-state-of- art product introductions.

Thirdly, while this dataset concentrates on the longer range and 100+ passenger airplane models; even within this segmentation there are subsets of airplane models built to accommodate more specific range requirements and smaller numbers of passengers. This could potentially account for some of the product differentiation results. Also, it may form part of the airplane manufacturer's strategy to design an initial model with higher priority on reaching a market segmentation first; potentially sacrificing some design and/or performance capability, even if considered non-state-of-art.

Trends in non-state-of-art, efficiency and overall technological rate of change match fairly well with historic knowledge of airplane competitiveness; for example, after the initial DC8, airplane model state of art introductions, the manufacturer found itself uncompetitive in the market place with its subsequent DC10 models and the dominance of the Boeing 747 performance.

The DC8-62 is a good example to use in which to further explain the actual trends. To simplify, one set of parameters and rate-of-change results will be discussed (passengers, range, and passenger fuel efficiency). The third column, Efficiency at Time of Release corresponds to $\phi_{DC8-62}^{t_{DC8-62}}$ and again, the value of one translates to the DC8-62 as being released as state-of-art upon its first flight in 1966. However, in 2007, it is now being compared against newer airplanes that would outperform it by at least 22.4% on every output. A technology rate-of-change, γ_{DC8-62}^{2007}, is determined to be $(1.224)^{1/(2007-1966)}=1.0049$. In other words, the model shows that DC8-62's obsolescence is explained by an annual improvement of nearly .5%. As expected most older airplane models no longer qualify as efficient in 2007. Note, however, that Airbus' first introduction of the A330-300 remains efficient in 2007 (this will be reviewed later in the study). One model to note is that when introduced, the 747-400 had the max output in 3 of the 5 parameters; range, passengers, and max speed. If all the parameters were used in the analysis, then two of the Boeing 747s (747-300 and 747-400) would also still qualify as state-of-art with respect to 2007 in at least one, or some combination, of the outputs. As expected with a product given these characteristics, models introduced since 2004 also qualify as state-of-art.

Table 5: Efficiency & Rate of Change Results (Past Models)

			Parameters: Passengers, Range, PFE			Passengers, Range, PFE, Max Speed & Cruise Speed		
	Airplane Model	Year	Efficiency at Time of Release	Efficiency Relative to 2007 State of Art	Rate of Change (RoC) - Gamma Estimate	Efficiency at Time of Release	Efficiency Relative to 2007 State of Art	Rate of Change (RoC) - Gamma Estimate
1	**DC8-55**	1965	1	1.31306	1.006506	1	1.036782	1.00086
2	**DC8-62**	1966	1	1.224527	1.004953	1	1.012435	1.000301
3	**747-100**	1969	1	1.121813	1.003029	1	1.010078	1.000264
4	**747-200**	1971	1	1.066136	1.00178	1	1.010078	1.000279
5	**DC10-30**	1972	1.085832	1.186446		1.018338	1.036782	
6	**DC10-40**	1973	1.115439	1.221014		1.018338	1.036782	
7	**L1011-TriStar_500**	1979	1.05457	1.152885		1	1.011211	1.000398
8	**747-300**	1983	1	1.023841	1.000982	1	1	
9	**767-200ER**	1984	1.016489	1.072785		1.016492	1.046808	
10	**767-300ER**	1988	1	1.050501	1.002596	1	1.033532	1.001737
11	**747-400**	1989	1	1.020941	1.001152	1	1	
12	**MD-11**	1990	1.018599	1.06799		1.017837	1.032142	
13	**A330-300**	1993	1	1		1	1	
14	**A340-200**	1993	1	1.048588	1.003395	1	1.029588	1.002085
15	**A340-300**	1993	1	1.030277	1.002133	1	1.024468	1.001728
16	**MD-11ER**	1996	1.026105	1.058958		1.016798	1.030187	
17	**777-200ER**	1997	1.007184	1.051809		1	1.009574	1.000953
18	**777-300**	1998	1.045742	1.061711		1.011211	1.011211	
19	**A330-200**	1998	1.06489	1.093434		1.036782	1.036782	
20	**A340-600**	2002	1	1.006888	1.00137	1	1.006888	1.001374
21	**A340-500**	2003	1	1.028063	1.006943	1	1.014706	1.003656
22	**777-300ER**	2004	1	1		1	1	
23	**777-200LR**	2006	1	1		1	1	
24	**A380-800**	2007	1	1		1	1	
				Total Avg RoC=	**1.00317**		Total Avg RoC=	**1.00124**

The Boeing 767 family is a good example of an evolving product in which the manufacturer prioritizes market entry above technology performance. The Boeing 767 was not initially introduced for very long ranges (it was initially introduced as a medium range—out of scope for our dataset—but was given some improvements to reach the long-range market, thus the extended range designator ER, 767-200ER, and the model reflects Boeing's need to get into this market segment by indicating it was not competitive at the time of its release in 1984, yet further improvements by Boeing then decreased passenger capacity which enabled the highest PFE of all previous airplanes in our dataset then enabling the 767-300ER, to be introduced as state-of-art in 1988. The model, for the most part reflecting technological evolution, has predicted earlier technological improvements than what market and other exogenous factors would allow for as well as Boeing retrofitting a previous airplane structure.

Both Boeing and Airbus introduced incremental plane models (777-300 and 330-200 respectively) in 1998 that, according to both the three and five output models, were technologically inefficient. The 777-300 was introduced to replace earlier 747 models (747-100 and 747-200), and although the goal of surpassing 747-200 fuel efficiency was met, technological changes were kept to a minimum in order to maintain maximum commonality to 777-200 to minimize maintenance costs for the airlines. As previously referred to, the decision to introduce a new airplane model is mitigated highly by market, economic, political and other exogenous factors (Esposito, 2004; Fraser, 1985; Gillett & Stekler, 1995; A. Lamb et al., 2010); so the decision by Boeing to maintain greater commonality in order to minimize maintenance costs for the airlines is another example of where the model indicates economic trade-offs in decision-making by airline manufacturers.

On the same note, the Airbus 330-200, in part, was introduced in 1998 to compete with the Boeing 767-300ER (interestingly introduced ten years earlier in 1988), and although the 330-200 outperforms or equals its intended competitor in four of the five performance outputs; the 767-300ER still outperformed in passenger fuel efficiency. As this example indicates, with superior performance models introduced in between long periods of development time—this last point reflects a good part of the reason why forecasters have had difficulty in applying forecasting methods to commercial airplanes (Ashford, 1985; Esposito, 2004; Gillett & Stekler, 1995).

4.3.1.1. Technology Rate-of-Change (RoC)

The measurement of technological progress discussed in the section above, and how one technology surpasses another over time, combine to determine the technological rate-of-change (RoC). The airplane models that were released as state-of-art, as well as having been surpassed by subsequent aircraft model technology, are used to calculate the rate at which overall airplane technology progressed ($\bar{\gamma}$). The model RoC variant used for this study is further explained in Appendix 2. The RoC calculation for each technology (airplane model) is:

$$\gamma_k^{t_f} = \left(\phi_k^{t_f}\right)^{1/(t_f - t_k)} \ \forall\ k \text{, such that } \phi_k^{t_k} \le 1 \text{ , } \phi_k^{t_f} > 1 \qquad (8)$$

.

Table 5 shows which airplane models fit these criteria and thus contribute to the overall RoC for commercial airplanes. One example is the 747-300, efficient when released, but compared to 2007 has now been surpassed by subsequent airplane models and therefore contributes a RoC of 1.000982 = $(1.023841)^{1/(2007-1983)}$. As shown in Table 5, the three parameter model (passengers, range, and passenger fuel efficiency) average annualized RoC for this set of aircraft is 1.003. This corresponds to technology progressing at just 3/10s of a percent average change annually. In contrast, the slower average annual RoC (taking into account all five parameters) is just 1.001; 1/10s of a percent change annually. Both RoC seem low; however, as the authors showed in initial analysis of this study (A. Lamb et al., 2010), when considering the physical challenges in regards to speed of sound barriers, the high product development costs, as well as the conflicting exogenous factors (market, economic, environmental, and political)—the commercial airplane RoC appears to be more reasonable.

Additionally, the authors also considered two other RoC results in previous TFDEA studies; nearly 11% for wireless communications (Anderson et al., 2008), and approximately 3% for jet fighters (Inman et al., 2006), the commercial aircraft technology progress appears acceptable for our model forecast. "These comparatively slow RoCs are also consistent with the long production and service lifecycles of commercial passenger aircraft—if the RoC was faster, aircraft models would be retired much more quickly" (Lamb et al., 2010)

Again, utilizing TFDEA provided a quantitative-based method for R&D target-setting decision-makers to study past technological trends; a method which allows for relevant technological input/output indicators.

4.3.2. Forecasting

The same parameter output specifications were gathered on four future airplane models which Boeing and Airbus have announced development on Table 6. While most specifications were drawn from a key source on aircraft performance (Jackson et al., 2009), some triangulation of data sources was necessary to ensure parameters were for 3-class passenger data.

Table 6: Suggested Specifications for Forecasted Models

Parameter:	Airplane Model: 787-8 Dreamliner	747-8	787-9 Dreamliner	A350-900
Year	2010	2011	2013	2013
Cruising Speed	902	908	902	902
Maximum Speed	945	977	945	945
Range	15.7	14.816	15.75	15
Passengers	242	467	280	315
Fuel Capacity	126.9	243.1	126.54	135.8
Passenger Fuel Efficiency (PFE)	29.940	28.462	34.851	34.794
PFE_{log10}	3.399	3.349	3.55	3.549

Specifications for future products are difficult for forecasters as they tend to alter closer to the release date. Given this, the primary airplane model where some assumption was made on latest data was the Boeing 747-8. Originally, Boeing had made the assumption the airlines would be prioritizing passenger comfort with wider seats and lounge area; however, in reality, as more actual orders are made, the airlines are putting a higher priority on revenue and ordering options with increased passenger seating. The shift in priorities and associated economic and profit strategies; however, provides for a more realistic view of the commercial passenger new product introduction.

Using the above specifications and running the model with both the 3 and 5 parameter RoCs provides the results in Table 7. Eq. (9) is the output-oriented equation for determining the results in the column: Predicted Efficiency at Time of Release. The outputs are multiplied by the coefficient of technological progress (γ) --in other words RoC, raised to an exponent equal to the number of time periods that have passed from forecast year assessment (2007 in our model) to the manufacturer's stated introduction year for the technology (Inman, 2004).

$$y^{t}_{r,k} = y^{t}_{r,k} \times (\gamma)^{t-t_k}, \ \forall r \in \{1,\ldots,s\} \quad (9)$$

Table 7: Forecasts of Future State-of-Art & Release Dates

Airplane Model (Forecast)	Manufacturer Provided Year of Introduction	Passengers, Range, PFE: RoC=1.003 — Efficiency Relative to 2007 State of Art	Predicted Efficiency at Time of Release	Fcst Year of Introduction	Passengers, Range, PFE, Max Speed & Cruise Speed: RoC=1.001 — Efficiency Relative to 2007 State of Art	Predicted Efficiency at Time of Release	Fcst Year of Introduction
787-8 Dreamliner	2010	0.996501	1	2003.8	0.989973	1	2011.4
747-8	2011	0.979892	1	2012	0.975083	1	2022.2
787-9 Dreamliner	2013	0.956494	1	2015.7	0.956494	1	2037.5
A350-900	2013	0.959307	1	2013.6	0.959307	1	2034
			MAD=	**2.67**		MAD=	**14.55**

**Note: If efficiency relative to 2007 SoA<1, then future planes are expected to be efficient compared to all previous planes introduced prior to 2007. If predicted efficiency at time of release =1; then that model is expected to be efficient given the model output parameters used.*

With the 3 parameter RoC of 3/10s of a percent, the model, while not too far off for the last three model forecasts, shows that with technological progress specifications of the 787-8 Dreamliner, the forecast with the current measured variables shows the airplane could have been introduced in late 2003 although still considered SoA relative to 2007 frontier. While not covered in detail in this paper, TFDEA uses a composite comparison of prior airplanes to compare the 787-8 Dreamliner to; in this case it is compared 25% to Airbus' A330-300 and 75% to Boeing's own 777-200LR. The composite outputs show the 787-8 Dreamliner having superior performance to the composite airplane in both range and PFE. However, being compared 75% to the 777-200LR introduced in 2006 results in the predicted year of release being closer to the 777-200LR (787-8 Dreamliner predicted year of release at 2003), rather than the A330-300 year of 1993. TFDEA comparison composites are explained in detail in (Inman, 2004).

These results could also be an indication of the model not being able to capture the differences and investment needed for new structural airplane models as opposed to follow-on models. Details of the huge design investment Boeing made in incorporating 50% composite materials into the 787-8 Dreamliner (whereas it had not had a long-range airplane model prior to this with more than 10%) are covered in depth in (A. Lamb et al., 2010). A second example of this to watch is that when Airbus first announced plans for the A350-900, the plans entailed fewer changes to the structure than what the airliner customers demanded for design changes to include into the fuselage—this model is; therefore, an interesting one to monitor for actual compared to model predictions. A possible third example of how the model may not reflect new structural models compared to follow-on models is to look at the 5-parameter RoC predicts the 787-8 Dreamliner first customer flight date fairly accurately. Upon reflection this could be expected as a more radical structure would have higher numbers of performance parameters to have a greater influence and interdependencies on the overall design.

Given the results from the trending and forecasting sections, further exploration in the model is recommended in order to more accurately depict differences between more or less design structure changes (new or follow-on models). One suggestion would be to include an input/cost variable: ‘Design man weeks to first service per passenger’ was suggested as a possible proxy cost variable for commercial airplanes (Matlack, 2006, Oct. 10; Pinto, 2009).

Some additional technological developments (as input parameters) that could be compelling in this model (and would need a way to measure) are: Engine developments (Mecham, 2005b; Wall, 2006a; Wall & Mecham, 2005; *www.boeing.com*, 2009); plane construction and aerodynamics (Anon, 2006; Mecham, 2005a; Wall, Flottau, & Anselmo, 2006; Wall & Mecham, 2006); composite material structure (Anon, 2006; Mecham, 2005a; Read, 2005; Toensmeier, 2005; "www.aerospace.org," 2009; *www.boeing.com*, 2009), and expected use of advanced systems controls (Mecham, 2006; Wall et al., 2006; Wall & Mecham, 2006; Watkins & Walter, 2007). Researchers in this section mention the frustration in the industry with the importance of advancements in these technologies, but with the difficulty of measuring them particularly as a cost in new design airplanes.

With any of these inputs, it is recommended to explore a different underlying math (or constraint) to the TFDEA model, with testing results given a “Decreasing returns to scale (DRS) [which] refers to diminishing returns for additional input beyond points of inflection” (Inman, 2004). Obtaining a 5% increase in passenger fuel efficiency performance for the highest performing commercial airplanes (or new structural models) may cost significantly more than 5% increase for the remaining models (or follow-on models)—a possible explanation for the model predicting the 787-8 Dreamliner introduction to be much earlier than reality. Eq. (2) in Appendix 1 would be replaced with $\sum_{j=1}^{n} \lambda_{j,k}^{h} \le 1$. Both the resulting forecast and historical technological performance data can be used to address the remaining R&D difficulty: **Human-based motivation factors**.

4.4. Human-based motivation factors

Recent research indicates the growing attention to difficulties in R&D target-setting based on human motivation and its associative effects on setting targets. Target-setting is intended to motivate managers involved in the target-setting process (Bremser & Barsky, 2004) yet there is increasing evidence that managers set technological target goals based on what they believe has a high probability of success—thereby increasing odds of receiving benefits tied to meeting those targets (Sunghan Lee et al., 2009). Technological progress could be sacrificed to the more immediate concern of receiving benefits. The TFDEA method is particularly well-suited to address this concern.

As shown earlier through the TFDEA commercial airplane example: 1) **Inputs and outputs as reliable yardsticks**; 2) **external/competitor technology monitoring**; and 3) **trend analysis and forecasting**; are all exposed to decision-makers in an objective and quantifiable method for R&D target-setting. By utilizing historical product introductions and actual technological performance data, critical data pertaining to the technology is captured as part of the target-setting decision-making process. While TFDEA can also be combined with less quantitative-based methods in order to better capture expert opinion and other qualitative inputs; using the TFDEA results leaves less room for managers to base target decisions on only the most achievable goals. Decisions can now be based on rewards for meeting lower ends of possible technological progress or possibly higher rewards for reaching technological breakthroughs and pushing the SoA.

Using the data from this study, one case of this could include: Boeing's 2005 747-8 announcement stated, "…the 747-8 will burn 13% less fuel per seat than a 416-seat 747-400" (Thomas, 2005). Testing this claim, the performance data in the model shows (25.803/28.462=91%) → 9%. Using passenger fuel efficiency, the 747-8 will burn 9% less fuel. (Caution should be used in this assessment, as the exact parameters used in Boeing's less fuel per seat are unknown; and their model could have included more or fewer parameters.) Given this, the results are still significant, showing a clear improvement in fuel efficiency for the 747-8.

In the same announcement, Boeing compared the 747-8 with Airbus' 380, "…the 747-8 will burn 12% less [fuel] than a 542-seat A380"(Thomas, 2005). In this case, the performance data in our study (altering the A380-8 passenger seating from 525 to 542 passengers) indicates (26.575/28.462=93%) → 7% less fuel.

Rewards could be easily scaled based on the lower or higher expected technological performance gains. Using the last example of burning less fuel, higher rewards could be given to managers who reach the 12% less fuel burned; and lower rewards if technological progress prove to be at the lower end of the target of 7% less fuel burned.

5. Findings To-Date/Research Implications

To date, this study has contributed to research in the field of R&D target-setting by compiling a list of difficulties in R&D target-setting from the literature and it is hoped it can be a starting basis particularly for those managers and researchers interested in collaborating on this topic for further development. This study addresses: 1) **Methods needed which focus on measuring technology inputs and outputs/reliable yardsticks**; 2) **external/competitor technology monitoring**; 3) **trend analysis/forecasting needed**; and 4) **human-based motivation factors**. These difficulties have been discussed and analyzed using TFDEA with respect to applicability of using the method to address R&D target-setting.

The study showcases the capability of TFDEA to be applied to strategic decision-making in new product planning; and in particular, provides a step-by-step process of one approach to overcome four areas of R&D target-setting difficulties. It is an initial step toward addressing limitations in earlier commercial aircraft forecast studies; as well as from an earlier study on commercial airplanes which found multiple regression, linear regression, and growth curve forecasting methods too limiting on numbers of inputs and/or outputs which could be measured with this data (A. Lamb et al., 2010).

There are also several implications of this study for practitioners. As shown in the trend of literature on this topic, prior to this study, few examples have delved deeper into addressing specific difficulties for organizations facing the difficult decision of how to set R&D targets; it is hoped by the authors that by using the commercial aircraft example it aids the understanding of how some of these difficulties can be addressed. Specifically, airline manufacturers are able to use the TFDEA model for projecting state-of-art for future aircraft models while observing the rate of technological change (RoC) and output parameter performance needed. The results from this type of analysis can be used in new product development in order to validate, or invalidate, design plans and R&D target-setting. In conjunction, the aircraft suppliers can also use the RoC to project the necessary performance capabilities of airplane parts.

6. Limitations/Future Research Opportunities

There are several limitations to this study. First of all, the study focused on gaps in the difficulty in R&D target-setting literature and while every effort was made to bring forward specific difficulties, interviews with R&D managers and case studies on the same topic could expose even further areas of difficulties which the current literature may be missing. It is hoped this study can be a starting basis for researchers interested in R&D target-setting difficulties; but it is fully expected by the authors that much more can be gained for the research field with increased academic pursuit on this topic in future.

Future work could include:

- Further additions to reasons for difficulties in R&D target-setting. Examples could include; the difficult decision to pursue incremental or breakthrough technology development (Bosetti et al., 2009; Sungjoo Lee et al., 2007; Trajtenberg, 2002); the need to be vision-driven and depart from neutrality (Okuyama & Matsui, 2003; Trajtenberg, 2002); the need for inter-dependent component technology methods (Edler et al., 2002; Kosugi et al., 2004; Sungjoo Lee et al., 2007; Sabhasri & Yuthavong, 1983; Zinkle, 2005); high costs of R&D target-setting processes (Bosetti et al., 2009; Edler et al., 2002; Kosugi et al., 2004; Okuyama & Matsui, 2003);
- Adding further depth and discussion to the same four R&D target-setting difficulties with additional quantitative and qualitative methods;
- Additionally, while this study focused on five performance output parameters; a next step in developing this model could be to take into account not only additional output parameters, but

also current design (input) parameters to see how these might change both the state-of-art trends and forecast outlook.

- Another opportunity for continuing the development of this model would be to add a form of cost as an input in order to deepen analysis comparison between new and follow-on airplane models.

Any of the above input variables could be used in order to better understand overall technology advancement of each plane being introduced as well as to help with predictor estimates where needed.

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APPENDICES

Appendix 1: TFDEA Mathematical Notation, Output-Oriented DEA Model (Anderson & Inman, 2011)

Mathematical Notation for TFDEA	Eq.
Maximize $\sum_{k=1}^{n}(\phi_k^R + \phi_k^C)$	(1)
s.t. $\sum_{j=1}^{n}\lambda_{j,k}^{h} = 1, \quad h \in \{R,C\}, k \in \{1,2,...n\}$	(2)
$\sum_{j=1}^{n} X_{i,j}\,\lambda_{j,k}^{h} + s_{i,k}^{+,h} = X_{i,k}, \quad h \in \{R,C\}, k \in \{1,2,...n\}, i \in \{Inputs\}$	(3)
$\sum_{j=1}^{n} Y_{r,j}\,\lambda_{j,k}^{h} - s_{r,k}^{-,h} = \phi_k^h Y_{r,k}, \quad h \in \{R,C\}, k \in \{1,2,...n\}, r \in \{Outputs\}$	(4)
$\lambda_{j,k}^{R} = 0 \quad \forall (j,k) \mid t_j > t_k$	(5)
$\lambda_{j,k}^{C} = 0 \quad \forall (j,k) \mid t_j > T$	(6)
$\lambda_{j,k}^{h} \geq 0, \quad \forall (j,k), \; h \in \{R,C\}; \; s_{i,k}^{+,h}, \; s_{r,k}^{-,h} \geq 0 \;\; \forall (h,i,r,k)$	(7)

Details of the above math is outlined in (Anderson & Inman, 2011)

Appendix 2: Rate of Change Mathematical Notation for Constant (Static) Frontier Year

Mathematical Notation for Rate of Change, Constant Frontier Year	Eq.
$\gamma_k^{t_f} = \left(\phi_k^{t_f}\right)^{1/(t_f - t_k)} \;\; \forall \; k$, such that $\phi_k^{t_k} \leq 1$, $\phi_k^{t_f} > 1$	(8)

An overview of the above math is outlined in (Inman, 2004). While in most cases a variable frontier year seems to fit with our expectation of how technology develops, in this case, a constant (or static) frontier year was utilized given a static technological frontier is likely to be much more parsimonious in fitting (Akaike, 1974), and thus can be much more robustly fit given limited or low-quality performance data. Thus, it could be useful within a current generation of technology, or useful for when technologies within a generation are richly differentiated with features or options; for example seating options within an airplane model with +/- 10% difference in passenger seating arrangements. Additionally, tests were conducted by the authors to find that for this particular dataset, static frontier year had the lowest MAD.