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Technology Trajectory Mapping Using Data Envelopment Analysis: The Ex-ante use of Disruptive Innovation Theory on Flat Panel Technologies

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Technology Trajectory Mapping using Data Envelopment Analysis : The Ex-ante use of Disruptive Innovation Theory on Flat Panel Technologies

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Abstract- In this paper, we propose a technology trajectory mapping approach using Data Envelopment Analysis (DEA) that scrutinizes technology progress patterns from multidimensional perspectives. Literature reviews on technology trajectory mappings have revealed that it is imperative to identify key performance measures that can represent different value propositions and then apply them to the investigation of technology systems in order to capture indications of the future disruption. The proposed approach provides a flexibility not only to take multiple characteristics of technology systems into account but also to deal with various tradeoffs among technology attributes by imposing weight restrictions in the DEA model. The application of this approach to the flat panel technologies is provided to give a strategic insight for the players involved.

1. Introduction

Technological forecasting methods can be classified as either exploratory or normative by whether they extend present trends (exploratory) or look backward from a desired future to determine the developments needed to achieve it (normative) (Porter et al. 2011). The correct assessment of future environment and of the corresponding goals, requirements, and human desires can be better made when exploratory and normative components are joined in an iterative feedback cycle (Jantsch 1967). Here, it is crucial to have an accurate understanding of the technological inertia we have today so that exploratory methods extend the progress while normative methods determine how much the speed of such progress need to be adjusted. However, as technology systems become sophisticated, the rate of change varies more significantly, being affected by the maturity levels of component technologies (Lim et al. 2014).

This structural complexity makes today's forecasting even more challenging, which leads to the question: which set of attributes have the disruptive potential to be scaled up (or down) in the future?

Technology frontier analysis has been used in several ways to consider this multidimensional and combinatorial characteristics of technology systems (Gu and Kusiak 1993; Hazelrigg 1996; Martino 1993). The simplest form is the planar frontier model (or hyper-plane method) suggested by Alexander and Nelson (Alexander and Nelson 1973). Although this approach has an advantage of a simple implementation based on multiple regression analysis, a fitted functional form of the frontier based on a linearity assumption disallows to consider dynamic tradeoffs among technology attributes. As a non-linear frontier model, Dodson proposed an ellipsoid frontier formation (Dodson 1985). This model attempts to fit the technology frontier into *a priori* functional form from which tradeoffs among attributes can be explained. However, ellipsoid frontier model requires that the rate of one technical capability being relinquished for the advancement of the others rely on the predefined functional form rather than the nature of data at hand. Dodson's choice of an ellipsoid shape is analytically sound for the representation of a strictly convex surface but may not always be representative. Moreover, this model doesn't provide a time dependent measure to estimate the future state of the technology frontier. To tackle this issue, Danner suggested the iso-time frontier using Multi-Dimensional Growth Models (MDGM) (Danner 2006). In this approach, the frontier surface is formed by a composite relationship between time and technological characteristics. Therefore, the frontier can be navigated to project multiple characteristics into the future (Cole 2009). Possibly the greatest limitation to the utility of MDGM is the requirement that all dimensions of technical capability integrated must be statistically independent. This presupposes that the time required to advance each attribute towards corresponding upper limit can be linearly combined to explain the technology systems' growth rate. However, the higher the complexity of technology systems under evaluation is, the more individual growth rates are likely to be interrelated hence generated iso-time frontier without consideration on concurrent advancement would not provide an accurate picture of the feasible combinations of technical capabilities.

To overcome the disadvantages of the aforementioned methods, this study proposes an approach that can be used as a composite measure of technical capabilities as well as a tool for investigating rate of changes that enables to project the current technology frontier into the future.

2. Literature review on technology trajectory mapping

Mapping performance of technology over time can be helpful to identify potential disruptive technologies as well as to examine the maturity of incumbent technologies. Clayton Christensen and Michael Overdorf explained the theory of disruptive innovation by suggesting that "graph the trajectories of performance improvement demanded in the market versus the performance improvement supplied by the technology… Such charts are the best method I know for identifying disruptive technologies (C. M. Christensen and Overdorf 2000)."

Trajectory mapping has been employed in a wide range of applications. The most famous application of a trajectory map may be the hard disk drive case from Christensen's original work (C. M. Christensen 1993). He used disk capacity as a performance axis and interpreted the dynamics of industry that smaller disks have replaced bigger ones improving their capacities over time. Schmidt later extended Christensen's work by classifying the disk drive case as a low-end encroachment that eventually diffused upward to the high-end (Schmidt 2011). Martinelli conducted patent analysis in the telecommunication switching industry to find out seven generations of technological advances from the different paradigmatic trajectories (Martinelli 2012). Kassicieh and Rahal also adopted patent publication as a performance measure in search of potential disruptive technologies in therapeutics (Kassicieh and Rahal 2007). Phaal *et al.* proposed a framework that has been tested by developing more than 25 diverse 'emergence maps,' analogous to trajectory map, of historical industrial evolution, building confidence that the framework might be applicable to current and future emergence (Phaal et al. 2011). Keller and Hüsig analyzed Google's web-based office application to see if it can pose a disruptive threat to incumbent technologies, namely Microsoft's desktop office application (Keller and Hüsig 2009). Barberá-Tomás and Consoli tried to identify potential disruptive innovation in medical industry, especially on artificial disc, by counting the number of granted patent over time (Barberá-Tomás and Consoli 2012). Husig *et al.* (2005) conducted one of rare *ex ante* analyses that mapped out trajectories of both the incumbent technology and a potential disruptive technology (Husig, Hipp, and Dowling 2005). They made a forecast based on trajectory map that Wireless Local Area Network (W-LAN) technologies would not be disruptive for incumbent mobile communications network operators in Germany. This is because the average growth rate of the bandwidth supplied by W-LAN had been overshooting the average growth rate of the bandwidth requirements of all customer groups.

There are a few studies that used composite performance measures to draw the technology trajectories. Adamson plotted R^2 values from the multiple regression analysis on the trajectory map to investigate the fuel cell vehicle industry (Adamson 2005). The results showed that subcompact vehicle's R^2 values were increasing over time while compact vehicles' were decreasing. The author interpreted that the technological advancement of subcompact vehicle was becoming similar to that of compact vehicle. This study has significant implications for identifying key drivers of technology progress using the trajectory map. Letchumanan and Kodama mapped out the correlation between Revealed Comparative Advantage (RCA), which is generally used to measure the export competitiveness of a product from a particular country in terms of world market share, and R&D intensity to examine who was making the most disruptive advancement at a national level (Letchumanan and Kodama 2000). Even though Koh and Magee didn't utilize any function to develop composite performance measures, their research has a significance as they took different trade-offs into consideration to draw a trajectory map (Koh and Magee 2006). Their results suggested that some new information transformation embodiment such as a quantum or optical computing might continue the trends given the fact that information transformation technologies have shown a steady progress.

Table 1 summarizes 40 studies from 1997 to 2012 that have used trajectory map to identify disruptive alternatives including technology, product, and service. The majority of the studies adopted a single performance measure and simply connected time series data points, indicated as data accumulation, to draw the trajectory map.

A trajectory map should take multiple perspectives into account not to miss potential disruptive indications. This involves predicting what performance the market will demand along various dimensions and what performance levels will be able to supply (Danneels 2004). It is often recognized that new technologies would not always be superior to the prior one as well as performance disruption, i.e. intersection between trajectories, could occur from the technology that had been crossed in the past (Sood and Tellis 2005). Many *ex post* case studies have shown that disruptions have happened from an entirely new type of performance measure that hadn't been considered. This implies that current performance measure may be no longer capable of capturing advancement in a new direction. Therefore, it is crucial to examine not only which performance measures are playing a major role in current progress but also which alternate technologies show disruptive potential with respect to the emerging performance measures.

Table 1 Summary of literatures on the technology trajectory mapping

Author (year)	Application area	Performance measure	Plotting method
Walsh (2004)	Microsystems	Critical dimension	Growth curve
Keller & Hüsig (2009)	Office application	Number of operations	Data accumulation
Martinelli (2012)	Telecommunication	Patent citation	Data accumulation
Phaal et al. (2011)	S&T based industry	Sales	Data accumulation
Padgett & Mulvey (2007)	Brokerage market	Level of service integration	Data accumulation
X. Huang & Sošić (2010)	General industry	Capacity & Price	Data accumulation
Kaslow (2004)	Vaccine	Efficacy	Data accumulation
Kassicieh & Rahal (2007)	Therapeutics	Patent publication	Patent mapping
Christensen (1997)	Disk drive	Capacity	Data accumulation
Schmidt (2011)	Disk drive	Part-worth	Data accumulation
Rao et al. (2006)	P2P and VoIP	Data transfer	Data accumulation
Bradley (2009)	Medical operation (MRgFUS[1])	Noninvasiveness	Data accumulation
Lucas & Goh (2009)	Photography	Price, convenience, etc.	Data accumulation
Madjdi & Hüsig (2011)	W-LAN	Active Hotspot ratio	Data accumulation
Husig et al. (2005)	W-LAN	Data rates	Data accumulation
Walsh et al. (2005)	Silicon industry	Number of firms	Data accumulation
Figueiredo (2010)	Forestry industry	Novelty & complexity level	Data accumulation
Caulkins et al. (2011)	General industry	Market connection	Skiba curve
Adamson (2005)	Fuel cell vehicle	Utility coefficient values	Data accumulation
Belis-Bergouignan et al. (2004)	Organic compound	Environmental performance	Data accumulation
Ho (2011)	General industry (Taiwan)	Technology sources and innovation drivers	Data accumulation
Werfel & Jaffe (2012)	Smoking cessation products	Patent	Reduced form model
No & Park (2010)	Nano-biotechnology	Patent	Data accumulation
Letchumanan & Kodama (2000)	General industry (High-tech)	Correlation between Exports and R&D intensity	Data accumulation
Spanos & Voudouris (2009)	Manufacturing SMEs (Greek)	AMT[2]	Data accumulation
Frenken & Leydesdorff (2000)	Civil aircraft	Diffusion rate (Entropy statistics)	Data accumulation
Watanabe et al. (2009)	Printers	Sales and price	Technology price function
Hobo et al. (2006)	Service oriented manufacturing industry	Sales, income, employees, and productivity	Data accumulation
Watanabe et al. (2005)	Electrical machinery (Japan)	Marginal productivity	Data accumulation
S.-H. Chen et al. (2012)	Smart grid	Average age	Data accumulation
Epicoco (2012)	Semiconductor	Devices per chip	Data accumulation
Funk (2005)	Mobile phone	Mobile subscribers	Data accumulation
Raven (2006)	Renewable energy	Energy production(TJ/yr)	Data accumulation
Castellacci (2008)	Manufacturing and service industries	Labor productivity	Data accumulation
Kash & Rycoft (2000)	Radiation therapy	Capability	Growth curve
Arqué-Castells (2012)	General industry (Spain)	Patent	Poisson model
W.-J. Kim et al. (2005)	DRAM	DRAM shipment and Memory density	Data accumulation
C.-Y. Lee et al. (2008)	Home networking (Korea)	Units of new household/year	Data accumulation
Koh & Magee (2006)	Information technology	Megabits	Data accumulation
Barberá-Tomás & Consoli (2012)	Artificial disc	Patent	Data accumulation

[1]: *MR-guided Focused Ultrasound*

[2]: *Advanced Manufacturing Technology*

3. Methodology

To supply insight into the approach we are proposing, this section introduces Technology Forecasting using Data Envelopment Analysis (TFDEA.) The DEA model, which underlies TFDEA, is unique in that it allows each Decision Making Unit (DMU) to freely choose its own weighting scheme, and as such, the efficiency measure will show it in the best possible light (Charnes, Cooper, and Rhodes 1978; Fried, Lovell, and Schmidt 2008). This flexible weighting characteristic has shown practical advantages in a wide range of applications especially when the assessment involves complex tradeoffs that are difficult to model as a universal set of weights (Lim, Anderson, and Kim 2012). When the application area calls for limits on relative weights, upper or lower bounds of weights can also be implemented by imposing weight restrictions (Dyson and Thanassoulis 1988; R G Thompson et al. 1986; Russell G Thompson et al. 1990; Wong and Beasley 1990).

Based on the strengths of DEA, TFDEA has been used in a number of forecasting applications since the first introduction in *PICMET '01* (Anderson, Hollingsworth, and Inman 2001; Cole 2009; Lim, Anderson, and Shott 2014; Tudorie 2012). Figure 1 shows the TFDEA rate of change (RoC) calculation process with AR-I (Assurance Region type 1) weight restrictions implementation in a multiplier model (R G Thompson et al. 1986). Specifically, the variable $g_k^{t_f}$ serves as the objective function and represents the weighted sum of inputs using the most favorable set of weights, v_i, u_r, for technology k at time period t_f. Since each reference set only includes technologies that had been released up to t_f, $g_k^{t_f}$ indicates how superior (or efficient) the technology k is at the time of release. The effective year, t_k^{eff}, is determined by calculation of (1) to specify a weighted average of the old technologies that technology k is being compared against. Note that the benchmarking parameter, $\lambda_{j,k}$, is obtained from the envelopment model and calculation of (1) can be simplified as (2) in the case of VRS.

$$t_k^{eff} = \frac{\sum_j t_j \cdot \lambda_{j,k}}{\sum_j \lambda_{j,k}}, \quad \forall k \qquad (1)$$

$$t_k^{eff} = \sum_j t_j \cdot \lambda_{j,k}, \quad \forall k \qquad (2)$$

The RoC, $\gamma_k^{t_f}$ may then be calculated taking all DMUs that were efficient at the time of release, $g_k^{t_k} = 1$, but were superseded by technology at time t_f, $g_k^{t_f} > 1$. For a more comprehensive treatment of TFDEA, the interested reader is referred to earlier studies (Inman 2004; Lim, Anderson, and Inman 2014).

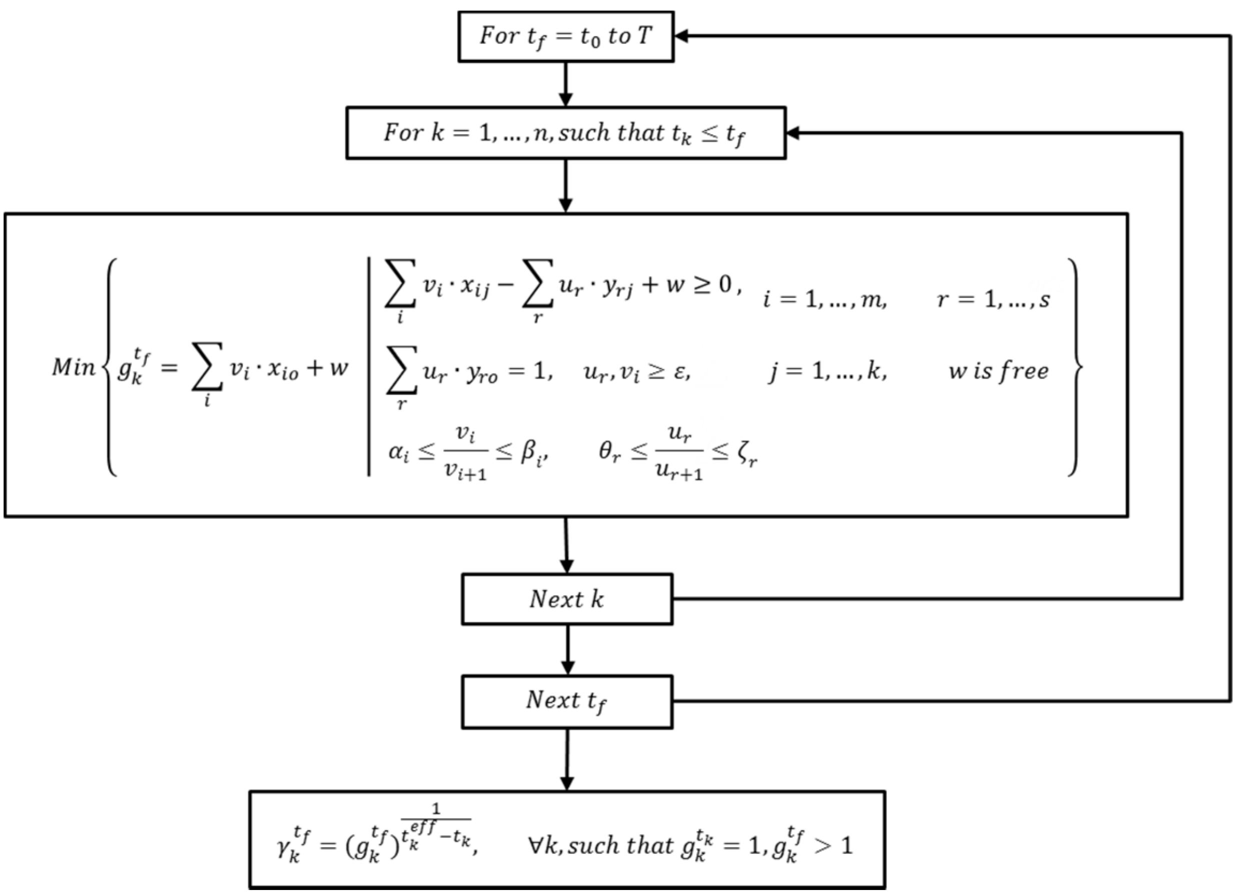

Figure 1 TFDEA RoC calculation process with AR-I implementation

4. Trajectory mapping on flat panel industry

To illustrate the use of the methodology presented in this paper, we provide an example of trajectory mappings that is applied to the flat panel industry to examine technology progresses from various perspectives.

4.1. Dataset

Lim, Runde, and Anderson investigated the technology advancement of Liquid Crystal Display (LCD) to forecast future state of the arts (SOAs) specifications (Lim, Runde, and Anderson 2013). This study examined 389 LCD panels with five characteristics that were determined from a group of LCD technologists. As a follow up study, the dataset has been updated to include 442 LCD panels and 29 Organic Light Emitting Diode (OLED) panels that have been introduced from 1998 to 2012 (see Table 2 for the summary of data). Variables included for this study are as follows:

- Company / Name (text): manufacturer and name of panel
- Backlight (text): illuminating source
- Year (year):year of release
- Screen Size (inches): diagonal length
- Bezel Size (millimeters): length from the outside shell to the beginning of the active area
- Weight (kilograms)
- Resolution (pixels): horizontal times vertical resolution
- Contrast Ratio (ratio): the ratio of luminance of brightness 0 to 100% energized pixel(s)

- Viewing Angle (degrees): the maximum horizontal angle at which a display can be viewed
- Response Time (milliseconds): amount of time a pixel takes to go from one value to another
- Energy Consumption (watts): sum of panel and lamp power consumptions in maximum brightness condition
- Brightness (cd/m^2): candela per square meter, equivalent to Nit or lux

Table 2 Dataset summary

Screen Type	LCD			OLED	Total
Backlight	CCFL	RGBLED	WLED		
No. of Products(Manufacturers)	260 (25)	21 (6)	87 (11)	28(5)	396 (29)
Years	1998~2012	2004~2012	2008~2012	2007~2012	1997~2012
Average Size (inches)	37.59	20.31	39.34	6.49	34.86
Average Weight (kilograms)	13.44	2.47	11.62	1.62	11.57
Average Resolution (pixels)	2.05 million	2.28 million	2.23 million	0.47 million	2.00 million
Average Contrast Ratio (ratio)	1,939.73:1	777.62:1	1,872.41:1	226,250.00:1	17,558.15:1
Average Viewing Angle (degrees)	172.72	167.43	174.85	168.71	172.68
Average Response Time (milliseconds)	8.79	14.85	6.11	0.22	7.90
Average Energy Consumption (watts)	188.98	40.46	176.20	14.73	165.28
Average Brightness (cd/m^2)	456.46	264.76	425.98	188.75	420.46

4.2. Analysis

The analysis was performed using the software developed by Lim and Anderson (2012). To facilitate the implementation of weight restrictions in an output oriented model, a constant 1 was used for an input and eight variables (screen size, weight, resolution, contrast ratio, viewing angle, response time, energy consumption, and brightness) were used as outputs for the model.

Since outputs need to be goods where increasing values are considered better, reciprocals of weight, response time, and energy consumption were used for the analysis (Cooper 2001; Färe and Grosskopf 2000). The VRS was used because both increasing and decreasing panel sizes cause major challenges. The frontier year was fixed as 2012 so that the technology progress was examined throughout the timeframe in the dataset.

Figure 2 illustrates technology trajectories of four representative panels: CCFL (Cold-Cathode Fluorescent Lamps) backlit LCD, RGBLED (Red-Green-Blue LED) backlit LCD, WLED (White LED) backlit LCD, and OLED. Solid (dotted) lines indicate trajectories of the level of top (average) performing panels in each year against the frontier year of 2012. Therefore, performance level of 100% indicates that the panel has a performance good enough to be identified as a state-of-the-art (SOA) in 2012. A performance level higher than 100% denotes super-efficiency from the DEA model which can show how superior each panel is to the SOA. For example, the first CCFL backlit LCD panel, ViewSonic VP140 in 1998, shows an efficiency score of 1.783191 which indicates that this panel should have produced at least 78% more of each output to be competitive with state of the art panels. In other words, the performance level of this panel is 56.08% (1/1.783) of the SOA frontier in 2012.

The trajectory of CCFL backlit LCD shows a continuous improvement over time. Samsung's 570DX introduced in 2007 was identified as the top performing CCFL backlit LCD with super-efficiency of 0.660749, that is, performance level of 151.3% compared to the SOA frontier. Note that post-2007 CCFL backlit LCDs are also considered to be SOA products-just not as outstanding as the 570DX. This special panel was intended to be a Digital Information Display (DID) that ensures superior performance even in the outdoor environments; full HD 1080p with 2.07 million pixels in total, 5000:1 contrast ratio in dynamic mode, 8ms response time, 178 degree viewing angle, and brightness of 600 cd/m^2 across the large (57″) screen.

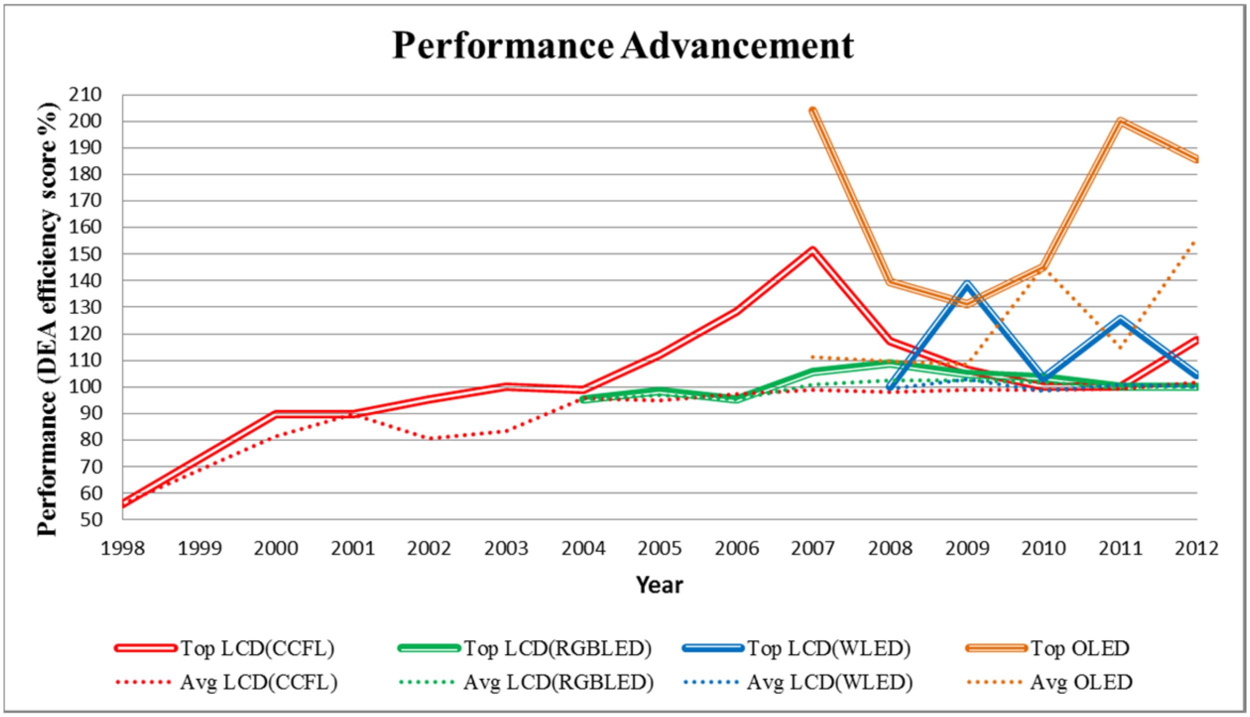

Figure 2 Trajectory map (unrestricted model)

The LED backlit LCDs began to be introduced to the market in 2004. The first RGBLED backlit panel, AUO M230UW01 V0, made a debut with a performance level similar to CCFLs in 2004 (95.15%). However, RGBLED backlit LCDs have not shown a distinct superiority over CCFL backlit LCDs. In contrast, WLED backlit LCDs have posed a threat to CCFLs since their first release in 2008. Table 3 summarizes the distinct features of top performing CCFL and WLED backlit LCDs from 2009 to 2011. It can be seen that WLED backlit LCDs were successful outperforming CCFLs with large screen, high contrast ratio and brightness.

The trajectory of OLED panels was identified to be ‘highly outstanding.’ This can be attributed to several unique characteristics of OLED displays. First of all, OLEDs are able to directly emit light rather than relying on a backlight. This enables OLED to display deeper black levels and therefore very high contrast ratios, a minimum of 10^5:1, whereas similar sized LCD panels are almost two orders of magnitude lower (see Table 3 ranging from 1000:1 to 2000:1.)

Additionally, OLED's self-emitting feature makes it possible for OLED panels to reduce power consumption while LCDs consume energy even when displaying black color. OLED panels also have a response time less than 0.1ms which is almost 1,000 times faster than typical LCD panels. Consequently, these extreme features placed OLED panels on the SOA frontier.

Table 3 State of the art CCFL/WLED backlit LCDs from 2009 to 2011 (unrestricted model)

Co.	Name	Year	Backlight	Size (Inches)	Contrast Ratio (ratio)	Brightness (cd/m^2)	DEA Score (%)
Sharp	LK636R3LZ1x	2009	CCFL	63.3	1300	350	106.67*
LG	LM300WQ5-SLA1	2010	CCFL	30	1000	370	99.98
LG	LM240WU7-SLB3	2011	CCFL	24	1000	400	99.94
Samsung	LTI700HD02	2009	WLED	70	2000	2000	138.80*
Samsung	LTM270HT03	2010	WLED	27	1000	300	103.38*
Berise	BR720D20	2011	WLED	72	1100	2000	125.59*

*: Super-efficiency score

Once the efficiency measurement is completed, TFDEA calculates a rate of change (RoC) which shows how much overall performance has improved enough to create the new technology frontier. In this sense, the average RoC of each technology can serve as an indication for future technological disruption. It should also be noted here that average RoC doesn't necessarily represent the overall slope of trajectories since the rate of change is calculated based on the frontier levels against the frontier year of 2012. That being said, inferior technologies to the previous year are presented on the trajectory map to show the technology progress pattern, however, they are excluded from the rate of change calculation since they didn't contribute to the evolution of the state of the art frontier.

Table 4 presents average RoC of four panels. The CCFL backlit LCD's average RoC is found to be 1.037864 which means efficiency score of SOA CCFLs have been increased by 3.8%

every year from 1998 to 2012. This may be interpreted that outputs of the CCFLs have been improving by 3.8% annually. The advancement of OLED technology shows the fastest progress of 4.7%. This again supports the disruptive potential of OLED panels in the future coupled with current superior level of performances.

Table 4 Average Rate of Change of four panels (unrestricted model)

CCFL backlit LCD	RGBLED backlit LCD	WLED backlit LCD	OLED
1.037864	1.012439	1.011571	1.046848

We now turn to our approach using restricted models. As previously noted, a dynamic weighting scheme can explain various possibilities of tradeoffs between inputs and outputs in DEA model. However, DEA studies often suffer from occurrence of unrealistic weight solutions and this becomes a motivation for applying the weight restrictions (Allen and Thanassoulis 2004). In our previous example, it was possible for the model to identify SOA products if panels had extreme characteristics in any attribute(s) that might not be key factors to be a better panel. Sony's OLED XEL-1, for example, had the highest DEA score of 203.99. This panel stands out against others because of the overwhelming contrast ratio (10^6:1) despite the fact that it may not be an appropriate panel for home TV use due to its very small size (11″) and low resolution (518,400 pixels) which is far below the HDTV requirements. The XEL-1 received its high score by placing a high weight on contrast ratio and disregarding important outputs on which it was very weak.

Imposing weight restrictions prevents key attributes from being omitted from the assessment and reflects a prior view into the assessment to ensure that tradeoffs in the DEA model are in line with practical knowledge. This has an implication in trajectory mapping that different progress patterns can be identified under the imposed conditions such as more significance was put on certain attribute(s) than others. These what-if analyses on trajectory mapping may also be useful when one tries to identify disruptive technologies for different market segments where customer's value propositions vary.

To illustrate restricted models, we applied two different weight restrictions to represent perspectives of 'casual home users' and 'technical artists.' The casual home users were assumed to pay more attention to screen size, resolution, viewing angle, brightness, and power consumption. This was implemented such that more weights were assigned to those attributes than others when panels were evaluated as seen in (3). Note the outputs were rescaled by dividing each panel's output value by the mean of that output in the full dataset. This is a commonly used transformation (Talluri and Yoon 2000) and was done prior to weight restrictions. Note that the dual approach is also possible using production trade-offs in the envelopment model (Podinovski and Bouzdine-Chameeva 2013).

$$u_{r\in CHU^c} \le u_{r\in CHU},$$
$$\forall r, CHU = \{Screen\ size, Resolution, Viewing\ angle, Brightness, Power\ consumption\} \quad (3)$$

The restricted model result for casual home users is shown in the Fig. 3. Unlike the unrestricted model, CCFL backlit LCDs now show higher performance compared to the other technologies. This is because CCFL backlit LCDs perform well on the specifications favored by casual home users. Indeed, manufacturers have been producing larger CCFL backlit panels with high resolutions, wider viewing angles, and brighter colors based on improving production processes. On the other hand, the relative weaknesses of CCFLs such as weight and response time are less important for casual home users which also assist CCFL panels' score more highly.

This is consistent with the success of the CCFL panels in the home HDTV television market through 2010.

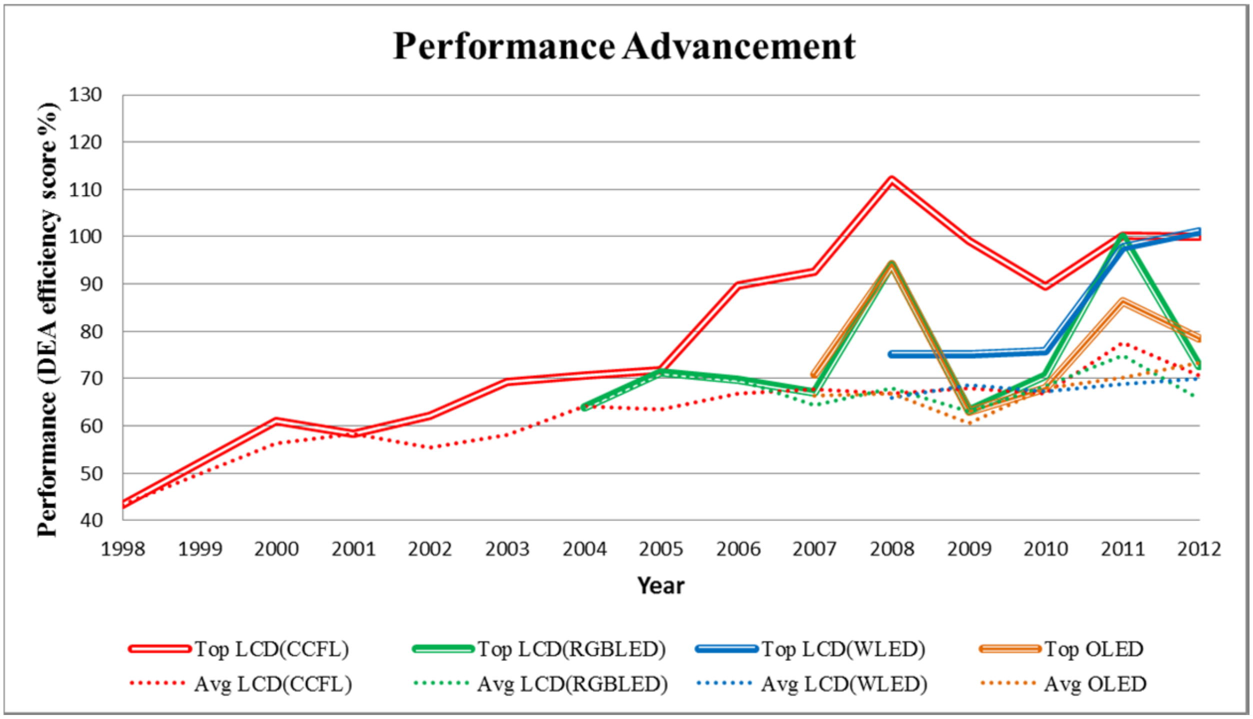

Figure 3 Trajectory map for casual home users restricted model 1)

Figure 3 is consistent with the unrestricted model that WLED backlit LCDs have recently become a threat to CCFLs. Table 5 summarizes distinct features of top performing CCFL and WLED backlit panels from 2010 to 2012. One can see that WLED backlit panels have been scaling up the screen size with high resolutions and improving response time dramatically. As a result, the comparative advantages of CCFLs in large size screens with respectable resolutions have been finally superseded by WLED backlit LCD in 2012.

The difference between the unrestricted and restricted models becomes more obvious when comparing trajectories of OLEDs. Although OLED panels inherently have excellent contrast ratios, response times, and energy consumption, manufacturers have introduced relatively smaller screen sizes (~24.5″), lower resolutions (~2megapixel) and brightness (~550cm/m^2) due to their target markets and mass production barriers (Park et al. 2012). Since the restricted model prioritized attributes for casual home users, OLED panel's advantages did not overcome their weaknesses. Note that those disadvantages had been overcome by other extreme features in the unrestricted model as previously discussed. Consequently, the bounded model penalized OLED panels that any model couldn't reach to the SOA frontier.

Table 5 State of the art CCFL/WLED backlit LCDs from 2010 to 2012 (restricted model 1)

Co.	Name	Year	Backlight	Size (Inches)	Resolution (Megapixel)	Resp. Time (ms)	DEA Score (%)
LG	LD470WUB-SCA1	2010	CCFL	47	2.1	5	89.40
ChimeiInnolux	V520H1-L05	2011	CCFL	52	2.1	9	100.13*
ChimeiInnolux	V320BJ3-L01	2012	CCFL	31.5	1.0	9	100.00*
CMO	M236H3-LA2	2010	WLED	23.6	2.1	6.5	75.71
Berise	BR720D20	2011	WLED	72	2.1	8.5	97.69
LG	LC840EQD-SEF1	2012	WLED	84	8.3	1.5	101.18*

*: Super-efficiency score

Table 6 presents average RoCs of this restricted model. Not surprisingly, the WLED backlit LCDs have shown the fastest rate of change, 2.7%, even within a short time period. This reconfirms that WLED backlit LCDs are posing a disruptive threat on CCFL backlit LCDs with fast technological advancement as well as competitive level of performances in the casual home user market. In contrast, the average RoC of OLED becomes lower than the unrestricted model. This indicates that OLED panels need to increase the screen size, pixels, and brightness to be accepted by casual home users.

Table 6 Average Rate of Change of four panels (restricted model 1)

CCFL backlit LCD	RGBLED backlit LCD	WLED backlit LCD	OLED
1.019215	1.019824	1.027056	1.011052

Turning to an assessment from a different perspective, one may assume that technical artists would pay more attention to pixel density (i.e. pixels per inch: PPI), contrast ratio, and response time. This can be reflected in the model using weight restrictions such that greater weights were to be attached to those attributes when panels were compared one another. This is shown in (4).

$$u_{r\in TA^c} \leq u_{r\in TA},$$
$$\forall r, TA = \{PPI, Contrast\ ratio, Response\ time\} \qquad (4)$$

This restricted model indicated that top performing WLED backlit LCDs have exceeded the performance level of CCFLs since 2009 (see Fig. 4.) Even though the CCFL backlit LCD LC-19D45U is still SOA since its release in 2007 and has a higher performance than other backlit LCDs, post-2007 CCFLs haven't performed as well as the WLEDs, largely due to contrast ratio and response time. This could be interpreted as a sign of disruption for CCFL backlit panel targeting technical user groups.

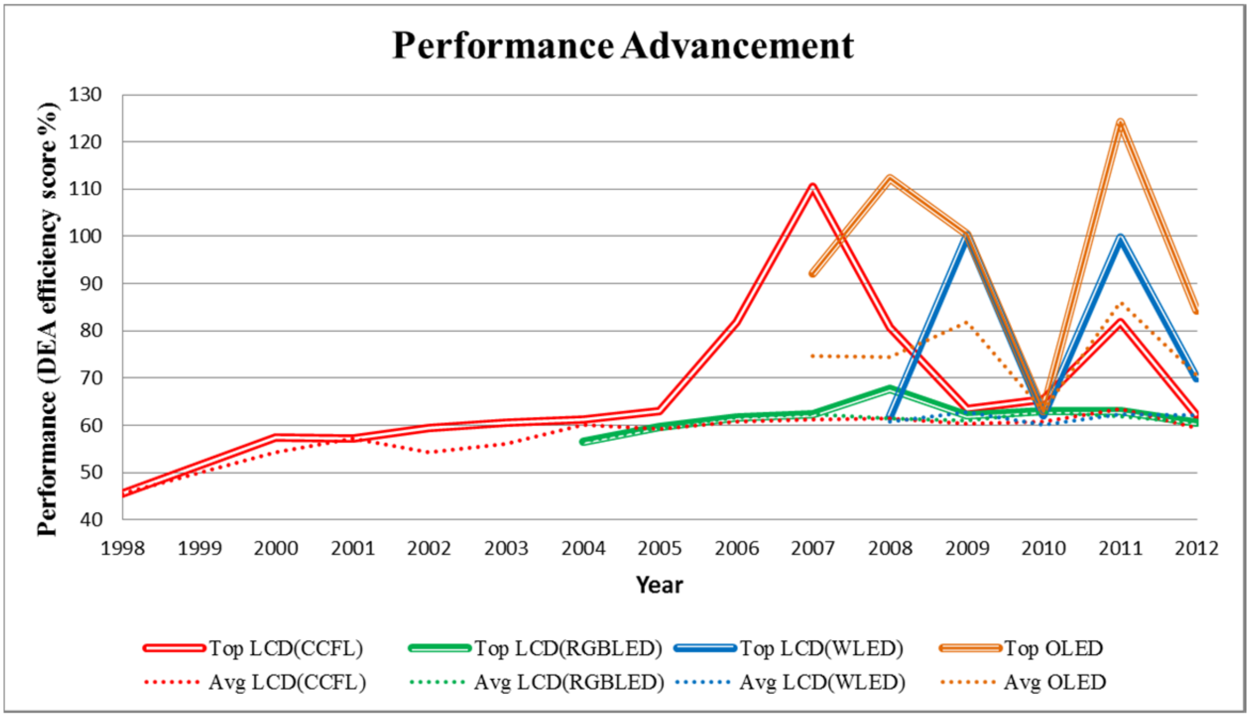

Figure 4 Trajectory map for technical artists (restricted model 2)

Under the second restricted model with preferences for the technical artists, the OLED panels are shown to be the strongest performing LCD panels. Specifically, the top performing OLED panel, CHIMEL P0430WQLA-T, surpassed the level of the top performing CCFL panel, Sharp LC-19D45U, in 2008. In addition, the top performing OLED panel, Sony PVM-740, became superior to top performing WLED panel, Berise BR650D15, in 2011. Table 7 summarizes the capabilities of those panels. Obviously, the top performing OLED panels have superior performance on the attributes that were valued by the technical artists' model.

Table 7 State of the art CCFL/WLED/OLED panels in 2007, 2008 and 2011 (restricted model 2)

Co.	Name	Year	Backlight (or Panel)	Pixel Density (PPI)	Contrast Ratio (ratio)	Resp. Time (ms)	DEA Score (%)
Sharp	LC-19D45U	2007	CCFL	26.86	1,500	6	110.57*
CHIMEL	P0430WQLA-T	2008	OLED	128.30	10,000	0.05	112.22*
Berise	BR650D15	2011	WLED	34.15	5,000	5.5	99.83
Sony	PVM-740	2011	OLED	172.10	1,000,000	0.01	124.21*

*: Super-efficiency score

The average RoCs from this bounded model are presented in Table 8. One can expect fierce competition between WLED backlit LCD and OLED for the time being with their fast rates of change and current outstanding levels of performance. In particular, OLED's 12.6% annual progress may pose a major threat to LCD panels in the technical users' market over coming years.

Table 8 Average Rate of Change of four panels (restricted model 2)

CCFL backlit LCD	RGBLED backlit LCD	WLED backlit LCD	OLED
1.024467	1.019296	1.059148	1.126141

5. Discussion

Few researchers have proposed the predictive approach of the disruptive innovation theory considering multidimensional aspects of technology systems. Schmidt suggested using part-worth curves in search of low-end encroachment (Schmidt 2011). Paap and Katz provided general guidance for *ex ante* identification of future disruption drivers (Paap and Katz 2004). Several authors have suggested using extant methods for technological forecasting to assess potential disruptive technologies (Danneels 2004; Yu and Hang 2010). Govindarajan and Kopalle argued that capturing firm's willingness to cannibalize could be a sign of *ex ante* prediction of disruptive innovation (Govindarajan and Kopalle 2006). Doering and Parayre presented a technology assessment procedure that iterates among searching, scoping, evaluating, and committing (Doering and Roch 2000). The main idea of these approaches is that the disruptive characteristic can be found by investigating technology systems from various possible angles, some of which might be secondary performance metrics where the disruptive potential may exist. Nevertheless, how to actually calibrate the path of technological changes has not received extensive attention in innovation strategy literature.

The approach proposed in this study provides a flexible measurement system to investigate the level of performance from multidimensional perspectives over time. In our example, the first restricted model that focused more on structural characteristics identified that CCFL backlit LCDs have shown steady technological advancement but are now being challenged by WLED backlit LCDs while OLED panels are struggling to ramp up panel sizes. The second restricted model, that highlighted functional characteristics, showed that top performing OLED panels have already surpassed the performance level of CCFL as well as WLED backlit LCDs. This is an example of a premise of disruptive innovation theory that the OLED is a new technology initially underperformed the dominant one along certain dimensions in market but was superior on other dimensions and, as time goes on, meets the demand of incumbent markets and could dethrone prior ones. In this regard, our approach makes it possible for practitioners to scrutinize various aspects of technology progress by exploring different tradeoffs among the attributes.

In contrast to a widely held belief that technological evolution follows a distinct pattern (Utterback 1996), several empirical studies have proven that technological performance generally does not follow *a priori* functional forms such as S-curves (Sood and Tellis 2005; Tellis 2006). Likewise, disruptive innovation theory illustrated by parallel straight lines is rarely seen in practice (Cohan 2010). In fact, the path of technological change seems largely random;

neither linear nor monotonic. The salient question is then whether the technology will be good enough to be adopted by a given tier of the market (C. M. Christensen 2006). The market demand can be met not only by sustaining improvement of low-end technologies but by repositioning of high-end technologies. The dynamics of technology, therefore, need to be investigated by focusing on current levels of technological capability with respect to the market demand rather than cumulative growth levels (Modis 2007). It is interesting to note here that there are two definitions of 'state-of-the-art' that are usually conflated. One refers to 'the most advanced state' and the other refers to 'the most recent state' (Oxford English Dictionary 2010). One can argue that both technological evolution and disruptive innovation predicates their theories on the former definition since they don't take current levels, which might not be the most advanced state, into consideration.

The approach presented in this paper addresses the importance of measuring current levels of technological capabilities to identify both low-end and high-end disruptive potentials. This is depicted in Fig.5. Technology A serves as a high-end technology and it has a spin-off design, technology A′, to target low-end market niche whereas technology B used to serve as a low-end technology but its current performance is able to meet the demand of high-end market. This figure can be viewed as disruptive innovation patterns based on raw level of technologies as seen from the trajectory of spin-off technology A′.

Now let's consider the technology adoption decision at time t. High-end customers will have found out that both high-end product P_{A1}, $P_{A'2}$ and a product that was once regarded as a low-end, P_{B2}, can meet their demand and could adopt P_{B2}, which is the traditional case of low-end disruption.

On the other hand, low-end customers will have found out that both product P_{B1} and product $P_{A'3}$ can satisfy their demand and be swayed by the discounted price of P_{B1} versus premium for $P_{A'3}$. This, so-called, high-end disruption (or strategy) is frequently observed in today's business including Digital Video Recorder (DVR), IP telephony, BMW, Miele, and NetJets (Constantiou, Papazafeiropoulou, and Dwivedi 2009; Kameda 2004; Van Orden, van der Rhee, and Schmidt 2011). However, this type of disruption that a technology once regarded as an upper level technology could pose a disruptive threat on the low-end market is not captured when the evolution of technology is examined by only looking at accumulated level of technological capabilities.

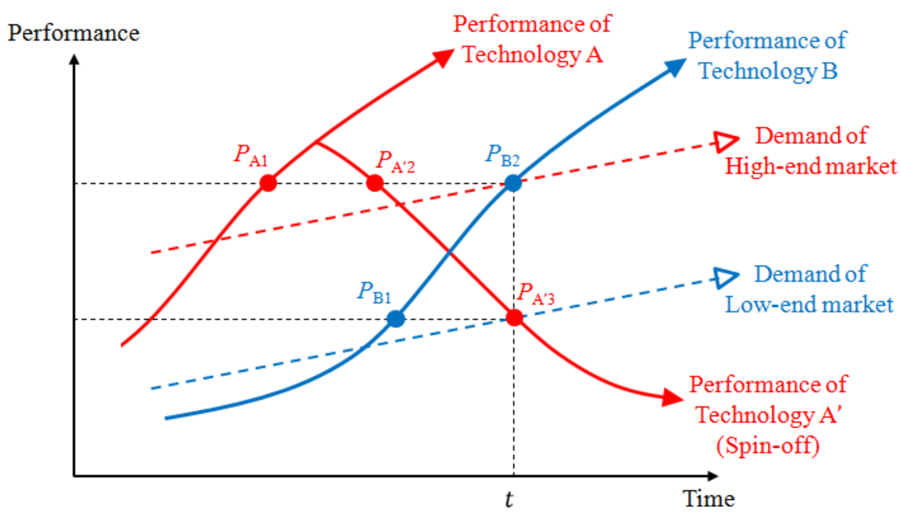

Figure 5 Trajectory map based on raw capability of technologies

6. Limitations and future research directions

Although a time series application of DEA can provide various managerial insights, there are several limitations coming from its inherent nature. First, a DEA measure is by definition an equiproportional ratio of how the DMU being assessed can either reduce its inputs or augment its outputs to reach its virtual target (Charnes, Cooper, and Rhodes 1978; Farrell 1957). This radial efficiency score may not account for all sources of inefficiency by having input and/or output slacks that are not reflected in the collective proportion.

As pointed out by one of the reviewers, using a constant 1 as an input makes the efficiency measure confined to be an assessment of aggregated outputs (Collier, Johnson, and Ruggiero 2011). This further renders the input constraints to be a convexity constraint however this doesn’t affect our model since an output-oriented VRS (Seiford and Zhu 1998) was initially assumed for the flat panel displays . It should also be noted here that a similar approach can employ AR-II type of weight restrictions when output augmentation without detriment to multiple inputs are concerned.

Based on aforementioned limitations, future work could consider:

- Non-radial distance measure for estimating the frontier with consideration of the furthest target (Tone 2001), closest target (Portela, Borges, and Thanassoulis 2003), or target located in predefined direction (Grosskopf 2006);
- Capturing intermittent RoC and/or RoC from non-dominating technologies to make a stochastic forecast;
- Tracking demand trajectories in various market segments so that replacement of incumbents can actually be estimated along with technology trajectories;

- Choice of appropriate parameters for weight restrictions that can better represent value propositions of both extant and potential market segments. This includes determining how much certain attributes should be valued than others as well as how much maximum (or minimum) weight can be assigned to certain attributes.

7. Conclusion

In this paper, we have proposed a technology trajectory mapping approach using TFDEA that scrutinizes technology progress patterns from multidimensional perspectives. Literature reviews on technology trajectory mapping approaches have revealed that it is imperative to identify key performance measures that can represent various value propositions and then apply them to the investigation of technology systems in order to capture indications of disruptions. The proposed approach provides a flexibility not only to take multiple characteristics of technology systems into account but to deal with various tradeoffs between technology attributes by imposing weight restrictions in the DEA model. The empirical illustration of this approach applied to the flat panel technologies has shown that WLED backlit LCDs are surpassing the performance level of CCFL backlit LCDs while OLED panels have a disruptive potential with excellence in screen performances, albeit small scale yet, that is observed in another performance measure. This reconfirms one of disruptive innovation premises that the new technology started below the prior one in performance on the primary dimension but was superior on a secondary one.

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