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Comparing technological advancement of hybrid electric vehicles (HEV) in different market segments

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ABSTRACT

The Toyota Prius was first introduced in 1997 and since then over 150 hybrid electric vehicles (HEVs) have been brought to the automobile market around the world. This was spurred by a major interest in the future of vehicles using 'alternative fuel' for addressing environmental and fuel dependency concerns. Based upon previous work[1], which identified an input–output model that could successfully explain the progress of HEV technologies, this study evaluates and compares the technological advancement observed in different HEV market segments over the past 15 years. The results indicate that the introduction of a wide range of midsize HEVs is posing a threat to the two-seaters and compact HEV segments while an SUV segment shows a fast adoption with a significant performance improvement. The rates of change for each segment are also provided to give insights into the estimation of the future performance levels for new product development target setting purposes.

1. Introduction

Increasing fuel prices, government regulation, and a general desire to reduce environmental concerns have resulted in increased sales for fuel efficient vehicles. The Toyota Prius, introduced in 1997, was the first major hybrid electric vehicle (HEV) and since then most other manufacturers have introduced HEVs with varying success. While popular, the Prius and other vehicles were small and did not satisfy the needs of many other market segments. Over the following years, manufacturers developed HEVs to serve other segments.

Electric vehicles can be broadly categorized as 'pure-electric' (i.e. using only a battery and an electric motor for propulsion without tailpipe) or 'hybrid-electric' (i.e. combining the conventional internal combustion engine with an electric motor and battery). As the electric vehicle market grows, related technologies are progressing every year especially in terms of driving range and fuel economy. In particular, the anxiety on the travel range of pure electric vehicles has been reduced by the advent of HEV. Besides, the fuel economy of the HEV has been greatly improved in plug-in HEV that can be recharged from an external grid.

Jahromi et al. applied technology forecasting using data envelopment analysis (TFDEA) to the HEV industry in an attempt to build an accurate technological forecasting model [1]. Their work revisited the original study conducted by Tudorie [2] and identified the input and output parameters that can better explain the progress of HEV industry. Specifically, the original study selected two input parameters: weight of the vehicle and combined output power of electric motor and combustion engine. The output parameters were acceleration rate, CO_2 emission and fuel economy. Those parameters were mostly selected based on the dynamics of combustion engine and electric motors. The dataset used in this study included a diverse set of vehicles, which required more comprehensive assessment to take multifaceted performance factors into

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[1] An early version of this study was presented at the Portland International Conference on the Management of Engineering and Technology (PICMET '13) and published in the Proceedings [1].

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account. Jahromi et al. later revised the model by incorporating additional parameters; Manufacturing Suggested Retail Price (MSRP) was selected as the only input and acceleration rate, fuel economy, a measure for miles per gallon equivalent, and seating capacity were selected for outputs. The revised model was able to explain the technological advancement with improved forecasting accuracy.

The current study further extends the previously developed model considering different market segments as well as applies it to the up-to-date HEVs so that technological advancement observed over the past 15 years can be investigated. Furthermore, the rates of change for each segment are provided to give insights into the estimation of the future performance levels for new product development target setting purposes.

2. Research methodology

As technology becomes sophisticated, there are few technologies that truly possess only a single technical capability. The rate of change also varies over time, being affected by the maturity levels of component technologies. This structural complexity makes today's technological forecasting even more challenging, which leads to the question: how to combine growth patterns of each attribute to describe the multi-objective technology systems?

To tackle this multi-attribute problem, modern technological forecasting studies frequently use frontier analysis methods. The idea is to construct the production possibility set from the best practice technologies using multiple inputs and outputs of the systems so that underperforming technologies are identified and compared against constructed frontier of the production possibility set. The evolution of the frontier surfaces is then monitored over time to capture the rate of change by which future technological possibilities can be estimated. This approach is particularly advantageous when the multiple tradeoffs between product characteristics exist and vary by manufacturer, by market segment, and over time [3,4].

To accommodate time-series application of frontier analysis into technological forecasting, Inman developed a measure to quantify the rate of frontier expansion by which the arrival of following technologies can be estimated [5]. Specifically, his method, TFDEA, establishes the state-of-the-art technology frontier using the data points identified as relatively efficient using DEA (see Fig. 1). Note that the frontier is a set of convex combinations formed by state-of-the-art technologies hence it's not a curved surface but a piecewise linear combination. The tradeoffs between technical capabilities can be considered as a radial improvement within this frontier space. The TFDEA iterates the frontier formation process over time to track the rate of frontier shift. This momentum of progress is then used to make a forecast for the future technologies.

TFDEA, being an extreme point frontier analysis technique, uses only the state of the art technologies to measure the technological advancement. In contrast, central tendency approaches such as regression are influenced by non-state-of-the-arts or mediocre technologies as well. Comparisons of TFDEA to central tendency approaches have shown its usefulness in a wide range of technological forecasting applications [6–10].

TFDEA also inherits the ability to identify technology segments in an objective manner from its non-parametric nature (see Fig. 2.) The piecewise linear facets represent different tradeoffs, i.e. technologies subject to corresponding facet may have a similar mix of input–output levels [11], which makes it possible to distinguish fast/slow advancing technology segments within the benchmarking process. Lim and Anderson's study showed that capturing local rates of change from identified frontier facets and utilizing them for individual forecasting targets improve the forecasting accuracy in general [12].

Fig. 3 shows the process of TFDEA in the envelopment model assuming variable returns to scale and dynamic frontier year with three separate stages. The first stage, shown by (1)–(9), iterates efficiency measurement in a time series manner so that the evolution of the state-of-the-art frontier can be monitored. The variable $\phi_k^{h\,\in\,\{R,C\}}$ represents the radial output efficiency of technology k at the time of release (R) and current frontier time (C) in which the forecast is conducted. The variable, λ_{jk}^h, describes how much of technology j is used in setting a target of performance for technology k. The objective function (1) also incorporates minimizing effective dates to ensure reproducible outcomes

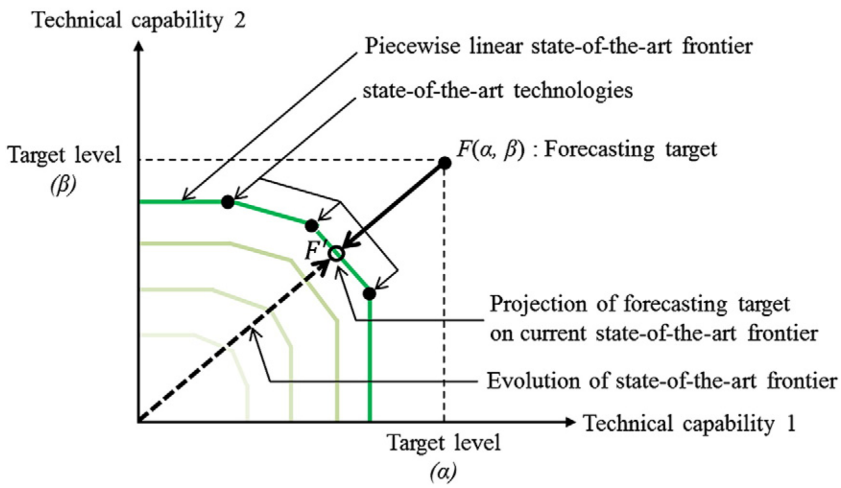

Fig. 1. Two-dimensional illustration of TFDEA.