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MARKET PERFORMANCE PREDICTION BASED CONCEPTUAL DESIGN OF MID-SIZED PASSENGER AIRCRAFTS

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ABSTRACT
In this paper, we introduce a design method applicable to the early development stage of a new product of long life-cycle time. Customer requirements employed at the early stage of a design process is critically important; however, those are easily outdated due to relatively long product development time and/or rapidly changing market situation. Addressing this critical issue, we provide a framework, strategic product design, in which one may design a product to be sustainable from unstable global economic situation, maximizing his or her profit. In the strategic product design, historical trends of customers' preference are analyzed and modeled as a market performance metric, incorporating economic factors. The established model is then used for predicting the future market performance of a new product (or concept) to be developed. For the validation of our approach, we employ a case of conceptual design of mid-sized passenger aircrafts, which requires more than 5 years of product development lead-time, assuming a number of scenarios with different future economic situations.

Keywords: strategic product design, customer-driven design, conceptual design, decision making, new product development

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1 INTRODUCTION

In a product design process, a well-known but critical issue is the management of conflicting objectives, which often emerges in the conceptual and embodiment design phase. Examples of conflicting objectives include power vs. fuel consumption in automotive vehicle design, weight vs. battery life in consumer electronics design, etc. In order to manage these conflicting objectives, various Multi-disciplinary Design Optimization (MDO) techniques, such as weighted sum, pre-emptive, goal programming, compromises decision support problems (Mistree et al, 1993), etc., are developed. With these techniques, however, designers still cannot handle this critical issue in a rigorous manner. Most designers obtain Pareto optimum sets and leave the process of selecting the best design to other decision-makers.

Value and utility (expected value) approaches have been adopted in various engineering design problems to answer to this issue (Fernandez et al., 2005, Simpson, 1998, Antonsson and Otto, 1995, Thevenot et al., 2007). However, achieving precise and useful utility function based on customers' preference in a market place has been known as another challenging problem. Recently a design paradigm, called 'design for market systems' has been proposed to overcome this challenging issue. In design for market systems, overall product value is modeled as a product market performance, such as sales volume or the value that customers dictate. Economic benefit derived from the customer choice probability with Discrete Choice Analysis (DCA) has been adopted as the single criterion in a multi-attribute selection decision-making problem (Wassenaar and Chen, 2003). Traditional product family design was extended considering market situation (Kumar et al., 2009). He and Chen further extended their work by providing product usage context as a stimulus of customer choice behavior in addition to the customer socioeconomic profile and product attributes (He and Chen, 2012).

Another critical problem that has not been issued in product design research is the uncertainty in modeling customers' preference due to the time and market situation. Product development usually requires a time range of several months to many years depending on product types and development levels. Consequently, customers' preference used for the decision-making at the early stage of a design process may be easily outdated at the time point of product introduction to a market because of ever-changing global market environment.

In order to accomplish these two challenging issues in the product design, 'strategic product design' (Withanage et al., 2010a, Withanage et al., 2010b) is employed as a framework. The product design must be strategically incorporated with an accurate forecast of future customers' preference represented as a product market performance at the time when the product will be introduced to a specific market. A manufacturer strategically maximizes market share and long-term revenue, finding a compromise on conflicting objectives based on future customers' preference which maximizes customer satisfaction and setting up barriers to competitors at the early stage of the new product development (Withanage et al., 2010b).

In this paper, we improve the method of strategic product design by incorporating economics concepts and validate it based on an example of mid-sized passenger aircrafts conceptual design. Development of new aircrafts requires large amount of resources and time. Especially, the development cycle time of mid-sized passenger aircraft is about 6 years (William et al., 2001); therefore, the aircraft concept selected at the early stage of aircraft development process may not be suitable to the potential future customers (airliners) of the aircraft. Consequently, introducing unsuitable passenger aircrafts to the market may result in significant financial losses of manufacturers.

In mid-sized passenger aircraft design, number of seats, speed, fuel consumption and take-off field length are considered as the product specifications to be designed. Because of technology limits, these variables conflict each other (i.e. speed vs fuel consumption, number of seats vs take-off field length, etc.) and a designer cannot design the aircraft satisfying every customer requirement. Various design concepts may be introduced to replace the ideal aircraft design and the most promising design among these concepts must be selected. This concept selection process for a new aircraft is critically important since the selected concept will cause significant financial loss of a company if a selected design does not accord with the customers' expectation. In strategic product design, the trend of past customers' preference is detected based on historical sales data of the mid-sized passenger aircrafts. Identification of the interaction between this preference and several economic factors may help for a designer to select the best concept for successful product development. In this study, we evaluate competing aircrafts of a future market place based on estimated market share, which may be useful for an aircraft concept selection problem.

2 METHODOLOGY

For the successful strategic product design, it is important for us to establish a systematic framework. In this work, a framework for strategic product design is employed for designers to estimate the future product market performance with given sets of product attributes.

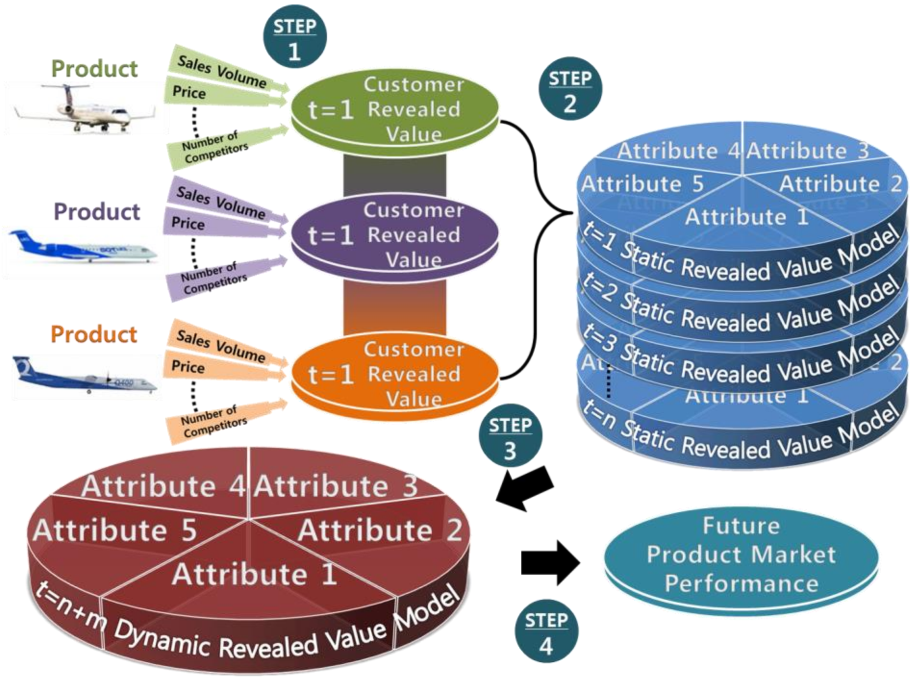

Figure 1. A framework for strategic product design.

Overall procedure of the framework is illustrated in Figure 1. It includes four main steps. Step 1 is converting given sales data to a product market performance. Step 2 is modeling the relationship between product attributes and the product market performance obtained in Step 1 at each historical time frame. The obtained model is called static Revealed Value Model (static RVM) in this work. Step 3 is a novel method for establishing RVM of the future (called dynamic RVM), employing a controlled forecasting technique. In Step 4, designers may use the dynamic RVM to evaluate design candidates. A detail description of these steps is discussed as in the following sections.

2.1 STEP 1: Convert sales data to a product market performance metric

The first step toward strategic product design is obtaining a measurement of product market performance. The value that we employ in this study is customer revealed value (CRV), which is a perceived value obtained using the S-model introduced by (Cook and Kolli, 1994) and (Cook and Wu, 2001), and it has been employed in automobile industry and airplane manufacturers (Downen et al. 2005). As shown in Eq.(1), CRV is derived from sales volumes and prices of products selected from a specific market segment, in which it is assumed that customer's expectation of a market is reflected by their product selection. In this step, all historical sales data of the products in a market segment is converted to CRV.

$$CRV_i = \frac{N}{(N+1)K}(D_i + D_T) + P_i \qquad (1)$$

CRV_i = customer revealed value of product i
N = the number of competitive products
K = partial derivative demand of price
D_i = demand of product i
D_T = total demand of market
P_i = the price of product i

2.2 STEP 2: Establish historical static CRV models

In Step 2, Partial Least Square (PLS) modeling technique (Wold et al., 2001) is employed to obtain a static RVM, which is a functional relationship between product attributes and the product market performance (i.e., CRV), avoiding the error of customer preference aggregation. PLS modeling technique is used because we need to obtain a relatively accurate model with limited sampling size (the sampling size is the number of existing product models in the market at a specific time) and predict the correlation between product attributes. Based on the regression coefficients of the obtained PLS models, customers' preference (i.e., how product attributes affect the product market performance?) in each year is analyzed. In this modeling step, a static RVM is implemented at each historical time frame. Eq. (2), $\mathbf{x}_{\mathbf{year}}$ is a set of vector of product attributes, of which values are normalized with scaling and shift. $\boldsymbol{\beta}_{\mathbf{year}}$ is a set of regression coefficients related to the customer preference for product attributes. If an estimated regression coefficient (β) of an attribute in $\boldsymbol{\beta}_{\mathbf{year}}$ is larger than others in a year, the attribute has the larger effect on customers' satisfaction in the year.

$$CRV_{\text{static}} = \mathbf{x}_{\text{year}} \boldsymbol{\beta}_{\text{year}}{}^{\mathrm{T}} + \varepsilon \tag{2}$$

$\mathbf{x}_{\mathbf{year}} = [1, x_1, x_2, \ldots, x_n]$,
$\boldsymbol{\beta}_{\mathbf{year}} = [\beta_0, \beta_1, \beta_2, \ldots, \beta_n]$, where n: number of product attributes and
ε = random error.

2.3 STEP 3: Develop a dynamic CRV model for future prediction

The next step, the key of this study, is to predict dynamic RVM based on the series of static RVMs obtained in Step 2. Changes in customers' preference due to variations of customer expectations unique to the corresponding market segment are captured in this step. Based on the dynamic RVM, designers may estimates the relationship between product attributes and the product market performance for the future considering related economic factors. As a result, we will have a dynamic RVM incorporating time and economic factors. The dynamic RVM is a hybrid model consisting of forecasted economic factors and the historical static RVMs formed in Step 2. In developing the dynamic RVM, the optimum PLS components of a given future time frame is obtained by minimizing the errors in PLS model formulation. Eq. (3) signifies the correlation between customer preference and economic factors. The $\mathbf{e}_{\mathbf{year}}$ is a vector of normalized economic factors of each year. The economic factors effect on customer preference is expressed by vector $\boldsymbol{\gamma}$.

$$\boldsymbol{\beta}_{\text{dynamic}} = \mathbf{e}_{\text{year}} \boldsymbol{\Gamma}^{\mathrm{T}} + \boldsymbol{\varepsilon} \tag{3}$$

$\mathbf{e}_{\mathbf{year}} = [1, e_1, e_2, \ldots, e_m]$, where e_i are economic factors and m is the number of economic factors, and
$\boldsymbol{\Gamma} = [\boldsymbol{\gamma}_0, \boldsymbol{\gamma}_1, \boldsymbol{\gamma}_2, \ldots, \boldsymbol{\gamma}_m]$, where $\boldsymbol{\gamma}_i$ are vectors of regression coefficients of a dynamic RVM.

From Eqs. (2) and (3), CRV of an unobserved future product is obtained based on the product attributes, economic factors of the year and the regression coefficients of a dynamic RVM as shown in Eq. (4).

$$CRV_{\text{dynamic}} = \mathbf{x}_{\text{year}} \boldsymbol{\Gamma} \mathbf{e}_{\text{year}}{}^{\mathrm{T}} + \varepsilon \tag{4}$$

2.4 STEP 4: Design a product to maximize product market performance based on the dynamic RVM

In product design, there are two different types of decision-making. One type is selection decision-making, in which a designer should select the most promising concept among a number of different ones to further develop as a final product. This selection process at the early stage of the design process is critically important since the selected concept will decide most of the characteristics of the final product. Dynamic RVM established in Step 3 will be employed to select the most promising concept at a targeted time of market introduction in the selection decision-making.
The other type is compromise decision-making, in which a designer combines a number of stakeholders' opinion at the later stage of a design process. The obtained dynamic RVM will facilitate the market-oriented trade-off between multiple conflicting objectives at the later design stages, such as embodiment and detail design.

Future market simulation which can help those stakeholders select the most promising concept is conducted based on future product market performance using Eq. (4), future product attributes and future economic factors. Based on the result of simulation, the stakeholder can make a good decision when they select the most promising concept or need judgment of the trade-off situation between multiple conflicting objectives.

3 RESULTS

3.1 Case study: mid-sized passenger aircraft conceptual design

In the conceptual design of mid-sized passenger aircrafts, product attributes, such as number of seats, speed, and operating range, are critically important and may be set as multiple conflicting goals. In addition, the aircraft design cycle time is relatively long (about 6 years) and the sales volume is very sensitive to the market situation. Moreover, unsuccessful introduction of a new aircraft to the market may lead the manufacture to be suffered from significant financial losses. Therefore, strategic conceptual design is a critically important issue in planning and designing the mid-sized passenger aircraft.

In this study, we investigate how customers' preference among the conflicting aircraft attributes varies along the change of economic factors (i.e., market situation). Firstly, the correlation between the attributes of mid-sized passenger aircrafts and their sales volume of each year is investigated, in which relative importance among the attributes is quantified. Secondly, change of the relative importance among the attributes of the aircraft due to global economic factors are analyzed and modeled. Finally, future market situation is predicted based on the predicted global oil price obtained from U.S. Department of Energy (DOE). We also consider the scenario of 60% of the predict oil price for this study.

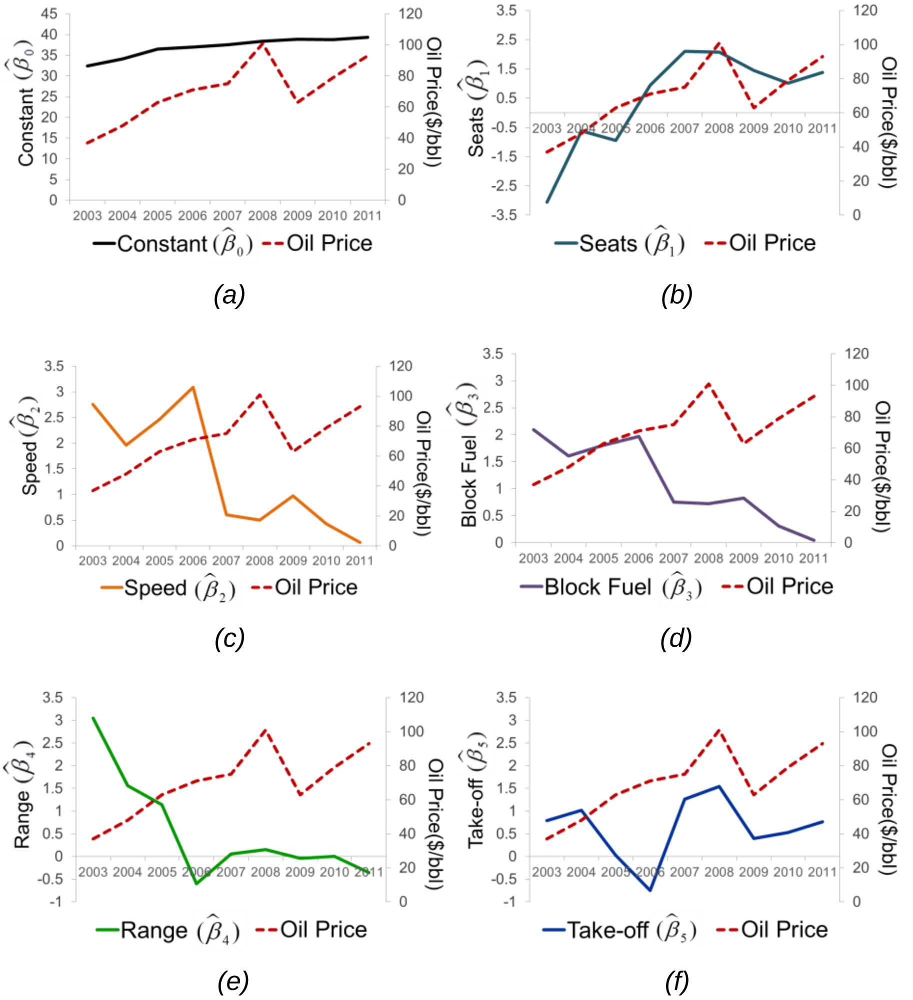

Figure 2. The correlations between importance of product attributes and oil price

For Step 1, we convert the sales data to CRV. For Step 2, we construct the static RVM of each year based on the CRV and five main aircraft attributes (i.e., number of seats, speed, block fuel, range and take-off field length) data utilizing the PLS method. Result from Step 2, regression coefficients of the obtained static RVMs are investigated to achieve the trends of the customer preference among the five attributes (relative importance of the product attributes) over the 9 years. For Step 3, dynamic RVM is developed based on the regression coefficient of the static RVMs obtained in Step 2. We analyzed how relative importance of the aircraft attributes is affected by the international economic factor – oil price. Finally, at the last step, we simulate the future market situation of the mid-sized passenger aircraft and evaluate the concepts of future aircrafts by estimating market share of each aircraft using dynamic RVM obtained at Step 3.

3.2 Static RVMs based on the CRVs of mid-sized passenger aircrafts

Figure 2 shows the correlation between oil price and regression coefficients (i.e., relative importance) of the product attributes for past 9 years. The attribute values of the aircraft shown in Figure 2 are normalized with scaling and shift. As shown in the figure, oil price has shown some rally in 2009 year, but continuously increases. Average CRV (i.e., β_0 in Figure 2 (a)) has continuously increased over the past 9 years. The importance of number of seats (β_1 in Figure 2 (b)) negatively affected the CRV in the early 2000s; however it gradually increased, and it positively affected the CRV in recent years. The importance of speed, block fuel and range shows a similar trend but contrary to the number of seat. In the early 2000s, these factors were very important to the CRVs or customer satisfaction, but lately, its importance continuously decreases.

3.3 Dynamic RVMs based on the static RVMs and oil price

In this section, we develop a dynamic RVM for future CRV estimation based on the static RVMs obtained in Section 3.2. The obtained dynamic RVM is

$$CRV_{\text{dynamic}} = \mathbf{x}_{\text{year}} \boldsymbol{\Gamma} \mathbf{e}_{\text{year}}{}^{\mathrm{T}}, \tag{5}$$

where the estimated coefficient matrix is

$$\begin{array}{cc} & \begin{array}{cc} \boldsymbol{\gamma}_0 & \boldsymbol{\gamma}_1 \end{array} \\ \boldsymbol{\Gamma} = & \begin{bmatrix} 36.987 & 1.998 \\ 0.486 & 1.408 \\ 1.429 & -0.811 \\ 1.127 & -0.563 \\ 0.552 & -0.906 \\ 0.623 & 0.149 \end{bmatrix} \end{array} \tag{6}$$

$\mathbf{x}_{\mathbf{year}}$ =[1, x_{seats}, x_{speed}, x_{block_fuel}, x_{range}, x_{take_off}], and $\mathbf{e}_{\mathbf{year}}$ = [1, e_{oil_price}].

Each row of $\boldsymbol{\Gamma}$ contains coefficients that define a linear combination of oil price and importance of the aircraft attributes (constant, seats, speed, block fuel, range and take-off field length of the order).

The first column of $\boldsymbol{\Gamma}$, $\boldsymbol{\gamma}_0$, indicates average importance of the aircraft attributes of all past years without considering the oil price effect. The second column, $\boldsymbol{\gamma}_1$ indicates the effect of oil price on the importance of the attributes. These values are obtained also normalized with scaling and shift.

Among the estimated coefficients in $\boldsymbol{\gamma}_0$, the coefficients of 1.429 and 1.127, which indicate the averaged importance of speed and block fuel regardless of oil price, are relatively large. This implies that these attributes (speed and block fuel) significantly influenced the customers' satisfaction in 2003-2011. The values in the second column, γ_1, represent relative oil price effects on the customer preference of each product attribute. Among the values, the averaged effect of oil price is 1.998, the interaction effect between oil price and seats 1.408 and the interaction effect between oil price and take-off field length 0.149, which are all positive value. This implies that customer revealed value increases when oil price and attributes values rise together. For example, while oil price is high, the aircraft with larger number of seats better satisfies the customers. In contrast, customer revealed value increases when speed, block fuel and range are decrease while the oil price rises. Moreover, the absolute magnitudes of the coefficients of dynamic RVM denote the sensitivity of CRV with the change of oil price and product attributes. For example, when oil price is high, CRV change rate is large with the change of the number of seats rather than other attributes, which means the number of seats is the most important product attribute when oil price is high.

3.4 Validation of the Dynamic RVMs

Before predicting the future market situation based on the predicted future customers' preferences, we validate accuracy of the dynamic RVMs by comparing the actual CRVs calculated from sales data in STEP 1 with the CRVs predicted based on the obtained dynamic RVMs. Figure 3 visualizes the difference between the actual CRVs and the predicted CRVs of 6 aircrafts. Accuracy of the prediction is reasonably high with some exception in ATR72, Q400, and CRJ900 due to the oil price fluctuation in 2008-2009.

3.5 Market prediction based on the dynamic RVM and future oil price

For the last step of this work, future importance of each product attributes is predicted based on the dynamic RVMs and the future oil price prediction (EIA-Energy in Brief, 2012). Based on the predicted future customers' preferences, we estimate the future CRV which following future economic circumstances (in figure 4, AEO2012 Reference line).

Finally, Eq. (1) is reversely employed to convert the predicted CRV back to future market share. Figure 4 shows the future market share of hypothetical aircraft models based on the predicted CRVs in 2018-2031.

Two cases are developed to check the variation of the future market situation using different oil prices. Market situation of Case A is predicted based on oil price which is predicted by DOE (average oil price is 132$/bbl). Case B is conducted based on 60% of the DOE's oil price prediction (average oil price is 79$/bbl).

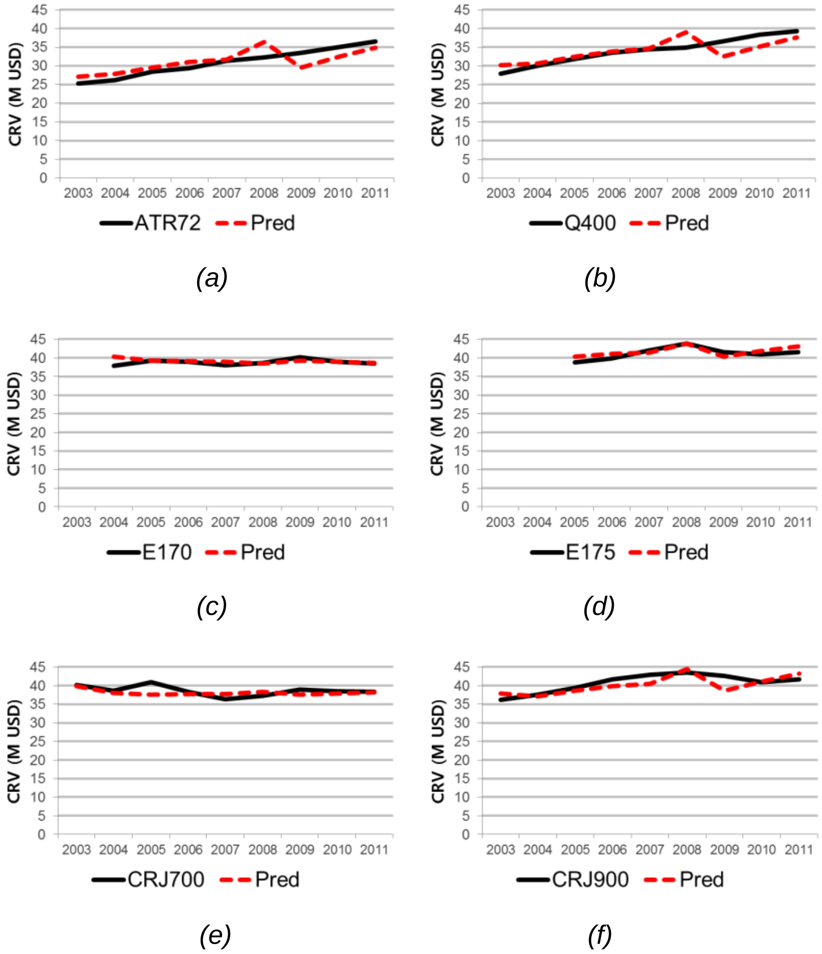

Figure 3. The actual CRV and predicted CRV based on the dynamic RVMs

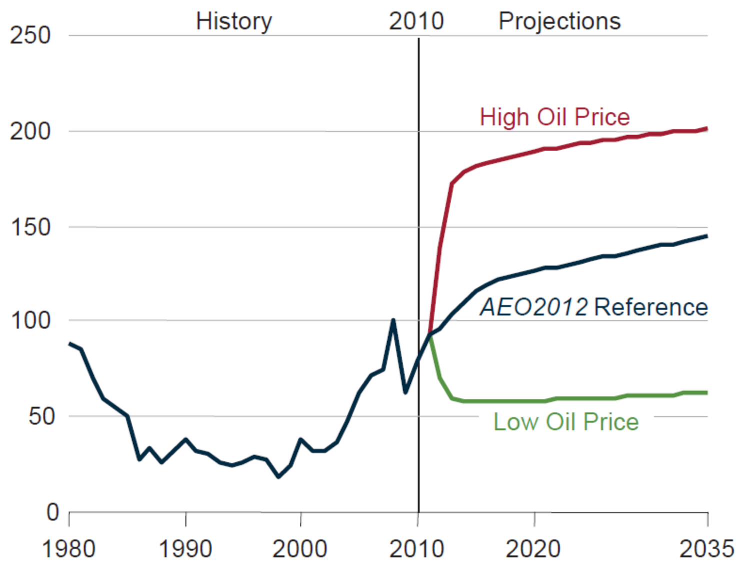

Figure 4. Average annual world oil prices in three cases, 1980-2035 (real 2010 dollars per barrel)

In mid-sized passenger aircraft, there are two types of aircraft. Turbo-prop is for short distance, slow and fuel-efficient. Turbo-jet is for long distance, fast, and low-mileage. In Case A (in figure 5 (a)), Prop 3 is expected to be the most popular model in the future which has large number of seats and high fuel-efficiency. In Case B (in figure 5 (b)), Fan 10 is expected to be the most popular model in the future which has small number of seats and navigates at high speed.
Figure 6 shows the effect of the oil price of each case to the result of the future turbo-prop market share prediction based on the dynamic RVMs in each case of oil price prediction. In Case A, relatively higher oil price scenario, the turbo-prop market shares are higher. This result indicates, if the oil price rises, customers prefer the turbo-prop aircraft which has better fuel efficiency than turbo-jet aircraft does.

4 DISCUSSION

In the case study of the mid-sized passenger aircraft, rising oil price positively affects the average CRV, the importance of seat number and the future turbo-prop market share. Trended of the customers' preference is observed over 9 years which obviously reflects the oil price. As oil price increases, aircraft models with the large number of seat and high fuel-efficiency are required by the customers. Based on the dynamic RVM coefficients, the dynamic model obtained in this work is quite reasonable, so the dynamic RVM may help to select the best concept of mid-sized passenger aircraft that will be introduced in a future market.

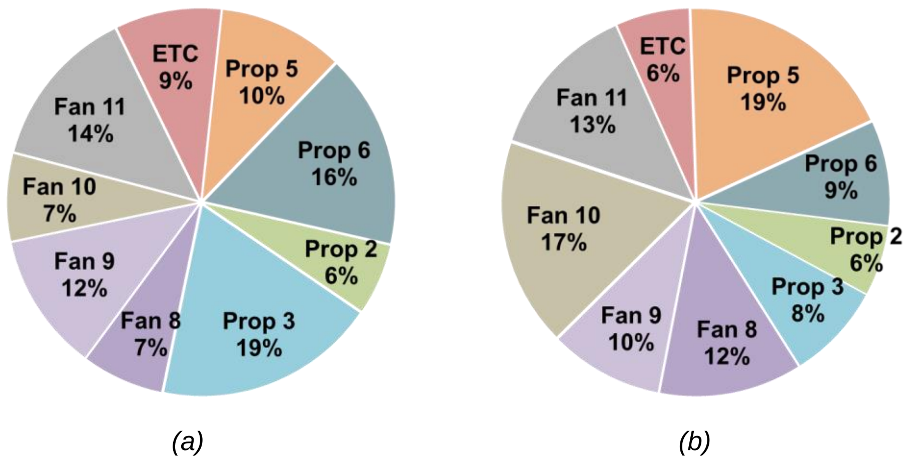

Figure 5. Future market share of each case; (a) Case A: Average oil price is 132$/bbl, (b) Case B: Average oil price is 79$/bbl

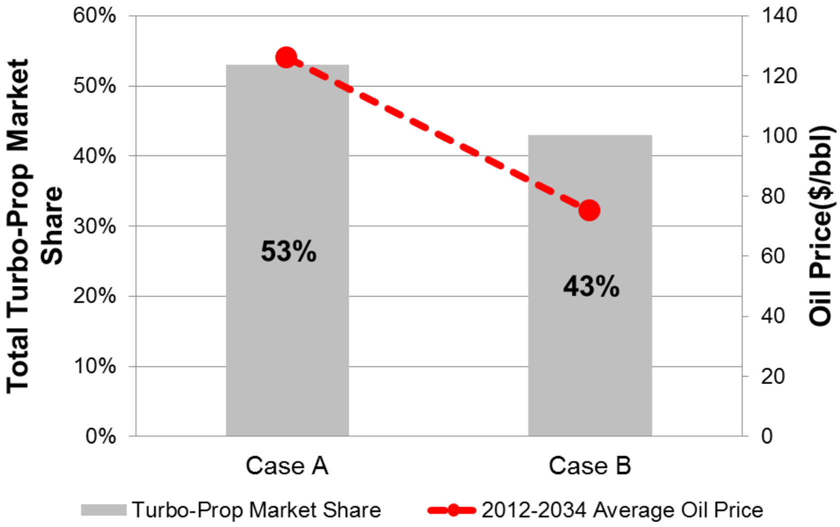

Figure 6. Predicted future turbo-prop market share and future oil price of each case study

5 CONCLUSION

Strategic product design or product design for future customer expectation is the main objective of this paper. A new approach that helps designers to make a decision at the conceptual design phase applying economic factors is introduced and validated with a conceptual design of mid-sized passenger aircraft. Mid-sized passenger aircraft conceptual design is performed for the validation of the method. In this paper, the changes of the customer requirements influenced by oil price are investigated and modeled. Future market situation is assumed and employed to find the correlation between those changes and oil price.

Strategic product design for mid-sized passenger aircraft conceptual design will be extended in the future work, including other product attributes and economic factors. More over validity of the strategic product design framework will be further checked with extended problems in a rigorous manner.

ACKNOWLEGMENT

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