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APPLICATION OF DYNAMIC VALUE-ATTRIBUTE MODELING IN A PRODUCT FAMILY

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ABSTRACT
Product families are used as a solution to cater the needs of diversified user groups, while minimizing the usage of resources. However, today's design decision makers require additional capabilities to manage the uncertainties brought by highly dynamic nature of the technological markets. Therefore, understanding the time varying behavior of preferences, in addition to the preference differences across market segments, has become an essential tool to survive the intense competition.
This paper provides a new approach to add time varying behavior of preferences to extend the currently two dimensional market segmentation grids. The newly added time dimension provides more information to the design decision makers, while minimizing uncertainties due to the dynamic market behavior. A precursor case study, using the US light truck market data from 2004-2010 was conducted to assess the dynamic nature of the preferences in the market niches. The case study results provide strong evidences of presence of the time variance preference in market niches. A dynamic preference modeling case study, with an extended set of market segment observations, is proposed as the immediate future work.

Keywords: product families, new product development, early design phases, dynamic preference modeling, multivariate analysis

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1 INTRODUCTION

In today's highly competitive technological market, product families can be seen in many industries offering diversified options to the customers. Usually, firms are offering different product variants based on a broad product platform to cover various market niches. The product variants are differentiated by targeting particular user groups or price/performance expectation of the niche. The market segmentation grid (Meyer and Lehnerd, 1997) is the most commonly used method to visualize the platform leveraging strategies (Kumar et al., 2009).

Automobile industry can be taken as one of the leading examples for the successful platform leveraging strategy practices. As an example, the light truck platform is shared by cross over utility vehicles (CUV), pick-ups (PU) and sports utility vehicles (SUV). This is called the horizontal leveraging of the product platform, and the vertical leveraging is done by differentiating the price/performance. The applications of this approach can be seen in many technological product markets, and more recent service family design area (Moon et al., 2010).

Mainly, product family design related literature aims at the problem of optimizing the commonality to share among product variants to minimize the costs and meet the required performance levels (Kumar et al. 2009). In the currently available literature, it is hard to find any significant work regarding the time variant behavior of customer preferences/product value-attribute functions, and preference differences across market niches/segments. Recently introduced dynamic value modeling in the design theory and methodology area (Withanage et al., 2010; Withanage et al., 2012), are aimed at minimizing the uncertainties due to the market dynamics. These dynamic models extend the customer driven design approach by predicting the future customer requirements. The main objective of this paper is applying the dynamic modeling methods to explore the time varying behavior of market segment/niche preferences to incorporate the future customer requirements into the product family planning process. Ultimately, the 2D structure of the market segmentation grid can be extended to 3D by adding time varying preferences, as an outcome of the proposed method.

The key focus of this paper is time varying properties of preferences, within well established market segments/niches of a product family. Preference elicitation can be recognized as the foundation of any dynamic preference modeling method. In the main stream design literature, conjoint analysis (Green and Rao, 1971) and discrete choice analysis (Wassanaar and Chen, 2003) are the most popular and widely used customer preference elicitation methods, with many industrial applications. However, these traditional stated preference type elicitation methods coming with many prerequisites such as consumer surveys, and interviews with consumers, before conducting the final analysis. They are complex and expensive exercises, consuming much needed time and other resources. Therefore, an alternative approach involving revealed preference elicitation is used in this paper as the value-attribute function estimation method.

Customer revealed value (CRV) (Cook and Kolli, 1994) is used as the overall product value for the analysis presented in this paper, whereas partial least squares regression (PLSR) (Wold et al., 2001) is used as the multivariate analysis technique for product value-attribute function estimation. In our previous papers (Withanage et al., 2010; Withanage et al., 2012) we have introduced these techniques, but this is the first time they are used outside the sedan market segment. Hence, generalizing the value-attribute modeling approach by using market segments beyond sedan market can be taken as a sub-objective of this research paper. The value-attribute function is formulated by considering CRV as the response variable and the levels of product attributes as the predictor variables of a PLSR model. This work can be considered as a precursor study, before formulating a full scale dynamic value modeling to cover all niches of a product family. The following subsections provide brief introductions, strengths and earlier applications of the core techniques used in the proposed method.

1.1 Customer Revealed Value (CRV)

CRV is an estimation of perceived value of a product, which is an alternative to surveys and other stated preference elicitation methods. It was introduced by H.E Cook (1994) and his co-authors in early 90s to provide a value metric to the domain of product design and development. CRV can be estimated using a demand-price (DP) analysis and is given in units of dollars or currency used in the DP analysis. The basis of the CRV is S-Model or Simple Market Model, in which demand of a product is given as a function of values and prices of products competing in the same market segment. The key steps of CRV theoretical formulation process is given in Equation 1-3.

Theoretical formulation of CRV is starts with the demand equation,

$$D_i = K\left\{(V_i - P_i) - \frac{1}{N}\sum_{j \neq i}(V_j - P_j)\right\}, \tag{1}$$

where D is demand of a product, K is the partial derivative of demand with price, V is value, P is price, and N is number of competitive products in a market segment. The partial derivative, K, is defined as

$$K = E_1 \frac{\overline{D}}{\overline{P}} \tag{2}$$

where, E_1 is the ratio of price elasticity, $\overline{D}$ is average demand, and $\overline{P}$ is average price. The ratio of the price elasticity is $E_1 = NE_2$, and E_2 is the price elasticity of the market segment. Using the total demand of the market segment D_T , the set of simultaneous equations of N competing products are solved to obtain CRV of a product in a unit of currency, used in the earlier demand formulation.

$$CRV_i = \frac{N}{(N+1)K}(D_i + D_T) + P_i \tag{3}$$

Most importantly, CRV can be directly equated to the value generated by the levels of product attributes (Cook and Kolli, 1994; Cook and Wissaman, 2007). Hence, CRV can be used as the overall value or the response variable for the value-attribute analysis presented in this paper. In addition to the sound theoretical background of CRV, it is a well established and generalized value metric with previous applications from different industries/market segments such as automobiles (Donndelinger and Cook, 1997) and passenger carrier air planes (Downen et al., 2005). Also, in our earlier papers (Withanage et al., 2010; Withanage et al. 2012) regarding dynamic value modeling, CRV was used as the sole value metric. The next subsection provides a brief introduction of PLSR, the multivariate analysis method, which is used as the "black box" estimation technique to estimate the value-attribute function for the market niches.

1.2 Partial Least Squares Regression (PLSR)

PLSR technique was developed by Herman Wold and contributors (Eriksson et al., 2006) to handle the high dimensional social sciences data with low structures. NIPALS (Nonlinear Iterative Partial Least Squares) algorithm was developed by them to estimate the PLSR model parameters. In this algorithm, model parameters are estimated by iterative calculations with respect to the slope of a simple bivariate regression or least squares regression (Eriksson et al., 2006).

PLSR has proven its effectiveness in Quantitative Structure Activity Relationship (QSAR) modeling, multivariate calibration and process monitoring optimization (Wold et al., 2001). In contrast to other regression methods, the accuracy of the model is increased with the number of relevant X variables. This method can deal with missing data and relatively small amount of observations successfully. The main strength of PLS is its powerful prediction, even in the situations, where number of observations may be lower and the number of variables to explore in the study can be higher and correlated (Eriksson et al., 2006, WoldSjöström and Eriksson, 2001). Therefore, strengths of PLSR can be utilized to address the main short comings of the product market segment data, where product attributes are highly correlated and the availability of samples is limited.

The linear PLS regression (PLSR) model represents the **X** predictor variables by estimated latent variables or their rotations. These new variables are called **X** scores usually given as **t** vectors. The number of score vectors is decided by the number of components used in the PLSR estimation. The matrices, **W'** and **C'** are called **X** and **Y** loadings. In PLS modeling, the predictor variables in **X** are not assumed to be independent of each other. This is realized by an assumption of the existence of latent variables that are related to **t**, **X** scores, and influence the responses in **Y**. Therefore, PLSR is insensitive to the correlation presence in the product attributes, or **x** variables (columns of **X**).

The **W**, **P** and **C** matrices obtained in the model estimation process are used to predict new observation. The response variable predictions $\mathbf{Y}_0$ are estimated using the new predictor variable values $\mathbf{X_0}$, as given below.

$$\mathbf{Y}_0 = \mathbf{X}_0\mathbf{W}(\mathbf{P}'\,\mathbf{W})^{-1}\mathbf{C}' \tag{4}$$

Mainly, the goodness of fit and goodness of prediction are the measures used to assess the quality of the model formulation and predictions. The goodness of fit is denoted by R^2 and Q^2 notation is used for the goodness of prediction. The residual and data sum of squares are used to calculate the goodness of fit.

$$R^2 = 1 - [SS_{residual} / SS_{data}] \tag{5}$$

Q^2 or goodness of prediction is calculated using cross validation. Observations are divided into sub groups. Without one of the sub groups a model is obtained to calculate the residuals. This process is carried out for all sub groups. Then, Q^2 is obtained similarly to the R^2 calculation.

$$Q^2 = 1 - [SS_{predict.residual} / SS_{data}] \tag{6}$$

In addition to the goodness of fit and goodness of predictions, VIP (variable importance for projection) (Eriksson et al., 2006) is another qualitative measure, widely used in PLSR modeling to identify the impact of a variable to the model. Mainly, it is used as a decision support tool for variable selection. VIP is proportional to the modulus of the **w** loading (elements of **W** matrix) of the variable. The following section presents the dynamic PLSR technique (Withanage et al., 2010), which is used to identify the important variables in the future.

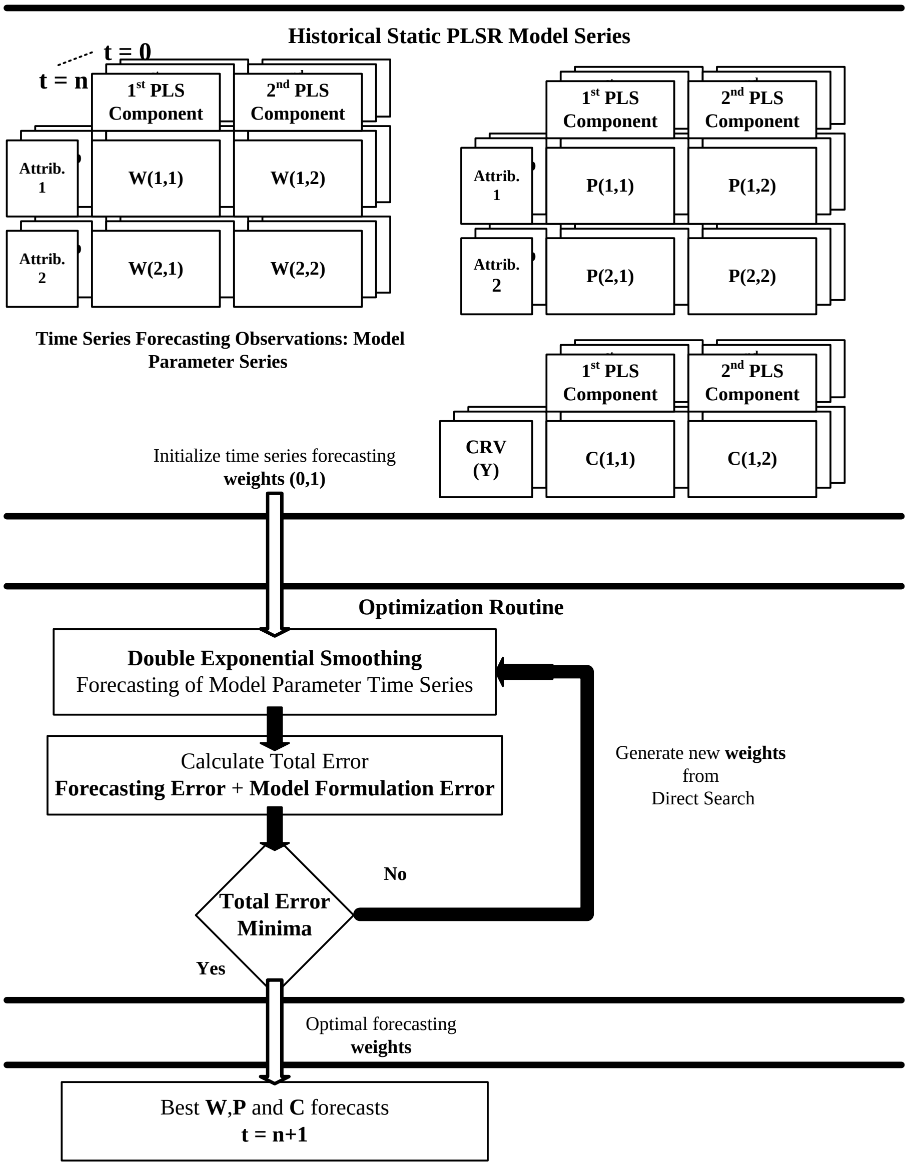

Figure 1. Dynamic PLSR algorithm (Withanage et al., 2010)

1.3 Dynamic Partial Least Squares Regression

Dynamic PLSR technique was introduced to specifically address the need of dynamic modeling technique to handle the time variant behavior of the customer preferences (Withanage et al., 2010). Product attribute levels are used as the predictor variables **X** and CRV is used as the response variable **Y**, in the dynamic PLSR model formulation. The key steps of the dynamic PLSR algorithm are given in Figure 1.

Dynamic PLSR is mainly consists of three steps. Formulating the static model series to get the model parameters, sending them to the optimization routine to get the optimal forecasting weights, and finally, projecting the parameters to the future. Model formulation errors (Withanage et al., 2010) are minimized, in addition to the forecasting errors in the unique optimization routine. This provides structurally sound future PLSR model parameters.

2 METHODOLOGY

The proposed methodology consists of three key steps; in order to achieve the final outcome of a 3D market segmentation grid with time varying preference information. The key steps and the activities involved in the process are given in the following paragraphs.

Observation selection and screening process: The most important basic step of any statistical analysis is accurately selecting the observations. In the proposed method, the given market should be clearly visualized and segregated into horizontal market segments and vertical niches by using the market segmentation grid. Well established market segments and prices/performances can be taken as the guidelines for the market segmentation grid formulation. The observations inside market segments/niches can be again screened-out to get more representative observations of the particular segment/niche by removing any outliers.

Static value-attribute model formulation: Static model series formulation is the next step of the proposed methodology. In this step, CRV is used as the response variable and the product attributes are used as the predictor variables. PLSR models are formulated for each and every time available time frame. A static model series is formulated for the each and every niche, which can represent the time varying behavior of the mean preferences.

Dynamic value-attribute model formulation: The dynamic value attribute models are formulated in the next step using the dynamic PLSR algorithm. The static PLSR parameter series is used as the observations and future model parameters are projected using forecasting methods.

The future model parameters can be used to formulate the future value-attribute functions for each and every market niche, which can represent the future mean preferences. The static model parameter time series and the dynamic PLSR algorithm adds the time varying preferences extends the market segmentation grid. This newly available information can used to plan the products for particular market segment/niche, minimizing the uncertainties due to the dynamic market behavior.

3 CASE STUDY

A case study is conducted from US light truck market to analyze the difference between value-attribute functions across market segments and time varying behavior of preferences. Mainly 3 market segments, SUV, CUV and PU are selected from 2004 model year to 2010 model year. The sales and product attribute level data from 2004-2010 were collected from Ward's Auto World, a well known automobile data analytics company. Ten product attributes (see Table 1) selected to represent the overall product value, CRV in this case.

The first step of the case study is observation screening and sample selection. As mentioned previously market segments were selected according to the well established market segments created by the body type and size of the vehicles (CUV, SUV and PU), Prices and sales of observations are used to screen the observations. Samples from the upper tail of the price distribution and lower tail of the sales were screened out to get popular, mid level light trucks. The selected observations were arranged in yearly

panels to represent the mean preferences of the market segments for each and every year (see Figure 2).
The next steps are CRV estimation and static PLSR model formulation for each and every market niche and every time frame. All together 21 models are formulated in the case study. The time varying behavior of the model parameters should be examined before starting the dynamic PLSR formulation. Dynamic PLSR is used to project the model parameters to the future, after preparing the PLSR static model parameter series.

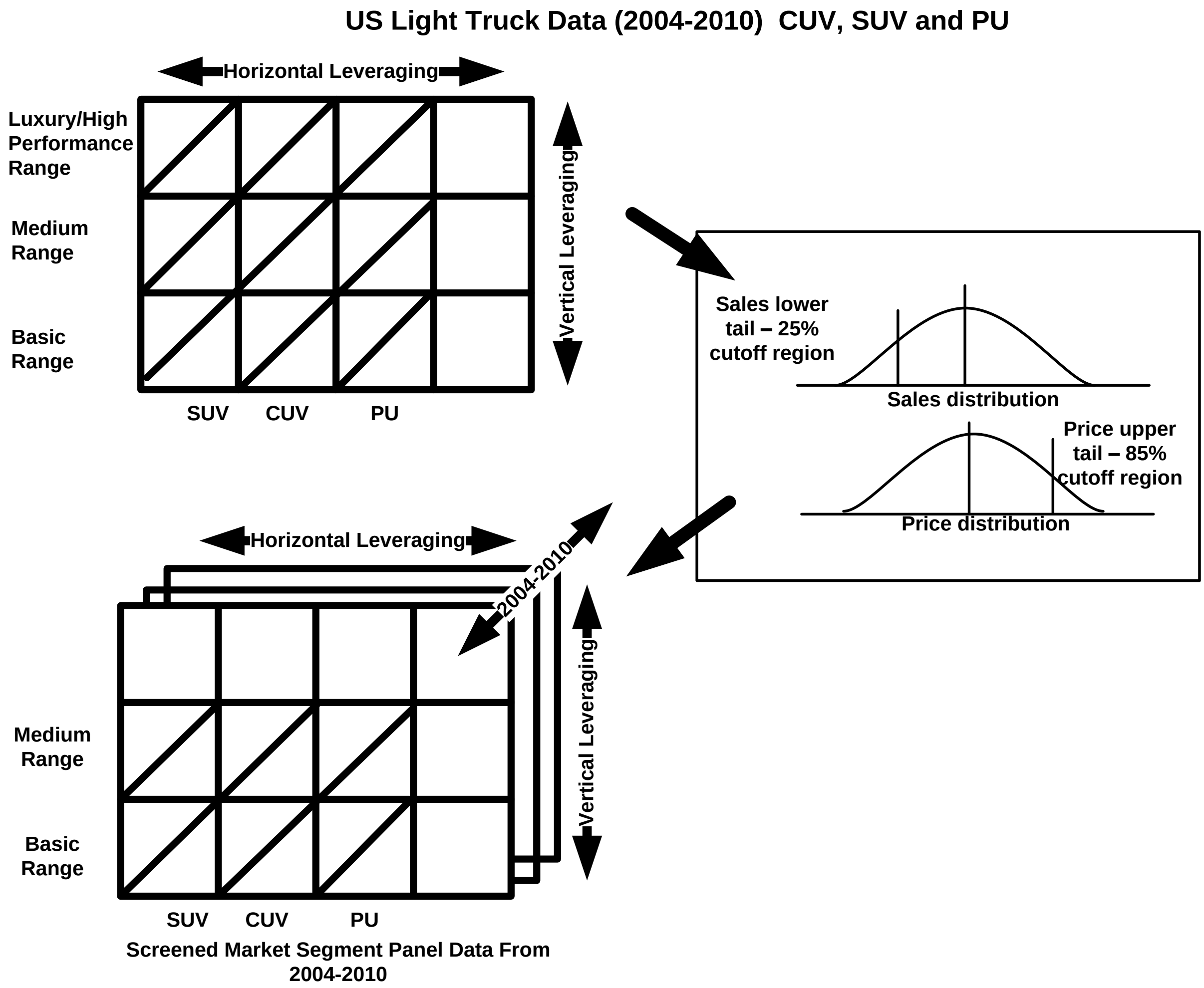

Figure 2. Case study observation selection procedure

Table 1. Selected product attributes

Higher level characteristics covered by product attributes	**Product attributes**
Engine Performance	Horsepower Torque Displacement
Comfort/convenience	Wheelbase Curb Weight
Cost	MPG city MPG highway
Image	Length Height Width

The PLSR static model series were formulated for CUV, SUV and PU market segments from 2004-2010. The 2010 PLSR model parameters were kept aside for the validation purposes. The product attributes were selected to represent the higher level characteristics of the light trucks. The availability of attribute data throughout the considered time period was another important factor used for the screening.

PLSR models were formulated from 2004-2010 using the product attributes given in Table 1 as **X** predictor variables and CRV as the **Y** response variable. All the variables were pre-treated by standardizing to remove any scaling difference. Thus, the results were not affected by the units of the product attribute levels. The model coefficients were compared across time panels and market segment to inspect the effect of time and different user needs in market niches. The static model parameter series from 2004-2009 was used with the dynamic PLSR algorithm to get the future 2010 one year ahead parameter forecasts. Double exponential smoothing (DES) (Gardner, 1985) was used as the time series forecasting algorithm, due to the limited number of observations. The results of the case study are given in the following section.

3.1 Results and discussion

Mainly, three results are presented in this section. They are results of the model validation process, the model parameter time series and finally the projected model parameters. R^2 and Q^2values are used as the main model validation measures. Standardized model coefficients and **w** loadings were selected as the key modeling parameters in this case study to check for the time varying behaviour of the value-attribute function. Mainly, **w** loadings were selected due to the proportionality with VIP value, which is used as an indicator, and a decision variable for the inclusion of variables to models in many studies. R^2 and Q^2values are given in Table 2.

Table 2 R^2 and Q^2values

	CUV		SUV		PU	
Year	R^2	Q^2	R^2	Q^2	R^2	Q^2
2004	0.819954	0.783752	0.84195	0.807008	0.773872	0.741847
2005	0.667828	0.571905	0.807832	0.785769	0.618863	0.475968
2006	0.604078	0.503683	0.78623	0.764165	0.80723	0.778823
2007	0.700677	0.610316	0.798068	0.746695	0.7734	0.738255
2008	0.650952	0.602358	0.824517	0.796135	0.889526	0.876258
2009	0.925182	0.91736	0.905922	0.866544	0.812398	0.757589
2010	0.800305	0.776777	0.729575	0.571956	0.729575	0.571956

The rule of thumb for is R^2 and Q^2 measurements higher than 0.5. All the PLSR models in this case study are in healthy region with goodness of fit and predictions values higher than 0.5, and most of them show highly significant values. Time series of the **w** loading of attributes are given in Table 3 and Figure 3. Here the most significant variables can be selected by selecting highest values, since VIP is proportional to the modulus of the **w** loadings.

The dynamic PLSR forecasts are not highly accurate looking at the values given in Table 3. The short observation series could be the main reason behind this. Also, DES, the forecasting technique used inside dynamic PLSR, is only capable of tracking the levels and trends of a time series. In addition, the origin of the forecast, year 2009, can bring errors to the model. This year was inside the recovery state after the economic recession and the sudden abnormal market behavior can cause some disruptions to the dynamic forecasts. Length, curb weight and displacement time series are given in Figure 3 to inspect the dynamic properties of **w** loadings.

The time series given in Figure 3 clearly shows the **w** loading forecasts are just following trends, and sudden changes around 2009 causes the errors. However, with the availability of more data panels the analysis can be lengthen and more accurate forecasting techniques can be used to pick the time series properties such as seasonality, which is not used here. The preferences are changing with time (see Figure 3) and dynamic preference modeling with more data will be able to provide more accurate results.

Table 3 Time series of **w** *loadings and 2010 forecasts*

		2004	2005	2006	2007	2008	2009	2010	2010 Forecasts
CUV	**WB**	0.270611	0.32619	0.239085	0.28014	0.254455	0.323795	0.27865	0.292845
	Length	0.338956	0.360641	0.325388	0.336219	0.301751	0.331768	0.306194	0.329630
	Width	0.330263	0.342504	0.319142	0.333515	0.267098	0.32005	0.269636	0.290079
	Height	0.085187	0.090518	0.028541	0.295996	0.316722	0.2684	0.231044	0.34954
	CW	0.332173	0.383184	0.365125	0.356757	0.342707	0.350652	0.347493	0.335583
	DP	0.33596	0.344567	0.390769	0.309286	0.328671	0.306891	0.340889	0.297737
	HP	0.372915	0.335052	0.381881	0.331212	0.370806	0.294157	0.35466	0.306176
	TQ	0.363446	0.354797	0.388154	0.318718	0.354457	0.317628	0.349763	0.329575
	City	-0.32445	-0.29553	-0.29278	-0.32151	-0.28974	-0.31948	-0.35581	-0.29905
	HW	-0.30971	-0.21679	-0.25702	-0.26841	-0.31621	-0.32248	-0.3014	-0.32591
SUV	**WB**	0.322461	0.299351	0.316578	0.297979	0.297959	0.175985	0.271271	0.227803
	Length	0.351477	0.31427	0.332093	0.327533	0.325198	0.208462	0.309566	0.200595
	Width	0.341156	0.276746	0.298901	0.31157	0.341488	0.354106	0.367633	0.349935
	Height	0.286036	0.301674	0.2827	0.289315	0.247552	0.268644	0.257665	0.251635
	CW	0.356756	0.363175	0.353125	0.355088	0.356792	0.356189	0.438499	0.356672
	DP	0.352159	0.335741	0.319925	0.349186	0.345127	0.390081	0.341124	0.345222
	HP	0.355348	0.32757	0.326294	0.317941	0.354319	0.372734	0.204821	0.38775
	TQ	0.349419	0.31427	0.31847	0.333733	0.344558	0.397823	0.34853	0.393175
	City	-0.23997	-0.30931	-0.30429	-0.32179	-0.275	-0.27158	-0.26253	-0.25763
	HW	-0.13053	-0.31253	-0.30447	-0.24315	-0.24753	-0.27851	-0.29672	-0.32313
PU	**WB**	0.249344	0.275792	0.316578	0.232115	0.273973	0.220658	0.179064	0.233787
	Length	0.248695	0.287462	0.332093	0.274704	0.310924	0.285433	0.268897	0.31145
	Width	0.377378	0.334733	0.298901	0.303295	0.288946	0.294645	0.307205	0.252481
	Height	0.314097	0.325603	0.2827	0.315339	0.297874	0.314333	0.337239	0.308547
	CW	0.337894	0.404507	0.353125	0.363772	0.345963	0.350002	0.359133	0.366678
	DP	0.355058	0.352939	0.319925	0.338956	0.349798	0.350056	0.367755	0.317769
	HP	0.343842	0.147938	0.326294	0.310027	0.270005	0.280265	0.278522	0.26456
	TQ	0.336667	0.278703	0.31847	0.332168	0.337198	0.340289	0.340355	0.344747
	City	-0.31163	-0.37673	-0.30429	-0.34485	-0.33895	-0.35694	-0.33235	-0.36963
	HW	-0.25687	-0.30588	-0.30447	-0.32656	-0.33542	-0.34268	-0.34559	-0.35847

4 CONCLUSIONS

This paper is an extended application of the dynamic revealed value modeling from the front-end decision support to the product family design and development area. Also, new market segments were used in the case study to generalize the dynamic modeling methods, beyond the Sedan cars used before. The goodness of fit and goodness of prediction values of the value-attribute models show the applicability of the modeling method beyond the sedan car market segment used in the previous case studies.

Using the proposed approach of dynamic value attribute modeling, market segmentation grid can be extended to 3D by incorporating the dynamic behavior of the preferences inside market segments/niches. Thus, added new time variable to the market segmentation grid provides more information about time variance preferences to the design decision makers. The forecasted values of **w** loadings, which are proportional to the VIP values, can be used to identify the most important attribute for the future markets in the product family planning process.

However, due to the limitation of data availability and highly volatile market behavior there are some errors in the forecasts. This study can be extended with availability of more data panels to capture more time series properties. The advanced forecasting techniques can be used with availability of more data to capture the seasonal and cyclical time series properties.

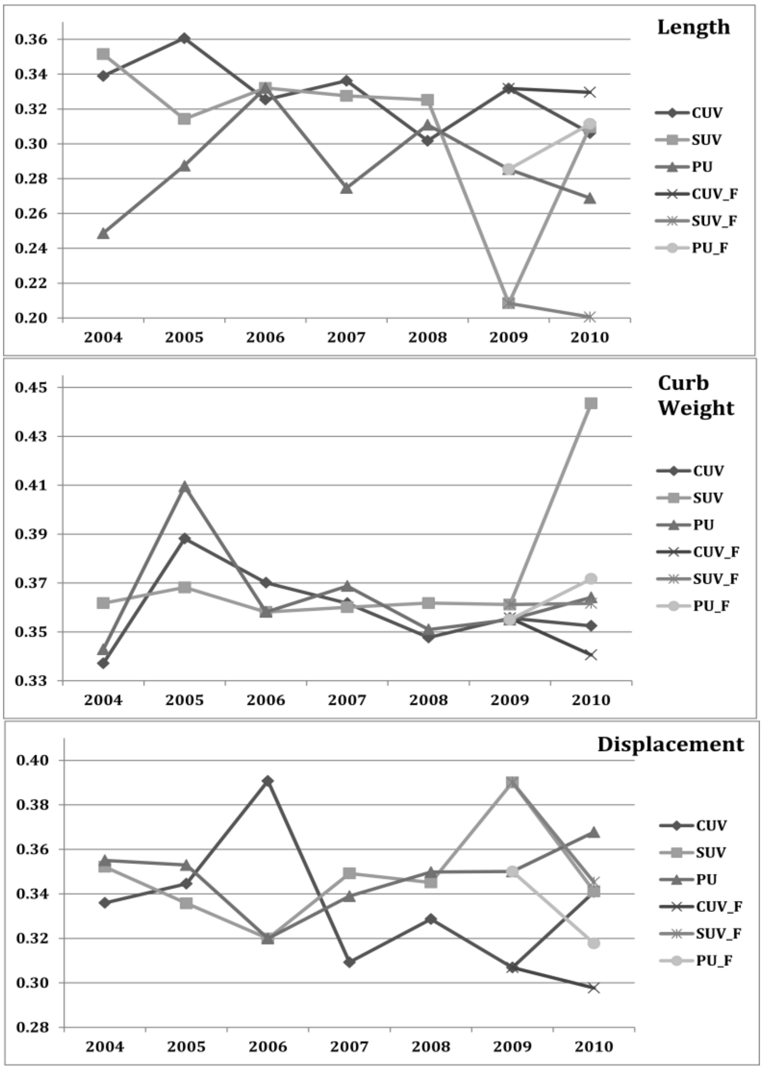

Figure 3 **w** *loadings and forecasts (f)*

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