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Demand Trend Mining for Predictive Life Cycle Design

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ABSTRACT

The promise of product and design analytics has been widespread and more engineering designers are attempting to extract valuable knowledge from large-scale data. This paper proposes a new demand modeling technique, Demand Trend Mining (DTM), for Predictive Life Cycle Design. The first contribution of this work is the development of the DTM algorithm for predictability. In order to capture hidden and upcoming trends of product demand, the algorithm combines three different models: decision tree for large-scale data, discrete choice analysis for demand modeling, and automatic time series forecasting for trend analysis. The DTM dynamically reveals design attribute pattern that affects demands. The second contribution is the new design framework, Predictive Life Cycle Design (PLCD), which connects the DTM and data-driven product design. This new optimization-based model enables a company to optimize its product design by considering the pre-life (manufacturing) and end-of-life (remanufacturing) stages of a product simultaneously. The DTM model interacts with the optimization-based model to maximize the total profit of a product. For illustration, the developed model is applied to an example of smart-phone design, assuming that used phones are taken back for remanufacturing after one year. The result shows that the PLCD framework with the DTM algorithm identifies a more profitable product design over a product life cycle when compared to traditional design approaches that focuses on the pre-life stage only.

1. Introduction

1.1. Demand Trend Mining in design analytics

Product design analytics or data-driven product design is emerging as a promising area by bridging benefits of large-scale data and product design decisions. With the popularity of social network and web devices, a large volume of data which has a characteristic of complexity, timeliness, heterogeneity, and lack of structure (Labrinidis and Jagadish, 2012) are being generated every day. Although the necessity of large-scale data analysis for product design is now being recognized broadly, only a few researchers have attempted to analyze large-scale data in the context of product and design analytics (Tucker and Kim, 2008, 2011b; Van Horn et al., 2012). This paper proposes Demand Trend Mining (DTM) as one of the analysis tools for large-scale data in order to capture the trend of demand as a function of design attributes. The DTM is a dynamic and adaptive model in that it mines the underlying changes of concept drift from time series data and builds a predictive model based on the changes. The model shows that it can realize Predictive Life Cycle Design which encompasses both the *pre-life* (i.e., manufacturing) and *end-of-life* (i.e., remanufacturing[1] and recycling) stages.

1.2. Remanufacturing and life cycle design

Remanufacturing has been a new profit opportunity for original equipment manufacturers (OEMs). Caterpillar, Xerox, and Sony are among the OEMs who have successfully taken this new opportunity (Hucal, 2008; King et al., 2006; Parker and Butler, 2007). In remanufacturing, used products are restored to a like-new condition and are given another life in the market. Remanufacturing can bring larger profits over the span of a product from an initial investment at low additional costs, typically 40%–65% less than new product costs because it reutilizes the materials and the value added to a product in its initial manufacturing (Pearce, 2008; Lund, 1984).

Remanufacturing also enables OEMs to improve their environmental performance. As awareness of environmental issues

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[1] In this paper, remanufacturing is used as an umbrella term which encompasses reuse, reconditioning, refurbishment, and cannibalization.

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increases, pressure from the public and policymakers have prompted OEMs to be responsible for the environmental impacts of their products. OEMs now need to extend their environmental efforts to encompass the entire life cycle of a product, from cradle (raw material extraction) to grave (end-of-life disposal). By remanufacturing a product, OEMs can reduce waste and minimize the need for raw material to make new products. It is known that remanufactured products (hereinafter *reman product*) can save up to 90% of the environmental impact of entirely new products (Charter and Gray, 2007; Parker and Butler, 2007).

In order for successful remanufacturing, design for life cycle (or life cycle design) is key for OEM remanufacturers. Product design determines not only the current profit from the pre-life stage but also the future profit from the end-of-life stage (Newcomb et al., 1998; Kwak and Kim, 2010; Zhao and Thurston, 2010). Therefore, to maximize the total profit from the entire life cycle of a product, OEM remanufacturers must optimize their design decisions considering both stages together.

1.3. Challenges and contributions

The main challenge in life cycle design is that there is a significant time gap (i.e., usage-life) between the pre-life and end-of-life stages. As illustrated in Fig. 1, suppose that the decision maker is at time $t^{prelife}$ (design stage), and the selling point of new product is t^{first}. In this research, it is assumed that the time gaps between $t^{prelife}$ and t^{first}, and t^{eol} and t^{second} are known. Also, it is assumed that the usage-life is h, remanufacturing will occur at time t^{eol}, and the remanufactured products will be sold at the market at time t^{second}. For instance, the typical usage-life of cell phones and laptops is known as 1.5 years (Cellular-Recycler, 2011) and 4 years (Deng et al., 2009), respectively. Considering rapid changes in technology and customer preferences, such a time gap between pre-life and end-of-life stages implies that life cycle design should consider and satisfy two sets of customer needs at the same time, i.e., needs for new products at the present and needs for reman products in the future. Although many demand models have been presented for capturing current demands at the new-product market (hereinafter *new market*), very few models are available for forecasting future demands at the remanufactured-product market (hereinafter *reman market*). Moreover, little research has been presented that combines a dynamic demand model with life cycle design, which considers the time gap and transforms a trend of customer preferences to projected demands.

Another challenge is uncertainty of returned products in terms of quantity, timing, and condition. Fig. 1 shows material flow starting from material extraction to part manufacturing, product assembly, recovery and disposal. The scope of the problem is clearly defined using solid arrows. In this paper, recovery options are categorized as material, part, and product levels. Product level recovery (e.g., reuse and reconditioning) only requires some minor value-added operations including polishing, cleaning, and lubricating. Part level recovery (e.g., cannibalization and refurbishment) needs disassembly as well as parts conditioning and change. Material level recovery (e.g., recycling) is usually conducted by recyclers and raw materials are recovered by shredding and refining. There are three possible cases that require corporations' end-of-life decisions: initial returns, returns within warranty period, and take-back program. The initial returns are caused by changes of purchase decisions in a short period of time. The returns within warranty period are induced by defects in any time. The focused case, take-back program, aims at boosting sales with re-purchasing contracts of sold products within specified period. In this case, the amount and condition of returned products should be considered in a model.

We propose the DTM algorithm which is depicted in Fig. 2 to systematically tackle some challenges: extracting valuable knowledge from large-scale data, building a demand model from the mined knowledge, and predicting a target demand in the future. The requirements for overcoming the challenges include 1) utilization of large-scale data, 2) estimation of demands, and 3) realization of demand trends over time. In order to fulfill these requirements, the DTM algorithm utilizes and combines three different models: discrete choice analysis (DCA), decision tree, and automatic time series forecasting. If $t = 1$ to $t = n$ data are available and $t = h$ ahead demand is needed, then the DTM provides a way to estimate demand at $t = n + h$ as shown in Fig. 2. To combine the DCA and decision tree, a class variable of a decision tree model is proposed to be expressed as utility. Also the concept of generational difference is adopted for a prevention of missing values and smooth forecasting in product design.

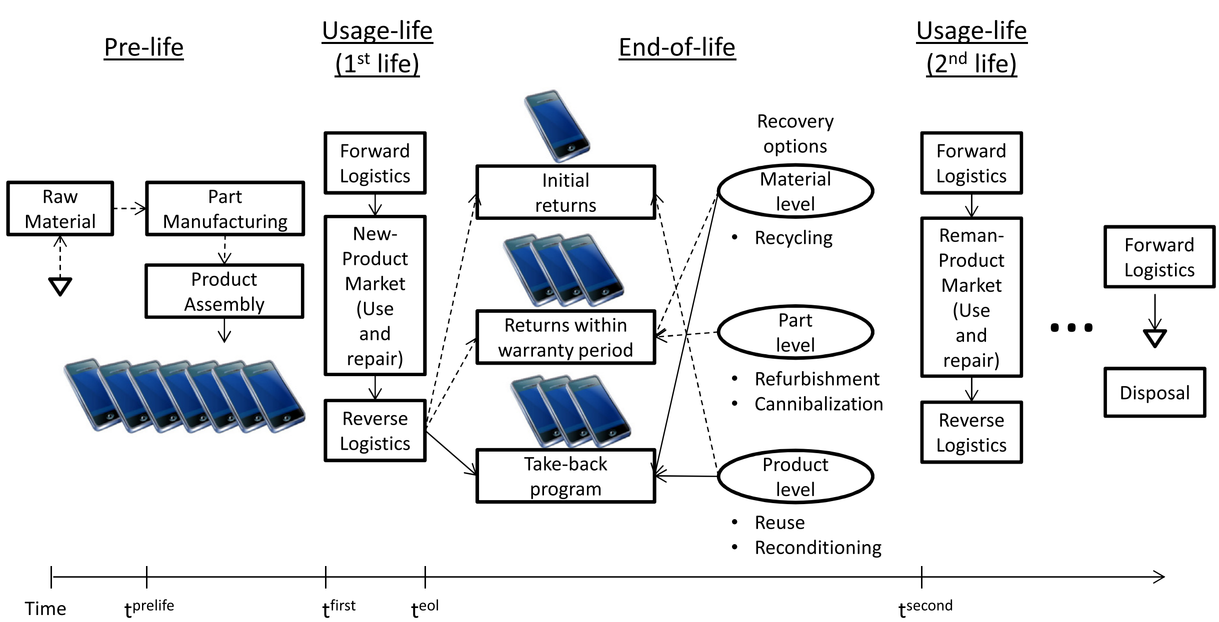

Fig. 1. Closing the loop of product life cycle and scope of the problem (solid arrow).