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Development, analysis and applications of a quantitative methodology for assessing customer satisfaction using evolutionary optimization

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ABSTRACT

Consumer-oriented companies are getting increasingly more sensitive about customer's perception of their products, not only to get a feedback on their popularity, but also to improve the quality and service through a better understanding of design issues for further development. However, a consumer's perception is often qualitative and is achieved through third party surveys or the company's recording of after-sale feedback through explicit surveys or warranty based commitments. In this paper, we consider an automobile company's warranty records for different vehicle models and suggest a data mining procedure to assign a customer satisfaction index (CSI) to each vehicle model based on the perceived notion of the level of satisfaction of customers. Based on the developed CSI function, customers are then divided into satisfied and dissatisfied customer groups. The warranty data are then clustered separately for each group and analyzed to find possible causes (field failures) and their relative effects on customer's satisfaction (or dissatisfaction) for a vehicle model. Finally, speculative introspection has been made to identify the amount of improvement in CSI that can be achieved by the reduction of some critical field failures through better design practices. Thus, this paper shows how warranty data from customers can be utilized to have a better perception of ranking of a product compared to its competitors in the market and also to identify possible causes for making some customers dissatisfied and eventually to help percolate these issues at the design level. This closes the design cycle loop in which after a design is converted into a product, its perceived level of satisfaction by customers can also provide valuable information to help make the design better in an iterative manner. The proposed methodology is generic and novel, and can be applied to other consumer products as well.

1. Introduction

Most companies spend a considerable amount of effort in improving their products from a technical point of view. Although it is right on its own merit, today's advancement in computing algorithms and fast computing hardware enable companies to obtain a more direct feedback on their products from their own customers. When a company produces a range of products (such as a platform of designs) with different trade-offs between cost, quality, and environmental effects, the level of satisfaction of one product over the other as perceived by customers bears a wealth of information about 'why a product is liked or not liked by users?'. Interestingly, such information, if derived from after-sale surveys or warranty data, can provide valuable information to the designers for a possible improvement of the product for the next design phase. Since this is somewhat intuitive and importantly many successful companies do collect and record warranty or other after-sales information, it is now a matter of a research study to devise a mechanism to retrieve hidden information from the data. In this paper, we make an effort in this direction using an automobile industry's warranty data to demonstrate the procedure.

Customer satisfaction has been defined in the literature as 'the state of mind that customers have about a company when their

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expectations have been met or exceeded over the lifetime of the product or service' [1,2]. Customer satisfaction leads to customer retention, customer loyalty and product repurchase. Thus its measurement is an important and integral part of an effective customer relationship management (CRM). Broadly speaking, satisfaction measures involve three psychological elements for evaluation of the product or service experience: (i) *cognitive*, which depends on the actual use of the product or service by the customer, (ii) *affective*, which depends on the customer's attitude towards the product or service or the company and (iii) *behavioral*, which depends on the customer's view regarding another product or service from the same company [3]. An important implication of the above definition for customer satisfaction is that it is subjective. Due to its non-quantifiability, most companies resort to a survey/questionnaire based assessment for the measurement of their products' perceived satisfaction. In this regard, years of research on customer behavior has led to specification of 10 domains of satisfaction, ranging from quality, efficiency, etc. to commitment to the customer and product innovation [4]. Surveys are designed to touch these domains. What actually to ask in the survey depends on the kind of product or service provided, the kinds of customers served, number of customers served, the longevity and frequency of customer/supplier interactions, and what is to be done with the results. The very nature of such surveys requires the customer to evaluate each statement on a psychometric scale (or a rating scale) [5]. Likert scales [6], semantic differential scales [7], smiling faces scales and percentage measures [8] are popular in that order. A typical five-level Likert item consists of a statement and asks the surveyee to choose among (a) strongly disagree, (b) disagree, (c) neutral, (d) agree, and (e) strongly agree. Several studies exist which show the merit and demerits of different rating scales and how they should be interpreted.

In the automotive sector, original equipment manufacturers (OEMs) depend on reports published by various marketing information firms, like the American Customer Satisfaction Index [9], J.D. Power and Associates [10] and Consumer Reports [11] for gaining insights into vehicle quality. Quality analysis data provided are often focused on questions related to number of failures in the field (namely, incidents per thousand vehicles (IPTV) [12] and problems per hundred vehicles (PPH)) for individual components like engine, transmission, etc. Limited emphasis is placed on the assessment of individual users' perception and satisfaction resulting from day-to-day use of the product. Moreover, survey based estimates rely on a small sample of the customers (around 200–400 per vehicle model [10]). Despite this, the surveys themselves are highly regarded and play a significant role in molding the customer's attitude towards a particular vehicle model. To some extent, the surveys also help the OEMs in identifying major problem areas. The CRM policy of OEMs should therefore be flexible enough to take into account the information contained in these survey reports published annually.

For service based companies, Parasuraman et al. [13,14] proposed the 'gaps model' for estimating satisfaction objectively by using the gap between the customer's expectation and perceived experience of performance. Apart from these and a few other related studies, quantitative measurement of customer satisfaction has not received much attention in the literature. The main reason is as follows: there are three practical approaches to measuring satisfaction, namely, post-purchase evaluation, periodic satisfaction surveys and continuous satisfaction tracking. Post-purchase evaluation (known as initial quality study in the automotive sector) deals with satisfaction assessment *shortly after* the delivery of product or service. Periodic satisfaction surveys provide occasional snapshots of customer perceptions. Continuous satisfaction tracking is much like post-purchase evaluation but carried out over time. Post-purchase evaluations are very common and seem to be used across all sectors. Most products and services are however, not amenable to periodic assessment and therefore not enough data is obtained for a single customer to warrant a quantitative study.

Table 1
Some basic statistics of the vehicle models relative to Model 5.

	Vehicle model number				
	1	2	3	4	5
Segment	Compact	Midsize	Luxury	Midsize	Luxury
Total customers	19.61 × C	13.35 × C	1.93 × C	30.19 × C	C
Total claims	11.10 × K	6.99 × K	1.57 × K	17.67 × K	K
Total field failures	1026	1084	776	1228	606

Automotive OEMs, on the other hand, provide customers a warranty period which covers repairs and mechanical faults as part of the sale. Claims can be made by the customers at authorized dealerships and service stations which keep customer-specific records of these claims. Warranty data consists of claims data and supplementary data. A review of warranty data analysis methods for identifying early warnings of abnormalities in products, providing useful information about failure modes to aid design modification, estimating product reliability for deciding on warranty policy, and forecasting future warranty claims needed for preparing fiscal plans can be found in [15]. In this paper, we go a step further and use the same warranty data for obtaining a *mathematical model* for predicting customer satisfaction. Typically, customer satisfaction is measured at the individual level, but it is almost always reported at an aggregate level. We ensure that this is true for our model by employing a bottom-up approach to modeling. To illustrate, Table 1 shows some basic statistics of the five vehicle models considered in this study. The numbers correspond to the warranty data of all vehicles serviced between January 2008 and August 2009. For anonymity, the total number of customers and claims for each model are shown relative to those of the model with the lowest customer base (Model 5). The last row of the table shows the number of unique field failures, a common constituent of IPTV or PPH figures, that occurred in a vehicle model during the said period. A *field failure* refers to any vehicle-related problem faced by the customer for which he/she had to visit a dealer or service station. Each unique field failure is associated with a corresponding repair code for classification purposes. Given the limited resources available with customer relation managers, it is only prudent to prioritize these field failures for a subsequent root-cause analysis and possible reduction in the next design phase. The methodology presented in this paper allows one to prioritize these unique field failures based on a quantitative measure of their potential for improvement in the customer's perception and hence the CSI. The method begins with the building of a quantitative model of the customer satisfaction index using an evolutionary optimization technique. The present work suggests an improvement to the method in [16] and validates it against Consumer Reports ratings of the vehicle models. The resulting CSI modeling function is then used to obtain the CSI improvement potential (CIP) for different types of field failures.

The rest of the paper is organized as follows. In Section 2 we describe the components of the dataset being used. Extraction of relevant features is described in Section 3. Section 4 describes the single-vehicle framework for the proposed satisfaction model built on these extracted features. Section 4.3 presents the bi-objective optimization problem for obtaining the satisfaction model for a given vehicle model and Section 4.4 presents the evolutionary optimization method used for solving this problem. Section 5 presents its extension to obtain a generalized satisfaction model when multiple vehicle models are involved. The results and their validation are presented in Section 6. A sensitivity analysis is also performed on the obtained CSI function. Next, Section 7 presents two