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A fuzzy logic based approach for modeling quality and reliability related customer satisfaction in the automotive domain

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ABSTRACT

This paper presents an approach to assess quality and reliability related customer satisfaction from field failure data at each individual customer level. The quality satisfaction has been modeled based on number of failures and severity of failures, while, reliability satisfaction has been modeled based on number of visits to dealer and time span between visits. The satisfaction modeled at an individual vehicle (customer) level is further aggregated to a vehicle model level to determine overall satisfaction of customers with that specific vehicle model. A fuzzy logic approach is used to construct the satisfaction model. A grid search technique is used to tune the model parameters such that the output of the model for specific vehicle models matches with survey based ratings assigned to the vehicle models.

1. Introduction

In the context of global competition, there has been an increasing awareness in improving the processes which are directly linked with customer satisfaction. Customer relationship management (CRM) has emerged as a prominent aspect of business. In this regard, one of the notable developments of quality movement is assessment of the customer satisfaction. Hernon and Whitman (2001) defined satisfaction as a sense of contentment that arises from an actual experience in relation to an expected experience. Customer satisfaction measures customer's subjective experience with a product and service. Two different conceptualizations, namely (a) transaction-specific and (b) cumulative have been reported in the literature (Andreassen, 2000; Boulding, Kalra, Staelin, & Zeithaml, 1993). Transaction-specific concept refers to satisfaction as the evaluation of single experience (Oliver, 1993). In contrast, cumulative satisfaction involves satisfaction as customer's up to date experience with a product or service (Fornell, Johnson, Anderson, Cha, & Bryant, 1996).

In literature, several conceptual models have been developed to define quality in terms of customer satisfaction, especially, in service sectors such as banking, telecom. However, very limited scientific literature has been reported on quantifying the customer satisfaction. The reported work on assessment of customer satisfaction in automotive domain is further scarce. Several factors (such as vehicle appeal, performance, ownership cost, service at dealership, quality and reliability) contribute to the customer satisfaction in automotive domain. However, factors related to quality and reliability contribute more than 40% in shaping customer perception and satisfaction (J. D. Power Associates., 2009) as depicted in Fig. 1. Generally speaking, in automotive domain, quality and reliability are assessed based on number of failures in the field, which are expressed as incidents per thousand vehicles (IPTV) or problems per hundred vehicles (PPH). Warranty data is often used to get the estimates of IPTV or PPH. Further, automotive manufacturers conduct surveys and also refer to published survey results (such as J.D. Power, Consumer Reports) for getting insight into the customer satisfaction. The customers define quality and reliability of a product from his or her experience with the product. Counting the number of problems per thousand (or per hundred) vehicles may be a good indication of quality. However, in the current challenging business scenario, it is essential to assess customer satisfaction at each customer level which drives the decision making process related to purchase of vehicle. However, currently very limited emphasis is given on measuring individual customer perception and satisfaction. The following quote of Lord Kelvin reflects the importance of measurement or evaluation:

"*When you can measure what you are speaking about and express it in numbers, you know something about it*...*(otherwise) your knowledge is a meager and unsatisfactory kind; it may be beginning of knowledge, but you have scarcely in thought advanced to the stage of science.*"......Words of Lord Kelvin (1824–1907).

In this regard, a quantified approach is needed to evaluate the satisfaction related to quality and reliability at an individual customer level. This will help to identify dissatisfied customers and to provide individual customer care which will result into improved brand perception and brand loyalty.

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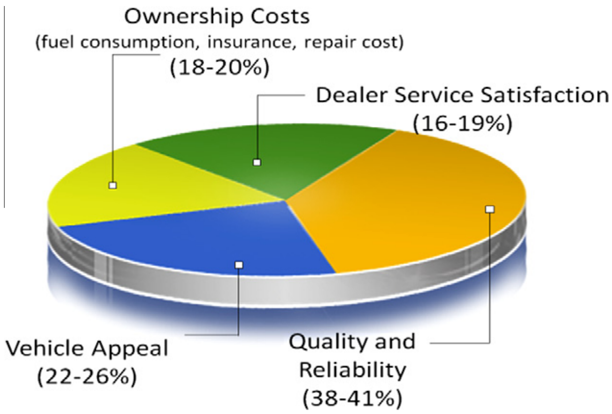

Fig. 1. J.D. Power Vehicle Ownership Satisfaction Study: The impact of service/repair on customer satisfaction.

In this paper, we present a novel approach to model customer satisfaction at an individual customer level from the field failure data that Original Equipment Manufacturers (OEMs) maintain. Here, we focus on modeling quality and reliability satisfaction. These have been expressed in terms of Personal Quality Satisfaction (*PQS*) and Personal Reliability Satisfaction (*PRS*). These indices have been aggregated to measure customer satisfaction in terms of *PQRS* (Personal Quality and Reliability Satisfaction) at an individual vehicle level and at vehicle model level. The customer satisfaction at an individual level has been modeled using fuzzy logic approach. Grid search technique has been used to tune various parameters in the satisfaction model. The overall objective of the parameter tuning is to minimize the difference between satisfaction values obtained from the proposed model and the target satisfaction ratings available in published by external agencies. In Section 2, we provide state-of-the-art review of different disciplines that are used in our approach. In Sections 3 and 4, we present a customer satisfaction model and an approach that has been used to tune various parameters related to satisfaction. Section 5 presents results while conclusions and future directions are presented in Section 6.

2. Related work

A significant work on relating customer satisfaction with consumer loyalty has been reported primarily in service sector such as banking, hospitality, E-commerce, and telecommunications (Danaher and Gallagher, 1997; Hallowell, 1996; Shankar, Smithb, & Rangaswamy, 2003). However, a very limited work has been reported on quantitative assessment of customer satisfaction. The work on assessment of customer satisfaction at individual customer level is further scare. One of the most cited models in the literature is American Customer Satisfaction Index (ACSI). Here, the satisfaction is measured on a 0 to 100 scale by several questions that assess customer's evaluation. Looking at the indices and the impacts, users can determine which drivers of satisfaction would have the most impact on customer loyalty (American Customer Satisfaction Index (ACSI), 2009).

In automotive domain, customer satisfaction index from J.D. Power and Associates, and Consumer Reports (CR) are popularly referred by consumers and OEMs to get insight into the customer satisfaction related to particular vehicle model or brand (Consumer Reports, 2010). These reports compare performance of various automotive makes and models in terms of customer satisfaction. These reports are based on surveys which assess the failures experienced by the customers. For example, the Initial Quality Study (IQS), conducted yearly by J.D. Power and Associates, provides information on new-vehicle quality after 90 days of ownership. Owners are surveyed regarding problems with their new vehicles (J.D. Power Associates., 2009). Similarly, J.D. Power and Associates Vehicle Dependability Study (VDS) focuses on problems experienced by owners of three-year-old vehicles. In these studies, the relative performance is measured using a "problems per 100 vehicles (PP100)" metric. A lower PP100 score indicates better performance and a higher PP100 score indicates worse performance.

Consumer Reports Organization is another independent organization that conducts surveys and lab tests to come up with product reviews and ratings on cars, electronics and other home appliances (Consumer Reports Organization., 2012). For new and used cars, Consumer Report publishes reliability ratings annually. Reliability scores are derived from annual surveys from subscribers of Consumer Reports based on incidences of failure in the last 12 months. Using these surveys, reliability ratings (such as average, above average, worse than average) are assigned to various vehicle models under consideration.

These survey based methods often rely on a smaller sample of population and may not always represent the real world facts. In contrast to these survey based methods, the current work relies on warranty data to estimate satisfaction level at an individual customer level and then aggregate it over a particular make or the model. In the current work, customer satisfaction has been modeled using fuzzy logic approach while grid search technique has been used for tuning various parameters in this model. Hence, these techniques have been reviewed in the next subsections along with their applications in related areas.

2.1. Fuzzy logic

Fuzzy set theory was introduced by Zadeh to deal with the decision problems in the absence of sharply defined criteria (Zadeh, 1965). It was developed based on the premise that, key elements in human thinking are not numbers, but linguistic terms or fuzzy sets that are not precisely defined (Zimmerman, 1982). The fuzzy set theory states that, a fuzzy number A is a special fuzzy subset of real numbers R. Its membership function fA (x), is a continuous mapping from R to an interval [0, 1]. Fuzzy logic gained acceptance because of its capability to handle impreciseness, and representing and manipulating linguistic variables (Dubois, 1978).

It has been explored in Quality Function Deployment (QFD) for modeling customer preferences/attributes (CAs) and engineering characteristic (ECs) that are expressed in linguistic terms. Khoo and Ho (1996) first proposed a framework for fuzzy QFD systems. Wang (1999) proposed a fuzzy ranking relation to model the imprecise preference relations between design requirements. Vanegas and Labib (2001) reported a fuzzy QFD model to derive target values of ECs based on fuzzy numbers that represent the imprecise nature of the judgments. Ramasamy and Selladurai (2004) developed a fuzzy rule-based knowledge system that defines the relationship between the ECs and the CAs. The fuzzy logic approach has also been used to model environmental concerns in QFD (Kuo, Wu, & Shieh, 2009).

Wong (2001) employed fuzzy *c*-means (FCM) clustering method to identify different customer segments by mining parameters related to customers' needs, characteristics and behavior. In this work, fuzzy theory is also used in quantifying the linguistic parameters. Weber and Weber and Crespo (2005) presented a dynamic data mining methodology based on fuzzy *c*-means for customer segmentation. Shah, Roy, and Tiwari (2006) developed fuzzy expert system 'Customer and Service Advisor (CSA)' to categorize and identify type of customer and then identify the advisor based on the age, demographic, experience, business value and behavioral attributes. Here, fuzzy logic is used to model the attributes that are expressed in linguistic terms (example, Age – young, middle age, old). Ahn and Sohn (2009) proposed a framework that employs fuzzy clustering and association rule mining to identify dissatisfied customer groups from surveys and to identify factors related to after-sales service that customers consider important.

2.2. Parameter tuning

Different deterministic (such as Gradient Descent, Grid Search Algorithm) and stochastic approaches (such as Simulated Annealing, Genetic Algorithms, and Evolutionary Algorithms) have been proposed in literature for parameter tuning. However, each of these methods has its own advantages and limitations. Gradient Descent methods (Cooper & Steinberg, 1970; Heath, 1997; Joshi & Moudgalya, 2004) are straightforward and tractable. However, they cannot avoid/escape local optima. The grid search algorithm (Cooper & Steinberg, 1970) is the simplest algorithm for finding the minimum and the corresponding minimum solution point of an objective function. This approach becomes prohibitive as the number of decision variables and the number of sample points for each dimension increase. In Simulated Annealing (SA), initially more random points can be generated (avoiding local minima), whereas during later stages SA focuses on promising regions. Genetic algorithms (GAs) (Davis 1991; Goldberg, 1989; Holland, 1975) and Evolution Strategies (ESs) (Beyer & Schwefel, 2002; Schwefel, 1995) both mimic the biological evolution mechanism. Although, these stochastic methods are not as efficient as gradient descent methods, they are more likely to avoid local optima.

As the current work involves limited number of parameters that need to be tuned, a grid search based approach is used for parameter tuning. The discretization of the parameters is performed to restrict the search space and then a complete enumeration of all (discretized) parameters has been performed for parameter tuning. The reason for this simplification is that we are using optimization only as an enabler in the current work. However, a more rigorous optimization that can enhance the effectiveness of parameter tuning is one of the future research directions.

Recently, Bandaru, Deb, Khare, and Chougule (2011) presented a customer satisfaction modeling method using the service (field failure) data of consumer vehicles. In this approach, some relevant variables extracted from the service data are used as inputs and a statistical (unsupervised) approach is used to develop the mathematical model for predicting the Customer Satisfaction Index or CSI. Our approach also builds a mathematical model for predicting CSI, however there are three main differences – (1) we derive the mathematical form of the CSI function using a heuristic approach and (2) optimize the model parameters using the Consumer Report ratings (supervised approach). (3) Further, we also allow variation in satisfaction with ownership period (for details please refer to Section 3.2.3).

In summary, customer satisfaction modeling has emerged as an important area of research, especially in service sector and several conceptual models have been proposed to assess the same. However, in automotive domain very limited work has been reported on assessment of customer satisfaction. The reported work is primarily focused on conducting surveys and analyzing the surveys to get insight into the customer satisfaction at vehicle model level. In contrast, the work reported in this paper facilitates assessment of satisfaction at each customer level from field failure data. Fuzzy logic approach has been applied for analyzing customer preferences, customer segmentation and clustering in CRM domain. However, the literature on using fuzzy logic in modeling customer satisfaction is scarce. In this work, a model has been developed to assess the quality and reliability related customer satisfaction at an individual customer level using field failure data. The satisfaction at each customer level has been further aggregated to assess satisfaction at vehicle model level.

3. Customer satisfaction modeling

Customer Satisfaction model presented here relies on field failure data collected at dealership. In this section, we first describe the field data and then present a model that uses the field data to assess quality and reliability satisfaction at each vehicle owner level as well as vehicle model level.

3.1. Field data

When a customer experiences an abnormal behavior in the vehicle he or she takes the vehicle to a dealership. Based on a specific concern the customer has about the vehicle, the technician usually goes through a series of steps in order to diagnose and fix the problem. Usually, a predefined set of codes, i.e. repair codes (RC) which characterize the nature of repair actions, are assigned to the repairing tasks that are performed by the technician to fix the vehicle problem. Typically, repair code descriptions contains part and action performed on that part (example, Engine Replacement, Powertrain control module reprogramming). The information related to repair codes along with the information related to vehicle identification number (VIN), vehicle model, model year, vehicle engine type, transmission type, repair date, repair time, parts changed, dealer (technician) involved and technician verbatim entries are stored in a database at dealers end. The data collected at dealership is then uploaded to central warranty database. Thus, warranty database contains data related to all historical repairs performed on vehicles. In a way, information related to part failures experienced by the vehicle owner over a period of time can be inferred from the repair data available in the warranty database. For each vehicle, following attribute values have been extracted from the field data:

- Number of repairs performed on each vehicle.
- Number of visits to dealership.
- Time span between two consecutive visits to dealership.

In addition, severity ratings have been assigned to each failure (repair code). The criteria used to assign the severity ratings are described in Section 3.2.1. Based on aforementioned attributes, quality and reliability satisfaction for each customer has been assessed using satisfaction model developed in this work.

3.2. Customer satisfaction model

As mentioned earlier, we primarily focus on modeling satisfaction related to quality and reliability at each vehicle owner level. The satisfaction levels related to these elements have been expressed in terms of Personal Quality Satisfaction (PQS_{veh}) and Personal Reliability Satisfaction (PRS_{veh}). These quality and reliability satisfactions have been further aggregated at an individual vehicle level to estimate 'Personal Quality and Reliability Satisfaction ($PQRS_{veh}$)'. These individual customer level satisfaction indices have been further aggregated for entire vehicle model to determine relative satisfaction levels for various vehicle models. These indices and their aggregation are described in details in following subsections.

3.2.1. Personal Quality Satisfaction (PQS)

Several definitions of quality have been reported in the literature, some of the important ones are: (a) ISO 9000 defined quality as a degree to which a set of inherent characteristic fulfills the

Table 1
Severity and customer impact classification.

Severity rating	Customer impact category
5	Non-operational or safety critical issue
4	Urgent repair needed
3	Important repair needed or customer convenience has been compromised
2	Minor repairs
1	Routine vehicle maintenance

requirements (ISO 9000., 2000). (b) Peter Drucker advocated that quality in a product or service is not what the supplier puts in, it is what the customer gets out and is willing to pay for (Drucker, 1995). (c) Garvin defined quality based on counting the incidence of internal failures (those observed before product leaves factory) and external failures in the field (Garvin, 1983). The customers define quality and reliability of a product from his or her experience with the product. Counting the number of problems per thousand vehicles may be a good indication of an aggregate quality. However, when the quality is considered from the perspective of the customer, one bad experience can be magnified in the mind of the customer and affect the quality related satisfaction of the product. In the current work, quality related satisfaction has been modeled based on the number of failure incidences and the severity of incidences. The severity of failure has been defined based on impact of the failure. Failures causing more inconvenience to customer (such as walk home situations or safety critical failures or expensive repairs) will have higher severity rating, while, routine maintenance repairs will have lower severity rating. These severity ratings have been assigned by a team of domain experts from various disciplines (product engineering, customer care and service). With the non operational, safety critical and expensive issues (example, engine replacement), the impact on customer in term of annoyance will be maximum and hence failures related to such issues have been assigned severity rating of 5. Repairs related to routine maintenance (example, oil change) have rating of 1. The rationale used to assign the severity ratings is given in Table 1.

To determine the quality satisfaction, the number of failure incidences at an individual vehicle level has been converted into *incidence equivalence* by considering frequency and severity of failure incidences. Let, j be the number of different failure incidences that are experienced by the customer, n_i be the number of times incidence i experienced by the customer and s_i be the severity of incidence i, then

$$Incidence\ equivalenece(IE_{eq}) = \sum_{i=1}^{j} n_i.s_i \tag{1}$$

If the number of incidence equivalence is less than a certain limit (say, IE_{min}) then customer will be very satisfied leading to quality satisfaction value one. If incidence equivalence is beyond certain limiting values (say, IE_{max}) then customer will be very dissatisfied leading to customer satisfaction value zero. For the intermediate values of incidence equivalence, satisfaction will vary from zero to one as depicted in Fig. 2.

$$f_1 = \begin{cases} 1 & \text{if } IE_{eq} \geqslant IE_{max} \\ 1 - \frac{IE_{max}-IE_{eq}}{IE_{max}-IE_{eq}} & \text{if } IE_{min} < IE_{eq} < IE_{max} \\ 0 & \text{if } IE_{eq} \leqslant IE_{min} \end{cases} \tag{2}$$

where,

f_1 = Dissatisfaction level because of quality.
IE_{max} = Maximum number of equivalent incidences that makes customer totally dissatisfied.
IE_{min} = Minimum number of equivalent incidences that customer can accept (here, 0).

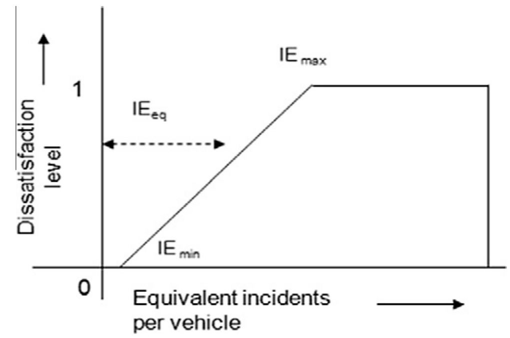

Fig. 2. Membership function to model quality satisfaction.

$$\text{Quality Satisfaction level or } PQS_{veh} = 1 - f_1 \tag{3}$$

3.2.2. Personal Reliability Satisfaction (PRS)

The IEEE defines reliability as an ability of a system or component to perform its required functions under stated conditions for a specified period of time (IEEE, 1990). Reliability is quantified as MTBF (Mean Time Between Failures) for repairable product and MTTF (Mean Time To Failure) for non-repairable product. However, pragmatically customer's satisfaction about the reliability not only depends on number of failures between a specified time period, but also, the time period between consecutive failures plays a crucial role in determining the satisfaction. For example, vehicle 1 and vehicle 2 shown in the Fig. 3 have same number of failures between given period of time. Although, the MTBF is same in both the cases, customer may perceive reliability of these two vehicles differently. Too many failures within short period of time will dissatisfy customers more.

In the current work, customer dissatisfaction because of reliability has been modeled using number of visit to dealer (say p) and time difference between two consecutive visits. If time difference between two consecutive visits to dealer (T_{act}) is less that certain limiting value (say, T_{min}) then it annoys customer more and if it is beyond certain limit (say, T_{max}) then the level of annoyance level will be zero. The annoyance level related to time difference between two consecutive visits (d_i) and number of visits (R_{act}) have been used to determine reliability satisfaction (Fig. 4). The equations to determine reliability satisfaction are given below:

$$d_i = \begin{cases} 1 & \text{if } 0 \leqslant T_{act} \leqslant T_{min} \\ 1 - \frac{T_{act}-T_{min}}{T_{max}-T_{min}} & \text{if } T_{min} < T_{act} < T_{max} \\ 0 & \text{if } T_{act} \geqslant T_{max} \end{cases} \tag{4}$$

$$\text{Equivalent no. of visits } (R_{eq}) = R_{act}\left(1 + \frac{\sum_{i=1}^{p-1} d_i}{p-1}\right) \tag{5}$$

This equivalent visits has been used to determine reliability satisfaction level of an individual customer. The values are computed in a way similar to described in Section 3.2.1. If the number of equivalent visits (R_{eq}) is zero then reliability satisfaction will be high leading to satisfaction value one, whereas, if equivalent visits number is beyond certain limiting values (say, R_{max}) then the satisfaction value is zero. For intermediate values of R_{eq} the satisfaction varies from 0 to 1.

$$f_2 = \begin{cases} 1 & \text{if } R_{eq} \geqslant R_{max} \\ 1 - \frac{R_{max}-R_{eq}}{R_{max}-R_{eq}} & \text{if } R_{min} < R_{eq} < R_{max} \\ 0 & \text{if } R_{eq} \leqslant R_{min} \end{cases} \tag{6}$$

where,

f_2 = Dissatisfaction level because of reliability.

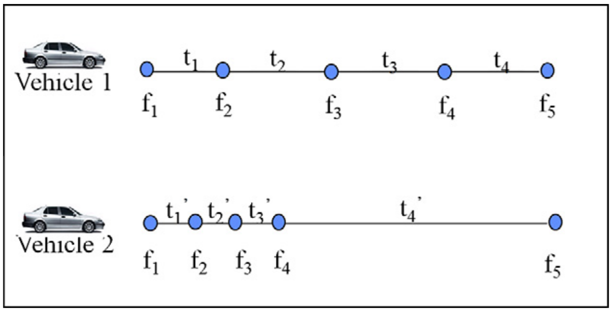

Fig. 3. Difference between reliability and reliability satisfaction (illustration).

R_{max} = Maximum number of equivalent visits that makes customer totally dissatisfied.
R_{min} = Minimum number of equivalent visits that customer can accept (here, 0).

$$\text{Reliability satisfaction level or } PRS_{veh} = 1 - f_2 \quad (7)$$

The satisfaction level related to quality and reliability at an individual customer level,

$$PQRS_{veh} = PQS_{veh} \times PRS_{veh} \quad (8)$$

The vehicles without any repair action (without warranty claim) will have PQS_{veh}, PRS_{veh} and $PQRS_{veh}$ values as 1, 1 and 1, respectively. As the number of claims increase, these values will become lower and lower.

3.2.3. Variation in satisfaction with ownership period

Pragmatically, ownership period is one of the important factors that affect satisfaction. As an example, if a vehicle owner experiences a significant number of quality problems during a small span of ownership period then his satisfaction level will be low at that time. However, if the same owner does not experience any quality issues later then his satisfaction will get improved. The satisfaction model has been enhanced to encapsulate such scenario by incorporating the notion of time dependent customer satisfaction. This has been achieved by making the fuzzy membership function parameters (i.e. IE_{max}, R_{max}) as a function of ownership period (days in use). The concept of time varying satisfaction has been illustrated in Fig. 5. Here, the threshold (i.e. IE_{max}) to estimate the quality related satisfaction for a 1 year old vehicle is 15, whereas, the same threshold for 2 year old vehicle is 30. Thus, if a vehicle owner experiences 15 equivalent failure incidences in 1 year of ownership experience then the quality related dissatisfaction will be 1 (i.e. 0 satisfaction level). If the same vehicle does not experience any failure in the next 1 year then at the end of 2 years the quality related dissatisfaction will be 0.5 (i.e. the satisfaction level will improve to 0.5).

3.2.4. Aggregating satisfaction at model level

The satisfaction level for a particular model has been determined by taking the mean of satisfaction level at individual vehicle ($PQRS_{veh}$) pertaining to that model. Thus,

$$PQRS_{model} = \sum_{i=1}^{q} PQRS^{l}_{veh}/q \quad (9)$$

where,

$PQRS_{model}$ = Satisfaction related to quality and reliability for a vehicle model.
$PQRS^{l}_{veh}$ = Quality and reliability satisfaction corresponding to lth vehicle of a given vehicle model.
q = Number of vehicles belonging to a given vehicle model.

Identifying appropriate values for parameters IE_{max}, T_{min}, T_{max} and T_{max} is an important step in the model development. The approach used to determine these values is described in detail in the next section.

4. Parameter tuning approach

One of the challenges in modeling the customer satisfaction using aforementioned approach is selecting appropriate values of various parameters. In the current work, the parameter values have been determined using supervised learning approach with grid search technique. As mentioned before, the overall objective of the parameter tuning exercise is to minimize the difference between the satisfaction values obtained from the proposed model and ratings given by the external agency. In the current work, reliability ratings available from Consumer Report, an industry wide accepted ground truth have been used. Here, parameters are tuned to match the quality and reliability customer satisfaction of a range of vehicle models to the reliability ratings from the Consumer Report. This match is performed to ensure that proposed satisfaction model adequately represents reality.

An overview of process used for parameter tuning is given in Fig. 6. The main steps involved in this process are:

1. Identification of parameter bounds.
2. Grid parameter search: This step further involves, (a) Discretizing parameter search space by specifying initial constraints, termination constraints and incremental values for parameters. (b) Initialize parameter values for computing satisfaction value at model level ($PQRS_{model}$). (c) Compute quality and reliability satisfaction value for all vehicle model under consideration. (d) Store parameter value set and satisfaction value at model level for all vehicle models in a database. (e) Increment parameter values to compute $PQRS_{model}$ over dicretized parameter space.

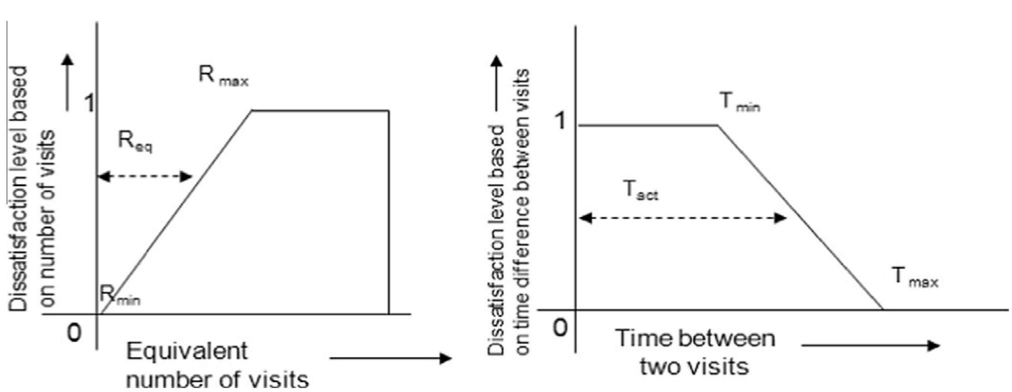

Fig. 4. Membership function to model reliability satisfaction.

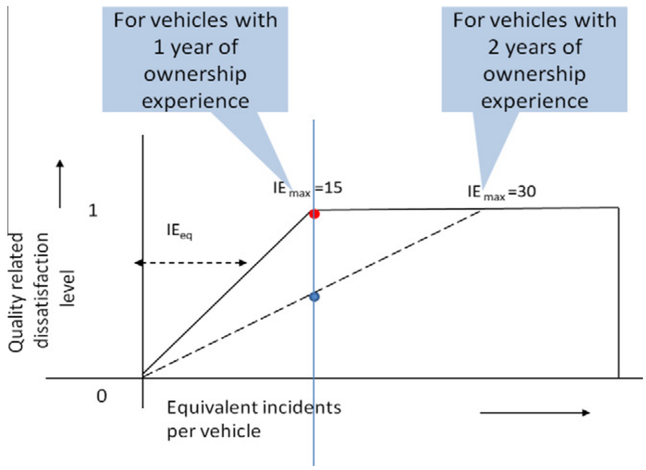

Fig. 5. Time varying satisfaction (illustration).

3. Compare computed satisfaction values with the target (linguistic reliability ratings from the Consumer Report) for all parameter combinations and select the best set of parameters.

The main steps are described in detail in following subsections.

4.1. Parameter bounds

The purpose of this step is to determine the allowable ranges for gird computation. For this, some initial experiments were performed on vehicles close to 1 year of ownership and pertaining to 12 vehicle models of 2009 Model Year (MY). The satisfaction level ($PQRS_{model}$) for these vehicle models was determined using proposed approach with some randomly selected parameters values. The results of these experiments are shown in the Fig. 7. Let us examine two sets of parameters from these results – the lowest values set or LVS (IE_{max} = 5, T_{min} = 5, T_{max} = 90, R_{max} = 5) and highest values set or HVS (IE_{max} = 50, T_{min} = 90, T_{max} = 365, R_{max} = 50). With LVS, the satisfaction values for all models are close to zero (all are less than 0.2) and with HVS, these values are close to one (all are greater than 0.85). Further, the difference between these values across all vehicle models is minimal for both of these sets. If we choose parameters with values less than LVS or more than HVS this difference will further reduce. For these reasons, we choose the lower and upper bounds on parameter values as the values present in LVS and HVS, respectively.

4.2. Grid parameter search

In order to perform a grid search on the parameter values between the lower and upper bound values identified, we choose a step size (or increment) Δ=10. Based on this step size we first calculate the $PQRS_{model}$ values for all models and for all possible parameter combinations and store those in a CSI database (please refer to Table 2). Once these values are calculated for each parameter combination, these are compared against the target linguistic reliability ratings from the Consumer Report (Section 5.3) and an optimal set of parameter values are obtained.

4.3. Comparison with the target and parameter set selection

This step involves comparison of satisfaction values for the vehicle models (for each set of parameters) with the target satisfaction ratings available from the Consumer Reports. This comparison is not straight forward because of the linguistic nature of reliability ratings available from the Consumer Report. Here, fuzzy

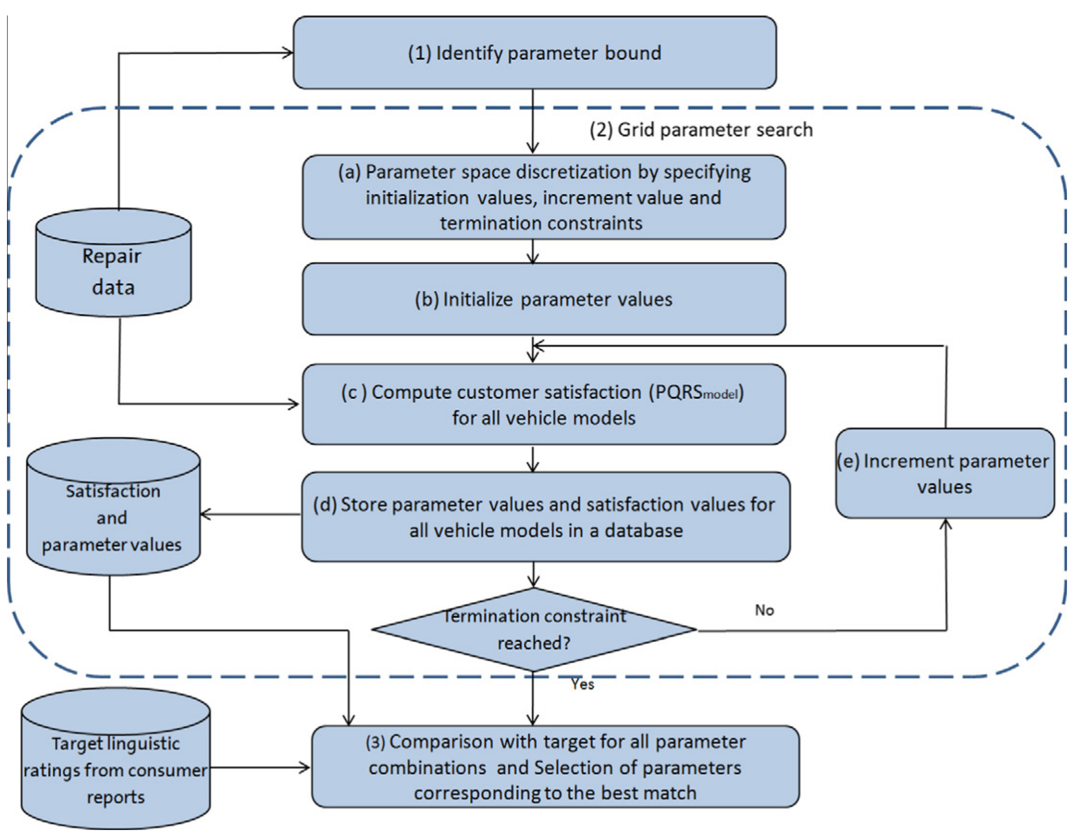

Fig. 6. Parameter tuning approach.

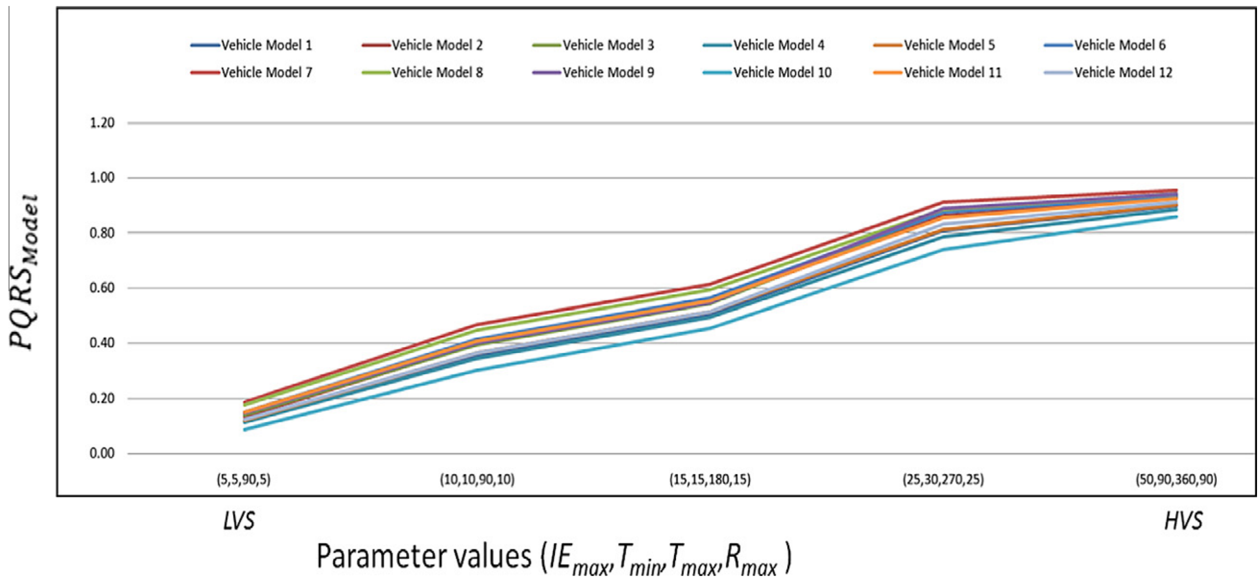

Fig. 7. CSI values for 12 vehicle models for five different parameter settings.

Table 2
Algorithm to calculate satisfaction values for various parameter combinations.

Algorithm. Populate_CSI_DataBase
Input: Upper and Lower bounds for each parameter and step size
($IE^L_{max}, T^L_{min}, T^L_{max}, R^L_{max}, IE^U_{max}, T^U_{min}, T^U_{max}, R^U_{max}, \Delta$)

Output: CSI_DataBase for various parameter settings

FOR IE_{max} = IE_{max}^L to IE_{max}^U
  FOR T_{min} = T_{min}^L to T_{min}^U
    FOR T_{max} = T_{max}^L to T_{max}^U
      FOR R_{max} = R_{max}^L to R_{max}^U
        Calculate $PQRS_{model}$ (IE_{max}, T_{min}, T_{max}, R_{max})→ CSI_DataBase
        $R_{max} = R_{max} + \Delta$
      END FOR
      $T_{max} = T_{max} + \Delta$
    END FOR
    $T_{min} = T_{min} + \Delta$
  END FOR
  $IE_{max} = IE_{max} + \Delta$
END FOR

logic approach has been used in comparison. It provides a fundamental basis to capture the uncertainty associated in comparing numeric satisfaction values and the target linguistic reliability rating. The numeric satisfaction values obtained from the satisfaction model are converted into linguistic customer satisfaction ratings using fuzzy scale shown in Fig. 8. To develop this scale, average satisfaction of all vehicle models (S^m_a) corresponding to each set of parameters is determined. This average satisfaction value forms the basis to determine the value of other variables corresponding to fuzzy sets (Fig. 8). These values are calculated by using the formulae given below,

$$S^l_a = \frac{\sum_{i=1}^{k} PQRS^k_{model}}{k} \ldots \quad \text{where,}$$
$$k = \text{Number of vehicle models under consideration} \tag{10}$$

$$S^l_a = S^m_a - (0.20 \times S^m_a) \tag{11}$$

$$S^u_a = S^m_a + (0.20 \times S^m_a) \tag{12}$$

$$S^l_w = S^m_a - (0.10 \times S^m_a) \tag{13}$$

$$S^l_b = S^m_a + (0.10 \times S^m_a) \tag{14}$$

These formulae have been derived based on literature reported by Consumer Reports Organization (Consumer Reports Organization, 2012) and discussion with subject matter experts. The conversion from numeric satisfaction value to linguistic rating has been facilitated by rules derived from the fuzzy sets. An example of such rule is,

- If ($S^l_a \leqslant PQRS_{model_k} \leqslant S^u_a$) then linguistic customer satisfaction rating for model k (CSL^k) is average.

As illustrated in Fig. 9, numerical value $PQRS_{model_k}$ can be a member of more than one fuzzy set. This implies that a particular vehicle model can have more than one linguistic rating. Let, CSL^k_s be the set of linguistic ratings obtained from proposed approach for model k for a given parameter set and T^k be the target linguistic rating from the Consumer Report. If $T^k \in CSL^k_s$ then it is considered that value obtained from proposed approach is in agreement with the rating given by the Consumer Report. On the other hand, if $T^k \notin CSL^k_s$ then it is considered as a mismatch.

Total numbers of matches for each parameter set are determined and parameter set corresponding to maximum matching cases is selected as optimum parameters for modeling the customer satisfaction (c.f. Section 3.2). In case of tie (i.e. more than one parameter sets have the same number of matching cases), the parameters corresponding to maximum spread (difference between calculated satisfaction value of the best and the worst vehicle model) are considered as appropriate parameters. Here, maximum spread criterion is used because it provides better distinction between the relative satisfaction levels of each vehicle model.

5. Results and discussions

In this section, we present the experiments performed to identify the parameter values to determine the quality and reliability related satisfaction. As discussed before, the lowest values set or LVS and highest values set or HVS are obtained by performing some initial experiments (Section 4.1). The values are presented in Table 3. The satisfaction values for 12 vehicle models with close to 1 year of ownership experience have been determined with the parameters set {$IE_{max}, T_{min}, T_{max}, R_{max}$} varying from {5,5,90,5} to {50,90,365,50} with a step size of 10. The variation in the

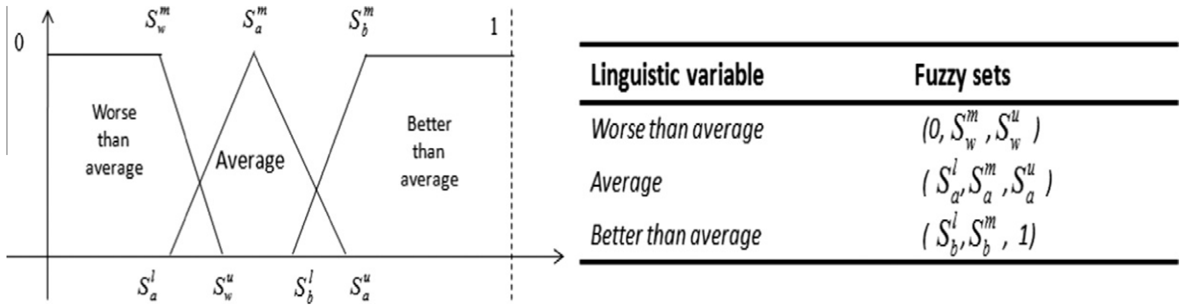

Fig. 8. Fuzzification scale.

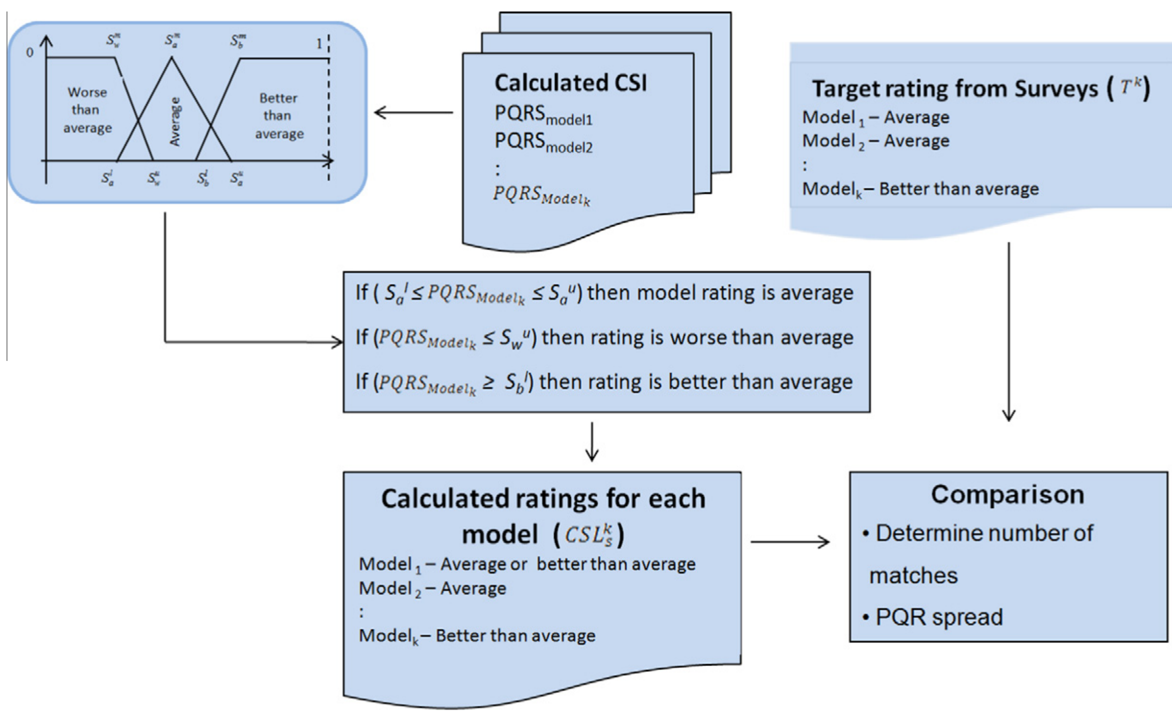

Fig. 9. Comparison between calculated satisfaction and Consumer Report reliability rating.

Table 3
Lower and upper bound for grid search.

Parameter	Lower bound	Upper bound
IE_{max}	5	50
T_{min}	5	90
T_{max}	90	365
R_{max}	5	50

satisfaction with parameters is shown in Fig. 10. As evident from the figure, parameters IE_{max} and R_{max} have more influence on satisfaction than that of T_{min} and T_{max} (cf. Section 3.2). Here, the satisfaction value at model level ($PQRS_{model}$) changes significantly with change in IE_{max} and R_{max} in comparison with T_{min} and T_{max}.

These satisfaction values have been converted into linguistic ratings (c.f. Section 4.3) and compared with the reliability rating values from the Consumer Report to determine the optimum parameters. The results of this comparison in terms of number of matches and spread are shown in Fig. 11. It was realized that, the parameter set {15,15,180,15} gives maximum number of matching cases and maximum spread. Out of 12 vehicle models, for 10 models the rating obtained using proposed method matched with the Consumer Report reliability ratings and the value of spread is 0.25. Only in 2 cases ratings did not match. Hence, these values are chosen as optimum parameters to determine quality and reliability related customer satisfaction for vehicles close to one year of ownership experience.

As mentioned before, satisfaction varies with time. In order to incorporate the notion of time varying satisfaction into the model, the parameters have been modified based on ownership period. The modified parameters have been determined by interpolating/extrapolating the parameters with respect to ownership period. In addition, inputs from domain expert are also considered while determining these values. The parameter values for various ownership period are given in Table 4. As an example, in the satisfaction model, for vehicles close to 1 year of ownership experience (330–390 days) the values of parameters IE_{max} and R_{max} have been used as 15, whereas, for vehicles with close to 2 years of ownership experience (690–750) these have been used as 30. Using these time varying parameters, the methodology has been validated by assessing the satisfaction level of the same 12 vehicle models (same MY) after 2 years of ownership period and comparing the results with the Consumer Reports reliability rating of these vehicles models. Again, we observed that, in 9 cases we matched the reliability ratings given by the Consumer Reports whereas in 3 cases there was a mismatch.

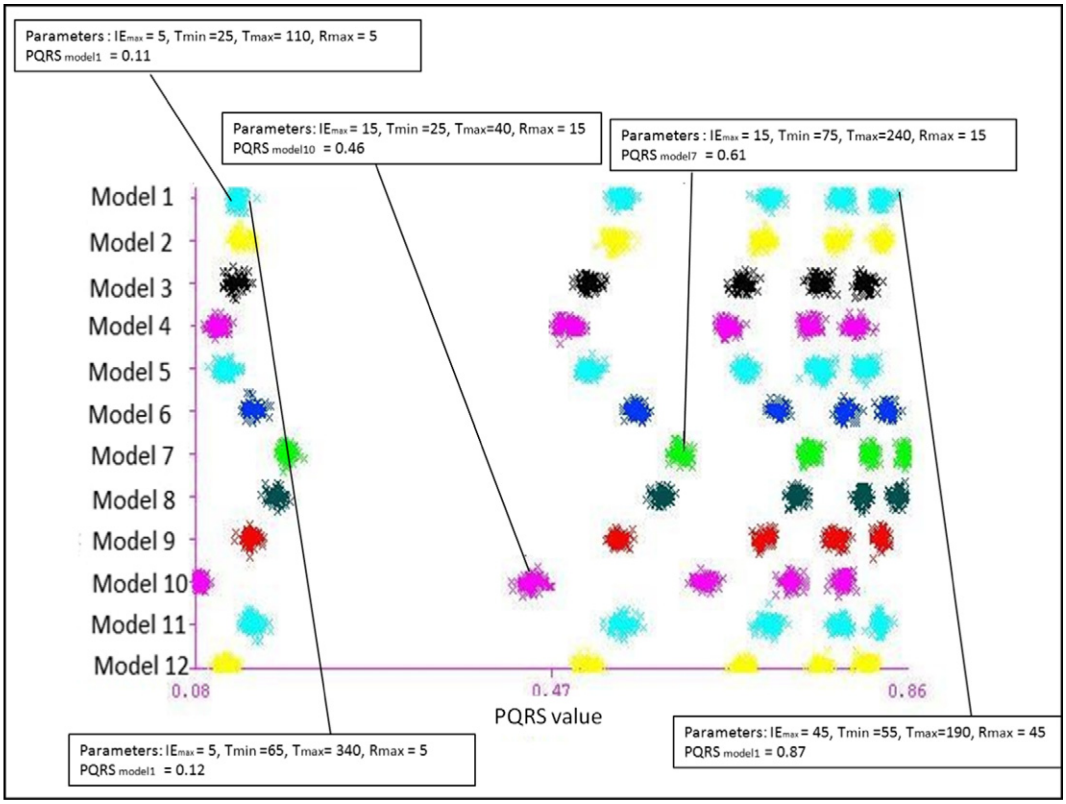

Fig. 10. Variation in satisfaction with parameters.

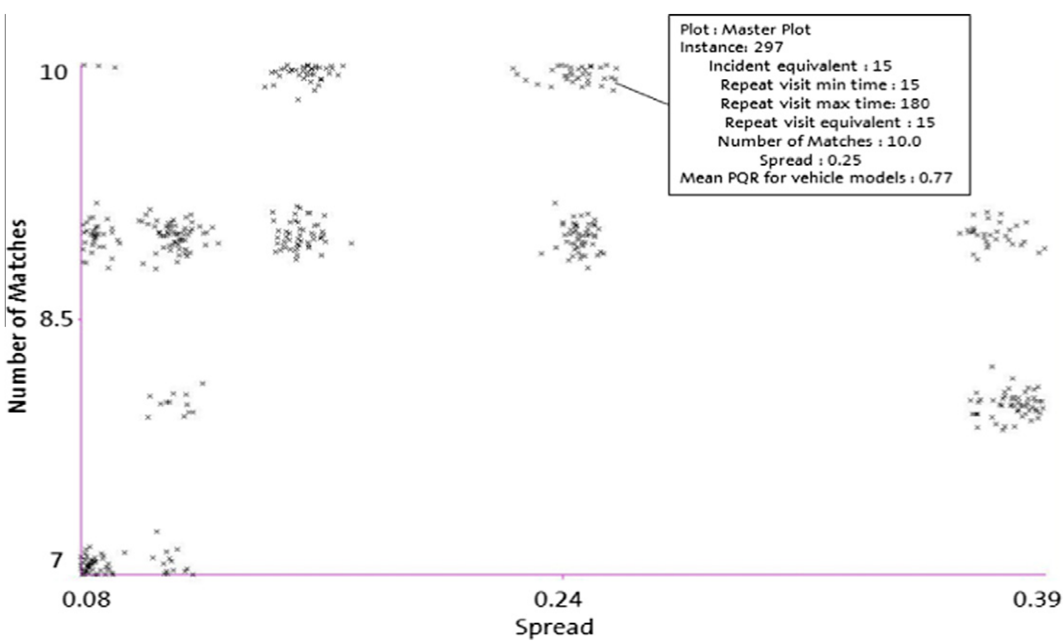

Fig. 11. Variation in number of matches and spread with parameters.

In addition, we compared the satisfaction rating obtained using above approach for 2010 MY vehicles after 1 year of ownership experience. We observed that, (a) In 9 cases, the reliability ratings given by the Consumer Reports matched with the satisfaction rating obtained using proposed approach, (b) For 1 vehicle model we did not match with Consumer Report rating (c) for 2 vehicle models Consumer Report organization did not publish ratings because of insufficient survey data. In this way, the proposed satisfaction model has been validated for various vehicles models corresponding to different model years and with two different ownership periods.

Table 4
Parameter variation with ownership period.

Ownership period	IE_{max}	R_{max}
0–90	3	3
90–150	5	5
150–210	8	8
210–270	10	10
270–330	12	12
330–390	15	15
390–450	17	17
450–510	20	20
510–570	22	22
570–630	25	25
630–690	27	27
690–750	30	30
750–810	32	32
:	:	:

6. Conclusion and future plan

Customer satisfaction is a key differentiator in many sectors, including automotive, manufacturing, retail and finance. Especially in the automotive domain, where the product undergoes a lot of scrutiny by the customers before the purchase, it assumes even more significance. Besides offering competitive advantage and revenue generation, better customer satisfaction also results in better brand image. On the other hand, dissatisfied customers not only exit but also spread bad publicity about the product. Due to these reasons, it is very crucial for the OEMs to assess the customer satisfaction for their products not only at an aggregate level, but also at the individual customer level.

As per the J.D. Power Vehicle Ownership Satisfaction Study (J.D. Power Associates., 2009), more than 40% of customer satisfaction can be attributed to vehicle quality and reliability. In the current work, a bottom-up approach is used for modeling quality and reliability related customer satisfaction. Information related to part failures experienced by the vehicle owner over a period of time is inferred from the repair data available in the warranty database. Subsequently, for each vehicle, various attributes including (1) Number of repairs performed; (2) Severity of repairs performed; (3) Number of visits to dealership; and (4) Time span between two consecutive visits is used to assess the quality and reliability satisfaction using the parametric satisfaction model developed in this work. The parameters in the satisfaction model are tuned using reliability ratings of 12 different vehicle models from Consumer Reports.

At present, the survey based methods are used to assess the customer satisfaction (such J D Power, ACSI, Consumer Reports). The proposed approach is different from the current assessment methods in two aspects – (1) Since data from all the vehicles are utilized to obtain the model, sampling errors can be eliminated; and (2) It provides assessment of customer satisfaction at an individual vehicle level, which allows the OEM to take pro-active actions to restore the customer satisfaction of the dissatisfied customers. Further, such an individual vehicle level customer satisfaction model can also be used for the root cause investigation of customer dissatisfaction. One such similar application is presented in Gaur, Bandaru, Deb, Khare, and Chougule (2012) where impact of various field failures are examined using a similar customer satisfaction model. Although, the work presented in this paper is focused on the automotive domain, similar approach can be applied to other domains (such as consumer electronics, home appliances) where field failure data and satisfaction ratings are available.

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