AN INVESTIGATION INTO DYNAMIC CUSTOMER REQUIREMENT USING COMPUTATIONAL INTELLIGENCE

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Keywords: Dynamic customer requirement, Product design, Artificial immune system, Artificial neural network, Design space framework.

Abstract: The twenty-first century is marked by fast evolution of customer tastes and needs. Research has shown that customer requirements could vary in the temporal space between product conceptualisation and market introduction. In markets characterized by fast changing consumer needs, products generated might often not fit the consumer needs as the companies have originally expected. This paper advocates the proactive management and analysis of the dynamic customer requirements in bid to lower the risk inherent in developing products for fast shifting markets. A customer requirements analysis and forecast (CRAF) system that can address the issue is introduced in this paper. Computational intelligence methodologies, viz. artificial immune system and artificial neural network, are found to be potential techniques in handling and analysing dynamic customer requirements. The investigation aims to support product development functions in the pursuit of generating products for near future markets.

1 INTRODUCTION

In the twenty-first century, new product development (NPD) businesses face the uncertainties of highly turbulent market. Changing customer needs is known to be a key driver of uncertainties that are inherent in NPD projects (Herstatt et al., 2006). While the processes of requirement management in product development have been relatively well-investigated, only few studies considered the temporal dimension of the critical information. The status is similar in the industry; studies have shown that companies in general have unjustly neglected the aspect during product development (Kärkkäinen et al., 2001). In a volatile market, it is clearly imprudent for one to comment on the validity of customer requirement data without making references to the frames of time. Requirement is the basis of product development, and it can vary with time. In other words, the requirements of the same customer can be different in different points of time. The variation of customer satisfaction attribute weights along the temporal dimension was elucidated in a longitudinal study (Mittal et al., 1999). Prior to ramping up production, design specifications are by necessity frozen. In cases where customer requirements shift substantially between the points of design freeze and market introduction, the product may satisfy the customers to a lesser extent than intended. Product developers, when unwary of this variable, might end up generating products not wanted by the customers. As the issue of dynamic customer requirements is increasingly valid due to globalisation and stiffening competition, it is urgent and critical to recognize customer needs as time-based variables, in both practice and research.

2 A BRIEF OVERVIEW OF THE CURRENT SOLUTIONS

Reichwald et al. (2005) commented that traditional market research methodologies focus only on current situation and often do not contribute to the correct assessments of future customer requirements. With historical data, time series methods can be employed for forecasting. Xie et al. (2003) employed the double exponential smoothing technique in projecting the importance level of the requirements, i.e. quantitatively. The method is however limited to forecasting quantitative data, and only of linear trend. Raharjo et al. (2006) proposed a

Chong Y. and Chen C. (2009).
AN INVESTIGATION INTO DYNAMIC CUSTOMER REQUIREMENT USING COMPUTATIONAL INTELLIGENCE.
In *Proceedings of the 11th International Conference on Enterprise Information Systems - Artificial Intelligence and Decision Support Systems*, pages 113-117
DOI: 10.5220/0001960801130117

method that prioritises the quality characteristics in the context of a dynamic QFD. The method identifies quality characteristics that have greater confidence in meeting future customer requirements. However, the method does not produce future customer requirement information; on the contrary, it requires the information as input. Chen and Yan (2008) analysed customer utility based on radial basis function neural network. While the method does not specifically ascertain the future customer needs, it predicts the future customer preferences over a range of design options.

Despite the importance of ascertaining future customer needs, product developers generally placed little attention to it (Kärkkäinen et al., 2001). Of the sparse studies in dynamic customer requirements, the direction is in general to counter the uncertainties the variable contributes to NPD. Given the increasingly fast moving product markets, research and development effort in the area is ever more valid. This work advocates product development organizations to proactively look into the future requirements of customers; an approach that analyses the variations of the customer requirements is introduced in this paper.

3 DATA REPRESENTATION OF DYNAMIC CUSTOMER REQUIREMENTS

A customer requirements analysis and forecast (CRAF) system is proposed to address the issue of dynamic customer requirement. In the CRAF system, dynamic customer requirement (DCR) information is modelled based on the Design Space Framework proposed by Chong et al. (2009). An adapted structure employed in this study is hereby referred to as the Requirement Space Framework (RSF), as shown in Figure 1. For the robustness of the data, customer requirements are represented in multiple levels of abstraction, as described along the *Z* axis of the RSF. Chong et al (2009) postulated that alternative values can exist for requirements, and details of the requirements can be further represented by co-requirements. Correspondingly (as shown in Figure 1), requirement options are represented along the *Y* axis while co-requirements are modelled along the *X* axis of the RSF. Apart from the three dimensions of the information, a fourth facet of the user needs data, i.e. time, is prescribed in this study. Figure 1 depicts a schematic snap-shot of the user needs data in a time instance.

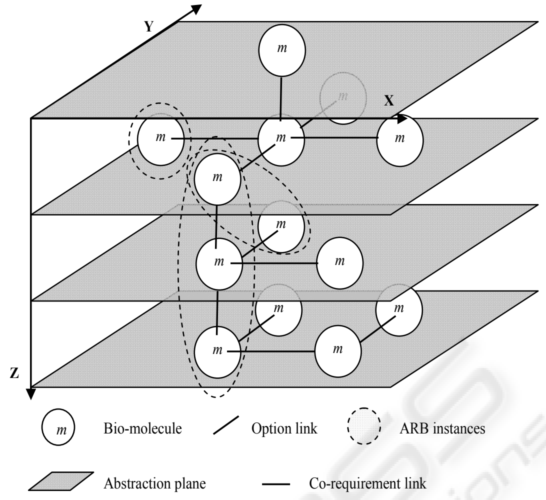

Figure 1: The Requirement Space Framework.

In this work, the learning and analysis of the dynamic customer needs data is primarily based on techniques of the artificial immune system (AIS). As such, the data representation scheme is based on the basic conventions in the AIS research (de Castro and Timmis, 2002). The following describes the mapping of the RSF model to the AIS-based data representation schemes. Customer requirements are represented by two types of data classes – the antigens (Ag) and B-cells. The DCR input data is modelled as Ag that 'infiltrates' the CRAF system, while the system memory is represented by B-cells, or more specifically, the artificial recognition balls (ARB) (see Table 1 and Figure 2). ARB represents a group of identical B-cells in the system (Timmis and Neal, 2001). States of ARBs are dichotomy, either active or inactive. Bio-molecules - the building blocks of the system data - are modelled with symbolic *attribute-value* pairs, e.g. $ARB_{3,2}$= <colour, black>. Undefined (i.e. 'don't care') bio-molecules of Ag and ARB are represented using the symbol #.

Table 1: The AIS-based system.

Vertebrate immune system	**CRAF System**
Antigens	Customer requirements (in product market)
B-cells/ ARB	Customer requirements (in system memory)
Biological environment	Product market

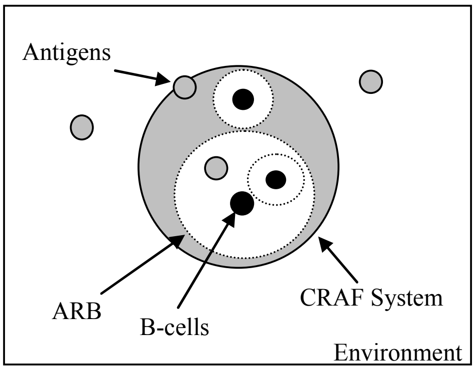

Figure 2: A schematic diagram of the CRAF system.

Concentration of B-cells within the system represents the importance level of attributes and the preference level of values of the respective ARB. The antibody concentration fluctuates as the result of the interacting mechanisms within the biological immune system, involving biological processes such as cloning, apoptosis, and cell activation. In this work, the dynamics of the B-cell population is metaphorically applied to model the dynamism of customer requirements in product markets.

4 THE CUSTOMER REQUIREMENT ANALYSIS AND FORECAST ALGORITHM

Immune system is described as adaptive, self-organizing in nature, maintaining a memory of past encounters, and has the ability to continually learn via new encounters (Dasgupta, 2006). An intrinsic and unique ability of AIS is its continuous capability to adapt to and to co-evolve with the environment. Based on established machine learning algorithms (e.g. Timmis and Neal, 2001), this work proposes a domain specific dynamic population-based clonal selection algorithm, i.e. the customer requirements analysis and forecast (CRAF) algorithm.

The concentration levels of the B-cells are of interest to this work. The temporal characteristics of the concentration levels represent the time-based profiles of the customer needs. Customer needs data can be non-linear, non-stationary, noisy and limited in quantity, all which poses challenges for the time-based learning in the CRAF system. Focused time delay neural network (FTDNN) with backpropagation training is embedded in the AIS-based system to learn the temporal system data. The proposed CRAF algorithm is described below.

1. **Initialisation.** A set of active ARBs at a predetermined concentration level of ARBT (ARB Threshold) at t = 1 is preinstalled in the system.
2. **Introduction of Antigens.** Antigenic data, *Ag*, is introduced to the system at time t.
3. **Secondary Immune Response.** Each of the introduced data packet *Ag* is presented to all active ARB for stimulation.
4. **Primary Immune Response.** Stimulation of inactive ARB is performed; cross-reactivity does not apply in the primary response, i.e. stimulation here requires exact match.
5. **Apoptosis.** The population of the B-cells in the system is maintained by the process of programmed cell death.
6. **Concentration Update.** The concentration level of each ARB is refreshed.
7. **Antigenic Learning.** Antigenic data unfamiliar to the system will be learnt when foreign antigen encountered is beyond the recognition of the existing ARB.
8. **Activeness Update.** If the concentration level of active ARB falls below the ARBT level for a specified period of time, it will be deactivated. This period is termed as *persistency period*, or PP. On the other hand, inactive ARB will be activated when the concentration level is maintained above the ARBT level over the specified PP.
9. **Neural Network Training.** The currently available set of B-cell concentration data is utilized to train the embedded focused time delay neural network.
10. **B-cells Concentration Forecast.** Trained neural network is simulated to forecast the future B-cell concentration of the respective ARB. The algorithm is looped (t=t+1) by proceeding to Step 2.

5 A CASE STUDY

The development of personal computer is challenging due to the fast moving market. The requirements of the customers evolve rapidly, relative to the time span of the product development cycle. Market foresight is in this case critical to the developers in acting and reacting to the industry. In highly competitive market, product customisation is an important strategy to increase market share. Robust customer requirements information therefore plays key role in the process of product planning, design, marketing and research and development,

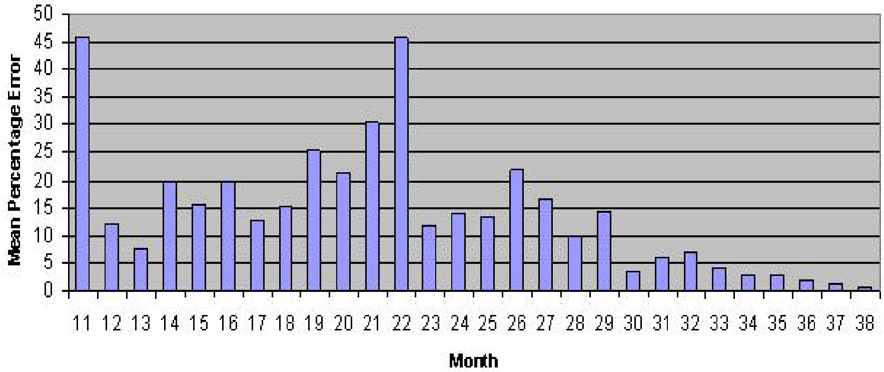

Figure 4: Mean percentage error of concentration forecast.

etc. Customer requirements information can be derived from market surveys, as the input to the CRAF system. Customer requirements may also be inferred from the sales of products, by regarding the acts of purchase as customer needs and preferences expressions.

In this study, an appropriately scaled and disguised proprietary dataset from a personal computer manufacturer is employed (Kurawarwala and Matsuo, 1998). The data relates the purchases of five types of PC over thirty-eight months in a particular market segment. P1 to P5 are the models of PC having the assumed features, as shown below.

- P1: Brand X processor 1.6GHz, Brand A operating system (OS), tower chassis, 1GB memory (RAM) (667MHz), 80 GB HDD (5400 RPM), Integrated graphic processor, CD-RW drive and diskette drive.
- P2: Brand Y processor 1.6GHz, Brand A OS, tower chassis, 1GB RAM (667MHz), 160 GB HDD (5400 RPM), Integrated graphic processor, DVD-ROM and diskette drive.
- P3: Brand X processor 2.0GHz, Brand B OS, desktop chassis, 2 GB RAM (800 MHz), 320 GB HDD (5400 RPM), discrete graphic processor Type 1, DVD-ROM drive.
- P4: Brand Y processor 2.0GHz, Brand A OS, desktop chassis, 2GB RAM (800 MHz), 320 GB HDD (7200 RPM), discrete graphic processor Type 1, DVD recordable drive.
- P5: Brand X processor 2.4GHz, Brand B OS, compact chassis, 4 GB RAM (1067MHz), 500 GB HDD (7200 RPM), discrete graphic processor Type 2, DVD recordable drive and media card reader.

The CRAF algorithm has been implemented in the Matlab environment for the purpose of the study. The simulated sequential process resulted in a set of ARB objects that reflects the patterns in the data, i.e. the qualitative and quantitative representations of the customer requirements at various levels of abstraction. Post-analysis of the data produced useful information including the relative preferences amongst the customer requirements. For instance, in this case study, the system reported the discrete type graphic card being relevant around the 25th month, and thereafter started to gain popularity against the integrated type (see Figure 3).

The forecast of the B-cells repertoire is made possible having modelled the dynamics of the evolution. Dynamic forecast of the B-cells concentration levels in the ARB was found to be improving over the months. The mean percentage error of forecast, in the current study, drops below 5% for the final sampled 6 months, with each lower than the previous (see Figure 4). The mean percentage error of forecast during the 38th month was noted to be 0.79%.

This study demonstrated the functions of the CRAF system as an indicator of the future customer requirements. The generated sets of customer needs data are cross-referenced to the temporal space, making them exceptionally valuable in highly time-sensitive markets.

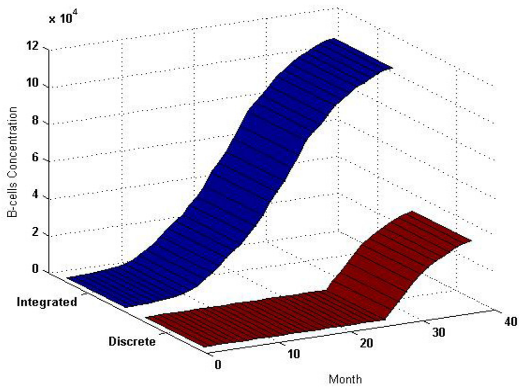

Figure 3: B-cells concentration of graphic card types.

6 CONCLUSIONS

The CRAF system introduced in this paper is aimed at addressing the problem of fast shifting customer needs. In general, the system studies the dynamics of pattern evolution to further perform data forecast. The algorithm is specified to operate continuously so as to track and to analyse the customer needs data dynamically. Such characteristic is in contrast with traditional methods that treat singular temporal customer data in discrete approaches. It is envisioned that the intelligence that could be derived from the proposed system may serve to reduce the uncertainties inherently found in product development projects. In view of the increasingly fast changing market, dynamic customer requirement analysis and forecast (as well as the applications of the generated intelligence on downstream activities) are vital areas for future research.

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