Management and forecast of dynamic customer needs : an immunity-based approach

Chong, Yih Tng

2010

Chong, Y. T. (2010). Management and forecast of dynamic customer needs : an immunity-based approach. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/42316>

<https://doi.org/10.32657/10356/42316>

**NANYANG
TECHNOLOGICAL
UNIVERSITY**

**MANAGEMENT AND FORECAST
OF DYNAMIC CUSTOMER NEEDS:
AN IMMUNITY-BASED APPROACH**

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**SCHOOL OF MECHANICAL & AEROSPACE
ENGINEERING**

2010

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DYNAMIC CUSTOMER NEEDS:
AN IMMUNITY-BASED APPROACH**

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A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirement for the degree of
Doctor of Philosophy

2010

Abstract

With rapidly growing competition intensity, globalization, and technological advancement, high volatility of consumer needs has been observed. Product developers in volatile markets face the challenge of capturing fast moving targets - customer requirements. Customer needs can vary considerably across the period between the time of requirement elicitation and market introduction of a product. The variation contributes to the uncertainties of the product's market acceptance. Therefore, it is crucial for developers to grasp the dynamism of customers' needs in the processes of making decisions during product development cycles, especially in markets where requirements fluctuate considerably across time. Modern technology allows companies to gather vast amount of data concerning individuals and their habits on a periodical basis. An approach to deal with the issue of fast shifting customer needs is to dynamically acquire requirement data through effective media such as the Internet. Information derived from analyzing the time-series data may therefore serve to reduce the uncertainties of success that are inherent in product development projects.

This study aims to advance the body of knowledge that is necessary to address the issue of dynamic customer needs. Research in the area of dynamic customer requirements and the potential solutions to the problem are reviewed. The boundaries of the research areas are identified and a set of research problems is accordingly defined.

To overcome the problem of representing complex requirement information, a robust customer requirement model termed as the Requirement Space Framework is established. An immunity-based dynamic and autonomic learning (iDal) technique is proposed as the backbone of a prototype customer requirement analysis and forecast (CRAF) system. In the development of the iDal technique, two immunology concepts (i.e. specificity index and the dynamism of antibody concentration) are introduced to the paradigm of immunity-based systems. The dynamic property of the iDal technique facilitates the temporal analysis of the customer need data, while the autonomic

property enables the system to independently learn the qualitative and quantitative aspects of customer need information. The prototype CRAF system is prescribed to approximate the temporal characteristics of customer requirement data, and therefore to perform non-linear forecasts. Investigations of the CRAF system are conducted based on a set of case data, on both the micro and macro levels. On a micro-level, the mechanisms of the system are explicated and studied; on a macro-level, the iDal technique is implemented on the MATLAB platform to demonstrate the overall behaviors and functions of the CRAF system. As the dynamism of customer requirements has been known to bear implications on functions of a product development organization, the proposed prototype CRAF system is demonstrated in this work to support the handling of a product design problem.

List of Publications

International Refereed Journals:

1. **Chong Y.T.** and Chen C.-H. (2010) Dynamic customer needs as moving targets: a review, International Journal of Advanced Manufacturing Technology, 48(1): 395-406 (EI & SCI)
2. **Chong Y.T.** and Chen C.-H. (2010) Management and forecast of dynamic customer needs: an artificial immune and neural system approach, Advanced Engineering Informatics, 24(1): 96-106 (EI & SCI)
3. **Chong Y.T.**, Chen C.-H. and Leong K.F. (2009) A heuristic-based approach to conceptual design, Research in Engineering Design, 20(2): 97-116 (EI & SCI)
4. **Chong Y.T.**, Chen C.-H. and Leong K.F. (2009) Human-centric product conceptualization using a Design Space Framework, Advanced Engineering Informatics, 23(2): 149-156 (EI & SCI)
5. Yan W., Chen C.-H., Chang D. and **Chong Y.T.** (2009) A stakeholders-oriented innovative product conceptualization strategy based on fuzzy integrals, Advanced Engineering Informatics, 23(2): 201-209 (EI & SCI)
6. Chen C.-H., **Chong Y.T.** and Yan W. (2007) Recent patents of product design technologies, Recent Patents on Engineering, 1(2): 195-202 (EI)

Conference Proceedings:

7. **Chong Y.T.** and Chen C.-H. (2009) An investigation into dynamic customer requirement using computational intelligence, in Proceedings of the 11th International Conference of Enterprise and Information System 2009, Volume AIDSS: 113-117, Milan, Italy

8. Chen C.-H., Lin M.-C., Tai Y.-Y., **Chong Y.T.** and Yan W. (2009) Product concept innovation using fuzzy integral, in Proceedings of the 5th International Conference of Planning and Design, Tainan, R.O.C.
9. **Chong Y.T.** and Chen C.-H. (2006) A general model of conceptual design, in Proceedings of the International Design Research Symposium 2006, 187-197, Seoul, R.O.K.
10. **Chong Y.T.** and Chen C.-H. (2005) A Design Space Framework for modeling customer-driven conceptual design, in Proceedings of the Design Nexus Conference 2005, Yunlin, R.O.C.
11. **Chong Y.T.**, Chen C.-H. and Leong K.F. (2005) A heuristic-based approach to customer-driven conceptual design, in Proceedings of the International Design Congress 2005 – International Association of Society of Design Research, Yunlin, R.O.C.

Acknowledgement

This research was supported by a Ph.D. Research Scholarship awarded by the Nanyang Technological University, from 3 January 2006 to 30 December 2009. The Ph.D. Oral Defense of this work was held on 13 September 2010.

First and foremost, my sincere appreciation goes to my academic advisor, Associate Professor Chen Chun-Hsien, for his invaluable guidance and unreserved support.

My earlier research for an M.Eng. degree, which later led to this Ph.D. work, began with the support of Professor Khoo Li Pheng. During my research, Associate Professor Leong Kah Fai has given me his support and insightful inputs. Associate Professor Lee Yong Tsui, Associate Professor Tor Shu Beng, and Associate Professor Gerald Seet who sit in the Ph.D. Confirmation and Oral Defense Panels have contributed enlightening advices during critical discourses. Internal and external examiners have shown me the concept and the rigorousness of a Ph.D. work. It would not have been possible without their considerable commitment in appreciating this research. Staffs of the school, including Mr Chia Yak Khoong and Ms Soh Meow Chng, were dedicated in providing technical and administrative assistances. I should also highlight that numerous referees of the international journals and conferences where publications of this research were made have dispensed conscientious and rigorous suggestions under the peer review processes. Members who served with me, within the school in the Alumni Association and the Graduate Students' Club, beyond the school in a Citizen Consultative Committee, Community Centre Management Committee and Youth Executive Committee, and from other organizations, have constantly shown care and concern for my studies. Close friends and fellow researchers have in their own unique and profound ways provided me with much needed companionships and support along the course. All of them have made my postgraduate journey an interesting, enjoyable, and memorable one.

Acknowledgement

To have a child, sibling, or a partner who is a full-time Ph.D. candidate truly requires some patience. I appreciate my parents, brother, sister-in-law, sister, brother-in-law, and my wife-to-be Peiqi for being supportive through the years of my postgraduate studies. This thesis is dedicated to them.

28 October 2010

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List of Abbreviations

AIS	Artificial immune system
ANN	Artificial neural network
ARB	Artificial Recognition Ball
ARBT	Artificial Recognition Ball Threshold
ARIMA	Autoregressive integrated moving average
CACD	Computer-aided conceptual design
CAD	Computer-aided design
CDH	Conceptual Design Heuristic
CI	Computational intelligence
CR	Customer requirement
CRAF	Customer requirements analysis and forecast
DSF	Design Space Framework
DCR	Dynamic customer requirements
EA	Evolutionary algorithm
FTDNN	Focused time delay neural network
HBCD	Heuristic-Based Conceptual Design
iDal	Immunity-based dynamic and autonomous learning
MLP	Multi-layer perceptron
MR	Merit Ratio
MSE	Mean squared error
NPD	New product development
NPS	New product success
PP	Persistency period
QFD	Quality Function Deployment
R&D	Research and development
RSF	Requirement Space Framework
SI	Specificity index
TAR	Threshold autoregressive model

Chapter 1 – Introduction

The background of the research is presented in Section 1.1. In the section, the issue of dynamic customer needs is illustrated, followed by the introduction of a computational intelligence approach – the artificial immune system. In the light of the background, the objective of the study is stated in Section 1.2. Further, the significances and the scope of the work are elucidated. Prior to the end of the introductory chapter, the organization of the thesis is presented.

1.1 Background

The profit made by a product development organization has a direct relationship with the value of the products they generate; *value* is a perception of the customers, according to how far their needs are addressed (by consuming the products) relative to the cost of product acquisition. Products are therefore in effect vehicles that facilitate the fulfillment of customer needs. Meeting or exceeding customer expectations to increase customer satisfaction is the ultimate target of total quality management (Kondo, 2001). Research has shown that world-class manufacturing organizations are better in aligning their products and services to customer needs than their competitors (Adiano and Roth, 1994). Customer requirement information in essence helps enterprises to focus on specifying product attributes that their customers need, which creates *value* in the products. Therefore, the importance of customer needs¹ should not be underestimated in the business of product development.

¹ “*Needs of customer*” and “*customer needs*” are defined in this work as information that describes the desire of consumers that a product may facilitate to fulfill, and *customer* here is referring to the intended recipients of specific products.

The timeliness of customer needs information

Data derived from the industry indicates that about 80% of a product's lifecycle cost is determined during the conceptual design phase (Smith and Reinertsen, 1997), where the framework of the product characteristics or attributes is conceived; customer requirement is a set of vital information utilized in this phase of design. Engelbrektsson and Soderman (2004) identified the problems of customer requirements missed or discovered untimely, leading to costly consequences. Quality function deployment (QFD) (Hauser and Clausing, 1998) and axiomatic design (Suh, 1990) are among the many methods proposed that employ customer requirements as the seed of design (Chong et al., 2009a). Such an approach, generally known as customer-driven, market-driven, or customer-oriented design, helps enterprises to focus on creating products desired by the customers and to improve an enterprise's market positions (Harding et al., 2001). These methodologies, however, have a common limitation in practice, i.e. they handle only static form of customer requirements (Wu and Shieh, 2006). In other words, the temporal dimension of the customer requirements is not considered in the methodologies.

With rapidly growing competition intensity, globalization and technological advancement, *high volatility* of consumer needs has been observed (Raharjo et al., 2006). Product developers in such markets face the challenge of capturing fast moving targets (i.e. customer requirements). In perspective, they are relentlessly fitting discrete products to the continuously evolving consumer needs. In the context of *Agile Manufacturing* (Christian et al., 2001), the dynamics of customer requirements has led to the need for enterprises to continuously assess the business environment and to behave in an adaptive and flexible manner.

Market research is necessary to assess customer needs. Methods and tools such as focus group, interview and conjoint analysis are some techniques used to identify customer requirements (CR). Reichwald et al. (2005) remarked that these market research methodologies focus only on current situation and often do not contribute to the correct assessment of future customer requirements. Wu and Shieh (2006) shared the same view. The results of these market research techniques are applicable at the time of data sampling, and a period thereafter they are no longer valid to describe market sentiments. This applicable period is especially brief for products of short lifecycle (e.g. mobile phones), where CR can change rapidly. The changes can be attributed to the evolving environment, in the social, economic and technical aspects.

Due to the fluctuations, data collection and analysis should be performed periodically to evaluate the trends of customer needs (Wu et al., 2005). In this light, “real-time economy” was coined to describe management and planning practices of enterprises as the direct responses to customer wishes, market demands and to the circumstances of external value partners (Reichwald et al., 2005). Reichwald et al. (2005) deemed that an important feature of a *real-time enterprise* is its ability to flexibly link output generation to existing customer wishes.

To possess the knowledge of the current (i.e. real-time) market sentiment prior to product design phase is unfortunately not a sufficient condition to generate products demanded by the market. That is, for products to fit market needs, product developers should not design their products based directly on the findings that are sampled a lagged time prior to the time of product introduction. The following hypothetical case explicates the assertion.

Figure 1.1 shows a case where a development period of three months exists between the market sampling activities and the time of product introduction. The presence of the lagged period is invariable, due to the series of activities required for product development that occur between market research activities and product introduction. Examples of such processes are design and manufacturing. In this case, the designers might have placed emphasis on customer requirement *B* over *A* as shown in Figure 1.1, based on the market survey done in March. During the time of product introduction, the customers, on the contrary to the designers’ impression, would have then placed higher importance on customer requirement *A* over *B*. As such, if the product was designed based straightforwardly on the market survey conducted in March, the product would not fit the needs of customers (as presumed by the designers) when introduced in June or beyond. This simple hypothetical case demonstrates *the fundamental problem of the dynamic customer requirements*².

² The issue explicated here is henceforth referred to as the ‘*problem of dynamic customer needs*’ in the rest of the thesis.

Figure 1.1 Hypothetical trends of customer requirements

Failure to consider the variation of customer requirements over the development period depicted in Figure 1.1 has numerous ramifications. Raharjo et al. (2006) observed that *past* voice of customers (VOC) has been commonly used as the basis in allocating resources for downstream processes of design phase; from this perspective, unaccounted variances of customer needs can lead to errors in resource planning and allocation. Due to the evolving needs of market, planning of resources for phases downstream of design phase, on the contrary, ought to take references from the future market requirements. For instance, the planning of manufacturing process capability should take cue from future customer needs, as aptly assumed by McLaughlin and Stratman (1997) in the corporate planning methodology that they have proposed. In this light, knowledge of *future* (as opposed to *real-time* or *current*) customer requirements is not only a necessity in the design stage, but also for rigorous product development planning where outcome hinges on customer needs. Examples of product development phases that can benefit from information of future customer requirements are manufacturing process, material resources and marketing planning. In the context of supply chain management, forecasted customer needs can be applied to achieve “just-in-time” flow of goods. In the words of Kusiak and Smith (2007):

Inventory and customers' needs can be better balanced to increase overall profitability.

Owing to the inevitable existence of the said lagged period during product development and the volatile nature of CR (especially of short lifecycle products), product developers should not simply react upon the elicited voices of customers, whether for design or downstream processes. Instead, it would be beneficial for them to dynamically *learn* the dynamic trends and keep their knowledge of the markets “up-to-the-minute” as far as possible. Possessing the latest dynamic knowledge of the markets, product developers will be in position to *forecast* their markets' requirements of their products. For instance, Japanese electronics firms, such as Murata, were reported to have established systems to ensure daily customer contacts, as the basis to project future customer requirements (Peeples and Boulton, 1995). Forecasting results provide ballpark figures that management can employ to manage risk. Forecasting is also a method to quantify uncertainty, and a tool to support decisions. In general, forecasted customer requirements put firms in better a position to timely fulfill customer needs, and consequently enhance their competitiveness in the marketplace.

Raharjo et al. (2006) suggested that pro-activeness is necessary to deal with dynamic conditions, in order to avoid producing unwanted products. Researchers have attempted to use product life cycle (Dowdy and Nikolchev, 1986) and S-curves (Lee et al., 2006; Nichols and Roslow, 1986) to predict future performances of products (i.e. sales volume) in market. These results are however not very successful in guiding designers for actions and reactions in product developments (Hollins and Pugh, 1990; Chen and Yan, 2008). On the other hand, methods, algorithms and philosophies that discover ‘future’ customer requirements (as opposed to future sales) were deemed as keys to benefit both product developers and customers (Wu et al., 2005). In the light of this background, a review of the state-of-the-art research in the area of *dynamic customer requirement* is presented in Chapter 2, with highlights of the existing knowledge gaps by the end of the chapter.

A computational intelligence approach

Important patterns may be hidden in data captured in the industry, for instance market data in the context here. Some innovations in design and manufacturing can be attributed to the growing use of data, as reported by Kusiak and Smith (2007); it was noted that data mining can be applied in product development work, for instance, to

discover dynamic trends that reflect customer interest shift. Besides enhancing innovation, the methods can reduce risk associated with conducting business and improve decision-making. Researchers postulated that data mining can be classified into two classes – descriptive and prescriptive. The former aims at discovering patterns, while the latter aims at building models to determine (or to predict) an outcome. In the framework, the research presented in this thesis belongs to the class of predictive data mining. Apart from the traditional methods of exploiting data, such as database query languages, computational intelligence (CI) methodologies have been intensively researched prior to this work. Among the range of CI methods (e.g. artificial neural network and genetic algorithm), artificial immune system (AIS) is a relatively new technique that has shown potential in terms of its niche functions and applications (Timmis, 2006).

Development of the AIS, as Hart and Timmis (2005) recommended, should depart from the *scattergun approach* adopted thus far by the AIS research community. It was suggested that the inherent competencies of the AIS that are inexistent in other CI paradigms to be further developed. The AIS research community asserts the unique strengths of the AIS as listed below.

- 1) An inherent ability of the AIS is its dynamic data analysis capability. Aickelin and Dasgupta (2005) stated that rather than one-off optimization, AIS is more suitable for problems that change over time, and ones that have to be solved over and over again. In the same vein, Hart and Timmis (2005) mentioned that applications of “static” algorithm repeatedly, disregarding previous data in time, might miss out vital clues that are only factorable across time. The proponents therefore encourage the exploration of AIS-based solutions for problem domains that require dynamic analysis.
- 2) Another intrinsic ability of the AIS is its continuous capability to adapt to and to co-evolve with the environment (Stepney et al., 2003). Hart and Timmis (2005) identified that *life-long learning* is a feature of an immune system, which could be tapped for computational applications.
- 3) The third outstanding characteristic of the AIS is the compound solution that it can offer. In evolutionary, swarm and ant algorithms, the results produced are the fittest members of the final populations. In the case of the AIS, the result is in the form of the entire final population (Stepney et al., 2004).

The above outstanding features of the AIS among other approaches render the approach as a potential avenue to address the problem of dynamic customer needs. Further analysis and discussion on the relative applicability of the AIS will be presented in Chapter 2.

The problem of dynamic customer requirements is a practical one. Product marketplaces, especially of consumer products, have seen the increasing volatility of user requirements (Raharjo et al., 2006). Modern technology makes it straightforward for companies to track trends by gathering vast amounts of data on a daily basis (Hart and Ross, 2003; Hart and Timmis, 2005). As observed by Gunasekaran et al. (2006), web-based systems have been developed to obtain requirements from customers. A potential facility that can address the issue of dynamic market is therefore the technologies of the Internet, which may serve to relay time-series customer requirement data for analysis. The relatively recent emergence of the Internet as a ubiquitous facility has indicated the computational approach as a potential means to address the issue of dynamic customer requirements.

1.2 Objective and scope

The objective of the research is to generate new knowledge that is applicable to address the problem of dynamic customer needs³. Based on a review of the state-of-the-art solutions that clarifies the frontiers of the research area, this work accordingly develops an immunity-based technique that enables the management and forecast of dynamic customer needs. The research aims to extend the existing body of knowledge, through the proposition and investigations of the technique in the context of the problem. With respect to the research objective, the scope of work is described as follows.

- 1) *A literature review.* A review of past research efforts is performed to identify the boundary of the research area. The review focuses on the areas of dynamic customer requirements and artificial immune system.
- 2) *An immunity-based technique.* A prototype CRAF (customer requirement analysis and forecast) system is prescribed, with a methodology termed as the iDal (immunity-based dynamic and autonomic learning) technique defined as the backbone of the system. For applications of the iDal technique on the

³ The issue of dynamic customer needs is stated in Section 1.1.

problem of dynamic customer needs, an information model called the Requirement Space Framework (RSF) is established.

- 3) *Investigations of the CRAF system.* The system is studied at two levels – micro and macro. At a micro-level, the mechanisms of the system are explicated and investigated based on a case study. To study the overall behaviors and functions of the CRAF system at a macro-level, the iDal technique is implemented on the MATLAB platform for experimentations.
- 4) *Investigation of an application of the CRAF system.* The CRAF system is applied to address a conceptual design problem. A HBCD (heuristic-based conceptual design) system is defined and integrated to the CRAF system for the study.

1.3 Significance

The fulfillment of the objective will contribute to the following two research areas.

- 1) *The research of dynamic customer requirements.* Customer needs information has largely been treated as static. Advancement of knowledge in this area of research will support the quantification and therefore the applications of the dynamism of customer needs. Product developers that operate in markets where customer requirements evolve considerably across time are stakeholders and potential applicants of the new knowledge.
- 2) *The development of artificial immune system as a computational intelligence technique.* AIS is deemed to be a paradigm of high potential, which has not been exploited to date (Timmis, 2006; Dasgupta, 2006). Based on the future research directions positioned by the AIS research community (see Section 2.2.7), this study is positioned to make contributions to the AIS research.

The above two areas cover the significance of this study in general. In the concluding Chapter 7 of the thesis, the contributions that fall within the two areas will be distinctively stated.

1.4 Organization of the thesis

The thesis is organized in the following order.

- Chapter 1 introduces the background, objective, significance and scope of the research.

- Chapter 2 presents a literature review on the areas of dynamic customer needs and artificial immune system. The implications, investigations, and state-of-the-art solutions of the issue of dynamic customer needs are discussed in detail. Previous research on artificial immune systems is reviewed. A set of research problems is stated at the end of the chapter.
- Chapter 3 proposes a prototype CRAF system, the iDal technique, and the RSF. The propositions are original work developed in this research. The architecture of the CRAF system is introduced in the context of a customer requirement management framework. Specifications of the iDal technique are presented, and finally, the RSF is introduced.
- Chapter 4 reports a micro-level investigation of the CRAF system. The CRAF system is further specified based on the Bass diffusion theory (1969), followed by the description of two sets of experiment. The results of the investigation are discussed and concluded.
- Chapter 5 reports a macro-level investigation of the CRAF system. In this investigation, a focused time delay neural network is specified as the forecast module of the CRAF system. A computational experiment based on MATLAB is described, followed by the presentation of results, discussion and conclusion.
- Chapter 6 presents an application study of the CRAF system. To study the application of the CRAF system on a conceptual design problem, a HBCD system is prescribed, including an embedded CDH (Conceptual Design Heuristic) algorithm. An architecture that integrates the two systems is proposed. Finally, a case study on a bicycle brake design problem is presented to demonstrate the functions of the integrated system.
- Chapter 7 summarizes the outcomes of the research and presents the future work of the area.

Chapter 2 – Literature Review

This chapter presents detailed background of the work that serves to establish the context of the thesis. As the research objective is to address the issue of dynamic customer requirements, Section 2.1 is accordingly devoted to elucidating the subject. Through critical evaluation of the existing solutions, this study establishes the boundaries of research and identifies the work required to address the set of problems. As discussed in Chapter 1, this work aims to develop a technique based on theoretical immunology, in general known as the artificial immune system (AIS). The research community deems that, for advancing the AIS research, the technique should be applied on problems that other methodologies cannot handle as well or equally well. For this reason, the exceptional capabilities of the AIS relative to other comparable methods such as statistical techniques and computational intelligence (CI) tools are studied and documented in Section 2.2. With references to the review of the state-of-the-art AIS research, the final parts of Section 2.2 (Sections 2.2.6 and 2.2.7) are devoted to describing the relevancy of the technique in addressing the issue of dynamic customer needs. Finally, the research problem is stated in Section 2.3.

2.1 The dynamism of customer needs

Product development organizations are facing the challenge of capturing fast moving targets in the volatile market of the twenty-first century. The key driver of market turbulence is known to be the rapidly evolving needs of customers (Blocker and Flint, 2007), which contribute to the uncertainty of product success. Research in dynamic customer requirements specifically aims to minimize the uncertainty. Market orientation, as a background of customer-oriented product development, is reviewed in Section 2.1.1. The subject of the thesis – dynamic customer needs – is discussed in detail in Section 2.1.2. Thereon, this section further frames the state-of-the-art research

of dynamic customer requirements by presenting the identified implications, the investigations and the range of previously proposed solutions. It was noted that the dynamism of requirements bears various forms of impact on the respective functions of product development organizations, as illustrated in Section 2.1.3, which is followed by a review of a series of investigations by the research community in Section 2.1.4. It is notable that the range of scientific investigations reviewed here indicated the validity, importance and multi-faceted characteristics of the dynamic customer needs. Finally, Section 2.1.5 presents and evaluates the three distinct categories of solutions that were previously postulated to address the issue.

2.1.1 Responsive and proactive market orientation

The concept of market orientation has been shaped since 1990s. It is considered as a multi-dimensional construct regarding organizational culture (Deshpandé et al., 1993) and organizational processes (Shapiro, 1989; Narver and Slater, 1990; Kohli and Jaworski, 1990). Based on Troilo's (2006) research, a general consensus is that market orientation is an organizational cultural trait that assigns primary importance to satisfying the interests of customers, and that organizations require resources and systems (consistent set of processes, activities and behaviors) to translate the philosophy in achieving market orientation.

Recent research has defined market orientation in two dimensions – responsive (or reactive) and proactive (Narver et al., 2004). Companies were also characterized as Reactors and Prospectors respectively by Kumar and Phrommathed (2005).

Figure 2.1 shows the reactive and proactive approaches in dealing with dynamic customer needs and evolving solutions in the market. Generally, 'reactive' and 'responsive' are synonymous with 'market-driven' while 'proactive' is with 'market-driving' in the market orientation literature.

Customer needs	Learn existing customer needs	Create new customer needs
	Learn existing solutions (me-too products)	Create new solutions (radical innovation)
Reactive (market-driven)		Proactive (market-driving)

Figure 2.1 Reactive and proactive approaches in dealing with dynamic customer needs and changing solutions

Reactive firms track existing available solutions and/or near real-time customer needs to develop similar products at lower cost, with no or minor innovations. On the other hand, proactive firms innovatively create new needs and solutions, to lead the market with new products that may possess radical innovations (Kumar and Phrommathed, 2005). Companies that produce goods based on existing solutions belong to the lower left quadrant of Figure 2.1. These companies are likely to produce ‘me-too’ products with incremental or minor innovations at best (Kumar et al., 2000). Companies that are apt in generating radically innovative solutions belong to the lower right quadrant. Companies that track and attempt to satisfy dynamic customer needs belong to the upper left quadrant. An instance is a furniture company that produces new space-saving products to satisfy customers living in densely populated cities. Lastly, the upper right quadrant covers companies that create new customer needs (quantitatively and/or qualitatively). For example, one may say that Apple Inc. has created consumers’ need for fashionability in the ownership and usage of personal computer (iMac) and laptop (MacBook).

The approaches classified in Figure 2.1 are not mutually exclusive for a given firm or product. For instance, a company can be reactive and proactive at the same time by designing products that can simultaneously satisfy both existing and newly created needs. In the fashion industry, as one would expect, new customer needs are proactively supply-driven (Jaworski et al., 2000). Needs for fashion products are at the same time known to be market-driven; it motivates the research of fashion forecasting

based on data mining techniques applied on textual content of the World Wide Web (Rickman and Cosenza, 2007). (*Note: with reference to Figure 2.1, this thesis focuses on the domain of customer needs, as opposed to design solution.*)

Reactive market orientation refers to a set of skills and procedures to generate, disseminate, and use market intelligence pertaining to current customers and their expressed needs (Atuahene-Gima et al., 2005; Narver et al., 2004). In short, it often means “hear the voice of the customer” and adapts offerings (Joworski et al., 2000). Various excellent companies such as Nestlé, Procter & Gamble, and Unilever effectively employ the market driven approach (Kumar et al., 2000).

Proactive firms influence and affect markets and consumers (Rice, 1997; Joworski et al., 2000) by actively searching for new information and knowledge (Atuahene-Gima et al., 2005; Narver et al., 2004). For instance, before the first text message “Merry Christmas” was sent by a cell phone in 1992, cell phone users had no explicit need for the then extra function. In this case, the production of cell phones with text messaging capability led to the change of customer needs. Many successful pioneering companies have created new markets and revolutionized existing industries through radical business innovations. These companies, such as Amazon.com, Body Shop, CNN, IKEA, Starbucks, and Swatch, can be described as market-driving (Kumar et al., 2000).

The important role of a proactive market orientation in firms’ product success is intuitively obvious, and is supported by numerous empirical studies. Beverland et al. (2006) stated that most successful firms were found to be market-driving, rather than those relying solely on relationships and reacting to changing market phenomena. Narver et al. (2004) in their empirical study concluded that for any business to create and to sustain product success, a responsive market orientation is not sufficient, and that a proactive market orientation plays a very important role in product success. It was also reported that companies that were both reactive and proactive would be more successful than ones that implement only one of the two strategies (Kumar and Phrommathed, 2005).

Best (2009) stated that a business with a strong market orientation seeks to understand the needs of its customers. Likewise with regards to the importance of customer needs in market orientation, Kohli and Jaworski (1990) proposed businesses to generate market intelligence on both current (i.e. being responsive) and future (i.e.

being proactive) customer needs. On a same note, Rice (1997) indicated that forecasting future customer needs is fundamental for proactive companies.

From the review above, it is clear that market orientation literature advocates product development businesses to be both responsive and proactive to the changing customer needs. This platform supports the direction of this research, which is to manage and forecast the dynamic customer needs.

2.1.2 The issue of dynamic customer requirement

Understanding customer needs

Drucker (1954) asserted that ‘there is only one valid definition of business purpose: to create a satisfied customer.’ On the note that customer satisfaction is the primary generator of companies’ profitability, Troilo (2006) highlighted the importance of theorizing and studies of managing customer related knowledge. Product development businesses often oversimplify the analysis of customer needs by narrowly focusing on specific product features (Best, 2009). However, customer needs are the premises of solutions; product development organizations ought to firstly understand the needs of their customers followed by fulfilling them through developing products. This thesis concerns the former process (i.e. the top row as opposed to the bottom row in Figure 2.1).

It was shown that customers are a prominent source of information required by product developers in reducing uncertainties inherent in new product development (NPD) projects (Herstatt et al., 2006). Uncertainty in NPD is contributed by numerous sources, including the two major ones – technology and market (Chen et al., 2005; Verworn et al., 2008). An empirical study suggested that an early reduction of both market and technical uncertainty has positive impact on the success rates of NPD projects (Verworn et al., 2008). In addition, the investigation indicated that market factor (including customer needs) has a higher impact. Research has shown that product development projects are more likely to succeed when they are based on carefully defined customer needs, than those based on new technological opportunities (Holt et al., 1984). In view that speed-to-market is generally positively associated with NPD successes, a study by Chen et al. (2005) suggested that while technological uncertainty does not affect the speed-success relationship, market uncertainty does. In a similar vein, it is known that speed of development is more frequently being

adversely affected by the weak understanding of the target market, than the poor understanding of technology (Reinertsen and Smith, 1991). In general, the above-mentioned studies indicated the high importance of recognizing the needs of customers, relative to the cognizant of other factors in NPD projects. On this note, this research is positioned to focus on the study of the market variation over time.

Customer requirement information is useful to such product development stakeholders as product managers, designers, manufacturers and marketers. Meeting or exceeding customer requirements to increase customer satisfaction is the ultimate target of total quality management (Kondo, 2001). This class of market information has been capitalized to better capture the product markets. The management of customer requirement information is in general concerned with requirement elicitation, analysis and specification (Jiao and Chen, 2006), as shown in Figure 2.2.

Figure 2.2 Customer requirement management process (Jiao and Chen, 2006)

In customer requirement elicitations (see Figure 2.2), firms try to acquire information on customer needs through qualitative and quantitative approaches. The qualitative approach includes focus groups, and the quantitative methods can be used to study a larger sample of a customer population. Chen et al. (2002) proposed a customer-oriented approach to requirement elicitation. Ten of the more common customer needs elicitation techniques were studied by van Kleef et al. (2005). The techniques were: (1) category appraisal, (2) conjoint analysis, (3) empathic design, (4) focus group, (5) free elicitation, (6) information acceleration, (7) Kelly repertory grid, (8) laddering, (9) lead user technique, and (10) Zaltman metaphor. The study classified

the range of methods in two dimensions – actionability and newness (i.e. incremental vs. radical) – as shown in Figure 2.3. The right hand side of Figure 2.3 covers methods that elicit out-of-the-box information which can be suitable to supporting the development of radically new products. The left hand side is a group of methods that supports incremental product development, since the information generated would revolve around ideas tied to the existing market. An extensive range of previous research that studied the process of customer needs elicitation was reviewed by Phua et al. (2007). *(Although the study of customer needs elicitation techniques is beyond the scope of this research, the characteristics of the information produced by the techniques are of interest, such as its actionability as discussed below.)*

Figure 2.3 Customer needs elicitation techniques in the dimensions of ‘newness of product considered’ and ‘actionability’ (van Kleef et al., 2005)

It is important for customer elicitation methods to provide actionable information for subsequent technical development stages (van Kleef et al., 2005; Ulwick, 2005). *Actionability* refers to the potential of information to indicate specific actions to be taken in order to achieve desired objectives (Shocker and Srinivasan, 1979). In a study done by Ulwick (2005) with Motorola cell phone users, it was found

that the ‘easy to use’ requirement could be expressed in twenty-one ways. They include “minimizing the time it takes to look up phone number,” and “minimizing the likelihood of calls being made by inadvertently hitting the keypad.” In each of those instances, the abstract and therefore hardly actionable phrase – ‘easy to use’ - takes on a different meaning and has different implications to designers. Adjectives such as ‘reliable’, ‘effective’ and ‘cool’ are imprecise, and the abstraction leaves interpretation to subjectivity. Designers have been known to often put the blame on market researchers as the abstract adjectives provided to them are non-actionable (Ulwick, 2005).

In the study by van Kleef et al. (2005), the abstractness of the information elicited by the respective methods is the dimension adopted to evaluate the actionability. The ten methods were found to produce information that differs in the dimension of actionability (i.e. abstraction), as shown in Figure 2.3. The more abstract is a consumer need, the less actionable is the information for technical stakeholders (e.g. designer and manufacturer). However, abstract information is required by ‘creative’ users such as designers and marketers (since abstract consumer needs provide freedom for creativity). Customer needs information that is robust should therefore be described in terms of multiple abstraction levels (Chong et al., 2009a); such information would better support the range of product development activities (including customer needs analysis and forecast in this research). In view of the issue of actionability, this research investigates techniques that can represent and operate on customer need information of various degrees of abstraction (Chong et al., 2009a). Apart from supporting actionability, representation of customer needs information in multiple levels of abstraction will also allow the capture of data generated by a wide range of elicitation methods (see Figure 2.3 for the methods and Figure 2.2 for the data flow).

Perceiving customer needs as time-variables

Information on customer needs is an important basis of product development projects, which is the result of possibly complex relationships involving multi-faceted factors internal and external to the consumers. Internal factors of individual or group customers include beliefs and past experiences; external factors are the environmental aspects, which may affect consumers’ perceived importance of various product attributes (Calantone and Sawyer, 1978). Examples of such factors are culture,

technology, legislation, competition and possibly the requirements posed by other existing related products. As the statuses of most factors are temporally dynamic, customer needs that businesses target to fulfill are consequently time-based variables by nature.

Need is the basis of all designs, and as discussed, it can vary with time. Ideally, the development of new products should be based on customer needs relevant at the time of market introduction, and during the period of product consumption (Holt et al., 1984; Kärkkäinen et al., 2001). The hypothetical case illustrated in Section 1.1 demonstrates the fundamental issue of dynamic customer requirement. That is, the invariably existing lagged period (see Figure 1.1) in product development cycle, coupled with the volatility of customer requirements may render the previously sampled customer voices irrelevant at the time of product introduction. Adams et al. (1998) phrased the phenomenon: *‘It is likely that what customers say now will not be relevant by the time the product is launched.’* If the product described in Figure 1.1 was designed with references to the customer needs elicited during March, it would theoretically not satisfy the consumers as intended by the designers when the product reaches the market in June or beyond. On the other hand, if the designers were sensitive to the dynamism of the customer requirements, the resulting product would more likely fulfill the needs of customers at the time of product introduction, and during the consumption period.

Developing products based on static forms of customer requirement data can be treacherous in product markets where needs are volatile. An instance is the cellular phone market, which is characterized by short product lifecycles. On the other hand, in cases where the development period is lengthy, the variation of customer needs will be amplified. As such, long development cycle and volatile market are situations where the considerations of customer needs as time variables are critical. Without the due considerations, customer requirements could be missed or discovered untimely, which could therefore lead to costly consequences (Engelbrektsson and Soderman, 2004). Product developers unwary of the pitfall may generate products not wanted by the customers. In today’s context, customers have greater choices than ever in most industries and markets; they therefore are less likely to accept sub-standard products (Maguire et al., 2007). Customers may drift away as a result. On the positive flipside, if product development organizations were to prudently consider the dynamism of the

customer needs in the process of product development, they stand better chances to gain competitive edges in the markets.

The extensiveness of the research and practice (or the lack thereof)

Due to globalization and stiffening competition, the issue of dynamic customer requirements is increasingly valid. Despite the criticality of future needs identification, studies have shown that companies in general neglected the aspect during product development (Szakonyi, 1988; Kärkkäinen et al. 2001).

Research in product development to date has likewise been modest where the dynamic property of customer needs is concerned. In an early study, Calantone and Sawyer (1978) observed large temporal shift in attribute importance weights among consumers and suggested that the *‘evidence of individual change might signal an opportunity to gain useful insight into the dynamic behaviour of consumer markets.’* However, as noted by Mittals et al. (1999), progress in this regard has not been significant. Similarly, relatively few research efforts in the area of manufacturing have addressed the issue of dynamic customer needs (e.g Kidd, 1994; Wu et al., 2005; Raharjo et al., 2006). Furthermore, these studies were largely restricted to the area of manufacturing.

Of the large volume of work on voices of customers to date, Xie et al. (2003) remarked that the scopes have largely been limited to *current* and *static* customer requirements, while only few have considered the dynamism of customer needs. Notably, the dynamic aspect of customer requirements has not stood out in a review of over a hundred literature on customer requirement management (Jiao and Chen, 2006). It is hence evident that the studies of requirement management (e.g. McKay et al., 2001) have most often focused on requirement representations in static forms.

A case in point is the well-known Quality Function Deployment (QFD) method that advocates the importance of customer needs in product development (Akao, 1990; Hauser and Clausing, 1988). The method ignores the notion of market clock, as noted by Reinertsen (1991). Further, myriads of QFD’s derivatives (see Bouchereau and Rowlands, 2000) do not, in their frameworks, treat customer attributes as time sensitive information, which forms a major limitation in the context of the problem identified here. The shortcoming of the methodologies can be detrimental to product developers since customer requirements of their products can be highly volatile (Christian et al., 2001). Exceptions are Adiano and Roth’s (1994) proposed dynamic

QFD, and several other propositions that function to forecast customer requirements based on the QFD method (see Section 2.1.5).

Summing up

The variation of customer needs during product development cycles is a significant source of uncertainty of the businesses. The research of dynamic customer requirement is an inquiry of the *uncertainty* in NPD resulted from the varying needs and preferences of customers during product lifecycles, i.e. from the expression of customer needs to the end of product life. Research that aims to manage business risk by minimizing this category of uncertainty has been increasingly capturing academic attention, as evident in Section 2.1.5. This study is therefore motivated by the urgent need for knowledge that is applicable to address the problem.

This research involves such disciplines as business, social science, engineering and design subjects. Despite the differentiated perspectives of the topic, this research found significant relativity across research tracks of the different fields. As such, the reviews and discussions are best presented in a cross-sectional manner. In the following sub-sections, three key distinct aspects of the research are reviewed in sequence, namely, the *implications* (i.e. the significance) of the uncertainty (Section 2.1.3), the *investigations* of the uncertainty (Section 2.1.4), and the *solutions* that were proposed to address the uncertainty (Section 2.1.5). The review structure adopted here reflects the process of problem solving, i.e., problem identification, investigation, followed by solution proposition. As with most research work, the individual work do not fall in only one of the three categories, nor do they usually cover the entire spectrum. In this case, the reviewed articles typically focus on either investigations or solution propositions. The structure proposed in this review serves to outline the respective forms of research work to date. It is anticipated that the review in such structure would facilitate the drawing of meaningful conclusions, which in turn could serve as a basis to the research.

2.1.3 Implications of dynamic customer requirements

The variation of customer requirements over time has impacts on the success of product development projects. Closer examination of literature shows that the effects on the overall product success are propagated through different functions of the

organizations. In other words, changing customer requirements is a global factor that should be considered cross-functionally by designers, manufacturers and marketers, etc. Table 2.1 shows the implications of the dynamic customer requirements on the various project stakeholders, and the respective references to literature. Likewise, the studies of market orientation (see Section 2.1.1) acknowledged that market intelligence permeates the entire organization, not only the marketing department (Shapiro, 1989; Narver and Slater, 1990; Kohli and Jaworski, 1990). The following paragraphs describe the implications of the issue on various functions of product development organizations.

Table 2.1 Implications of dynamic customer requirements on product development stakeholders

Stakeholders	Implications
Management	Product planning (Mittal et al., 1999; Kärkkäinen and Elfvengren, 2002; Chen et al., 2005)
Design	Product design (Mittal et al., 1999; Peeples and Boulton, 1995; Kärkkäinen and Elfvengren, 2002)
R&D	R&D planning (Peeples and Boulton, 1995; Szakonyi, 1988; Mclaughlin and Stratman, 1997)
Marketing	Product channeling, advertising and promotion (Calantone and Sawyer, 1978; Blocker and Flint, 2007; Langerak et al., 2008; Shankar et al., 1998; Ali, 2000)
Manufacturing	Supply chain management, Production planning (Christian et al., 2001; Reichwald et al., 2005; Reed and Walsh, 2002; Gunasekaran et al., 2006; Mclaughlin and Stratman, 1997; Adiano and Roth, 1994)
Service	Service planning (Mittal et al., 1999)

Product management

Kärkkäinen and Elfvengren (2002) asserted that customer need assessment is critical for product planning, evaluation and prioritization of new product development projects. In the empirical analysis, it was found that a series of cross-reinforcing managerial problems (e.g. untimely specification changes) could be resulted when assessment of future customer needs has not been given adequate attention. In a fast

changing market, product managers have to carefully consider the duration of the development cycle (see Figure 1.1). In the case where a product is introduced late, it might not aptly meet the customers' requirements. On the other hand, a highly compressed cycle time can undermine product quality (Chen et al., 2005).

Design

Designs that consider only static forms of customer requirements risk not able to satisfy future customer needs, especially in volatile markets. On the other hand, design specifications that were based on customers' future needs could satisfy the needs in a timely manner. Further, design iterations and rework could be reduced, as indicated by Kärkkäinen et al. (2001) and Kärkkäinen and Elfvengren (2002). In practice, it was reported that firms have had close contacts with their customers, as a way to collect information for projecting and defining future product requirements (Peeples and Boulton, 1995). Such elicited data are, in turn, applied as the basis for generating design for the near future markets.

Research and development (R&D)

R&D project selection is deemed critical for developing new products successfully, and is also known as a problem that plagues many companies (Szakonyi, 1988). The aim of R&D is to produce solutions capable of meeting customer needs that are anticipated in the future. The period of forecast can range from several years to more than ten years, which is necessary before the R&D work can bear fruits. As such, the selection of R&D projects requires foresight and good understanding of the dynamic market needs. When customers' future needs cannot be clearly identified, the investments in R&D projects bear higher risk, which may in turn undermine the overall NPD efforts. McLaughlin and Stratman (1997) recommended firms to accordingly initiate R&D programs when their technological capability is predicted to lag behind the market requirements of the future. In an inverse case, Peeples and Boulton (1995) reported that Sony and TDK dropped their efforts in developing superconductor technologies due to the lack of customer interest. As the dynamism of customer needs has profound effect on the R&D function, it is clearly important for product developers - in particular, ones with R&D functions - to consistently consider the dynamism of customer requirements.

Marketing

Segmentation has been called one of the most important concepts in marketing (Dickson, 1982). It is based on grouping customers' similar attributes and their corresponding needs. As noted by Blocker and Flint (2007), segmentation logic in its current form offers static pictures of moving marketplaces. An important question for marketing managers is therefore whether the identified market segments remain similar over time in terms of distinguishing characteristics and sizes (Calantone and Sawyer, 1978). The issue of market segment instability is becoming increasingly critical in today's highly turbulent market, induced by the more fundamental dynamism of customer needs. In the case of unstable market segments, it is important for marketers to realize the dynamism and thereby respond with appropriate revised marketing strategies, e.g. product repositioning and advertising appeals revamping, as suggested by Calantone and Sawyer (1978).

Research has shown that, in a changing market, launching a given product at the right time is a key to profitability (Langerak et al., 2008; Shankar et al., 1998; Ali, 2000). Therefore, the dynamism of customer needs has an implication on the schedule of product launch.

Manufacturing and supply chain

Christian et al. (2001) stated that manufacturing profitability requires satisfaction of customers' needs which are in a state of *permanent flux*. The uncertainty of customer orders is a factor that makes production planning a very difficult one (Persona et al., 2004). In particular, when the lead time between parts order and delivery can be as long as half a year (Spedding and Chan, 2000), the dynamism of customer needs has much implication on inventory management. It is therefore necessary for manufacturers to be flexible in the midst of the dynamic market. However, under-utilization of resources has unfortunately been a result of production flexibility. Reichwald et al. (2005) reported the common under-utilization rate of 20-50%, which causes massive cost disadvantages. Overall in this context, flexibility in manufacturing is itself a challenge since production facility usually has much more inertia than customer needs. McLaughlin and Stratman (1997) asserted that the study of the interactions between future customer requirements and process capability can be directive in anticipating future manufacturing needs. Where dimensions of product quality are determined by customers, it was summed that the ability to respond quickly

to an evolving market is an important characteristic of manufacturing firms (Garvin, 1987; Adiano and Roth, 1994).

In the context of supply chain, a holistic and dynamic view of customer needs is necessary across the value chain elements (Adiano and Roth, 1994). The uncertainty of the end-users' future requirements can be propagated and even amplified through the supply chain. In the case of technology-based industry, Reed and Walsh (2002) cautioned that smaller suppliers may not be sensitive enough to keep up with the development. The result would be capability *gaps* within the supply chain. Gunasekaran et al. (2006) contended that such lack of common understanding of customer needs in the supply chain is one of the reasons that the quality of the end products are not up to the expected standard.

Service

Requirements information of products and services should relate the needs of customers over the entire consumption period. The comprehension of the service attributes influences on customer satisfaction over the product consumption period is applicable in the processes of service planning. In the area of study, Mittal et al. (1999) examined whether attribute weights in determining overall customer satisfaction are temporally liable. Having demonstrated the dynamism of attribute weights, Mittal et al. (1999) recommended firms to dynamically rethink programs that can accommodate such temporal shift.

Summing up

This sub-section reviews the problems that dynamic customer requirement entails, from angles of different research concerns such as design, marketing and manufacturing. Though the issues that emerged are of different nature, they commonly have impact on product success. It is evident from the review that the dynamism of customer requirements bears implications on the key functions of the product development organizations. These implications form an arguably huge set of research problems, all of which can plausibly be approached from a more fundamental level of investigation and development, i.e. the studies of dynamic customer requirements. Studies on the dynamism of customer needs are therefore capable (if not key) to support "just-in-time" flow of resources (e.g. inventory, servicing programs and R&D output). Ideally, with the quantification and application of dynamic customer needs,

customers' expectations and organization resources can be better balanced to increase overall profitability (Kusiak and Smith, 2007).

2.1.4 Investigations on dynamic customer requirements

Calantone and Sawyer (1978) pioneered the studies of market segments stability over time. The study was from the perspective of the marketing discipline, and the treatment of customer requirements was based on the concept of market segments. Importance ratings of seventeen product attributes were solicited from households during two time periods two years apart. Analysis on individual household basis showed that a given household was likely to be classified in a segment other than its previous group designation. The early study demonstrated the instability of market segments, which is clearly a manifestation of changing consumer needs. Another study by Mittal et al. (1999) had the hypothesis that customer requirements were dynamic across product consumption periods. Accordingly, a longitudinal study based on data elicited from 5206 automobile owners was conducted. Based on a theoretical model and the empirical study, inter-temporal examination of attribute-level performance, satisfaction and behavioral intentions concluded several results. For instance, service satisfaction had a larger impact in determining the intentions toward the manufacturer in the initial stage of the product lifecycle. However, product satisfaction was found to be more influential in the later stages. The study overall demonstrated the variation of attribute weights in the temporal dimension, which were the basis and determinants of customer satisfaction.

Szakonyi (1988) surveyed 180 companies and found a majority of them weak in identifying customers' long term needs. In a particular case, the company realized that its marketing people could not identify the general characteristics of the products that they would be selling in just two years. The marketing managers indicated that many marketing people lacked the analytical skills to identify *future* needs. Though the changing customer requirement was an acknowledged problem, the study concluded that the surveyed companies (124 American and 56 European) did not pay adequate attention to it. Similar results were produced in a more recent study by Kärkkäinen et al. (2001). The research suggested that companies were still not adept in recognizing future customer needs. More than half of the surveyed companies stated that assessing new (hidden and future) customer needs were very important to their success. The

same respondents also estimated that they have used too little efforts in the assessments. In contrast to that attitude, a separate investigation in the Japanese electronic industry found that firms kept extremely tight coupling between the companies' product realization activities and their targeting of customers' needs (Peeples and Boulton, 1995). It was reportedly the tight coupling that facilitated the complete and accurate definition of *future* customer needs. Further, Japanese firms were known to have formed committees to solve customers' problems, and at the same time collecting requirements of future products.

Kärkkäinen and Elfvingren (2002) studied the role and importance of customer need assessment in five manufacturing companies. In a causal map of managerial problems generated by the study (see Figure 2.4), a self-reinforcing 'vicious' cycle was identified. Specifically, unexpected changes in the markets led to the appearances of new product requirements, which in turn contributed to the extensions of the project durations. The delay of projects completion saw new requirements emerged, which in effect closes the said cycle. Based on the identified vicious cycle, the study pinpointed the issue as the failure to communicate *long term* customer needs. The empirical study therefore recommended companies to develop better abilities to recognize customers' future needs, which is widely lacking as evident in series of studies described above.

Figure 2.4 A causal map of managerial problems (Kärkkäinen and Elfvingren, 2002)

A study by Chen et al. (2005) examined the relationship between speed-to-market and new product success (NPS) under different conditions of uncertainty. The results indicated that the relationship was positive and that market uncertainty moderates the direct effect. The defined market uncertainty is due to market newness and turbulence, i.e. the rate of change in the composition of customer needs and customer preferences. The study concluded that speed-to-market is less important to NPS under conditions of low market uncertainty and more important in unfamiliar, emerging, or fast-changing markets.

Discussion

Empirical research in this area of study especially of longitudinal type has been sparse. It can be attributed to the relatively high cost of such research that involves multiple surveys across a sustained period of time, and also to the difficulty of acquiring proprietary time-series data from the industry. The studies reviewed have in general indicated the phenomenon of customer requirement dynamism. The yardsticks of these investigations include market segments (Calantone and Sawyer, 1978; Blocker and Flint, 2007; Sung, 2007), attribute weights of satisfaction (Mittal et al., 1999) and composition of customer requirements (Kärkkäinen and Elfvengren, 2002; Chen et al., 2005), all of which were demonstrated to be temporal variables. The study by Chen et al. (2005) showed that strategies that minimize market uncertainty could serve to reduce firms' dependencies on the speed-to-market tactic. After all, rushing products to the marketplace has its limitations and caveats. As such, understanding the dynamism of customer needs could very well play an important role in product developers' overall strategy. Further, the identification of the vicious loop in product development projects by Kärkkäinen and Elfvengren (2002) underlines the critical role of future customer requirements information. Although the importance of the time variable was well-acknowledged by the industry, it was concluded that they were largely excluded from the product development pipelines (Szakonyi, 1988; Kärkkäinen et al., 2001). Japanese electronic firms were however deemed to be sensitive to future customer requirements, based largely on informal interactions with customers (Peeples and Boulton, 1995). There has been no known report of formal methodologies or common tools that were employed by organizations to facilitate the recognition of future customer needs. The absence of such applicable methods and tools as decision support systems and knowledge-based systems may explain the lack of attempt to identify

future customer needs. This supposition is coherent with Szakonyi's (1988) finding that the lack of attention in practice could be attributed to marketers' deficiency in analytical skills to identify future needs of customers.

More recently, Blocker and Flint (2007) addressed the issue of dynamic market segments. The authors conceptually explored the theoretical underpinnings and integrating related theory on customer value change to propose an agenda for future research. The work recommended future research to develop tools that forecast the direction and rate of change of market segments. This recommended research direction is in line with the general conclusions of other studies (e.g. Kärkkäinen and Elfvengren, 2002) that the industry needs better capability to recognize future customer needs.

2.1.5 The approaches of addressing dynamic customer requirements

The principle of addressing the issue of dynamic customer requirement is to minimize the uncertainty that the factor contributes to product development projects. A range of solutions have been proposed to date, which can be classified into three categories, namely 1) compressing development cycle time, 2) increasing sensitivity to the changes, and 3) forecasting. The reviews of these categories of propositions are respectively presented as follows.

Compressing development cycle time

The development cycle time is defined here as the elapse time between customer expression of need and product introduction to the market (see Figure 1.1). Reinertsen and Smith (1991) highlighted a *market clock* that starts ticking when the first firm in the industry begins the development process. Accordingly, customer needs being a time variable could start deviating as the *clock* ticks.

One of the strategy to mitigate the effect of fast changing customer needs is to compress the development cycle time, i.e., to increase the speed to market. Karagozoglu and Brown (1993) remarked that: ... *in high-growth markets involving short product lifecycle, the overall impact of speed-to-market on profitability is compelling*. Compressing the cycle time to achieve competitive edge has also been commonly referred to as time-based competition (Stalk, 1988). The approach has several rationales and has other benefits, which has been widely discussed and

developed in the literature (see Chen et al., 2005). In the context here, the strategy functions to contain the fluctuation of the dynamic customer requirements across the shortened time period. To help shorten product development cycle, Reinertsen and Smith (1991) recommended a division to better grasp the target market. The recommendation is based on their assertion that most delays in specifying a product arise from weak understanding of the target market. Chen et al. (2005) concluded in an empirical study that it is more important to execute a time-based strategy in an unfamiliar, emerging, or fast-changing market than in a familiar, existing, and stable market. Jetter (2003) summed that the compression of the cycle time in a turbulent market has a positive effect of reducing uncertainty. To achieve the same effect, Krishnan and Ulrich (2001) suggested the freezing of design specifications at a later stage.

As opposed to rapid product introduction, research has shown that the timing of product introduction is a key to success (Lane, 1980; Carpenter and Nakamoto, 1989; Bayus 1997). In other words, a speed-to-market strategy does not necessarily translate to a better chance of product success. Langerak et al. (2008) studied firms' proficiency in correctly balancing the risks of premature entry and the missed opportunity of late entry. The study based on seventy-two manufacturers demonstrated the importance of market entry timing in determining profits. In view that a late entry of innovative product to the market could outsell the market pioneer, Shankar et al. (1998) studied the phenomenon based on entry strategies – pioneering, innovative late entry, and non-innovative late entry. The research found that an innovative late mover can grow faster than the pioneer. Research has proposed that a strategic window of product launching is relevant to product developers (Ali, 2000). A pioneer product that enters the market before the opening of the strategic window may not generate less consumer interest. For instance, inexperienced customers may not be responsive to highly innovative products. On the other hand, products launched after the closure of the strategic window may fail due to shifted customer needs.

Increasing sensitivity to dynamic customer requirements

In the light of the problem identified here, it is not only necessary for product developers to listen to their customers, they further ought to listen frequently enough. The increasing volatility of customer requirements in marketplaces has called for new approaches and even paradigms in maintaining close contacts with customers.

On-going gathering of customer satisfaction data is said to be critical in managing a sustainable competitive advantage (Gupta et al., 2004). Flores (1993) offered a framework for active listening to customers' needs in today's rapidly changing business world. With a similar concern, Maguire et al. (2007) studied four companies and found that each has been using multiple customer listening tools to better understand their customers. Acknowledging the dynamic nature of customers' needs, Maguire et al. (2007) advocated the regular measurements and assessments of customer satisfaction. Wu and Shieh (2006) recommended that the probabilities of the requirements fluctuating from a state to another can be drawn from customer surveys. A tool was proposed based on Markov chain model and QFD to monitor dynamic customer requirements from probabilistic viewpoint. Chen et al. (2007) reviewed the state of the art patents on product design technologies filed in the last two decades. Under the category of customer-oriented design, practitioners' concerns for sensitively detecting changing taste of customers for swift reactions have been identified. For instance, a patent of Abelow (1999) addressed the concern with a microprocessor embedded in products for the dynamic bilateral communications between the users and product developers.

In fast shifting marketplaces, core manufacturing capabilities should be market-driven; customer voices should therefore be continuously incorporated into manufacturing decisions (Griffin and Hauser, 1992). Frameworks that aimed at increasing the sensitivity of production resources allocation to the changing demand have been proposed. As an example, agile manufacturing is a paradigm devised in response to turbulent business environments driven by individualizing customer requirements (Kidd, 1994). The framework advocates the assessment of customer requirements changes such that flexible production facilities can respond effectively to the changes (Christian et al., 2001). Adiano and Roth (1994) postulated a dynamic approach of QFD that is suited to handle constantly evolving customer needs; the proposed system functions by automatically monitoring a QFD matrix that is constantly and manually updated with latest customer needs information. The dynamic QFD however may not work with requirements that change rapidly, and the amount of input data required makes the implementation arduous (Xie et al., 2003). A limitation of the method is therefore the lack of autonomy, i.e., the customer surveys have to be *manually* reviewed and processed. However, the devised decision support system

could proactively alert the manufacturing department when the wrong customer requirements are in focused.

The uncertainty of end-users' future requirements can be propagated through supply chains. Likewise, the flow of dynamic customer needs information should be across the supply chain, whether physically or through the Internet. Reed and Walsh (2002) advocated the development of suppliers' technological capability through sharing of technological future plans within the supply-chains. The technological roadmaps of suppliers ought to be aligned to the buyers', who are likely to have better grasp of the end-users' future needs. In view of the dynamic market, Reichwald et al. (2005) proposed a new organization approach that can improve the sensitivity to requirement changes. It was proposed that the prevailing division of tasks between centralized production and distributed sales to be replaced by distributed mini-factory structures. The mini-factories are intended as the integration of sales, innovation, customer interaction and production units, which are at close proximity to the customers. The proponents deem that the configuration would enable real-time management of production facilities (i.e. the mini-factories) by virtue of physical proximity to the customers. The proposed paradigm aims to involve customers as an integral part of the dynamic value-added network, facilitating sensitivity to fast changing requirements.

Apart from physically moving closer to customers (Zotteri and Verganti, 2001), Internet has been used for customer relationship management (Maguire et al., 2007). Gunasekaran et al. (2006) proposed a web-enabled model that facilitates the continuous communication of customer needs information across the geographically dispersed supply chain. Product quality may therefore be improved with the acknowledgement of the changing expectations of customers.

Cooperation with customers in the development of product has always been a rule in business-to-business markets where there could be just a few large customers requiring made-to-order products (Best, 2009). However, companies such as BMW, Apple Inc., Fiat, and LEGO have solicited opinions from small samples of customers (lead-users) over discussion forums in the Internet (von Hippel, 2001; Best, 2009). The elicited information has helped them in developing, testing, and fine tuning new products. The sizes of customer samples are small in such cases. With the Internet, virtual platforms can be employed by firms to collect customer needs information (Sawhney and Prandelli, 2000), and effectively, communicate with millions of

customers in business-to-consumer markets (Troilo, 2006; Prandelli et al., 2008). However, to dynamically listen to customers in large numbers (thousands or more), a systematic approach is necessary.

Secondary data from online navigations and transactions histories (e.g. from eBay, PayPal, and Amazon) forms large datasets that can be made available in a timely and cost-effective manner. Nasraoui et al. (2008) applied clustering techniques to discover patterns of website users' behaviors, and therefore providing insights of the changing web users' needs; however, their method tracks only discrete status (e.g. active or inactive) while not able to track continuous functions across time. There have been recent appearances of online market intelligence services that monitor millions of traditional and social websites (e.g. blogs, forums, and bulletin boards) to identify trends in customer behaviors. Such services are provided by firms, such as Nielsen and Umbria. Nielsen developed a proprietary product called the BuzzMetrics. It monitors customer sentiment and consumer-generated media to uncover trends that can be useful for product development. Berkman (2008) however pointed out that social media research still cannot wholesale substitute traditional market research due to representativeness issue; they are nonetheless complementary for now.

Web users who are consumers at the same time can provide data for dynamic forecasting (Rickman and Cosenza, 2007). However, in the age of the Internet where information overloading is a problem (Berkman, 2008), toolsets that can extract and analyze data for essential and critical customer information will be important. This background forms a motivation of this research.

Dynamic customer requirement forecast

The Chartered Institute of Marketing defines marketing as 'the management process responsible for identifying, anticipating and satisfying consumers' requirements profitably'; the verbs 'identifying' and 'anticipating' imply forecasting (Rice, 1997). Rice (1997) questioned why businesses have regarded forecasts as critical given that the results would be proven inaccurate sooner or later. Rickman and Cosenza (2007) opined that every company must make decisions that reduce risk; in order to reduce risk, companies rely on planning – planning horizons that incorporate knowledge of the changing dynamics of customers. In the same vein, Rice (1997) reasoned that forecast is important for uncertainty reduction in planning of resources and early signaling of opportunity and threat. As there will be on-going changes in business

environment, those who can forecast can reduce risk and achieve dominance (Rickman and Cosenza, 2007).

Based on the well-established six sigma management framework of product development, Goh and Xie (2004) recommended two additional Ss of which one is Strategic Analysis. It consists of substantial component of scenario planning aimed at anticipating changes, managing dynamic market demands and forecasting novel lifestyles. Literature on forecasting has been growing in the last quarter century (Armstrong, 2006). In general, forecasting¹ of variables is one of the methods employed to manage risk due to uncertainties of the future. Forecasted variables of interest in the context of product development include market demand (Kalchschmidt et al., 2006), purchase intention (Armstrong et al., 2000), customer behavior (Verhoef and Franses, 2003; Sung, 2007), and customer needs (Kärkkäinen and Elfvengren, 2002). Of the different variables, market demand has been the major focus in product forecasting literature. Methodologies employed to forecast demand are of wide range, as comprehensively reviewed by Armstrong et al. (2006). These methods include Bass diffusion model (Bass, 1969; Lee et al., 2006) and hierarchical forecasting (Flüedner, 2001). Thomas (1994) asserted that new product forecasting is no longer limited to projections of future demand figures. The remark suggests the widening of the research thrust beyond forecasting consumer segments and sale figures, to such dimension as customer needs – the focus of this work.

Compared to market demand forecast, forecasting of dynamic customer needs has received considerable less research attention. Although these two temporal variables pertain to products, they are different information with dissimilar implications and applications. The forecasting of market demand concerns volume as the variable (Kotler, 1984; Thomas, 1987), usually of products or product categories with specific attributes. On the other hand, the forecasting of customer needs relates to product attributes that customers desire, possibly independent of specific products. In terms of applications, the former can be useful for managerial decisions such as production resources allocation and marketing strategy (Morrison, 1979; Kalchschmidt et al., 2006), while the forecasted customer requirement information can be directly

¹ There has been a class of research that “predicts consumer choices” (West et al., 1997). In general, such studies looked at the correlations between product attributes and customer attributes. It is noted that this category of research does not consider the temporal dimension of the information, although the word “predict” may suggest so. It should be noted that this class of work is independent of this thesis.

indicative to product designers (Chen and Yan, 2008) and also to other product development functions as respectively reviewed in Section 2.1.3. The research of dynamic customer requirements forecasting has been relatively sparse. However, an increasing trend has been observed, as noted in the following paragraphs.

Szakonyi (1988) recommended that marketing organizations be made aware of their responsibilities. Specifically, they include analyzing and identifying customers' future needs. Creating a new type of marketing specialist was further suggested. Flores (1993) observed that customers are striving to invent the future for themselves, and careful attention must be paid to discover where they head. Communication of long term (i.e. future) customer needs in companies was empirically concluded as a means to improve the success and outcomes of product development (Kärkkäinen and Elfvengren, 2002). The study therefore recommended companies to develop better ability to recognize customer's future needs.

Beside the management-oriented recommendations, technical methodologies have been devised. McLaughlin and Stratman (1997) proposed a forecasting method based on the combination of QFD and S-curve analysis. The S-curve technique serves to perform technological forecast, which is then tabled against future customer requirements using the QFD matrix. Raharjo et al. (2006) proposed a method to prioritize the quality characteristics in the context of a dynamic QFD. The aim is to identify quality characteristics that have greater confidence in meeting future customer requirements. Like McLaughlin and Stratman (1997), Raharjo et al. (2006) assumed the presence of future customer requirement information as the inputs to their methods. The research therefore in effect highlighted the need for tools that support the generation of future customer needs, as well as the applicability of the information.

Flores (1993) proposed a system that advocates companies to actively listen to customers' future concerns. It is reportedly adopted by such organizations as IBM, Sony and Nike to facilitate the generation of products that can meet the future needs. Such forecasting approach is essentially dependant on customers' perception of the future. In a similar vein, Shen et al. (2001) proposed a method that involves soliciting consumers' opinions on future customer requirements. Fuzzy set theory was applied to quantify the vague trend of importance information in QFD. These methods of generating future needs are useful, especially when histories of customer needs are unavailable for projections.

To mathematically forecast future customer needs, Xie et al. (2003) applied a time-series model, specifically, the double exponential smoothing technique. It was noted that the method is limited to forecast time-series data of linear trend. The limitation to an extent may deny the applicability of the method on practical problems where non-linearity can be dominant (Bass, 1969).

Wu et al. (2005) proposed the use of gray theory in the forecast, which requires only four past data points. This is in contrast to other time-series methods that require more data points (Ostrom, 1990). A common limitation of these methods is that human interventions are required to update newly emerged and out-dated customer needs along timeline. Solutions (e.g. autonomic computing (Sterritt et al., 2005)) that can autonomously evolve the relevant set of customer requirements would therefore be desirable for applications in fast changing markets. Chen and Yan (2008) analyzed the customer utility using radial basis function (RBF) neural network. Through the implementation of a moving window architecture, it was demonstrated that the strategy is able to reflect and forecast changes of customer desirability of a set of design concepts. In contrast to arriving at information on future customer needs per se, the method produces forecasted customer preferences over a range of design options.

Summary and discussion

The minimization of development cycle times (i.e. the first of the three approaches) without moderation carries negative ramifications and limitations. As product quality might be compromised and cost increased when the cycle time is shortened (Bayus, 1997), speed-to-market should be strategically moderated to balance with the quality of the products. The review above also highlighted that executing a speed-to-market strategy without considering the window of opportunity can produce ill results. Further, the shortening of development cycle may render the process too rigid, which (paradoxically) makes responses to customer-driven changes difficult (Crawford, 1992). In practice, it is clear that the development cycle time as shown in Figure 1.1 can be shortened, but cannot be nullified. It follows that the cycle time reduction approach per se cannot be a sole and complete solution to the problem. The approach can nonetheless be applied in conjunction with other measures that are based on different principles.

In tracking dynamic customer needs, product developers ought to possess certain levels of sensitivity to the changes. In other words, the rate of customer needs

sampling should match the rate of change. For instance, in the cell phone market which is relatively dynamic, the rate of customer needs sampling (e.g. focus groups and customer complaint summary report) should be adequately high. Further, to dynamically tune the levels of sensitivity, firms may need awareness regarding the changes in market volatility (i.e. the second order changes). New methods to integrate customers into the process of development, whether physically or virtually are under research. The solution patented by Abelow (1999) is a fine example. Apart from the need to consistently detect changes, it is necessary for firms to have mechanisms in place to swiftly react to the detected changes.

Solutions proposed in the literature that link real-time customer needs to product development functions have been focused almost exclusively on supporting manufacturing (e.g. Adiano and Roth, 1994; Griffin and Hauser, 1992). It is deemed that broader scope of product development stakeholders should likewise benefit from the market intelligence (as discussed in Section 2.1.3). In other words, the continuous sharing of (near) real-time dynamic customer needs information should be across implicated groups as listed in Table 2.1. Each function may therefore monitor the changing pulses of the customers and in a coordinated manner dynamically adjust any product development parameter.

Reichwald et al. (2005) commented that traditional market research methodologies focus only on current situation and often do not contribute to the correct assessment of future customer requirements. However, being sensitive to the changing customer needs through periodical market research is clearly the premise of forecasting the future market needs. To address the issue of dynamic requirements, having near real-time information is therefore a necessity. It is however insufficient, as noted by Reichwald et al. (2005), since even real-time enterprises face the problems of dynamic markets. The second approach of being sensitive to the market is therefore a necessary but insufficient measure – a reactive measure, as opposed to a proactive one (refer to a review of reactive and proactive market orientation in Section 2.1.1). To handle the dynamism of customer needs, it is therefore necessary for organizations to be sensitive to the latest customers' voices, and be steps ahead by producing for the near future needs; the key strategy is to preempt the changes.

There have been few proposed methods that forecast customer requirements, which can be classified into two types: 1) survey of target customers' perceptions on their future needs, and 2) extrapolation based on historical data. The dependability of

the first approach hinges on, among other factors, the consumers' ability to forecast his/her personal needs and preferences of the future. This could be the reason why the second means is more actively pursued, according to the number of publications reviewed here. Of the reviewed work that approached the problem via the second means, they were found to be limited to linear problems. The limitation denies the applicability of the methods in the real-world. As each method has its merits and demerits, they might be complemented for better results.

At this juncture, it is worthy to point out that a notable number of the methodologies reviewed (see Table 2.2) are based on the original QFD (Akao, 1990; Hauser and Clausing, 1988). They are prescriptions to account for and/or forecast customer needs. These include the work of Adiano and Roth (1994), McLaughlin and Stratman (1997), Xie et al. (2003), Wu et al. (2005), Wu and Shieh (2006), Raharjo et al. (2006) and Gunasekaran et al. (2006). Raharjo et al. (2006) remarked that the myriad of research efforts made in the past to analyze the VoC based on QFD is unable to satisfy the need of quantifying future customer needs. This observation is reasonable as QFD was originally designed as a visual connective process that can help teams to focus on the needs of the customers throughout the development cycle (Bouchereau and Rowlands, 2000). Although QFD is an effective tool to improve customer satisfaction, it is not able to handle the dynamism of customer requirements. As such, in cases of research work listed above where QFD was applied to the problem identified in this work (see Section 2.1.2), in general, three inadequacies of QFD would undermine the proposed methodologies.

1) Bouchereau and Rowlands (2000) asserted: *QFD is primarily a people system. Nothing happens without people*. QFD is not designed as a computational approach for autonomously (e.g. autonomic computing (Sterritt et al., 2005)) monitoring the dynamic customer requirements, which can evolve and grow or decline in their importance. The appearances and disappearances of the requirements along the timeline is a common phenomenon. Most, if not all, dynamic customer requirement methods (including the QFD-based ones) thus far have not been designed to handle these occurrences. Human intervention is therefore required to update the list of customer requirements, as noted by the proponents of the QFD-based methods (Xie et al., 2003).

2) QFD is a snapshot of relationships in one point of time (Adiano and Roth, 1994), which ignores the notion of market clock (Reinertsen, 1991). Further, myriads

of QFD's derivatives (see Bouchereau and Rowlands, 2000) do not in their frameworks treat customer attributes as time sensitive information. The *temporal insensitivity* of QFD means that dynamic customer requirements that are variable across the time space cannot be captured for further applications.

3) QFD is designed to represent customer requirements of a single abstraction layer. However, requirements as in typical classes of information (especially complex information) can be better captured in multiple abstraction layers (Chong et al., 2009a). Furthermore, representing customer needs information in multiple abstraction levels can address the issue of 'actionability', and accommodate information generated by a wide range of customer needs elicitation techniques (as discussed in Section 2.1.2).

Customer requirement information consists of both the qualitative and quantitative aspects (Xie et al., 2003). The former represents the types (or objects) of requirement, while the latter represents the degrees of importance or preference. Xie et al. (2003) employed double exponential smoothing technique in projecting the importance level of the requirements, i.e. quantitatively. The method is limited to forecasting quantitative data. The quantitative dimension is typically the variable of interest focused in previous studies (e.g. Wu et al., 2005). Nonetheless, Szakonyi (1988) recommended that customer's future needs should be identified in terms of new product characteristics (i.e. qualitative terms). In the case of the dynamic QFD proposed by Adiano and Roth (1994), customer surveys are manually reviewed for the process of updating the matrix. In this light, a solution that can autonomously account for new customer requirements that appear and current ones that disappear (i.e. obsolete) along the timeline will be useful. Due to the need to holistically analyze and forecast customer requirements, an autonomic approach (Sterritt et al., 2005) that addresses both the qualitative and quantitative variations of the customer requirement is proposed in this thesis.

The above paragraphs summarize the limitations of the solutions previously proposed to address the issue of research here. The limitations are used to formulate the research problem described in Section 2.3.

Table 2.2 Characteristics of the reviewed solutions

Characteristic	Methodology									
	Adiano and Roth (1994): dynamic QFD	McLaughlin and Stratman (1997): dynamic QFD	Christian et al. (2001): Agile Manufacturing	Xie et al. (2003): QFD-based double exponential smoothing	Xie et al. (2003): QFD-based fuzzy trend analysis	Wu et al. (2005): grey theory in QFD	Wu and Shieh (2006): Markov chain model in QFD	Raharjo et al. (2006): dynamic QFD	Gunasekaran et al. (2006): QFD-based web-enabled system	Chen and Yan (2008): Neural network customer utility analysis
Recognize the need to determine future CR	●	●	●	●	●	●	●	●	●	●
Consider temporal dimension of CR	●	●	●	●	●	●	●	○	●	●
Autonomic mechanism	○	○	-	○	○	○	○	○	○	○
Address the problem of changing CR between design freeze and market introduction	○	○	-	●	●	●	○	○	○	●
Independency of the forecasted CR and of customers' forecast	-	-	-	●	○	●	-	-	-	-
Forecast non-linear CR trend	-	-	-	○	-	-	-	-	-	-
Represent CR in multiple abstraction levels	○	○	-	○	○	○	○	○	○	-
Represent alternative CR	○	○	-	○	○	○	○	○	○	●
Notations ●: Yes ○: No -: not applicable CR: customer requirements										

2.2 Artificial immune systems

Immunity is defined as resistance to and eradication of diseases, specifically infectious diseases. The study of immunology has in a direct manner benefited our livelihood since the discovery of vaccination about two hundred years ago. The knowledge has enabled us to not only cure, but also to prevent diseases. To perform these tasks, the immune system has evolved sophisticated pattern recognition and response mechanisms (Dagupta, 2006). The vertebrate immune system has been perceived by Cohen (2000) as a cognitive system that, like the brain, forms an internal history, self-organises (learning and memory) and make deterministic decisions. It was not until about mere twenty years ago in 1986 when this field of science was first tapped on to solving problems beyond the field of biology. This paradigm of problem solving is labeled as artificial immune system (AIS) by the research community. Such research gained momentum in the 1990s. To date, it remains relatively preliminary, active and attractive.

This review firstly addresses the history, key theories and important discoveries of immunological science. The aspects are fundamental to the artificial immune system. Although these reviewed topics are not directly applicable in this work, they are however the sole avenue to comprehend AIS as a computational intelligence (CI) paradigm. As such, this part of the review is included in Appendix A as reference and for completeness.

Section 2.2 starts with the introduction of AIS in Sections 2.2.1, 2.2.2, and 2.2.3. In Section 2.2.4, several AIS theories applicable in this work are reviewed. The review then goes on to address state of the art applications of AIS, such as anomaly detection and optimization, in Section 2.2.5. With the clarification of AIS' theories and applications, Section 2.2.6 discusses the uniqueness of AIS as a CI tool as perceived by the research community. By the end of the AIS review, Section 2.2.7 presents the collective views of the AIS proponents regarding roadmap and prospects of this unique problem-solving paradigm.

2.2.1 An overview of artificial immune system

Nature works. The mechanisms of nature have been effective and fine-tuned towards perfection, according to Darwin's theory of evolution. In solving problems, man has studied natural phenomena to gain insight on how solutions are generated by natural

systems. The mechanisms of nature were then replicated on computer systems, in effort to solve a wide range of problems. A successful example is the development of artificial neural network, inspired by how our brain works – neurology. More recently, vertebrate immune system is thought to contain much intelligence, which can be adapted to deal with problems beyond the scope of immunology. This new area, with much to uncover, is currently receiving increasing attention by researchers. It is a new CI paradigm, in the league of the more established artificial intelligence (AI) methods such as neural network, fuzzy logic and genetic algorithm (See Figure 2.5).

Figure 2.5 AIS as a branch of Computational Intelligence (Dasgupta, 2006)

Aickelin and Dasgupta (2005) described the immune system as highly adaptive, highly distributed, self-organizing in nature, maintain a memory of past encounters, and has the ability to continually learn about new encounters. From a computational information-processing perspective, the immune system is a remarkable parallel and distributed adaptive system with (partial) decentralized control mechanism. It uses feature extraction, signaling, learning, memory and associative retrieval to deal with recognition and classification tasks. In addition, the individual local interactions in an immune system result in the overall emergent property of the system. These abilities provide several important aspects in the field of computation (Dasgupta, 2006).

2.2.2 Definition of artificial immune system

This thesis defines artificial immune systems (AIS) as computational systems based to a certain degree on knowledge of the immunology discipline that aim to solve problems outside the scope of immunology. There have been numerous definitions that attempt to describe AIS and there are also several names to such systems. Other synonymous terminologies include immunity-based system (Ishida, 2004), biological immune system (Dasgupta, 2006), immunological computation, immunocomputing (Tarakanov, 2003) and computational immunology (Forrest et al., 1994). The term ‘AIS’ is in recent years seen as the generally agreed name. De Castro and Timmis (2002) defined AIS as *adaptive systems, inspired by theoretical immunology and observed immune functions, principles and models, which are applied to problem solving*. Sieburg et al. (1990) were among the first few to raise the term ‘AIS’ in the year 1990. However, in Sieburg et al.’s (1990) context, AIS denotes a computational system used to simulate human or biological immune system for the purpose of immunological work. Such systems are not of interest of this work, as delimited by the definition of AIS stated in the beginning of this paragraph.

2.2.3 The general development of artificial immune system

Two publications separately authored by Farmer et al. (1986) and Hoffman (1986) marked the pioneering efforts, in the path of AIS development. Hoffman (1986) studied both nervous and immune system for application on a neural network model. The work was followed by a series of network theory introduced by Ishida (1990) and Vertosick and Kelly (1991). On the other hand, Farmer et al.’s (1986) proposition of a dynamic immune network theory found a unique edge in the field of CI. The ability of the model to learn and to adapt was seen attractive in the problem areas of optimization and robotic navigation for instances. The immune network theory, though validity was being debated under the science of immunology, was being successfully applied to other problem domains.

Bersini and Varela (1990) are known to be the first to apply immune algorithm to problem solving. The areas of machine learning, optimization and adaptive control have been explored. In the early 1990s, studies have been conducted on the pattern recognition capabilities of binary immune system models using genetic algorithms (Forest and Perelson, 1991). From this point of development, researchers (e.g. Forrest

et al., 1997) and corporate such as IBM have seen the potential in using the immune system metaphor in designing systems that protect computers from unwanted external influences, such as computer virus and unauthorized intrusions. A term used to denote such work is *computer immunology*. Since 1995, AIS has caught the attention of other domains and research tracks began to diversify. The array of problem domains that adopted the idea of AIS will be further elaborated in Section 2.2.5.

From the academia perspective, one can similarly see the growth of the interest in AIS. Since 1996, starting with IMBS (Immunity-Based Systems) Workshops, there has been several other workshops, special tracks, presentations and tutorials concerning AIS. In 1998, Ishida et al. (1998) edited the first book on AIS in Japanese. The first edited book in English entitled “Artificial Immune Systems and their Applications” was launched by Dasgupta (1999). In 2002, the journal IEEE Transactions on Evolutionary Computation published the first special issue on AIS. Also in 2002, the first International Conference on Artificial Immune Systems (ICARIS) was held in the University of Kent at Canterbury, United Kingdom.

2.2.4 The theoretical perspective of artificial immune system

Recent development of AIS focused on three main immunological theories: clonal selection, immune network and negative selection (Timmis, 2006). The first two theories provide the essence of system learning and memory, which is discussed below. The scores of AIS theories originated from biological processes formalized either by Burnet’s (1959) clonal selection theory or Jerne’s (1974) immune network theory (Timmis, 2002). Accordingly, this pool of immune algorithms can be divided into mainly two categories: population-based and network-based respectively. Reviews of these two theories are presented in Appendix A. Negative selection theory, on the other hand, is fundamental in the range of work that deals with anomaly detection; It should be noted that this area of work is not in the scope and interest of the thesis.

It is seen that in the early years of AIS development, many of the immune network algorithms and clonal selection algorithm have been catered for optimization, classification and clustering problems. These applications are the ones that the AIS proponents (who are also involved in AI paradigms like artificial neural network (ANN) and evolutionary algorithm (EA)) have been mainly accustomed to deal with.

Notwithstanding that, it is recommended that further classes of problems can be treated with the AIS paradigm (to be discussed in Section 2.2.7)

Clonal Selection based Immune system

Early work of artificial clonal selection grew out of computational models of theoretical immunology, for the purpose of immunological studies (Chowdhury et al., 1990). This immunological research hinted the prospects of clonal selection for applications in the CI field. Several years later, abstractions of the immunological models were then applied on computational problems, including resource allocation (Mori et al., 1993). Clonal selection theory was also found to be extremely suitable for optimization. Consequently, a large part of the AIS literature was dedicated to optimization problems, such as Garrett's (2004) parameter free clonal selection, Artificial Immune Recognition System (AIRS) (Watkins, 2001; Watkins and Timmis, 2004), and the more popular one, CLONALG (CLONal selection ALGORITHM) by de Castro and von Zuben (2002). Those CI methods that based on the clonal selection theory are population-based, a category beside the network-based algorithm inspired by the immune network theory.

In general for optimization problems, the solution space is modeled as a population of B-cells, which are individually candidate solutions (*Note: in AIS literature, often no distinction is made between B-cells and anti-bodies. Both are subsumed under the word "antibody" or simply Ab (Aickelin and Dasgupta, 2005)).* The invading antigens (Ag) play the role of the function to be optimized. Under this setting, B-cells undergo the process of activation, cloning, affinity maturation and metadynamics according to the devised algorithm. In activation, the affinity between the function and candidate solution is assessed. Subsequently, the process of cloning or proliferation will be affinity-based, while the process of affinity maturation will be inversely affinity-based. It should be noted here that affinity maturation or data mutation process may not make sense for some problems, as commented by Alickin and Dasgupta (2005). Metadynamics ensure the death of weak B-cells (solutions) and the production of new random B-cells (solution). Above descriptions are the general ideas of all immune-based optimization algorithms. There are versions of these algorithms that cater to dynamic environment (Secker et al., 2003; Kim and Bentley, 2002), which is thought to be the capability of the original human immune system. In these work, the solution can be maintain over a period of time. The work to be

described in Chapter 3 similarly employs the dynamic capabilities of the AIS to handle the problem of continuously evolving customer requirement.

Clonal selection model can be considered to be one of the population-based models, including EAs, swarm algorithm and social insect algorithm (Stepney et al., 2004). The models have various aspects of similarities, such as: 1) they consist of individual agents each with fitness level, 2) and they have been used to optimize or perform some similar tasks. The models are different in aspects such as that the clonal selection algorithm treats the entire population as solutions, while the others regard only the fittest solution. This unique characteristic of clonal selection algorithm renders it exceptionally applicable to address problems related to customer requirement (see Section 2.3).

Immune network based systems

The idiotypic effect is first proposed by Jerne (1974) and formalized as a model by Farmer et al. (1986), known as the ‘Farmer-Packard-Perelson’ (FPP) model. This immune model is a type of *continuous model*, since it is quantified by a set of differential equations. Farmer et al. (1986) assumed a single epitope-binding region on each antigen (Ag) and antibody (Ab), and a single paratope-binding region on each antibody. They seminally suggested the usage of a network immune model for *machine learning*. Fukuda et al. (1993) proposed a similar immune network system to the FPP model. Both models represent paratope in binary and are concerned with concentration of antibody types. Although different in many other aspects, the models aim to maximize the Ag-Ab affinity (for improved solutions) and minimize the concentration of antibodies (for diversity). The activation and suppression of antibodies under the immune theory has been used in several manners. For instance, in an artificial immune network model named aiNet (de Castro and von Zuben, 2001), diversity through the suppression of similar antibodies is encouraged. As seen in Figure 2.6, Ab3 and Ab1 are similar, thus their concentration can be reduced. Another effect of the network used in AIS is to maintain the immunological memory (Neal, 2002; 2003). In data clustering, clusters that are prominent and stimulated by network cells in proximity are kept alive. Otherwise, cells without substantial network and without stimulation from antigens will die out (Neal, 2002). (*Note: This notion of stimulation and decay is applied in the present work, to be presented in Chapter 3.*)

Figure 2.6 Illustration of the idiotypic effect (Aickelin and Dasgupta, 2005)

Besides the *continuous model*, models that rely on looping of algorithms for the function of adaptation are classified by de Castro and Timmis (2003) under the *discrete model*. Timmis (2000) formed a resource limited artificial immune network, abbreviated as RAIN. It is self-limiting in nature due to the mechanisms that requires antibodies to compete for limited resources. Neal (2002) introduced the metadynamics ‘death term’ of the FPP model to achieve a self-stabilizing immune network. aiNet (de Castro and von Zuben, 2001) is proposed based on CLONALG, taking into account the network properties of the immune system. It is applicable to automatically compress and find clusters of data.

Garrett (2003) pointed out that immune network has to be highly simplified before it is tamed enough for use in clustering and optimization problems. For instance, an antigen is assumed (by Farmer et al. (1986)) to have only one epitope, which in the immunological reality has several. Vertosick and Kelly (1991) defied this assumption in an investigation into the immune network, which was also seen as a neural network in essence. In that case, the immune network was labeled as a multi-epitope recognizing neural network.

Timmis (2006) asserted that there is little commonality to unify the above network algorithms; a similarity is that they are based on the idea of clonal selection. In addition to the framework of clonal selection, the network models account for the stimulation and suppression caused by the cellular interactions as a form of regulatory mechanism. In fact, Garrett (2003) has pointed out that clonal selection may be considered a simplification of some form of immune network. AIS networks, metabolic networks, autocatalytic chemical reaction networks, hormone and growth

factor signaling networks, ecological food webs, are all examples of biological networks (Stepney et al., 2004). These complicated networks function in a distributed fashion; they operate individually based on principles to give the system the adaptable, emergent and robust properties. The lack of understanding of the immune network's dynamics, from the immunological science perspective, has limited its applicability (Hart and Ross, 2004).

2.2.5 The problem perspective of artificial immune system

This section reviews the applications of AIS to date. Among the volume of AIS literature (which is relatively small due to the discipline's young age), papers are selectively reviewed. The selected coverage is aimed to focus and reflect an accurate picture of central efforts and research boundaries. Literature that this thesis will later based on in Chapter 3 will be discussed in greater depth.

AIS application literature can generally be demarcated into the following three areas: 1) anomaly detection, 2) optimization, and 3) classification and clustering. It should be noted that the applications might not be exclusive to any single area, as overlapping of functions is possible.

Anomaly detection

Typically in this type of immune-based system, a set of detector is trained to indicate possible system anomaly. Commonly based on is the negative selection algorithm. This area is pioneered by Forrest et al. (1994), which led to a great deal of research and proposals of immune inspired anomaly detection systems (Forrest et al., 1997). Network security (Kim and Bentley, 2001), fault detection and diagnosis (Ishida, 1990) are some of the researched applications. The research was extended by combining the negative selection algorithm with clonal selection algorithm (Kim and Bentley, 2002) for computer security.

An issue with these approaches is the scalability and coverage problem (Garrett, 2005; Hart and Timmis, 2005). In-depth theoretical analysis of the negative selection algorithm highlighted various inadequacies when the algorithm is applied to real-world problems (Stibor et al., 2005). Mainly, high false positive rates and high computational overhead dogged the algorithm. Aickelin et al. (2003) proposed the adoption of *danger theory* approach to underlie anomaly detection systems. This

approach however has yet to be proven to answer the needs of anomaly detection to date.

Optimization

A comparatively large number of AIS publications relates to solving optimization problems. Typically used were the clonal selection theory and the immune network theory as metaphor for devising the optimization algorithms (See Section 2.2.4 for more details). Few of the resultant algorithms are CLONALG (de Castro and von Zuben, 2000), opt-aiNet (de Castro and von Zuben, 2001). CLONALG has been applied to uni-modal, combinatorial and multi-modal optimization and to the problem of initializing the centers of radial basis functions (de Castro and von Zuben, 2001).

Hart and Timmis (2005) conjectured that there is no added value in applying an immune algorithm to *static* function optimization problems. Although B-cells algorithm has proven to use significantly fewer evaluations than a hybrid genetic algorithm on some problems (Timmis et al., 2004), Hart and Timmis (2005) believe that static function optimization is not the *Holy Grail* of immune algorithms. Applying immune algorithms on combinatory optimization problem yields the same conclusion – there is no obvious benefit in AIS in this aspect. To that end, Hart and Timmis (2005) highlighted the dynamic property of vertebrate immune system; the natural system is known to continuously adapt and track moving targets. In this vein, Gaspar and Collard (1999) proposed an AIS to deal with time-dependant optimization problem, aiming to locate successive optima of non-stationary functions. In Aickelin and Dasgupta's (2005) opinion, AIS are not 'pure' optimizer, just as pure genetic algorithms are not 'function optimizers'; AIS are deemed as more suited as optimizer where multiple solutions are of benefit, e.g. when a neighborhood of solutions is to be produced.

Classification and clustering

Another significant part of immune system application research is targeted at data clustering and classification. Supervised algorithm such as AIRS (Watkins and Timmis, 2004) and aiINet (de Castro and von Zuben, 2001) are based on clonal selection theory, while Neal's (2003) is based on the immune network theory. AIRS uses the concept of Antigen Recognition Ball (ARB), which is a data structure that represent multiple identical antibodies. (*Note: the concept of ARB is later applied in*

this work.) Each ARB can be quantified by a certain cell-concentration value. aiNet has moved away from pure clonal selection theory; it combines CLONALG with aspects of the immune network model.

Classification and clustering require the functions of feature extraction, recognition and learning, which are also the key features of AIS. Hart and Timmis (2005), however, asserted that these features are features of many machine-learning algorithms. There is therefore no feature of the problem domain that indicates an immune algorithm has anything unique to offer, above other machine-learning methods. Hart and Timmis (2005) indicated that *dynamic* clustering and classification is however a promising application, which bears uniqueness among the other CI paradigms. Though few, there have been work that cluster dynamic data, such as those by Neal (2003), Hart and Ross (2003), Secker et al. (2003) and Kim and Bentley (2002).

Remarks

The above branches of AIS applications have been developed to date. The appearance of the above first three areas is largely *accidental*, in the words of Hart and Timmis (2005). A supporting rationale offered is that the research community that extract biological inspirations, including ones who study evolutionary computing, tend to apply AIS methods to the same problems that they are typically concerned with, e.g. optimization (Hart and Timmis, 2005). In this light, AIS might not have been, to date, carefully contrived for mapping to problems. Instead, those *accidents* have often led to unnatural problem representations, in the words of Hart and Timmis (2006). To move forward, AIS should be repositioned, developed and driven into niche areas, as suggested by scholars (e.g. Hart and Timmis, 2005; Timmis, 2006; Aickelin and Dasgupta, 2005). While many of AIS have been catered for optimization, classification and clustering problems, further AIS research should move towards treating other classes of problems. The recommended directions of future work should be based on the unique strengths of AIS, as reviewed in Sections 2.2.6 and 2.2.7 below.

2.2.6 The uniqueness of artificial immune system as a computational intelligence paradigm

Farmer (1990) asserted that the expressions and processes used in immune networks may be similar to other methods, but they are sufficiently different that they should be pursued as a separate field. Dasgupta (1999) provided a seminal list of features that defines immune system from a computational perspective: recognition, feature extraction, diversity, learning, memory, distributed detection, self-regulation, thresholds, co-stimulation, dynamic protection and probabilistic detection. These definitions are of the immune systems, but are not necessary unique to the rest of the CI systems. To justify the usage of the AIS in any work, there should be clear benefits of using the AIS technology, which cannot be arrived at through other techniques (Hart and Timmis, 2008). Hence, what does AIS possess, which are valuable, and which other *existing* soft computing paradigms lack of?

To evaluate AIS through surveying the key basis of the method (including the clonal selection and immune network theory), Garrett (2005) argued that AIS would be ‘useful’ when it is both *distinct* and *effective*. In evaluating the *distinctiveness* against other methods such as ANN and EA, Garrett (2005) suggested a set of test questions with criteria as: 1) unique symbol, 2) novel expressions, and 3) unique processes. A method can be said to be distinctive if the symbols, expressions and processes *as a whole* cannot be made equivalent to others. To assess the *effectiveness* of an AIS method, the essences of the test questions are: 1) unique results, 2) better results, and 3) faster results. A positive answer to any of these criteria suggests the AIS as effective. If a method is both indistinct and ineffective, it should not be researched further. However, it should be noted that this assessment methodology is not a complete theoretical analysis, but a practical comparison (Garrett, 2005). On this note, it is recalled that that in 1969, ANNs were shown to be somewhat lacking in effectiveness (Minsky and Papert, 1969); nonetheless, further research produced the back-propagation method – one of the most effective AI method reported. Garrett (2005) concluded that clonal selection is different from EAs and mutation-based genetic algorithms (GA) in terms of the process, specifically: the controls of the mutation rate and clonal proliferation rate are *novel*. While EAs and GAs define constants for the control, most clonal selection algorithm functionally defines the mutation and proliferation rate. Furthermore, Garrett (2004) previously proposed a

parameter-free clonal selection algorithm that evolves the proliferation function. It was compared to pre-parameterized EAs over four testing functions, and the proposed clonal selection algorithm is found to be more effective. Farmer et al. (1990) suggested that immune network AIS, classifier systems, autocatalytic reaction networks and ANNs are all instances of connectionist systems. From this perspective, AIS must be more than a connectionist system, since clonal selection, a member of AIS, may be classified as a form of immune network with connectivity or networking set to zero.

It was asserted that AIS researchers are required to diverge the search of its strengths and uniqueness in order to possibly stand out as a valuable unit (Stepney et al., 2003; Andrew and Timmis, 2005; Timmis, 2007). The unique strengths of AIS as asserted by the research community can be summarized and listed as follows.

- 1) An inherent ability of the AIS is its dynamic data analysis capability. Aickelin and Dasgupta (2005) stated that rather than one-off optimization, AIS is more suitable for problems that change over time, and need to be solved over and over again. Relevant to this point, Hart and Timmis (2005; 2008) mentioned that applications of “static” algorithm repeatedly, disregarding previous data in time, might miss out vital clues only factorable across time. The exploration of AIS-based solutions for problem domains that require dynamic analysis was thus encouraged. This dynamic feature will be a clear advantage over other biological inspired paradigms such as ANN and EA (Hart and Ross, 2003; Hart and Timmis, 2005). ANN generally performs static pattern-matching tasks and EA accounts for changes over extremely long time-frames, which have the emphasis of static data analysis, thus differing from AIS (Hart and Ross, 2003).
- 2) Another intrinsic ability of the AIS is its continuous capability to adapt to and to co-evolve with the environment (Stepney et al., 2003). Hart and Timmis (2005; 2008) identified that *life-long learning* is a feature of immune system, which could be tapped for computational applications. A dynamic immune-based learning system is clearly distinct from other CI paradigms, such as EA and ANN. The latter two produce fixed solution and terminate (Hart and Timmis, 2005), while the former facilitates a continuous learning capability. Hart and Timmis (2008) advocate the application of AIS to problems that require continuous learning capability of the technique, as a way forward for the research area.

- 3) The third outstanding characteristic of the AIS is the compound solution that it can offer. ‘Why not use ANN instead?’ asked Aickelin and Dasgupta (2005). It was accordingly pointed out that one might miss out on the benefits of a population of solutions, and the evolutionary selection pressure and mutation. Also mentioned by them is that AIS does not require any effort to optimize the parameter since they are self-organizing. In other methods such as EAs, the mechanism of selection and mutation are also present as in the AIS. Aickelin and Dasgupta (2005) also queried ‘Why not use genetic algorithm instead?’ It was clarified that AIS carries the extra beneficial effects of idiotypic network (see Section 2.2.4 under Immune-based system). Further, in EAs, swarm and ants algorithms, the results produced are the fittest member of the final population. Whereas in the case of AIS, the result is in the form of the entire final population (Stepney et al., 2004). Such form of outcome is suited, in this case here, to demonstrate the results of the full set of customer requirements pertaining to a certain product, instead of having only certain dominant customer requirement as the outcome.
- 4) Aickelin and Dasgupta (2005) pointed out that the patterns that AIS has learnt can be examined explicitly, unlike ones of the ANN.

The above list indicates the promising avenues of AIS development, as elaborated in the next section.

2.2.7 The recommended future development of artificial immune system

As aforementioned, the history of the artificial immune system (AIS) is relatively short, which could have started 20 years ago since Farmer’s (1986) publication. It is young when contrasted against other CI paradigms such as neural network, which has progressively matured for at least the last 50 years since Hebb (1949) hypothesized the Hebbian learning. Although relatively new, AIS is emerging as an active and attractive field involving models, techniques and applications of greater diversity. AIS research has been producing work, in a somewhat scattergun manner (Hart and Timmis, 2005). ‘Scattergun’ carries the notion of randomness and thoughtlessness. Hart and Timmis (2005) remarked that this is a normal and healthy phenomenon for any newly found paradigm, and argued that it was time to stock take and chart out the

areas where AIS is able to and thus should further add value in. In a bid to divert from the past approach and to strategically advance the development of AIS, the research community has analyzed and conjectured on where the value might lie beneath the surfaces seen today (Garrett, 2003; Stepney et al., 2003; Dasgupta, 2006; Hart and Timmis, 2005; 2008; Timmis, 2006; 2007). The identified areas are aligned with the AIS' distinctive niches, as compiled in Section 2.2.6. Below lists the collective recommended future developments by the AIS research community.

1. *Novel, rich and accurate metaphor.* In more recent years, work on AIS has drifted away from the more biologically appealing models and attention to biological details, with focus on more engineering-oriented approach. This has led to systems that are examples of reasoning by metaphor (Stepney et al., 2004). One example is the network models' simplified view that each antigen possesses only one epitope, when in reality more than one is present. As such, one can say that typically naive approaches to extracting metaphors from the immune system have been taken. In view of this, Stepney et al (2004) encourage interactions between mathematicians and immunologists to undertake specific experimentations that can create useful models.

Among the possibilities of advanced metaphorical extraction, Hart and Timmis (2005) and Garrett (2005) separately suggested the modeling of the innate immune system, its interaction with the adaptive immune system, and the phenomenon of parallel attack by the systems, which have been almost without exception ignored in the AIS literature. In general AIS should place emphasis on understanding and extracting key biological properties (Andrew and Timmis, 2005). Cohen (2001) introduced a model of immune system, postulating a range of *immune dialogue* amongst the elements, i.e. B-cells, T-cells, macrophages, and the two immune sub-systems, i.e. innate and adaptive. Argued by Cohen (2001), this explains the specificity and the collaboration between the two sub-systems.

2. *The compound solution of the AIS.* Aickelin and Dasgupta (2005) asserted that although AIS can be made to work for pure optimization problem, e.g. traveling salesman problem and job shop scheduling problem, such work is probably missing the point. In EAs, swarm and ants algorithms, the result is the fittest member of the final population. In the AIS, however, the result is the entire final population (Stepney et al., 2004). AIS is powerful when a

population of solution is essential (Aickelin and Dasgupa, 2005). The problem has to also have some concept of ‘matching’, remarked by Aickelin and Dasgupa (2005).

3. *Dynamic data analysis.* Biological immune system works in a continuous manner, dynamically across the time domain. The body is under constant challenge from the environment to respond along a continuum of behaviour (Dasgupa, 2006), and it needs to adapt itself accordingly. Currently, mathematical and computational descriptions of the biological network structures, including immune network, tend to be static, having *no time component* to the architecture; they thus do not address time-varying databases (Hart and Ross, 2001; 2003; Stepney et al., 2004). Few have proposed learning systems in continuously evolving environment, including dynamic optimization (Gaspar and Collard, 1999) and dynamic clustering (Neals, 2003; Hart and Ross, 2001; 2003). In the view of the research community, such dynamic systems ought to be more intensively further explored. Modern technology makes it incredibly straightforward for companies to gather vast amounts of data concerning individuals and their habits on a daily basis (Hart and Ross, 2003; Hart and Timmis, 2005). These datasets can be applied for pattern and trend tracking, to gain competitive advantages. For instance, information on the use of credit cards and supermarket loyalty cards is flowing in a continuous manner, and the timely analysis requires a dynamic system (Hart and Ross, 2003). Continuously classifying electronic mails is another exemplary application of such system (Secker et al., 2003). As discussed in Section 2.2.6, AIS is particularly suitable for problems that change over time, where information hidden across time can be analyzed. The exploration of AIS-based solutions for problem domains that require continuous learning from dynamic environment is therefore encouraged. In this vein, Stepney et al. (2003) have envisaged AIS as a dynamic opened system that break the classical computation paradigm.
4. *The continuous adaptation, randomness, emergent and openness of the AIS.* In general, immune system can inspire a computational system that is capable of maintaining its own internal steady state in a varying environment, i.e. the homeostatic characteristic. The UK Grand Challenge 7 (GC-7) for Computing Research is an initiative to map out ambitious key areas for research and

exploration in the next 10 to 15 years (Stepney et al., 2003). AIS is deemed to sit squarely on the composite proposal of *Non-classical Computation* (Timmis, 2007). One of the classical computing paradigms, the algorithm paradigm, is one which future AIS research should challenge. For example, Stepney et al. (2003) raised that a system may be an ongoing adaptive process, with input provided over time, with system values dependant on how it interacts with the opened environment. Identical inputs may provide different outputs, as the system learns and adapts to its history of interactions; further, there may be no prespecified end point. Computer may be in a continuous interactive dialogue with users and other computers. Randomness and chaos, which are known to work in nature, should be incorporated into computational system. Another classical paradigm, the *refinement paradigm*, says that emergence is undesirable. However, when tractability in ever-growing complex system is an issue, emergent properties may become an important way out. Algorithm format of computing tends to be *closed* (Stepney et al., 2004). Opened system, such as the immune system should therefore be further studied. For instance, inoculation or injection of information to a system any time along the process can yield different results. In terms of AIS, dynamic communication of the system with the users or other computers through vaccination or feedback can be explored.

5. *Applications of AIS*. Work on AIS to date simply concentrated on what other paradigms does, such as optimization, clustering, classification, pattern recognition and learning. While these applications are productive, there has been a lack of thought (in the AIS community) regarding the applications of AIS, as remarked by Timmis (2007). To move forward, AIS should be repositioned, developed and driven into niche areas, as suggested by many scholars (e.g. Hart and Timmis, 2005; Timmis, 2006; Aickelin and Dasgupa, 2005). Timmis (2006) pointed to the direction of looking for *killer application* of AIS, which the benefits of adopting AIS would be clear. As such, non-conventional applications should be explored.

Generally speaking, two approaches to the future of AIS can be inferred from the present literature review. The first emphasized on the educated and strategic divergence at various levels in the exploration of this field (Timmis, 2006; 2007; Stepney et al., 2003; 2004; Garrett, 2005, Andrew and Timmis, 2005; Hart and

Timmis, 2005). This approach involves the return to the field of immunology for better models, and more well thought applications that need not be similar to what other CI paradigm can solve. Using this approach, new non-classical computation can possibly be discovered (Stepney et al., 2003). On the other hand, the second recommended approach towards the future of AIS is the refinement and unification strategy. Dasgupta (2006) concluded that existing work, i.e. clustering, pattern recognition, anomaly detection and optimization, still do not scale well. Hence, future research to improve the efficiency of the algorithms, enhancement of the representation, introduction of other immune mechanisms, and develop a unified architecture that can integrate several models were recommended (Dasgupta, 2006). These two channels of advancement for AIS, in the author's opinion, are both necessary. This is as in the design of entities, i.e. divergence and convergence of design space alternatively and/or simultaneously is the natural and best method to progressively concretize designs.

In the development of this work, the above list of recommended strategies were considered and adopted. These strategies contribute to the specification of the research problem described in Section 2.3.

2.3 Specification of the research problem

Changing needs and evolving preferences of customers, as concluded by Blocker and Flint (2007), represent the key drivers of market turbulence. In a highly volatile environment, uncertainty management is an important basis of competitive advantage. Research in the dynamism of customer requirements is therefore critical to producing applications that can address the increasingly fast moving business environment. Modern technology makes it incredibly straightforward for companies to gather vast amounts of data concerning individuals and their habit on a daily basis (Hart and Ross, 2003; Hart and Timmis, 2005; Gunasekaran et al., 2006). A potential facility to address this challenge is the Internet, which can relay dynamic (time-series) customer requirement data for analysis (see review in Section 2.1.5). According to Berkman (2008), strategic listening is critical to firms, and in recent years, near real-time market intelligence comes from the Internet; capitalizing on dynamic data streams containing customer information allows firms to 'anticipate emerging social and industry trends and better serve their current and future customers'. The objective of this study is

therefore to advance the body of knowledge that supports the computational approach of addressing the issue of dynamic customer needs².

The problem of dynamic customer needs has been validated by various empirical studies (Calantone and Sawyer, 1978; Peebles and Boulton, 1995; Mittal et al., 1999; Szakonyi, 1988; Kärkkäinen and Elfvengren, 2001; 2002). Research has consistently highlighted the importance of addressing the issue (see Section 2.1.4). Groups of proponents (e.g. Szakonyi, 1988; Kärkkäinen et al., 2001) further found that the critical issue of the dynamic variable has however not been receiving fair amount of attention from practitioners. As reviewed in Section 2.1.1, proponents of market orientation have advocated forecast as an important activity in NPD. Kahn et al. (2003) noted that new product forecasting was an under-researched area relative to other NPD topics. In the same vein, Blocker and Flint (2007) observed that most approaches proposed to address segment instability have been reactive, and no attempt to forecast shift in customer needs has been done. Kahn et al. (2003) advocated the research for tools and methods for addressing the uncertainties in product development. In this light, an instructive assertion was made: *more theory development exploring the dynamic nature of customer value perceptions is an important next step* (Brangule-Vlagsma et al., 2002).

Despite that the research is in preliminary stages, a considerable number of researchers have proposed methodologies³ that *forecast customer needs*. However, they are technically limited in the ways to address the dynamism of customer needs. In view of the existing research boundaries (see discussion in Section 2.1.5), a list of characteristics that a solution should bear is listed as follows.

- 1) Robust representation of customer needs.
- 2) Temporally sensitive system architecture.
- 3) Autonomic⁴ learning mechanisms in dynamic environment.
- 4) Ability to forecast customer needs (to handle non-linear problems; forecast to be independent of customers' ability to predict).

² The issue of dynamic customer needs is expressed in Section 1.1.

³ It was noted that no existing research on customer requirements forecasting known to the author has employed real data for validation (Xie et al., 2003; Wu et al., 2005). One of the reasons to this trend could be due to the proprietary nature of the relevant data.

⁴ Autonomic has been expressed as the automation of system adaptation (Tianfield and Unland, 2004).

In view of the abovementioned requirements in handling the issue of dynamic customer requirements, AIS was found to be a potential platform to advance the research. The selection of AIS as the subject of study is due to its advantages *unique* among the range of CI paradigms. Namely, AIS is outstanding in the following aspects that specifically address the present research problem.

- 1) It has the population (instead of individual elements) as the solution.
- 2) It possesses the framework for dynamic analysis of time-series data.
- 3) It has the underlying mechanisms for continuous learning/adaptation by autonomously co-evolving with the environment.

Further, AIS also possesses the ability (though non-unique to AIS) to deal with non-linear problem, and to represent data more robustly using multiple abstraction levels.

As presented in the next chapter, the research proposes and investigates an AIS, termed as the CRAF system, as the avenue to advance the body of knowledge that is required to address the issue identified in Section 2.1. From the perspective of contributing to the AIS research, Hart and Timmis (2008) deemed that an algorithm must achieve something that cannot be achieved by any other means in order to earn its place in history. In this light, this study exploits the above listed unique capabilities of the AIS to address the research problem. In this manner, this research is positioned to contribute in both the areas of dynamic customer requirement and AIS.

In the beginning of Chapter 3 (Section 3.1), a set of system requirements corresponding to the research problem is specified with the aim of achieving the objective of the research.

Chapter 3 - The CRAF System

Researchers have used strategies based on biological systems to successfully deal with complexity, dynamism, heterogeneity and uncertainty (Sterritt et al., 2005). This work takes a problem-oriented approach to prescribing an immunity-based system (also known as AIS), with the aim of addressing the research issues identified in Chapter 2. As suggested by Freitas and Timmis (2007), the design of an AIS should take into account the application domain and the characteristics of the data to be analyzed. That is, the components of an AIS such as its representation, affinity function and immune process should be tailored to the problem. According to the research problems identified previously, a system termed as the CRAF (Customer Requirement Analysis and Forecast) system is specified as the vehicle of investigations. A set of requirements of the CRAF system is therefore listed in Section 3.1, with respect to the research problem established in Section 2.3.

The architecture of the CRAF system is described in Section 3.2. An immunity-based dynamic and autonomic learning (iDal) technique is developed as the backbone of the system, which will be presented in Section 3.3. The technique is generic, instead of problem-specific. To specifically apply the iDal technique to the dynamic customer requirement problem, a novel data representation model termed as the Requirement Space Framework (RSF) is introduced (in Section 3.4). In effect, the RSF serves to facilitate the mapping of data from the problem domain to the data structure of the iDal technique.

3.1 System requirements

This study primarily aims at contributing to the research area of dynamic customer requirements, and at the same time to the AIS research. To address the set of research issues identified in the literature review presented in Chapter 2, a novel AIS-based

CRAF system is proposed as the vehicle of investigations. For the purpose of the study, the proposed system needs to address four requirements as follows.

1. Robust modeling of customer requirements. Quantitative and qualitative customer requirement information (Xie et al., 2003) should be represented in multiple abstraction levels, and should also represent both co-requirements and alternative requirements.
2. Ability to perform analysis dynamically with the temporal dimension underlying the system architecture.
3. Ability to perform forecast of customer requirements, and the ability to handle non-linear problems.
4. Autonomic learning of customer requirement data by co-evolving with the dynamic environment.

The set of system requirements is employed to evaluate the investigations in Chapters 4 and 5, and for facilitating the research conclusions in Chapter 7.

3.2 System architecture

Figure 3.1 illustrates the CRAF system architecture in the context of customer requirement management (see also Figure 2.2). The figure shows three distinct phases - elicitation, analysis and specification, as suggested by Jiao and Chen (2006).

As shown in Figure 3.1, customer needs elicitation process is the source of data for the CRAF system. The process can be conducted by market research companies or by marketing department within product development firms. Techniques involved in the process of elicitation can be qualitative (e.g. focus group) and quantitative (e.g. questionnaire) (see a review of the elicitation techniques in Section 2.1.2). Apart from the traditional methods, Internet-based customer needs elicitation is getting more common in the recent years; many companies have collected customer requirements over the Internet (see a review in Section 2.1.5).

The data required by the CRAF system is (1) of customer requirement information, (2) in time-series (i.e. with time dimension), (3) qualitative (i.e. text-based), and (4) quantitative (i.e. numeral). As with all software, data preparation¹ will be necessary to render raw input data compatible for the CRAF system. The

¹ Data preparation involves checking for accuracy, data entry into computer, data transformation, and database structure development and documentation.

preparation process is dependant on the characteristics of the data generated by the respective elicitation techniques (Weiss and Indurkha, 1998).

On the other end (i.e. the right side portion of Figure 3.1), computational intelligence methods have been widely researched to deal with problems in the downstream processes of requirement analysis, such as design; a review of this range of work was reported by Saridakis and Dentsoras (2008). It should be noted that the focus of this work is on the analysis of the customer needs, in the context of data collection (i.e. pre-process) and data application (i.e. post-process).

Figure 3.1 CRAF system architecture and context

The iDal technique, which is the backbone of the CRAF system, lies in the iDal module of the architecture. The module receives time-based customer requirement (CR) data for analysis and output to the forecast module in a dynamic manner. The result produced by the forecast module is in turn fed to the CR database for storage. While the CRAF system users may query for datasets via the user interface layer, the stored data may also be dynamically applied by downstream product development processes such as design, manufacturing and marketing. A study on an application of the data for design is reported in Chapter 6.

The iDal technique is described in the rest of the Chapter 3. In this research, the CRAF system will be evaluated against the set of requirements listed in Section 3.1; two types of forecast module of the CRAF system will be specified according to the means of the investigations, as documented in Chapters 4 and 5 respectively.

3.3 The iDal technique

This section introduces an immunity-based dynamic and autonomic learning (iDal) technique. Sub-section 3.3.1 presents the abstraction of theoretical immunology in relation to the research problem. As shown in Figure 3.2, the implementation of immunity-based technique can be broken down into several steps. Accordingly, Sections 3.3.2 to 3.3.7 specify the iDal technique in terms of its immune entities, representation, affinity measures, and immune algorithm.

Figure 3.2 Implementation steps of AIS (Dasgupta, 2006)

3.3.1 The abstraction of biological immune system

Metaphors, a biological one in the case of this study, have been employed in the prescriptions of computational tools. Useful mechanisms underlying the sources of inspiration were in varying degree mapped to the computational domain. As demonstrated in the past, in the cases of artificial neural network (ANN) and evolutionary algorithm (EA), only somewhat high abstraction of the biological systems were extracted for use. In the aspect of abstraction, Andrew and Timmis (2005) highlighted that one of the main problems involved in designing bio-inspired algorithms is to decide which aspects of the biology are necessary in generating the required behaviours, and which aspects are surplus to requirements. There is however a caveat to the abstraction process. Stepney et al. (2003) criticized that naive assumptions have been made in numerous AIS propositions and thus have impeded the

development of the systems or algorithms. The solutions were said to be weak analogies of the biological systems. It was proposed that the utilization of biological observations and experiments to provide partial views of the biological systems could inspire new views; these views would then be used to build abstract models of the biology, which would be opened for validation. Stepney et al. (2003) argued that this method would produce better models. A question at this juncture is: must the abstract model be biologically valid for the goal of solving problems computationally? The answer positioned in this thesis is that it is good to be, but not necessary.

Jerne's (1974) immune network theory has proven that models that are yet to be validated can be valuable from the perspective of computational intelligence (CI) scientists. This is because immune network theory, though widely refuted, is to date one of the widely used bases for computational problem solving. Non-compliance to biological facts is therefore inadequate to disprove the validity and usefulness of the derived computational model. In other words, the biological implausibility of a theoretical model does not necessarily preclude its usefulness in the computational context (Hone and van den Berg, 2007). Adding to the impracticality of using only validated biological model is the fact that immunologists themselves are in disagreements on numerous biological theories (Langman and Cohn, 2000). Besides, new discoveries that shift ideas are currently being made. Notwithstanding that, one of the advantages of fully adhering to proven biological theory is that the derived CI method can be highly scalable in its width and depth, limited only by the ever-growing scope of the proven biological theories. As mentioned above, it is therefore good to adopt biologically valid models for solving other problems computationally, but not less valid and effective when hypothesized models are used. The position of this work is to selectively adopt hypotheses (e.g. network theory) and/or facts (e.g. clonal selection theory) to suitably apply them in solving problems beyond the field of immunology.

Reviews of clonal selection and immune network theories were presented in Chapter 2 and Appendix A. It is a conjecture of these theories that the change in concentration of lymphocytes (or Ab concentration) is not all random, though some stochastic elements might be present. As seen in Figure 3.3, the depicted antibody concentration fluctuates with a certain profile, which is the result of the interacting mechanisms within the immune system, including cloning, apoptosis, metadynamics and cell activation (see Appendix A for background on immunology). Repeated

encounters of the same antigens send progressive signals to the immune system on the need for the specific lymphocytes. The system continuously senses and learns the dynamically changing antigenic environment, adapting the entity's global composition of its finite repertoire of lymphocytes to presumably best (or optimally) defend the vertebrate from pathogens in the said environment.

To understand the immune system, researchers have attempted to model the dynamisms of immune agents such as plasma, antibodies, and pathogens. Mathematical modeling plays an essential role in theoretical immunology (Hone and van den Berg, 2007). System of ordinary differential equations (ODE) has been used to model the dynamic system, possibly started with Bell (1970) who based his work on the clonal selection theory. Others have also more recently used ODE to account for the variations of antibody concentration levels over time (Perelson & Weisbuch 1997, Yoshida et al., 2007). This modeling method has been used to account for medical treatment optimization (Stengel et al., 2002). Figure 3.4 shows a case of natural response of the immune system to pathogenic attack. The lower left graph of Figure 3.4 shows the time-series concentration change of antibodies and the upper right graph shows the variation of cell concentration across time. The system is modeled by a set of nonlinear fourth order ODEs. It is however noted that the ODE model, a *reductionism approach*, has its limitations. It requires detailed knowledge of the kinetic parameters, which could be estimated or experimentally measured. In large number, the parameters will easily introduce inaccuracies into the system model (Morel et al., 2006). This is the same challenge as that of modeling social phenomena. Instead of the reductionists' approach, theoretically unsupported models, such as diffusion models (Bass, 1969), have been shown to usefully forecast time-series profile that can hardly be reduced (note: Bass diffusion model is further studied in Chapter 4).

Figure 3.3 The non-random profile of antibody concentration over the time domain (de Castro and Timmis, 2002)

Figure 3.4 The dynamics of the immune system during infection, modeled by nonlinear fourth order ODE (Stengel et al., 2002)

To date, few have employed the dynamic property of biological immune system as the metaphor to analyze time-series data (Neals, 2003; Hart and Ross, 2003). Hart and Ross (2001; 2003) presented a model for clustering large and non-static databases based on both immunological and sparse distributed memories metaphors. Neal (2003) proposed an AIS algorithm to produce meta-stable memory inspired by immune network theory. Due to the stability, it can be deployed to learn continuously. The above work has demonstrated the basic ability of the AIS to dynamically analyze continuous stream of input data, and in tracking spatial patterns. *Previous research has however not exploited the potentially useful temporal dimension of the data.* That is, the information that could be hidden amongst the data, observable only across the time domain. The work here builds on this unique technique (relative to other AI paradigm such as EA and ANN) to perform a function novel in the context of AIS research. Specifically, the function is to dynamically forecast the behaviour of modeled systems.

Vertebrate immune responses possess the functions to control and eradicate pathogens. More notably, the adaptive immune system has the ability to learn, adapt and even to preempt future invasions of the defense system. In non-random systems, such as the immune system, knowledge (even of the abstract kind) of the dynamism can aid to determine or forecast the systems' time-series profiles. Such knowledge may include experiences learnt in the past, which indeed is what the functions of the biological immune system depends on. With interest in modeling the dynamism of variables (i.e. antibody or B-cell population as described above), this work formalizes in the rest of this section the iDal technique.

3.3.2 Elements in the framework of the iDal technique

This section defines the elements that compose the framework of the iDal technique. Figure 3.5 depicts an abstract view of the framework coevolving with the environment.

Figure 3.5 A schematic diagram of the iDal framework

The properties of the iDal framework

In this work, an AIS (i.e. the iDal framework) is prescribed to represent entities with the following characteristics. Firstly, such an entity is *homeostatic*; it continuously adapts itself in seek of steady states in a dynamic environment (Besendovsky, 1996). In this sense, the entity learns from the environment and *coevolves* with it, much like the biological immune system.

Secondly, the entity ought to possess *inertia*. Immune system takes time to build up immunity and to lose it - an exhibition of the inertia property (Neal, 2002). In other words, the rate of change of the system contents (B-cells for instance) should be finite. It can be ruled that an entity that possesses inertia at rest will remain at rest and if moving with constant velocity will continue to do so, unless disturbed by an unbalanced force. The term *inertia* is borrowed by this study from the field of physical science. In the context here, however, the notion of movement, velocity and forces need not be in the physical space, but can be concepts such as certain social phenomenon that the iDal technique can model. Like a rolling ball with inertia, the systems could retain information across time and space, i.e. the memory of an immune system.

Thirdly, the dynamics of the system is *deterministic*. Although the vertebrate immune system and other forms of AIS contain stochastic elements, such as the receptor editing and somatic hypermutation processes (de Castro and Timmis, 2002), the framework postulated in this work does not adopt these properties. (*Note: Solving optimization problems of sorts using AIS employs these stochastic elements in the same way as genetic algorithms.*)

The pathogens in the environment of the iDal framework

The iDal framework, analogous to the vertebrate immune system, resides in an environment where it is susceptible to perturbations by external pathogens (i.e. unbalanced forces from the physical perspective). Biologically, pathogens are detected based on enzyme or toxin molecules found on epitopes at the surfaces. In a broad sense, any molecule that can be recognized by the immune system is referred to as antigen (Ag). These external agents metaphorically correspond to packets of computational data, which are transmitted continuously in the time domain. The medium of *transmission* (metaphorically speaking, *infection*) remains non-specific in this work. It can be Internet for instance. Examples of pathogens are time-series meteorological data, credit card transaction data and customer requirement data. (*Note: the process of acquiring these datasets is not within the scope of this work, as stated in Section 3.2).*

The immunological memory of the iDal framework

Immune system can be divided into innate and adaptive systems. The iDal technique is inspired by the adaptive immune system, which holds the immunological memory. The elements of the memory system are lymphocytes, a class of white blood cells, consisting of both T-cells and B-cells. T-cells in theoretical immunology are known to engulf pathogens and send out cytokine amongst their other functions. However, this study is less concerned with the detailed mechanisms of how intruders of human body are eliminated, and is more interested in the temporal evolution of lymphocytes repertoire in an antigenic environment. Therefore, T-cells are not considered in this work. Consequently, the terminologies of lymphocytes, B-cells and immunocompetent cells would be synonymous here. Further, this work does not distinguish between B-cells, BCR (B-cells receptors) and antibodies (Ab), as in some of the AIS literature. BCR is in fact Ab or chains of protein molecules that is found on the surfaces of B-cells. Upon cell activation, they are released into the blood and lymphatic streams. (*Note: background on immunology can be found in Appendix A.*)

Traditionally in the AIS literature, B-cell has been represented as an individual entity. This work adopts the concept of *Artificial Recognition Ball* (ARB) to represent a class of the lymphocytes that are identical, to a range of extend. ARB was originally introduced by Timmis and Neal (2001). Depicted in Figure 3.6 is a space V that

completely covers all possibly existing BCR, which is a concatenation of gene segments. This antibody configuration space, also called the *shape space*, supports Perelson's (1989) postulation that *a finite number of antibody types can possibly detect infinite types of antigens*. In space V , dark circles represent paratopes while x represent epitopes. The circle around each antibody's paratope represents the artificial recognition ball, denoted by V_e . The coverage of the ARB can be characterized by ϵ , a parameter of the iDal framework. Epitopes that are found within the ball is said to share an affinity with the paratope, and hence can be recognized. The recognition degree, or the strength of the bond between an Ab and an Ag, varies within the ARB (Neal, 2003). Since infinite number of epitopes can be placed in each ARB, this model supports Perelson's above-mentioned postulation. Using this as a metaphor in this work, an ARB is representative of a sub-population group of B-cells that is identical to a certain degree specifiable. Therefore, in the iDal framework, ARBs constitute the immunological system memory.

Figure 3.6 ARB's influences in the shape space of immune system (Timmis and Neal, 2001)

3.3.3 Data representation in the iDal technique

Part of the intelligence of the AIS lies in the interactions between antigens and antibodies. The ability of B-cells in recognizing antigens is based on the molecular *complementarity* or the *affinity* that quantifies the degree of match between the

paratopes and epitopes on the respective cells. Immunological researcher Perelson (1989) introduced the model of shape-space to study Ag-Ab interactions in theoretical immunology. *Generalized shapes* of molecules can be employed to characterize Ag and Ab, as far as binding studies is concerned. Assuming a set of L parameters defines the shape, a point in the L -dimensional space, called *shape space*, therefore would represent a particular shape type. This L -dimensional shape-space is the basis of the ARB concept described in the previous section (see Figure 3.6).

In the studies of immunology (Cohn, 2005; Langman, 2000), specificity index (SI) was proposed to characterize the repertoire of cells' ability to discern self from non-self. SI of zero denotes B-cells as universal glue, while SI of value one denotes infinite specificity. *This research adopts the immunology concept of SI for application in the AIS, i.e. the iDal technique, to support the modeling of information with a range of specificity levels.*

Accordingly, the *generalized shapes* that model the molecules of the binding regions of B-cells and pathogens can be mathematically represented by a string of L -length variables of certain attributes set, as shown in Equation 3.1 (i.e. $1 \leq l \leq L$). L is the upper limit of specificity level that corresponds to the lowest abstraction level representing information in the iDal framework. A point in shape-space S of L -dimension is denoted as $m \in S^L$. For molecule m_i ,

$$m_i = \langle m_{i1}, \dots, m_{iL} \rangle \quad (3.1)$$

where i ($1 \leq i \leq I$) is the index of the molecule set and l ($1 \leq l \leq L$) is the specificity level.

Molecules of binding regions can be of either antigens (Ag) or ARBs, i.e. Equation 3.2.

$$m \in \{Ag, ARB\} \quad (3.2)$$

Molecules m can be characterized by different attribute-types such as real values, integers, binaries and symbols, which would result in different types of shape-space, i.e. real-valued, integer, Hamming and symbolic shape-space respectively. The selection of the type of data representation is dependent on the problem domain that the iDal technique is applied on. As with all computational intelligence (CI) applications, domain knowledge is necessary and important in specifying the appropriate data representation.

The object of interest in iDal framework is the real-time concentration level of B-cells in the ARBs. Figure 3.7 shows a schematic snap-shot of the concentration levels of ARBs in a memory space. Schematically depicted in the figure are two ARBs

of differing coverage (i.e., generality). The numerical values of the B-cell concentration level in ARBs can be defined by function $Conc$, e.g. $Conc(m_i, t) = 500$, i.e. concentration of type m_i is 500 in the system by the end of period t .

Figure 3.7 Concentrations of ARBs with differing specificities

3.3.4 Affinity measurement of the iDal technique

The shape-space type adopted in an application problem will point to the possible methods for quantifying the affinity between two molecules. For real-valued shape-space, Euclidean (Equation 3.3) distance measure can be used. For Hamming shape-space, where k is the number of states possible (e.g. for binary: $k=2$, $k \in \{1,0\}$), the Hamming distance measure is defined in Equation 3.4.

$$D_{ij} = \sqrt{\sum_{l=1}^L (m_{il} - m_{jl})^2} \quad (3.3)$$

$$D_{ij} = \sum_{l=1}^L \alpha_l \text{ where } \alpha_l = \begin{cases} 1 & \text{if } m_{il} \neq m_{jl} \\ 0 & \text{otherwise} \end{cases} \quad (3.4)$$

where l ($1 \leq l \leq L$) is the specificity level, while i ($1 \leq i \leq I$) and j ($1 \leq j \leq J$) are the indexes of the two molecules m (operands) of the D function.

In application problems where individual antigenic attributes have unequal weightage towards the measurement of affinity between two subjects, the applied affinity measure (such as Equations 3.3 and 3.4) can be modified with weight w_l factor as shown in Equations 3.5 and 3.6.

$$D_{ij} = \sqrt{\sum_{l=1}^L (w_l (m_{il} - m_{jl}))^2} \quad (3.5)$$

$$D_{ij} = \sum_{l=1}^L w_l \alpha_l \text{ where } \alpha_l = \begin{cases} 1 & \text{if } m_{il} \neq m_{jl} \\ 0 & \text{otherwise} \end{cases} \quad (3.6)$$

where w_l is the weight factor (value range is application dependant), l ($1 \leq l \leq L$) is the specificity level, while i ($1 \leq i \leq I$) and j ($1 \leq j \leq J$) are the indexes of the two molecules m (operands) of the D function.

The Affinity-Distance function

The Affinity-Distance (A-D) function is the criterion that the iDal technique uses to discern if the recognition between two molecules is positive ($A=1$), negative ($A=0$), or positive to a certain degree, i.e. $0 < A(m_i, m_j) \leq 1.00$. Generally, affinity and distance are related inversely. Affinity between two molecules is normalized by A-D functions, as the examples shown in Figure 3.7. A-D function determines the level of stimulation of antigens to the ARBs. The theory of cross-reactivity underlies the *fuzzy* stimulations. In this case, shorter distance (higher affinity) improves the chance (under the criteria of a discrete A-D function), or increases the level of stimulation (under the criteria of a continuous A-D function). The A-D functions can be a simple discrete binary step function or others such as a sigmoid function, which is an instance of continuous functions that can be used for fuzzy inferences, as in the affinity value for cross-reactions. The type suitable for specific situation and application problem should be selected for use. For instances, if $L = 6$ (i.e., the upper limit of specificity is 6), examples of threshold, sigmoid and linear A-D functions are shown in Figures 3.8 (a), (b) and (c) respectively.

Figure 3.8 Examples of A-D functions (a) Threshold A-D function, (b) Sigmoid A-D function, and (c) Linear A-D function

3.3.5 The iDal algorithm

According to Jerne's (1974) network theory, foreign antigens shape the network of the immune system. The result is an internal image of network that reflects the universe of

antigen the immune system is residing in. AIS algorithms, in general, are analogous to the life-long learning and adaptation functions that vertebrate immune system is capable of (Hart and Timmis, 2005). Such AIS algorithms² as RAIN (Timmis, 2000), aiNet (de Castro and von Zuben, 2000a) and CLONALG (de Castro and von Zuben, 2000b) were typically developed for pattern recognition, optimization, data clustering and data compression (e.g. de Castro and Timmis, 2002; 2003; Timmis, 2006).

The iDal algorithm which can be classified as a discrete immune network model (Timmis, 2002) is driven by a set of iterative processes of adaptation. Relative to the current AIS methodology, the iDal algorithm is theoretically advanced due to the two newly introduced concepts from the discipline of immunology (i.e. specificity index and dynamism of B-cell concentration). By using the concept of specificity index that immunologists apply to describe the generality of BCR and therefore cells' ability to discern self and non-self, the iDal technique is able to discern and operate on information in levels of abstraction. Unlike other AIS algorithms, the iDal algorithm analyses for the concentration levels of B-cells across the time domain, and further exploits the information for temporal characterizations – the premise for useful data inferences such as forecast.

The unsupervised iDal algorithm generates a network of ARBs which collectively captures structures and relationships of self-discovered classes within time-series data. Based on the generated data, the iDal technique characterizes and forecasts the time-based development of the ARBs' population. The iDal algorithm loops continuously along real time without stopping criterion, as shown below.

1. Immune network initialization
2. Antigens introduction
3. Secondary immune response
4. Primary immune response
5. Apoptosis
6. Concentration update
7. Antigenic learning
8. Activeness update
9. Concentration forecast

² Comparison studies have been performed by Timmis et al. (1999), which showed the advantages of AIS algorithm for data analysis.

10. Repertoire data production: The resultant datasets are produced. The algorithm loops back to Step 2 with $t=t+1$.

The details of each of the above functions are presented in Section 3.3.7. Figure 3.9 illustrates the flow of the functions, representing the iDal algorithm.

Figure 3.9 Flowchart of the iDal algorithm

3.3.6 Parameters and variables of the iDal algorithm

Time period t

In the iDal algorithm, one unit of computational period t can be set to correspond to real time interval, according to the frequency of data sampling. For instances, in control applications, the unit of t can be in seconds, while in drug tests, t can be in years. In practice, the resolution of the acquired time-series input data can be used to determine or guide the representative period of t . For example, if the resolution of the time-series data is 120 seconds, each unit of t can represent 120 seconds of real time.

ARB threshold (ARBT) and persistency period (PP)

The parameter *ARBT* is a specified level of B-cell concentration that governs the creation and the maintenance of the ARBs. Neal (2003) used a similar parameter called *mortality*. ARBs with B-cell concentration level below this threshold level, for *PP* units of time, will be inactivated by the system. On the other hand, new Ag that stimulates B-cells beyond this level, for *PP* units of time, will be activated (see Figure 3.10). The *PP* parameter is introduced into the operation of the algorithm to control its degree of stability versus sensitivity, with reference to the level of noise present in the data.

Figure 3.10 The immune responses on lymphocytes

Recognition distance parameter ε_r

The recognition distance parameter ε_r , where $0 < \varepsilon_r \leq L$ is the parameter that facilitates discerning the necessity to perform antigenic learning. In effect, the parameter defines the threshold of *difference* between a pair of entities. When the distance between a pair of entities is beyond a threshold value, the system will consider the pair to be distinctive enough to be separately accounted in different ARBs.

The sliding window period of forecast ω and forecast period τ

The iDal technique can be set to forecast τ periods into the future (i.e. $t + \tau$). Only the latest ω period of time is considered in the forecast. In many systems, readings taken beyond a certain point of time in the past may not be helpful to forecasting future values. In business and social applications, new trends may emerge, rendering old data less relevant. Likewise in engineering applications, systems' operating conditions and error characteristics can drift as time passes. The size of the sliding window can be a non-variable or a time variable with respect to each problem.

Decay parameter d

The process of apoptosis moderates the population size of B-cells within the system. In the process, the rate of decay is controlled by parameter d , where $0 \leq d \leq 1$.

3.3.7 Functions of the iDal algorithmImmune Network Initialization

A set of arbitrary ARBs is initialized in the beginning of the algorithm, as represented in Equation 3.7. The initial ARBs can be acquired from domains that are related to the current area of interest, as an estimated initial configuration. For instance, the initializing ARBs can be a more prominent or arbitrary sample of antigens available (Neal, 2003). They can be the ARBs of the siblings or of the previous generation problems, or can be manually specified based on users' experiences. The concentration levels of B-cell in the initialized ARBs are activated at the ARBT level, at $t = 1$. That is, $Conc(ARB_k, 0 | \forall k) = ARBT$; $Active(ARB_k | \forall k) = 1$.

$$ARB^0 = \langle ARB_1, ARB_k, \dots, ARB_K \rangle \quad (3.7)$$

Antigens Introduction

The set of Ag introduced during time period t can be represented as Equation 3.8. As antigens are relevant only during the t^{th} period when they are introduced, a superscript is imposed to denote their period of relevancy.

$$Ag^t = \langle Ag_I^t, \dots, Ag_i^t, \dots, Ag_I^t \rangle \quad (3.8)$$

where I is the total number of Ag introduced during period t .

Immune Responses

The reactions of the immune system to incoming antigens have been described in terms of primary and secondary (see Figure 3.3). Reactions to unfamiliar antigens are termed as primary while reactions to familiar antigens are classified as secondary. In theory, secondary response precedes primary due to the lower time lag (faster response) of the former reaction (see Figure 3.3). In the research and applications of the AIS, distinction between the mechanisms of the primary and secondary immune responses is uncommon; the natural phenomenon has not been widely exploited as a metaphor by the AIS community. In one case, Neal (2003) used the distinction in clustering mechanisms based on ARBs. In this work, with the adoption of the ARB concept, the distinction can be similarly made. The proliferation of B-cells can happen during both the primary and secondary immune responses (see Figure 3.10), as described below.

a) Secondary Immune Response: Each introduced data packet Ag is presented to all active ARBs for stimulation. As depicted in Figure 3.3, the biological immune system launches secondary responses when similar previously encountered antigens are detected. Likewise, the iDal algorithm computes the levels of stimulation for all current encounters. As understood in theoretical immunology, pathogens can be recognized by more than one type of B-cells, and vice-versa. The stimulation levels S_k^t of the ARBs are therefore the summation of stimulations by the incoming Ag . Based on the theory of *cross-reactivity*, the degree of affinity A between an Ag and an ARB determines the level of stimulation in the encounter (with reference to the specified A-D function), as represented by Equation 3.9.

$$S_k^t = \sum_{i=1}^I [A(Ag_i^t, ARB_k) \times Conc(Ag_i^t)] \quad (3.9)$$

where function A produces the affinity between the two operands, given by the affinity-distance relationship.

b) Primary Immune Response: In the stimulation of inactive ARB, cross-reactivity does not apply. That is, stimulation here requires exact match, as expressed in Equation 3.10.

$$S_k^t = \sum_{i=1}^I \text{Conc}[Ag_i^t | D(Ag_i^t, ARB_k) = 0] \quad (3.10)$$

where D is the distance function (see Equations 3.3 to 3.6).

Apoptosis

The population of the B-cells in the system is maintained by the process of programmed cell death. The decay can be computed using Equation 3.11.

$$\text{Decay}(t) = d \left(\frac{\sum_{k=1}^K S_k^t}{K} \right) \text{ where } d (0 \leq d \leq 1) \text{ is the decay factor} \quad (3.11)$$

Concentration Update

In the immune responses, stimulations lead to the cloning process. The result is the increase of B-cell concentration levels in the existing ARBs. The concentration level of each ARB is updated in the system based on the stimulations and apoptosis processes, as shown in Equation 3.12.

$$\text{Conc}(ARB_k, t) = \text{Conc}(ARB_k, t-1) + S_k^t - \text{Decay}(t) \quad (3.12)$$

Antigenic Learning

Immunologists have discovered that it is during the primary response when human body *memorizes* the profile of unprecedented pathogens, so that it can more readily fight against it subsequently, by functions of the secondary immune response (see Figure 3.3). From an immunology perspective, under the condition that a previously unseen antigen is sufficiently different from the system's ARBs (i.e. memory) to an extent dictated by parameter ε_r , a new inactive ARB of the same attributes and values will be registered in the system memory. Computationally speaking, in an event where an unprecedented packet of data that is beyond recognition by the existing ARB (as the condition shown in Equation 3.13) is detected, a new sensor (i.e. ARB) as memory cells is created. Note that in this work, newly generated ARBs have full affinity (i.e. $A = 1.0$) with the stimulants Ag_i^t . This assertion is aligned with the theory of immunological instructionism, instead of the selectivism theory (Ishida, 2004).

$$D(Ag_i^t, ARB_k) \geq \varepsilon_r \quad (3.13)$$

where D is the distance function (see Equations 3.3 to 3.6).

Activeness Update

When any of the inactive ARB's concentration level exceeds the value of ARB_T for PP periods of time, the ARB is activated. Upon activation, the ARB is ready to perform fuzzy recognitions of the introduced antigens (see Figure 3.3). On the other hand, the iDal algorithm deactivates ARB that has been neglected due to the lack of stimulations. ARBs that have their B-cell concentration levels dropped below the ARB_T level for PP units of time will be deactivated, as depicted in Figure 3.10.

Concentration Forecast

Previous research on dynamic AIS has not exploited the potentially useful temporal dimension of the data analyzed (Neals, 2003; Hart and Ross, 2003). In this work, the behavior of a system in a continuously varying environment is dynamically forecasted based on the autonomic learning function of the AIS-based iDal technique. The iDal technique is specified to capture and to analyze univariate time-series data, while the forecast function is supported by a technique embedded in the CRAF system.

The principal goal of forecasting is to *extrapolate* beyond the confines of the sample and thereby make generalizations to non-sample situations (Klein, 1971). Therefore, forecast is defined here as the attempt to make scientific statements about non-sample situations on the basis of relationships determined from sample observations (Klein, 1971). Note that the terms *forecast* and *predictions* are at times used interchangeably in the literature. Nevertheless, each field tends to use one consistently. There is an area of the research, mostly in the field of data-mining, which is concerned with *prediction* of classes that sets of data should belong to (Weiss and Indurkha, 1998); this class of work needs not involve the dimension of time. On the other hand, in the area of time-series projection, the term *forecast* has been consistently used, as in this work.

Existing methods of forecast can be generalized into two groups: judgmental and quantitative/statistical methods (see Figure 3.11). The latter class is of interest in this study. (*Note: judgmental methods may be secondarily applied to structurally adjust the results obtained from quantitative methods, as discussed in a later subsection on vaccination*). Of the range of statistical methods, a variety of forecasting

approach may be embedded in the CRAF system, according to the requirements of specific problems. Figure 3.11 shows some general guidelines for the selection of forecasting methods. In the investigations presented in Chapters 4 and 5, forecasting theories will be adopted to support the investigations in each chapter. The method suitable for application in the CRAF system depends on the characteristics of the input data and problem domain. Points of consideration include the followings.

1. The input data:
 - a. Number and quality of data points (variance)
 - b. Stability of trend over time
 - c. The availability of the additionally required data other than time-series data.
2. The problem domain:
 - a. Linearity or non-linearity of the modeled entity,
 - b. Availability of trend model hypothesis.

Figure 3.11 Forecasting method selection tree (Armstrong, 2006)

Artificial neural network, exponential smoothing technique and diffusion models are the tenable methods of extrapolation identified (*Note: merits and demerits of each forecasting technique were reviewed in detail by Armstrong (2006)*). For linear problems (point 2a above), forecast methods such as exponential smoothing and linear

regression can be employed. On the other hand, neural network and nonlinear structural equations such as logistic functions can be employed to model nonlinear problems. If the characteristics of the variable can be hypothesized to follow certain trend model (point 2b above), such as a logistic function, diffusion model can be the basis of forecasts. In this case, however, additional data such as the saturation level of the variable may be additionally required from the problem domain (point 1c above).

Regardless of the type of forecasting technique used, the following definitions, formulas and mechanisms are applicable in the CRAF system. For further simplification of the notation, Equation 3.14 defines the concentration of the B-Cells in the k^{th} ARB, at time t , while Equation 3.15 expresses the cumulative concentration level of k^{th} ARB at time t .

$$\text{Conc}(\text{ARB}_k, t) = c_{kt} \quad (3.14)$$

$$C_{kt} = \sum_{t'=1}^t c_{kt'} \quad (3.15)$$

Accordingly, the rate of change of a B-cell subpopulation k can be denoted by the differential expression $\frac{dc_{kt}}{dt}$. The basic input to the forecast function is a set of current and historical B-cell concentration values $\{c_{k(t_n)}, c_{k(t_n-1)}, \dots, c_{k(t_n-\omega)} \mid \forall k\}$, and the values returned by this function of the algorithm is the set of forecasted B-cell concentration level $\{\hat{c}_{k(t_n+\tau)} \mid \forall k\}$.

Vaccination

While the forecasting approaches described above employ historical data as the basis, human judgment is pertinent in forecasting (Ostram, 1990; Twiss, 1992). In the context of customer behaviour forecast, research has shown that it is often possible through analysis to indicate in advance how customers would react to unexpected development. For instance in 1969-70, consumers' potential reactions to peace in Vietnam were forecasted (Katona, 1971). As such, information not present in historical data can be used to improve forecasting results. This type of forecast technique is termed as *structured judgmental adjustment* (Armstrong, 2006), as shown in Figure 3.11.

In the biological immune system, lymphocytes react to both diseases and vaccines (i.e. two types of input data, computationally). Immunologists inoculate

subjects with vaccines to *pre-empt* the attack of specific diseases. In this process, attenuated or inactivated pathogens are injected into human body to stimulate development of the respective antibodies or B-cells. Accordingly, apart from the mainstream data source of the iDal technique, secondary data that the technique could use may be accounted in the system. Secondary data injection can be performed by the system users to structurally adjust the results produced by the iDal technique. In the iDal technique, inoculation is performed by injecting a set of specific antigens Ag into the system memory pool over a period of time; the result is the positive recognition of the inoculated antigens by the ARBs.

Further specifications

The general data interface and the requirements of the forecast module of the CRAF system are defined above in this section. Two sets of forecast modules will be further specified to support the means of the investigations in Chapters 4 and 5 respectively.

As mentioned in the forewords of this chapter, the iDal technique is a general solution; as the name suggests, it is a dynamic and autonomic learning technique based on immunology. To specifically apply the iDal technique to the dynamic customer requirement problem, a novel data representation model termed the Requirement Space Framework (RSF) is necessary, as presented in Section 3.4; the RSF is formulated to facilitate the mapping of data from the problem domain to the data structure of the iDal technique (see Section 3.3.3).

3.4 Requirement Space Framework

The Requirement Space Framework (RSF) is a data model defined to represent customer requirement information. The RSF can be mapped to the data modeling scheme of the iDal technique (see Section 3.3.3), which thereby facilitates the operations and analysis of dynamic customer requirement (DCR) data by the iDal technique.

The RSF is a reduced form of the Design Space Framework (DSF). DSF is theorized to represent rationales, processes and outcomes of design conceptualization work (Chong et al., 2009a). The proposition is established by an ordered series of formal definitions and mathematical assertions, which characterizes the complete theoretical model. The formalization of the DSF is presented from Sections 3.4.1 to

3.4.3. In Section 3.4.4, the reduction of DSF which leads to the definition of the RSF is described; the same section illustrates the mapping of the RSF to the iDal technique's data representation scheme.

3.4.1 Knowledge objects in domain D

Firstly, prior to the definitions of the DSF, a domain of knowledge that can completely describe any design concept is necessary (Dougherty and Giardina, 1988; Luger, 2005). The domain is defined as D . Under the framework, knowledge involved in conceptual design can be decomposed and generalized into three classes of information. N is defined as the set of finite knowledge objects considered in D .

In the customer-driven design paradigm, customer needs are perceived as an important class of design information, especially in product conceptualization (Chong et al., 2005; Chong et al., 2009b). This class of information can be obtained through market research efforts such as focus groups and interviews. Customer requirements are represented by $c_i \in C$, specifically $C = \{c_i | i = 1, \dots, I\}$, where i is the sequential order for element c_i , and I is the total number of element c_i in a design problem.

Product requirements are formalized in design process to document the required product characteristics that can satisfy the customer needs. This class of information, in customer-oriented design philosophy, bridges between the customer needs and the design solutions. It is formalized as $p_j \in P$, specifically $P = \{p_j | j = 1, \dots, J\}$, where j is the sequential order for element p_j , and J is the total number of element p_j in a design problem.

Solution to design is regarded as another class of information in the DSF model. Unlike the former two classes of information C and P , solutions may have alternatives in the context of product design. Hence, alternative solutions, if any, have to be inclusively represented. Design solutions therefore can be represented in this framework as $s_k^l \in S$, specifically $S = \{s_k^l | k = 1, \dots, K \wedge l = 1, \dots, L_k\}$, where k is the sequential order for element s_k ; K is the total number of element s_k in a design problem; l is the sequential order for alternative solutions of s_k , while L_k is the total number of alternative solutions of s_k .

Any complete product, for instances a bicycle or a mug, can be perceived as a form of solution to a main problem. From this perspective, a special case of $s_k^l \in S$, where $k=l=0$ (i.e. $s_0^0 \in S$) is predefined to denote the solution of the highest abstraction level within a given problem. In other words, s_0^0 represents the most abstract solution in a given case.

Frames are classes of data structures, consisting of slots holding attributes-value pairs pertaining to specific represented objects (Luger, 2005). As the information structures within the defined object classes (C , P and S) are typical, they are suitable for frame-based representations. Therefore, the objects are proposed to be computationally represented based on frames (see the application of frames in Chapter 6).

3.4.2 Inter-relationships of knowledge objects

Nishioka et al. (1996) commented that knowledge is characterized by the connections among them. Apart from identifying the primitive objects described in Section 3.4.1, the connections, or the relationships amongst them can be formalized. E is defined as the set of finite design relationships among the design objects considered in D .

In various design methodologies (e.g. Ulrich and Eppinger, 2000; Hauser and Clausing, 1988), direct relationships exist between customer requirements and product requirements as well as between product requirements and design solutions. These two classes of relationships are respectively defined as U and V . The relationships between objects C and P are represented by $u_{i,j} \in U$, specifically $U = \{u_{i,j} \mid \forall i \in \{1, \dots, I\}, \forall j \in \{1, \dots, J\}\}$. On the other hand, the relationships between objects P and S are represented by $v_{j,k}^l \in V$, specifically $V = \{v_{j,k}^l \mid \forall j \in \{1, \dots, J\}, \forall k \in \{1, \dots, K\} \wedge \forall l \in \{1, \dots, L_k\}\}$. Figure 3.12 illustrates the two sets of relationships U and V .

Figure 3.12 The two relationships between objects C , P and S

This work proposes that there exists a third set of *relationships* in the discourse of conceptual design. Consider the assertion by Davidson and Sternberg (2003): ‘*The solution to one problem becomes the basis of the next*’. In real life problem solving, it is a fact that every solution can be a problem, possibly awaiting further resolutions. For instance, the decision to buy a car may solve a traveling problem, but will inevitably lead to further problems such as which make and model to purchase. This sub-problem would require further analysis and solutions. In this manner, the problem-solution pattern can be repetitive. As such, the repetition would result in a progressive detailing of the solution. To this end, an inquiry may well arise: when does this cyclical process terminate? One may relate that only when one needs to clarify the details of a solution, one would then consider the solution as a problem. In solving design problems, this logic is similarly applicable. An assertion that underlies the third set of relationships amongst the knowledge objects is: *a design solution is a design problem if and only if further detail of the solution is required*. The assertion relates that elements $s \in S$ may be perceived as design problems. For instance, a dynamo may be a solution to the electrical requirements of a bicycle. The dynamo itself could be then perceived as a sub-problem when the designers intend to further examine it. Common to various design methodologies, the step after problem definition is to elicit customer requirements based on the defined problem (Ulrich and Eppinger, 2000). This common procedure suggests that a defined problem can be the premise for object C . Since the mentioned assertion (conditionally) equates design problem to design solution, it can be inferred that object S (design solution) is the premise of object C (customer requirement). Based on such inferences, the causal relationship between S and C in the

process of product conceptualization can be defined $w_{k,i}^l \in W$, specifically $W = \{w_{k,i}^l \mid [\exists k \in \{1, \dots, K\} \wedge \exists l \in \{1, \dots, L_k\}] \vee k = l = 0, \forall i \in \{1, \dots, I\}\}$.

The inter-relationships between the knowledge objects can be further represented using frames. In effect, the model of the conceptual design is, under the Design Space Framework (DSF), a cyclical process of design knowledge generation, progressing towards the emergence of design concepts. Such a model is illustrated in Figure 3.13.

Figure 3.13 A novel model of conceptual design process

3.4.3 Design Space Framework

Researchers have identified two types of operations between sketches during conceptual design process (Goel, 1995; Meniru et al., 2003), viz. lateral transformation and vertical transformation. Lateral transformation brings sketching from one idea to another, i.e. evolving alternatives. Vertical transformation brings sketching work to a different depth or abstraction level. Sketching, as a product conceptualization activity, can therefore be perceived as an act of exploring design space vertically and laterally. It is a reflection of designers' thoughts and working processes. Based on such human cognition during design, this work proposes two *dimensions* in the design space D - vertical and lateral. A third dimension is further postulated to hold the components (or the divisions) of objects.

D , as first discussed in the beginning of Section 3.4, is further defined below as a space that can be characterized along three dimensions. It will accommodate Design Space Framework (DSF) in the form of a graph³. The three dimensions of space D are X , Y and Z , where

- X : Sibling objects along dimension X are the decomposed constituents of their parents, having AND relationships amongst them.
- Y : Sibling objects along dimension Y are alternative children available for the parent, where only one is relevant to the parent at any instance, hence having OR relationships amongst them.
- Z : Objects generated along dimension Z are of incremental detailing.

Thus far, three important formalisms have been established:

1. The three dimensions of D ,
2. the objects in D , and
3. the objects' inter-relationships in D .

On the basis of these definitions, any instance of design concepts to a particular design problem can be represented as a type of mathematical graph, defined as G .

3.4.4 Requirement Space Framework in the CRAF system

Design Space Framework (DSF) is a model applicable to address conceptual design problems, which is demonstrated in Chapter 6 (Chong et al., 2009b). In the context of dynamic customer requirement analysis, however, a reduced form of the DSF will be fit for application. The simplified model of the DSF is termed as the Requirement Space Framework (RSF). *(Note: to apply the results of the requirement analysis process, an extension of the RSF model (e.g. DSF) will be instrumental, as demonstrated in Chapter 6.)*

DSF is reduced by considering only the customer requirement data objects C in the proposed space of 3 axes. The result is the RSF data structure, which can be adopted to robustly represent customer requirement information. An instance of the RSF is shown in Figure 3.14. Customer requirements are represented in multiple levels of abstraction, as described along the Z axis of the RSF. Alternative values can exist for requirements, and details of the requirements can be further represented by

³ Graph, with nodes representing concepts and arcs representing relationships, is a technique used to define knowledge in the studies of artificial intelligence (Luger, 2005).

co-requirements. Correspondingly (as shown in Figure 3.14), requirement options are represented along the Y axis while co-requirements are modeled along the X axis of the RSF. Apart from the three dimensions of the information, a fourth facet of the customer requirement data, i.e. time, is prescribed in this study to facilitate the modeling of dynamic models. Figure 3.14 depicts an example of the RSF in a time instance.

Figure 3.14 The Requirement Space Framework

In the CRAF system, the machine learning and analysis of dynamic customer needs data is based on the principles of the artificial immune system embedded in the iDal technique. The data representation scheme of the iDal technique is basically in accordance with the conventions established in the AIS research, as formalized in Section 3.3.3 (de Castro and Timmis, 2002; 2003). Therefore, to apply the iDal technique to the problem of dynamic customer requirement in the CRAF system context, mapping of the customer requirement information (represented by the RSF) to the iDal technique's data structure is required.

Figure 3.14 shows an abstraction of the data elements and Table 3.1 shows the correspondences between the iDal framework and the domain-specific CRAF system. Customer requirement information in the structure of RSF corresponds to two types of data classes in the iDal technique – the antigens (Ag) and the B-cells (i.e. the ARB). Antigens, the in-coming data for analysis, correspond to the customer needs data elicited from markets. On the other hand, B-cells of the iDal technique correspond to

customer needs data in the CRAF system memory. The concept of ARB - a result of previous research (Timmis and Neal, 2001; Neal, 2003) - is applied in this work to represent groups of similar B-cells in the system. Accordingly, an ARB (i.e. a chain of bio-molecules as defined in Section 3.3.3) corresponds to a chain of customer needs objects of the RSF (as shown in Figure 3.14). An advantage of the representation technique is that the depth (in terms of abstraction levels) of customer requirement information can be modeled.

Table 3.1 iDal framework and the corresponding domain-specific CRAF System

iDal framework	CRAF system (with RSF)
Antigens	Customer requirements (in product market)
B-cells/ ARB	Customer requirements (in system memory)
Environment	Product market

Antigens of I number at time t is represented as set $Ag^t = \langle Ag_1^t, Ag_i^t, \dots, Ag_I^t \rangle$, and the representation of each antigen is in turn based on a chain of bio-molecules, i.e. $Ag_i^t = \langle Ag_{i,1}^t, Ag_{i,l}^t, \dots, Ag_{i,L}^t \rangle$. Index l , where $1 < l \leq L$, represents the specificity levels of the bio-molecules (as described in Section 3.3.3). Upper limit L denotes the lowest abstraction level in the system, while the highest abstraction level where bio-molecules can reside is 1. Note that Figure 3.14 illustrates an instance of the RSF with $L=3$. The concept of specificity in immunological studies is in this work adopted to model the generality of customer needs information. A special case of a bio-molecule m_0 that exists on the theoretical specificity level of zero is pre-defined in each RSF. The node is predefined to represent the root (i.e. most abstract) requirement of a given product.

Memory B-cells in the CRAF system at time t is categorically represented as $ARB^t = \langle ARB_1, ARB_k, \dots, ARB_K \rangle$. Representation of each memory B-cell group is, as discussed, similarly based on a string of bio-molecules, each of which describes data at distinct levels of abstraction, i.e. $ARB_k = \langle ARB_{k,1}, ARB_{k,l}, \dots, ARB_{k,L} \rangle$. States of ARBs are dichotomy, either active or inactive i.e. $Active(ARB_k) = 1$ or 0.

Bio-molecules - the building blocks of the CRAF system data - are modeled with *symbolic attribute-value* pairs, $ARB_{k,l} = \langle \text{att}, \text{val} \rangle$, e.g. $ARB_{3,2} = \langle \text{colour}, \text{black} \rangle$. Undefined (i.e. ‘don’t care’) bio-molecules of Ag and ARB are represented using the symbol $\#$, e.g. $Ag_{3,2}^5 = \langle \text{colour}, \# \rangle$. The attribute-value pair of bio-molecule m_0 serves as the tag of the given product or problem, which can be arbitrarily assigned.

Concentration of B-cells represents the importance levels of attributes and the preference level of values of the respective customer requirements. Function $Conc(ARB_k, t)$ gives the non-negative number of B-cells in ARB_k at time t . In this work, the dynamism of B-cell population is metaphorically applied to model the dynamism of customer requirements.

3.5 Summary

Aiming to address the identified set of research problems summarized in Section 2.3, a set of system requirements was proposed in Section 3.1. A prototype CRAF system is formulated, which aims to satisfy the set of requirements. In this chapter, the architecture of the proposed prototype CRAF system was illustrated (in Section 3.2), followed by the definition of the system’s backbone – the iDal technique (in Section 3.3). The section also highlighted the manner by which the theoretical iDal technique advances the research of the AIS, i.e. through the novel introduction of two immunology concepts - specificity index and the dynamism of antibody concentration. To apply the iDal technique (a general solution) to the problem of dynamic customer requirement, a data model RSF (specific to the problem domain) was established and mapped to the data structure of the technique (Section 3.4).

In this research, investigations were performed to evaluate the CRAF system against the requirements listed in Section 3.1. Chapters 4 and 5 separately document two studies that provide grounds for discussions and conclusions with respect to the system requirements.

Chapter 4 - A Micro Perspective Investigation into the CRAF System

The study presented in this chapter investigates the system from a micro perspective. The mechanisms of the CRAF system are explicated through a case study, and assessments are made based on the system requirements listed in Section 3.1.

In Section 4.1, the background of a problem is described. Section 4.2 introduces a secondary data set that was originally acquired from a personal computer manufacturer. In Section 4.3, a diffusion model employed for the purpose of this investigation is specified. Section 4.4 describes the experimental set up followed by an explication of the iDal algorithm in operation. Finally, results and conclusions of the case study are presented in Sections 4.5 and 4.6 respectively.

4.1 Case background

Many products have short life cycles from a few years down to several months. Increasing customer sophistication, intensifying competition and high competency of the consumer electronic industry are some factors that led to the high rate of product introduction. Typical demand patterns for such products are characterized by rapid growth, maturity, and decline phases. The requirements of customers rapidly evolve, relative to the time span of product development cycles. One such type of product is personal computer (PC). It was estimated that the value of PC depreciates by an average of fifty-percent for every year of use (Doms et al., 2003). In essence, developers are attempting to fit the generated products, which are inherently discrete, to the continuously evolving needs of the customers; the issue that they face is

therefore the volatility of customer needs. Market foresight is in this context critical to product developers in acting and reacting to the market. Facing fast moving targets, a solution is to track and forecast the market requirements. In tracking shifting customer needs, market surveys can be performed. Customer requirements may also be inferred from the sales of products, by regarding the acts of purchase as customer needs and preference expressions.

Kurawarwala and Matsuo (1998) studied the forecast of short life-cycle products using growth models. Common in the forecasting literature, sales of individual or classes of products are subjects of forecast. These forecasted results are typically intended for applications in manufacturing resource planning. On this note, it should be noted that the present study is not only interested in the market affinity trajectory of discrete products, but also of products' characteristics in levels of abstraction. For instance, from complex and massive credit card transactions time-series data, companies could gain insights on the current and future demands of products features, not just of specific products. This type of information can be useful during product development phases (e.g. design conceptualization), apart from during manufacturing process.

This chapter illustrates the mechanisms of the CRAF system based on a set of personal computer sales data. In this case, the acts of product purchase are regarded as customer needs and preference expressions. The CRAF system is set to perform medium-term (monthly) forecasts of a product feature, i.e. the processor units of personal computers.

4.2 Data for study

The univariate time-series data used by Kurawarwala and Matsuo (1998) is employed in this study. The proprietary dataset originated from a personal computer company. It was appropriately scaled and disguised, as shown in Table 4.1. Based on the historical records of the company's performance in an undisclosed market, Kurawarwala and Matsuo (1998) hypothesized the monopolistic demand of the products. The researchers proceeded to support the hypothesis based on empirical studies. P1 to P5 are five different types of personal computers (PC) marketed to the Fortune Five Hundreds companies. The manufacturers recorded 38 months of sales history of the PCs. In this case, the unit of variable t is in term of months.

Table 4.1 Disguised personal computer sales data (Kurawarwala and Matsuo,1998)

Month	P1	P2	P3	P4	P5
1	3	0	0	0	0
2	24	0	0	0	0
3	49	0	0	0	0
4	58	0	0	0	0
5	67	0	0	0	0
6	71	0	0	0	0
7	85	0	0	0	0
8	92	0	0	0	0
9	155	28	0	0	0
10	80	206	0	0	0
11	145	253	0	0	0
12	198	352	0	0	0
13	195	290	42	0	0
14	237	362	75	0	0
15	309	317	112	0	0
16	302	224	121	0	0
17	205	204	144	66	0
18	413	339	166	108	0
19	314	175	135	127	0
20	378	190	134	496	0
21	452	196	180	751	0
22	334	177	119	507	11
23	239	272	160	407	128
24	250	216	230	465	353
25	139	203	276	308	518
26	255	137	468	389	386
27	69	80	323	256	312
28	20	69	173	298	319
29	30	149	206	285	378
30	18	111	259	277	420
31	0	133	218	117	298
32	0	92	192	43	291
33	0	73	201	89	335
34	0	60	151	0	178
35	0	66	156	0	231
36	0	56	183	0	215
37	0	1	123	0	226
38	0	0	68	0	77

To study the functions of the CRAF system in data analysis and forecasting, assumptions were made on the product features of the PCs, i.e. P1 to P5. It is clear from the data in Table 4.1 that their market introduction time is sequential. As such,

the features of the PCs introduced earlier were assumed to be more primitive. Table 4.2 shows the assumed features.

Table 4.2 Feature types for personal computer

Features \ Products		P1	P2	P3	P4	P5
1	Processor (1: Brand A/ 2.6 GHz, 2: Brand B/ 3.6 GHz, 3: Brand A/ 4.0 GHz)	1	1	2	2	3
2	Operating System (1:Brand A, 2: Brand B)	1	2	1	2	1
3	Memory (1: 512 MB, 2: 1 GB, 3: 2 GB)	1	2	2	2	3
4	Hard Drive (1: 80 GB, 2: 160 GB, 3: 250 GB)	1	1	2	3	3
5	Media Reader (1:3.5 inch and CD-ROM, 2: CD-ROM and DVD-ROM)	1	1	2	2	2
6	Sound cards (1: Brand A/ type1, 2: Brand B/ type 1, 3: Brand A/ type2)	2	2	1	1	3
7	Graphics (1: Brand A/ type 1, 2: Brand B/ type 1, 3: Brand A/ type 2)	1	2	1	3	3
8	Chassis (1: Type A, 2: Type B)	1	1	1	2	2

4.3 System specifications

In this section, the data representation (in Sub-section 4.3.1) and affinity measurement (in Sub-section 4.3.2) of the CRAF system are defined with respect to the case problem presented in Section 4.2. As mentioned in Chapter 3, the forecast module of the CRAF system will be specified for the purpose of the investigation; a diffusion model that is applicable to support the study is introduced in Section 4.3.3.

4.3.1 Data representation

A Hamming space¹ (see Sections 3.3.3 and 3.3.4) of 8 dimensions is employed to accommodate the elements in the CRAF system. The elements are the B-cells (i.e. ARB) and the antigens. In this case, $L=8$, for there are 8 dimensions to characterize the product. For instance, an antigenic molecule that represents the products in general is

¹ In statistics and coding theory, Hamming space is the set of all 2^N binary strings of length N .

modeled as $Ag_i = \langle Ag_{i1}, Ag_{i2}, Ag_{i3}, Ag_{i4}, Ag_{i5}, Ag_{i6}, Ag_{i7}, Ag_{i8} \rangle$; and an ARB is represented by $ARB_k = \langle ARB_{k1}, ARB_{k2}, ARB_{k3}, ARB_{k4}, ARB_{k5}, ARB_{k6}, ARB_{k7}, ARB_{k8} \rangle$.

If a feature of analysis of interest to the system users is not of equal importance to the rest, weights can be assigned to the dimensions of the cells. Since in this case study, the interest is in analyzing and forecasting the trend of the computers' processor, the molecules can be assigned a decaying weight distribution scheme as shown in Equation 4.1. This weightage scheme allows the specification of threshold level to dictate the identification level (i.e. first level being the processor in this case) of the data to which discrimination for primary response (i.e. memorizing unrecognized antigens) can be authenticated. (*Note: the summation of all weights is not equal to one; the weight distribution scheme should be consistently applied to all data in the problem.*)

$$w_l = 1 - \sum_{l'=1}^l \frac{1}{2^{l'}} \quad (4.1)$$

4.3.2 Affinity measurements

Equation 3.6 of Chapter 3 measures the Hamming distance between two entities. In this case the distance threshold for discriminating the primary response and stimulation of ARBs are set at the value of $\varepsilon_r = 0.5$ in the course of the experiment. The value facilitates the recognition of data patterns of features of interest, each of which can be forecasted separately.

$$D_{ij} = \sum_{l=1}^L w_l \alpha_l \text{ where } \alpha_l = \begin{cases} 1 & \text{if } m_{il} \neq m_{jl} \\ 0 & \text{otherwise} \end{cases} \quad (3.6)$$

A discrete binary A-D function is adopted here to characterize the affinity between two entities (see Figure 4.1). This is because the results required by the CRAF system in this case is in distinct terms of the products and their characteristics, unlike in cases where fuzzy cross-reactivity might be necessary to account for degrees of responses (see Sections 3.3.4, 3.3.7 and A.2.4).

Figure 4.1 A discrete binary A-D function

4.3.3 Specification of the forecast module

In this investigation, a forecasting model that is suitable for the study of the CRAF system mechanism is specified. A diffusion theory, known as the Bass diffusion model (Bass, 1969) is of interest in this study.

The Bass diffusion model is a time series approach proposed by Frank Bass (1969). The model describes the growth of new product acceptability in markets, as a result of interactions between product users and potential users; it is widely used in forecasting, especially product forecasting and technology forecasting. It can provide a disciplined approach to supporting product launch timing decision, and a wide range of new product planning challenges (Kahn, 2006). Diffusion models assume a *sigmoid* curve (see Figure 4.2); a theoretical basis of the curve is intricate to derive. Nevertheless, there has been sufficient weight in historical evidence to give forecasters high degree of confidence in the assumption that the form of past progress will apply in the future (Twiss, 1992). Diffusion models in general have been used to analytically describe temporal phenomena of diffusion, in social, biological, and ecological contexts. In the social context, it has been widely applied in marketing science and econometrics literature to describe the spread of information in societal systems (Mahajan and Peterson, 1985). The needs of customers, essentially the perceptions of customers, can be classified a class of information as first defined in Section 1.1 and subsequently formalized in Section 3.4. The class of information is assumed to be subjected to diffusion. The diffusion of ideas is through communication over time (i.e.

non-instantaneous) involving the members (i.e. customers) of a societal system – in this case a product market.

The Bass diffusion model (Bass, 1969) is selected upon the following considerations.

- 1) To study the CRAF system from a micro perspective, explication of the iDal algorithm in processing the data is required. The variables of diffusion models are explicit (e.g. $\hat{a}$ and $\hat{b}$, as shown in the later part of this section), which can be presented and discussed in the context, allowing the investigation of data processing in the CRAF system. In contrast, the significances of the variables of forecasting methods, such as node weights in artificial neural network (ANN), are implicit - commonly known as black-box. Further, forecasting methods commonly involve large amount of calculations to be performed computationally (e.g. search functions in optimization of variables), where explication of the algorithm steps and loops are not practical in this case. As such, adopting the Bass diffusion model is suitable for the study of the system mechanisms.
- 2) The type of product involved in this investigation, personal computer, can be considered as a type of consumer durable (i.e. manufactured product that has a relatively long useful life) that has been shown to respect the Bass diffusion theory (Bass, 1969).
- 3) There is a range of diffusion models that possesses different degrees of variability. (*Note: a detailed review of these models can be found in Mahajan and Wind (1986)*). According to Twiss (1992), the applications of the variants are unlikely to have a significant impact on the outcome of the forecast, since the quality of data is likely to have larger influence than the types of diffusion model employed.
- 4) Sales data of short lifecycle product is scarce for academic investigations and, if obtainable, it is usually not with high details (Kurawarwala and Matsuo, 1998). The time-series data available is relatively sparse, not suitable for use by many time-series methods such as decomposition and Box-Jerkin methods (Mahajan and Peterson, 1985). These methods require higher number of data points for parameters estimation.
- 5) In this case, the trend fluctuates to a relatively high degree. Smoothing methods such as moving averages, simple and linear exponential smoothing, and related

approaches are best applied to steady trends only (Kurawarwala and Matsuo, 1998).

- 6) Judgmental forecast methods do not possess capability to process time-series data that the CRAF system should be capable of.

Due to the above factors, the Bass diffusion model was selected as a theory for application in the investigation of CRAF system.

Implicit in most diffusion models used is the assumption that diffusion spreads through a static environment (Bretschneider and Mahajan, 1980). However, due to the changing characteristics of the potential adopter population, technological changes, product modifications, pricing changes, general economic conditions, and other exogenous and endogenous factors, the parameters are likely to be dynamic, i.e., to change over time (Bretschneider and Mahajan, 1980). For this reason, the application of the Bass diffusion model in this study will be *non-static*. Two key parameters, i.e. a and b , of the model in the CRAF system are consequently specified as time-variants in the study. In other words, the prescribed model would be adaptive to the changing environment. The dynamic treatment of the theory here is attributed to the continuous mechanism of the proposed CRAF system. This study hypothesizes that the time-variant (i.e. dynamic) parameters yield better forecast than the time-invariant counterparts. Note that this hypothesis originated from Bretschneider and Mahajan's (1980) view that market conditions are invariably dynamic, as described above. Figure 4.2 shows the profile of a Bass model, which can be described by Equation 4.2.

Figure 4.2 A logistic curve (variable of interest against time)

$$C_{kt} = \frac{m}{1 + ae^{bt}} \quad (4.2)$$

where C_{kt} is the cumulative concentration level of k^{th} ARB at time t , m is the estimated saturation value of C_{kt} and a and b are constants (Twiss, 1992). In this investigation, the constants are treated as variables, which enable the logistic curve to dynamically adjust to the changing environment. In Step 9 of the iDal algorithm, parameters a and b of time t are optimized using the least square regression technique; the process produces a unique set of values for the parameters at the respective time instances t (this step is illustrated in Section 4.4.3). The optimized a and b values at time t is labeled as $\hat{a}_t$ and $\hat{b}_t$ respectively. The input data of the optimization, like the results, is time-variant. The data is acquired based on the sliding window of forecast, ω , as introduced in Chapter 3. The following paragraphs describe the technique of deriving the dynamic values of $\hat{a}_t$ and $\hat{b}_t$.

Rearranging Equation 4.2 and taking natural logarithm on both sides gives Equation 4.3. Introducing a change of variables, Equation 4.3 can be transformed to Equation 4.4, i.e. a linear form for the purpose of regression.

$$\ln\left(\frac{m}{C_{kt}} - 1\right) = \ln a + bt \quad (4.3)$$

$$y = a_0 + a_1x + e \quad (4.4)$$

where $y = \ln\left(\frac{m}{C_{kt}} - 1\right)$, $x = t$, $a_0 = \ln a$, $a_1 = b$, and e is the error term, or the residual;

note that a_0 and a_1 are coefficients representing the intercept and slope of Equation 4.4 respectively. The objective of the optimization is to minimize S_r , the sum of squares of the residual errors (Equation 4.5) for all data points under consideration. Amongst the advantages of this optimization criterion is that it yields an immediate and unique solution for the given set of data (Chapra and Canale, 2006).

$$S_r = \sum_{t=t_n-\omega}^{t_n} e_t^2 = \sum_{t=t_n-\omega}^{t_n} (y_t - a_0 - a_1x_t)^2 \quad (4.5)$$

Equation 4.5 is differentiated with respect to a_0 and a_1 to produce two differential equations, which are equated to zero. The two differentiated equations can be solved simultaneously to arrive at Equations 4.6 and 4.7.

$$a_1 = \frac{\omega \sum_{t=t_n-\omega}^{t_n} x_t y_t - \sum_{t=t_n-\omega}^{\omega} x_t \sum_{t=t_n-\omega}^{\omega} y_t}{\omega \sum_{t=t_n-\omega}^{\omega} x_t^2 - \left(\sum_{t=t_n-\omega}^{\omega} x_t \right)^2} \quad (4.6)$$

$$a_0 = \bar{y} - a_1 \bar{x} \quad (4.7)$$

where $\bar{y}$ and $\bar{x}$ are the means of y and x respectively.

Arriving at the values of a_0 and a_1 will lead to the values of a and b , with reference to Equation 4.4. The a and b values generated by the above regression procedures are optimized for the point of time t ; as such, they are labeled as $\hat{a}_t$ and $\hat{b}_t$ respectively (*note: $\hat{a}_t$ and $\hat{b}_t$ have subscripts t to represent the period since they are not time constants*). Forecast of the k^{th} ARB concentration level beyond the present time t_n can be derived using the logistic curve Equation 4.8 below.

$$C_{k(t_n+\tau)} = \frac{m}{1 + \hat{a}_{t_n} e^{\hat{b}_{t_n}(t_n+\tau)}} \quad (4.8)$$

It should be noted that in using the Bass diffusion model, there is no assumption that the forecasted variable has any direct relationship with time. The variation can be due to many exogenous factors, which can be impractical to model in many cases. Therefore, forecasts based on diffusion theories are by definition based on resultant patterns observed through history, which implicitly account for the unknown factors.

4.4 The experiments

This section describes the assumptions, parameter settings, initialization, and the two sets of experiment performed. A cycle of the iDal algorithm is presented in the final sub-section.

4.4.1 Assumptions, parameter settings and initialization

Empirical studies have shown that stable and robust estimates for the parameters of diffusion models are not obtained unless one uses at least *eight* data points (Mahajan and Wind, 1986). The sliding window period of forecast ω is therefore initialized at 10 periods, i.e. $\omega = 10$. In this experiment, the period of forecast τ is set at 1, $\tau = 1$. This

experiment requires an estimate for m , the ceiling of the cumulative value of the forecasted variable (i.e. ARB concentration level). Such an estimation can, in practice, be arrived at via analogues (e.g. inferring similar past products) or expert judgment (Mahajan and Peterson, 1985). For personal computer, prior similar products are available for such estimation. In this case, it is assumed that the estimates are available, as declared in the experiment documented in Appendix B (e.g. $m_1=11,000$, the ceiling figure of processor type 1). An assumption here is that the ceiling value of each product/feature is constant. The ARBT and PP parameters can be set arbitrarily to run the experiment. The higher the values, the more stable is the ARB population in the presence of noise in the data. The values of these parameters can be adjusted during the initial few cycles of the experiment to achieve a balance of sensitivity and noise filtering. In this case study, the ARBT was set at 3, and PP set at 2. The decay factor was initialized at 0.3.

The Bass diffusion model assumes that the product is sold in a monopoly market. The data shown in Table 4.1 was empirically demonstrated by Kurawarwala and Matsuo (1998) to be of a monopolistic market, supporting the assumption here. The regression model employed assumes several characteristics of the data: 1) each value of the independent variable (i.e. time) is without error; 2) the B-cell concentrations across time are independent variables and have the same variance; and 3) the B-cell concentration values at any given time must be normally distributed when multiple samples are taken.

The immune memory is initialized with an ARB set, $ARB = \langle ARB_I \rangle$, where $ARB_I = \langle 1, 1, 1, 1, 1, 2, 1, 1 \rangle$. ARB_I is the representation of the personal computer that the company has started to market at the beginning of the time period.

4.4.2 Experiment sets

In the first set of the experiments, continuous delivery of the time-series data (as shown in Table 4.1) to the CRAF system was simulated using Microsoft Excel. The calculations are assisted by the functions of Microsoft Excel (documented in Appendix B). In the second set of the experiment, the same set of data was applied to generate the modeling logistic curve, albeit performed in a static manner, i.e. without utilizing the iDal algorithm. All else where applicable are kept the same for both experiments.

4.4.3 The functions of the iDal algorithm

The mechanisms of the iDal algorithm operating on the time-series data set are illustrated as follows. References can be made to Figure 3.9, the flowchart of the iDal algorithm, and the set of equations stated in Chapter 3.

1. *Immune network initialization (initial condition, $t = 0$).* The immune memory is initialized with an ARB set, $ARB = \langle ARB_I \rangle$, and therefore B-cells in the memory is $ARB_I = \langle 1, 1, 1, 1, 1, 2, 1, 1 \rangle$. $Conc(ARB_I, 0) = 3$. Update time counter $t = t + 1 = 1$.
2. *Introduction of Ag during period $t = 1$.* $Ag^I = \langle Ag_I^I \rangle$ where $Conc(Ag_I^I, 1) = 3$.
3. *Secondary response.* For every active ARB, compute the total stimulation level by all I antigens. As ARB_I is active, by Equation 3.9, the stimulation level is $S_1^I = \sum_{i=1}^I [A(Ag_i^I, ARB_I) \times Conc(Ag_i^I)] = 3$, since by Equation 3.6 $D_{1,1} = \sum_{l=1}^8 w_l \alpha_l = 0$, $A_{1,1} = A(Ag_1^I, ARB_I) = 1$ according to the discrete A-D function.
4. *Primary response:* In this cycle, no primary response is invoked due to the absence of inactive ARB.
5. *Apoptosis:* Using Equation 3.11, $Decay(1) = 0.9$.
6. *Concentration Update:* The new stimulated concentration level of ARB_I , by Equation 3.12, $Conc(ARB_I, 1) = Conc(ARB_I, 0) + S_1^I - Decay(1)$
7. *Antigenic Learning:* With reference to Equation 3.13, as $D(Ag_1^I, ARB_I) = 0$ and $0 \leq \varepsilon_r$, none of the Ag^I satisfies the condition for learning.
8. *Activeness Update:* No ARB meets the condition for activation/deactivation.
9. *Concentration Forecast:* In the application of linear regression in this case study, 10 data points in the sliding window were used to generate the time-varying optimal set of $\hat{a}_t$ and $\hat{b}_t$. The mathematical calculations (tabulated in Table B2 of Appendix B) at the 10th cycle are therefore: (i) using Equations 4.6 and 4.7, the line intercept $a_0 = 6.87$ and gradient $a_1 = -0.49$; (ii) reversing the change of variable using the relationships $a_0 = \ln \hat{a}$ and $a_1 = \hat{b}$, the parameters of forecasting can be found as $\hat{a}_t = 966.93$ and $\hat{b}_t = -0.45$. Equation 4.8 was used to generate the forecast.

10. *Repertoire Data Production*: Forecast of ARB_1 concentration level for the period $(t + 1=2)$ is output as 1941.71. (Note: measurement of forecast error is discussed in the next section.) Counter of time period is updated $(t = 1 + 1 = 2)$, and proceeded to Step 2.

4.5 Result and discussion

Three ARBs were stimulated in the experiment, with their respective B-cell concentration levels time-based profile shown in Figure 4.3. The ARB_1 , ARB_2 and ARB_3 represent the trend of the product feature of interest, in this case, the type 1, 2 and 3 processors of personal computers respectively. Their time cumulative plots are shown in Figure 4.4.

Figure 4.3 Plot of B-cell concentration levels vs. time periods

Figure 4.4 Plot of cumulative B-cell concentration levels vs. time periods

Assuming that the time-based plots of ARB cumulative concentration levels (Figure 4.4) can be characterized by a logistic curve equation, the plots are linearized as shown in Section 4.3.3. The results of linearization can be graphically shown by plotting y against x ; in this case according to Equation 4.3, $y = \ln\left(\frac{m}{C_{kt}} - 1\right)$ and $x = t$.

Figure 4.5 therefore shows the respective data points that are the basis of linear regression. The plot shows that the initial readings were visibly less conforming to straight lines, relative to the later portion. This suggests that the logistic function could better model the fluctuation of the B-cell concentration levels after the first few initial periods. As such, the forecast error can be expected to reduce as time increases.

Figure 4.5 Plot of $\text{Ln}[(m/C_{kt})-1]$ vs. t

Of the three highlighted ARBs, further stages of the experiment and analysis were conducted on ARB_1 . In the first set of the experiments, the CRAF system dynamically generated a series of optimized parameters time-variant $\hat{a}_t$ and $\hat{b}_t$ (see Section 4.4.3). The variations of the parameters with time are summarized in Figures 4.6 and 4.7 respectively. In contrast, the second experiment worked based on the time-invariant parameters - $\hat{a}$ and $\hat{b}$. The values of the parameters are derived using static linear regression across the 38 time periods (i.e. month). The static parameters $\hat{a}$ and $\hat{b}$ have the values of 159.84 and -0.238 respectively, which are constant across time. In the first experiment, the two parameters were expected to vary with time due to possible influences of exogenous factors, such as economic conditions. The impact of these exogenous factors on the sales figures can be reflected in the more recent sales data, which manifested as the varied parameters via the CRAF system. As such, forecasts made based on the dynamic platform can be expected to yield better results.

Figure 4.6 Time-variant optimized parameter $\hat{a}_t$ of ARB_1 Figure 4.7 Time-variant optimized parameter $\hat{b}_t$ of ARB_1

Figure 4.8 shows the results of the two experiments. Besides the actual data acquired from the personal computer manufacturer are the two other cumulative concentration levels of ARB_1 . In the figure, the static characterization of the B-cell concentration level based on the logistic curve is shown. Based on Figure 4.8, it understated the actual B-cell concentration level at most of the points in time. On the other hand, the result of the dynamic forecast by the CRAF system was characterized by a relatively non-smooth profile; the observation can be attributed to the time-variation of the forecast parameters. The forecast inaccuracies visible from Figure 4.8 can be quantified as described below.

Figure 4.8 Actual and forecasted cumulative concentration levels of ARB_1

All forecasts are not expected to contain zero error; amongst the reasons, inappropriate assumptions and logic (Twiss, 1992). Unaccounted events, such as natural disasters can too affect the forecast. Apart from that, forecasted results usually contain random disturbance component and sampling errors (Ostrom, 1990). The error term in Equation 4.4 was assumed to have a mean of zero and a constant variance over all observations. It is also assumed that the error terms corresponding to different points in time are not correlated, i.e. non-autocorrelated. To quantify the errors of each forecast in the time domain, the percentage error of the forecast can be calculated by Equation 4.9. Figure 4.9 shows the percentage forecast errors of the two experiments. The percentage error of the first experiment based on the CRAF system is visibly lower than that of the second for most of the instances. To better compare the two experiments in an absolute manner, compounded errors quantification for the two experiments are required.

$$\text{Percentage error } (k,t) = \frac{\hat{C}_{kt} - C_{kt}}{C_{kt}} \times 100 \quad (4.9)$$

Figure 4.9 Percentage errors of forecasted cumulative ARB_1

Forecast results can in an absolute manner be evaluated for its *accuracy* using the standard deviation around the line of perfect forecast, such as the root mean square error or $RMSE_f$ (Klein, 1974) shown in Equation 4.10. $RMSE_f$ measures the average dispersion around the line of perfect forecast in the same units as the actual realization. The $RMSE_f$, in effect, represents the degree of error of the forecasts (over 38 periods) by each method.

$$RMSE_f = \sqrt{\sum (\hat{C}_{kt} - C_{kt})^2 / T} \quad (4.10)$$

where T is the total number of data points taken into account. The computed $RMSE_f$ for the first and second experiments are respectively 329.72 and 1103.72 units of B-cells. (Note: the results of the calculations above are documented in Table B3 of Appendix B.) The $RMSE_f$ of the first experiment can be evaluated as 0.299 times the $RMSE_f$ of the second experiment. Since all factors of the two experiments were kept constant (including the Bass model and the input data) other than the method of data analysis, it is concluded that the impact on the forecast results of the first method over the second is positive. The result therefore shows that the dynamic properties of the CRAF system improved the forecasting results. (Note: the absolute forecast accuracies are however not the main concern of the study presented in this chapter.)

4.6 Summary

In this chapter, the CRAF system was specified to analyze the time-series data from a computer manufacturer, and to perform monthly forecasts. Two sets of experiments (i.e. dynamic and static analysis) were performed, and a cycle of the iDal algorithm is documented in Section 4.4.3 to illustrate the mechanisms. As stated in the forewords of the chapter, the demonstration of the CRAF system (from a micro perspective) aims to provide grounds for discussion and assessment of the system.

The dynamic process by which the CRAF system handles the time-series data is shown stepwise in terms of the iDal algorithm. Stepwise calculations (aided by Microsoft Excel) demonstrated the time-based developments of the ARBs' concentration levels as shown by the profiles in Figure 4.3. The explicated processes include the stimulated variations of the ARB entities (i.e. immune responses), apoptosis, and the concentration forecasts. These dynamic mechanisms are exemplified in Section 4.4.3 with the results described in Section 4.5. The case study shows that the temporal architecture of CRAF system facilitates the dynamic analysis of the variable of interest. This aspect supports the satisfaction of the second requirement of the CRAF system listed in Section 3.1.

The study of parameters $\hat{a}_t$ and $\hat{b}_t$ (time-variant) as well as $\hat{a}$ and $\hat{b}$ (time-invariant) of the diffusion model² demonstrated the dynamic forecast mechanisms of the CRAF system. As shown in Figures 4.6 and 4.7, the parameters $\hat{a}_t$ and $\hat{b}_t$ are optimized in every cycle of the algorithm, as compared to the static counterparts $\hat{a}$ and $\hat{b}$ derived without the use of the iDal algorithm. Forecasts of the concentration levels of ARB_1 by the CRAF system were shown with low errors, relative to static characterizations (as depicted in Figure 4.9). In other words, the dynamic treatment of the data has improved the forecasting results, relative to the static treatment based on the same forecasting model. This is due to the rationale that in the case of dynamic treatment, forecast is based on time-sensitive parameters, while the static case is not. This rationale applies too to customer requirement data, which itself is time-varying. The experiment shows that analyzing time-based customer requirements data using the

² While the Bass diffusion model is able to support the CRAF system in forecasting in this case, it should be noted that the model is limited to durable products in monopoly market and an assumption of the structured non-linear sigmoid model was made.

dynamic architecture possesses positive benefits in terms of forecasting accuracy. In this investigation, the forecast is not dependent on customers' opinions of their future needs (see limitation of previous work in Section 2.1.5). The CRAF system was shown to be capable of supporting the forecast of non-linear univariate time series data, of which dynamic customer requirement data is an instance. In the light of the work reported in this chapter, the satisfaction of the third requirement of the CRAF system (listed in Section 3.1) is supported.

The investigation described in this chapter serves to clarify the working mechanisms of the CRAF system, which demonstrated the system's dynamic property, as well as the ability to perform forecast of customer requirements. The next chapter presents an advanced investigation performed to further address the set of system requirements.

Chapter 5 - A Macro Perspective Investigation into the CRAF System

With the aim of developing self-managing systems, IBM introduced the Autonomic Computing initiative in 2001 (Horn, 2001). Autonomic has been expressed as the automation of system adaptation (Tianfield and Unland, 2004), which is a requirement of the CRAF system as stated in Section 3.1.

The investigation reported in Chapter 4 analyzed the mechanisms of the CRAF system, which demonstrated the dynamic property and the forecasting function of the system. To study the overall behaviours and functions of the CRAF system, in particular its autonomic property, it is imperative to investigate from a macro perspective. In this investigation, the set of system requirements listed in Section 3.1 will be employed for the examination of the system.

To investigate the CRAF system at a macro level, it is required to implement the iDal algorithm by programming it in accordance to specifications. The forecast module for the purpose of this investigation is specified in Section 5.1, while the iDal algorithm is accordingly specified in Section 5.2. Based on the specifications, the iDal algorithm is programmed on the MATLAB platform. Computational experiments are conducted, with the outcomes and discussions presented in Section 5.3. Finally, Section 5.4 puts forward the conclusions of the studies covered in this chapter.

5.1 Specification of the forecast module

This investigation specifies an artificial neural network (ANN) in the forecast module of the CRAF system. Specifically, the focused time delay neural network (FTDNN) is employed. The FTDNN is described as *focused* since the short term memory is only at the filtering input layer, whereby static backpropagation can be employed for network

training. With input signal, the memory structure transforms samples into points in the input space. Time delay neural network, first applied by Waibel (1989) for speech recognition, is a feedforward network with each synapse of the network designed as finite impulse response filters. The following describes the rationales of applying the FTDNN method in this investigation.

- *Function modelling*: Customer needs data can be non-linear, which poses challenge for analysis in time-based systems in the context of this work. Although the Bass diffusion model applied in Chapter 4 was shown to handle a non-linear problem, it is limited to cases of durable products in monopoly markets and to the assumed sigmoid model. In contrast, artificial neural networks (ANN) have been proven to be universal approximators when adequate numbers of hidden neuron are used (Park and Sandberg, 1991). Compared to traditional statistical time-series modelling that have limitations in modelling complex systems, ANNs are more general and flexible to give better performances (West et al., 1997). Traditional time-series models such as Box-Jenkins and ARIMA (autoregressive integrated moving average) methods assume that the time-series under study are generated from linear processes (Zhang et al., 1998). Further, the Box-Jenkins approach to time-series modelling relies entirely on the stationary assumption when trends in time-series are known to violate the assumption (Qi and Zhang, 2008). As it is clearly neither reasonable nor practical to assume that customer need variations are linear over time, direct applications of such traditional methods would be non-optimal. ANN models usually outperform the above traditional techniques when time-series are non-linear and noisy (Menezes and Barreto, 2006). Polynomial series (often used in control engineering) have been applied to model non-linearity where coefficients are adjusted to provide least mean square error fits (Mathews, 1991). However, when high order polynomials are used to model general problems that are not polynomial in nature, the number of coefficients increases, making the method inefficient (Azoff, 1994). Other non-linear models such as TAR (threshold autoregressive model) and state-space models require the model types and complexities predefined. Like many types of practical time-series, the *a priori* models of customer needs are unknown. In contrast to other non-linear methods, the ANN approach is nonparametric and model free, i.e. data driven. The

generalization capability of the method frees users from the need to assume function forms beforehand and is therefore applicable in the CRAF system.

- *Autonomy and dynamism*: ANN can be broadly classified into static and dynamic neural networks. Static networks per se, such as the multi-layer perceptron (MLP), suffer from limitation in modelling dynamic systems where time delay affects the dynamism (Sinha et al., 2000). FTDNN on the other hand has topologies that explicitly address the dynamic input-output space. Generally, where time imposes a structure in input space, the dynamic FTDNN is a more rigorous approach as compared to static networks. Specifically, FTDNN is a dynamic ANN that has short term memory or delay elements built *within* the learning machine, differing from static networks that are at times coupled to windowed input signal. Due to this feature, FTDNN can be implemented to independently and dynamically tune the delay size and weights of the network where applicable via training. For supporting the demonstration of the autonomic and dynamic characteristics of the CRAF system, the FTDNN in the forecast module is suitable.
- *Targeted training*: Compared to unsupervised ANNs, FTDNN's supervised backpropagation training is able to approximate the model in a targeted manner given the training data.
- *Usability*: Amongst the types of dynamic ANN, FTDNN is reported as a balanced network for both processing power and simplicity (Principe et al., 2000).

5.2 Specification of the iDal algorithm with focused time delay neural network function

In this investigation, the iDal algorithm with the FTDNN is specified to handle the issue of dynamic customer requirement. Figure 5.1 illustrates the specified iDal algorithm. Compared to Figure 3.9, Figure 5.1 has a *neural network training* phase inserted before the concentration forecast step. (*Note: the time-based input data is captured during Step 2 of the algorithm while the 11th step generates the output results.*)

Figure 5.1 Flowchart representation of the iDal algorithm with FTDNN

The algorithm is specified as follows.

1. **Immune network initialisation:** A set of active ARBs at the predetermined concentration level of ARBT (ARB Threshold) at $t = 1$ is preinstalled in the system, i.e. $ARB^0 = \langle ARB_1, ARB_k, \dots, ARB_K \rangle$, where $Conc(ARB_k, 0 | \forall k) = ARBT$ and $Active(ARB_k | \forall k) = 1$
2. **Antigens introduction:** Data $Ag^t = \langle Ag_1^t, Ag_i^t, \dots, Ag_l^t \rangle$ is introduced to the system at time t .
3. **Secondary immune response:** Each introduced data packet Ag is presented to the active ARBs for stimulation. As understood in theoretical immunology, pathogens can be recognized by more than one type of B-cells, and vice-versa. It follows that the stimulation levels S_k^t of the ARBs can be computed using Equation 5.1.

$$S_k^t = \sum_{i=1}^I [A(Ag_i^t, ARB_k) \times Conc(Ag_i^t)] \quad (5.1)$$

where function A produces the affinity between the two operands, given by the affinity-distance relationship as shown in Figure 5.2. Distance function D that quantifies the dissimilarity between an Ag and an ARB is given by Equation 5.2.

$$D(Ag_i^t, ARB_k) = \sum_{l=1}^L \alpha_l \quad \text{where } \alpha_l = 0 \text{ if } Ag_{i,l}^t = ARB_{k,l} \text{ or } ARB_{k,l} = \#$$

$$\alpha_l = 1 \text{ if otherwise} \quad (5.2)$$

Figure 5.2 The affinity-distance relationship

4. **Primary immune response:** In the stimulation of inactive ARB here, cross-reactivity does not apply, i.e. stimulation here requires exact match, as expressed in Equation 5.3.

$$S_k^t = \sum_{i=1}^I \text{Conc}[Ag_i^t | D(Ag_i^t, ARB_k) = 0] \quad (5.3)$$

5. **Apoptosis:** The population of B-cells in the system is maintained by the process of programmed cell death. The decay is computed using Equation 5.4.

$$\text{Decay}(t) = d \left(\frac{\sum_{k=1}^K S_k^t}{K} \right) \quad \text{where } d \text{ is the decay factor.} \quad (5.4)$$

6. **Concentration update:** The concentration level of each ARB is refreshed based on Equation 5.5.

$$\text{Conc}(ARB_k, t) = \text{Conc}(ARB_k, t) + S_k^t - \text{Decay}(t) \quad (5.5)$$

7. **Antigenic learning:** Foreign antigenic datasets that are beyond the recognition of the existing ARBs are learnt by the system in this step. Under the condition that a

previously undetected antigen is sufficiently different from the system's ARBs to an extent dictated by the parameter ε_r (i.e. $D(Ag_i^t, ARB_k) \geq \varepsilon_r$), a new inactive ARB of the same attributes and values will be registered in the system memory.

8. **Activeness update:** When the concentration level of an active ARB falls below the ARBT level for a specified period of time, it is deactivated in this phase. The period is termed as *persistence 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 latest available set of B-cell concentration data is utilized to train the focused time delay neural network¹, based on static backpropagation algorithm². Concentrations of B-cells (denoted as c) in the respective ARB are passed to the ANN as vector $[c_1^t, \dots, c_K^t]$. The outputs of the network are in the format $[\hat{c}_1^{t+\tau}, \dots, \hat{c}_K^{t+\tau}]^T$.
10. **Concentration forecast:** The trained neural network is applied to forecast the future B-cell concentration of the respective ARBs.
11. **Repertoire data production:** The present and the forecasted population datasets are produced. The algorithm is looped ($t=t+1$) by proceeding to Step 2.

5.3 Experimentation using MATLAB

Customer requirements information can be derived from market surveys, as the input to the CRAF system. Customer requirements may also be inferred from the sale of products, by regarding the acts of purchase as customer need and preference expressions. In this study, the same data applied in the experiments of Chapter 4 is used. The data is an appropriately *scaled* and *disguised* proprietary dataset from a

¹ The numbers of delay, hidden layer and neuron are problem dependent. Experiments revealed that neural networks trained on inputs that are spaced by time interval τ would have the capability to forecast τ periods ahead, irrespective of the τ length (Alan and Robert, 1987). Longer term forecast of multiple τ can be implemented by the iterated multi/single-step approach (Menezes and Barreto, 2006; Azoff, 1994).

² The Levenberg and Marquardt algorithm (LMA) is employed for training. LMA reduces conditioning problem and does not require the calculation of second order derivatives thus offers fast convergence (Qi and Zhang, 2008).

personal computer manufacturer (Kurawarwala and Matsuo, 1998). The data relates the purchases of five types of PC, P1 to P5, over thirty-eight months in a particular market segment, as presented in Table 4.1. Similarly, the PCs have 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.

To study the CRAF system at a macro level, the iDal algorithm specified in Section 5.2 was computationally implemented; the instructions were coded and can be autonomously executed in the MATLAB environment (*Note: the sets of program code are attached in Appendix C.*). Table 5.1 shows the parameters and values applied in the study. During the execution of the program, the case data was fed to the system. The results generated are described in the rest of this section.

Table 5.1 Parameters of the iDal algorithm

Parameter	Value
ARBT	5
PP	3
d	0.3
ε_r	1
L	2
delay	8
hidden neurons	8

Figure 5.3 shows examples of the ARB generated in the study. The depicted bio-molecules are $m_0 = \langle \text{product, personal computer} \rangle$, $m_1 = \langle \text{chassis, tower} \rangle$, $m_2 = \langle \text{graphic, integrated} \rangle$, $m_3 = \langle \text{chassis, compact} \rangle$, $m_4 = \langle \text{chassis, desktop} \rangle$, $m_5 = \langle \text{graphic, discrete} \rangle$, $m_6 = \langle \text{type, X} \rangle$, $m_7 = \langle \text{type, B} \rangle$ and $m_8 = \langle \text{type, A} \rangle$. Note that bio-molecule m_2 is an option of m_5 , and is less specific than m_7 . ARB, which is defined by a chain of bio-molecules, ranges in terms of specificity. In Figure 5.3, the ARB that is defined by both m_5 and m_6 is more specific than the one that is only defined by m_5 . For example, let m_5 represents an animal known as horse (the attribute-value pair would be $m_5 = \langle \text{animal, horse} \rangle$), and let m_6 represents a colour known as white (i.e. $m_6 = \langle \text{colour, white} \rangle$). An ARB defined by m_5 and m_6 therefore represents “an animal known as horse in a colour known as white”. On the other hand, an ARB defined by only m_5 represents “an animal known as horse”, and the colour is non-specific. As such, an ARB defined by both m_5 and m_6 (i.e. white horse) would be more specific than the one defined only by m_5 (i.e. horse).

Figure 5.3 Examples of ARB in the case study

The computational process resulted in a set of ARB objects that reflects the temporal and instantaneous patterns in the data. The forecast of the B-cells repertoire was made possible having modelled the dynamics of the evolution, in this case,

facilitated by the neural network technique. Figure 5.4 depicts the qualitative learning of the system in terms of (1) total ARB – the aggregated objects learnt by the system over time, (2) inactive ARB – the premature and obsolete user needs, and (3) active ARB – the relevant user needs in points of time. Figure 5.4 therefore at the same time demonstrates the system's dynamic processes of ascertaining the valid and invalid (e.g. obsolete) customer needs over time. As discussed, customer requirements in the fast shifting PC market rapidly changed with time. The relatively less stimulated ARBs (i.e. customer needs) faded and were deactivated while new ARBs were learnt and activated through the processes of stimulation.

Figure 5.4 Total, active and inactive units of ARB

Past research has looked into stabilizing the size of the total B-cell population to ensure that the resultant data is tractable and meaningful. Timmis and Neal (2001) devised a resource limited scheme in the context of continuous learning; the population control is based on the competition amongst the ARBs for survival. In this work, the total population and the number of ARBs, though should exhibit tractability, are not limited at specific values considering the notion that new knowledge of customer needs is continuously learnt. As such, the iDal algorithm (in Step 5) maintains the overall population size by allowing only newly learnt B-cells to add to the total population. The decay of the B-cells through the apoptosis process in this work therefore performs the population regulation function. Figure 5.5 shows the controlled increase of the B-cell population in the system.

Figure 5.5 Repertoire size in the CRAF system

FTDNN was applied to sequentially learn the quantitative dynamism of the B-cell concentration. Backpropagation training algorithm was employed to train the network. Figure 5.6 shows an instance of the training result during the learning process, with mean squared error (MSE) as the performance index over the epochs. It was found that the MSE tended to zero during training, reflecting positive progressions in the task of function approximation. This study therefore demonstrated the capability of the artificial neural network in approximating the functions of B-cell concentration over the time domain.

Figure 5.6 An instance of FTDNN learning process

Dynamic forecasts of the B-cell concentration levels in the ARBs were found to be improving over the periods. Figure 5.7 shows the percentage errors for the nine ARBs that had non-zero concentration levels through the forecasting period (*note: forecast is not performed on ARB that has zero B-cells*). The mean percentage errors of forecast dropped below 5% for the final 6 months, with each lower than the previous as time passes (see Figure 5.8). The errors are maintained at low levels in the final periods of forecast, as shown in Figures 5.7 and 5.8. The mean percentage error of forecast during the final 38th month was noted to be 0.79%. The low error and the progressively improving accuracy indicate that the CRAF system is capable of generating results with degrees of accuracy that are potentially useful for practical applications.

Figure 5.7 Percentage error of concentration forecast

Figure 5.8 Mean percentage error of concentration forecast

Apart from reporting the qualitative information (attributes, values and “active or inactive” statuses) of the ARBs, the CRAF system generates the past, current and forecasted concentration levels of the ARBs. The concentration level outputs are the quantitative user needs information at various levels of abstraction. This case study demonstrated the post-analysis of the qualitative and quantitative data in constructing useful sets of information. For instance, in Figure 5.9, the system showed the rising preference for the tower type chassis, against the then common desktop type. The requirement for the compact type chassis though was premature in the market by the end of the 38th month, the forecast produced showed signs of increasing preference during the 37th and 38th months. In another instance, the system reported the discrete type graphic card being relevant (i.e. immunologically activated) around the 25th month, and thereafter started to gain popularity against the integrated type, as shown in Figure 5.10. Meaningful graphical representations of B-cell concentration levels can be generated based on sets of post-analysis functions (i.e. codes written in the MATLAB environment in this study).

The CRAF system was shown: (i) to learn new objects that are unknown (to a specific degree based on the parameter ε_r), (ii) to adjust the population sizes of the B-cells objects based on the level of stimulation, and (iii) to qualify customer needs as active (relevant) or inactive (premature or obsolete) based on the level of *sustained* stimulation (or the lack thereof). The investigation therefore demonstrated the dynamic and autonomic functions of the CRAF system in indicating the current and (forecasted) future customer requirements information, in both qualitative and quantitative forms. From a practical perspective, the generated sets of customer needs data are cross-referenced to the temporal space, making these datasets exceptionally valuable in time-sensitive markets.

Figure 5.9 B-cell concentrations of chassis designs

Figure 5.10 B-cell concentrations of graphic card types

5.4 Summary

The investigation reported in this chapter takes a macro view at the CRAF system in a bid to study the effective behaviours and the overall functions. The iDal algorithm was computationally implemented on the MATLAB platform. In the experiment, a set of time-series data was input to the program. With reference to the results and discussions presented in the preceding section, the following conclusions are made with references to the list of system requirements in Section 3.1.

- In the experiment, the CRAF system was supported by the robust modelling of customer requirement information using Requirement Space Framework (RSF), to which the ARB model founded in the AIS research was mapped. The program showed the RSF in modelling customer requirements using multiple levels of abstraction; the relationships among co-requirements and requirement options were

concurrently modelled, as shown in Figure 5.3. Additionally, qualitative and quantitative information of the customer requirements were represented. The RSF was mapped to the ARB data structure such that the iDal algorithm was able to operate on the data. As a result, the CRAF system was capable of generating multi-levelled customer needs information in contrast to previous methods that operate on limited abstraction levels of information (as discussed in Chapter 2). In addition, analyses of competing requirement options were facilitated, with instances shown in Figures 5.9 and 5.10. In that light, the first system requirement as stated in Section 3.1 is supported.

- The program developed on the MATLAB platform operated independently in accordance to the time-series data fed from the changing environment. The system coevolved with the dynamic environment by autonomously training itself qualitatively (i.e. with antigens' sets of attributes and values) and quantitatively (i.e. with antigens' concentration levels); the system was therefore able to output customer needs data of both the qualitative and quantitative kinds. Further, the system was shown to possess the capability to distinguish inactive (premature or obsolete) from active (current) customer requirements, which has been a problem that traditionally requires human designers' manual review (as discussed in Chapter 2). As the CRAF system is capable of self-adaptation (Tianfield and Unland, 2004) in addressing the problem of dynamic customer needs, the fourth system requirement listed in Section 3.1 is supported.
- Like many physical and social phenomena, the validity of customer requirement types over time is likely to be non-linear (i.e. they may not be written as linear combination of independent components). As shown in this investigation, the CRAF system supports the approximation of non-linearity. Furthermore, prior assumption of the approximating model is not required by the system. In view of that, the second system requirement listed in Section 3.1 is supported.

As the issue of dynamic customer needs bears impact on the various functions of product development organizations, the results of this research can therefore contribute to the respective functions, for examples, design, manufacturing, and R&D. On that basis, the next chapter presents an application of the CRAF system on a downstream problem, specifically, a problem in the product conceptualization phase.

Chapter 6 - An Application of the CRAF System in Product Concept Development

Information on dynamic customer needs derived from the CRAF system may serve to reduce uncertainties found inherently in product development projects. The literature review in Section 2.1.3 found that the dynamism of customer needs not only does bear implications on the design of products, but also on the wider spectrum of product development activities such as R&D, production, and marketing. Results of this research may therefore be of interest to various functions across product development organizations. In view of the increasingly fast changing markets, the analysis of dynamic customer requirement and the application of the generated information on downstream activities are expected to be important areas for future research. Against that background, this chapter describes an application of the CRAF system on a problem downstream of customer requirement analysis - a conceptual design problem. In system integration where the compatibility of data across product development functions is a common issue, the applicability of the data generated by the CRAF system (in the RSF format) on the downstream application is demonstrated.

Section 6.1 presents a description of the conceptual design problem while Section 6.2 introduces an approach to addressing it. A system is prescribed to embody the approach, termed as the Heuristic-Based Conceptual Design (HBCD) system. The conceptual design approach (like other design methodologies in general) bears the shortcoming attributed to the dynamism of customer needs, as introduced in Section 1.1. Section 6.3 presents the method by which the CRAF can be integrated to the HBCD system in addressing the shortcoming of the conceptual design approach. The integrated system, in effect, serves to demonstrate the applicability of the CRAF in the

functions of product development cycles. Section 6.4 presents the application using an example, and finally in Section 6.5, the functions of the CRAF system in the context of the conceptual design stage as well as in other product development phases are discussed.

6.1 Problem description

The front-end of the product development process involves the conceptualization of design (Ulrich and Eppinger, 2000). Research has shown that about 80% of the product lifecycle cost is determined during this phase (Smith and Reinertsen, 1997). It is known that detailed design of the highest standards cannot compensate for a poor design decision taken at the conceptual design phase. Due to the importance of this phase, proponents of design science have given considerable attention to this front-end process.

In practical design problems, the solution space is open-ended (Sim and Duffy 2003). Designers may attempt to generate solutions of the widest range to avoid unwittingly excluding any potential breakthrough concepts; the time available to do so is however often limited due to the common demand for short development cycles. The *time versus completeness* dilemma arises throughout the course of conceptual design. As a result, designers' navigations in the complex space of design, if unguided by principles and unassisted by computer, can be inefficient. A strategy that can assist designers in exploring and ascertaining design solutions within the often vast space of design is therefore crucial. In the light of this issue, this chapter (in Section 6.2) introduces a heuristic-based approach that strategically guides the exploration of solutions during product conceptualization (Chong et al., 2009b). The heuristic-based conceptual design approach, like other design methodologies, is susceptible to the problem of dynamic customer needs. As described in Section 1.1, if the tasks of conceptual design were to be based on static customer needs data, the output of the design process may not be valid by the time the product reaches the market (when it matters most). The application of CRAF to address the issue of dynamic customer needs in a downstream problem is therefore demonstrated in Section 6.3.

6.2 A heuristic-based approach to conceptual design

Human problem solving, a generalization of product design task, can be represented by search space, as illustrated by Newell (1990). The symbolic computations within this space capture the essence of problem solving processes. In the context of the propositions in this work, domain D (formalized in Section 3.4) is hereby proposed as the space put forward by Newell (1990). Researchers have proposed search algorithms such as the breath-first and depth-first search to systematically uncover solutions in design space. To increase the efficiency, best-first algorithms (Farreny, 1999; Bolc and Cytowshi, 1992) were suggested where *heuristics*, as explicit rules derived from human experiences and tacit knowledge, play decisive roles.

In product conceptualization, designers may be forced to relax optimality and settle for “good enough” solutions after expending certain amount of search effort. This is described as semi-optimization (Pearl, 1984) in heuristic-related literature. Research in cognitive psychology has long proven that in natural thinking, humans rarely strive for optimum solutions, but rather settle for *satisficing* solutions (Stempfle and Badke-Schaub, 2002). According to Simon (1969), *satisficing* solution is one where performance level exceeds certain threshold of acceptability.

Heuristics are rules-of-thumb that have been successful in producing “acceptable”, not necessarily “optimal” solution to a type of problem (Li et al., 1996). They are also criteria, methods, or principles for deciding which among several alternative courses of action promises to be the most effective in order to achieve the desired goals. Heuristics play an effective role in problem solving, such as in product design, by indicating a way to reduce the number of evaluations and to obtain product solutions within a reasonable time span. In the same vein, design is about finding solutions; not necessary (globally) optimal solutions since designers generally do not receive the resources needed to achieve optimality (Braha and Reich, 2003).

Having studied the applicability of heuristic algorithms on conceptual design problems, it was found that the nature of conceptual design problems is comparable to the problems that heuristic algorithms have been traditionally employed. There are however points of disparity between the problem domains. For instance, the solving of the Traveling Salesman problem and Road Map problem proceed along the *dimension of incremental quantity*. Algorithms (such as A*, HPA (Heuristic Path Algorithm), B*, BF (Best First) and D*) for solving such problems have *path length functions* which

add up the quantities of all sub-solutions to get the overall solution (Pearl, 1984). On the other hand, product conceptualization process is conducted along the *dimension of incremental detailing* (Chong et al., 2009b). For this difference, the path length functions of heuristic algorithms cannot be directly applied to a product conceptualization problem. Based on such understandings, this research adapted and specified a general-purpose heuristic algorithm, with the aim of addressing product conceptualization problems.

With reference to Section 3.4.4, the RSF is derived by the reduction of the Design Space Framework (DSF). The DSF was proposed in Section 3.4.3 as a data structure that can represent knowledge in conceptual design problems (Chong et al., 2009a). For the purpose of the study here, the DSF is defined mathematically as an AND/OR tree graph G (Dougherty and Giardina, 1988). Therefore, graph G can be represented in the three dimensional space D , which was defined in Section 3.4.3. Figure 6.1 shows an instantiated design concept modeled as graph G in the space D .

Figure 6.1 A case of Graph G in Space D

A specific heuristic algorithm, General Best First (GBF) (Pearl, 1984) is selected for adaptation to facilitate the exploration of product concepts. GBF algorithm possesses the logic framework to explore an AND/OR tree graph, which is a characteristic of graph G . GBF is a heuristic algorithm that is not restricted to specialized functions, thus allowing prescriptions according to the characteristics of conceptual design problems. This adapted heuristic algorithm is termed as the Conceptual Design Heuristic (CDH) algorithm. Section 6.2.1 declares the notations of

the CDH algorithm while Section 6.2.2 prescribes the four sub-functions of the algorithm. Finally, the adapted algorithm is presented in Section 6.2.3.

6.2.1 Notation definitions

In most problems of practical interest, a fully representative graph relevant to the problem is often too large for computer to meaningfully consider completely (Pearl 1984). In solving these problems, data can be selectively elicited from users and extracted from the design database to generate a partial graph from the start node in the desired directions incrementally. This generated graph is the *explicit* portion constructed, keeping most other parts unexplored. The objective of the CDH algorithm here is to ascertain a *satisficing* solution graph by explicating only the necessary portion of the implicit graph G . As such, it is necessary to define a subgraph G' . At a certain phase of a product conceptualization process, the *explicated or explored portion* of graph G is represented by the subgraph G' of G . A candidate solution, so-called a *solution base*, is subgraph G'' of G' , and the most promising solution candidate G'' is denoted as G_0 . Three separate conditions hold for G'' at all times.

1. G'' contains the start node s_0^0 .
2. If an expanded node n in G'' has its successors along dimension X (see Section 3.4.3 for definitions), then all these successors are also in G'' .
3. If an expanded node n in G'' has a certain successor with siblings along dimension Y , then only one of these siblings is in G'' .

In this model, a *Context* represents a set of nodes generated in one cycle of the CDH algorithm. This set of nodes contains C , P and S in sequence. Due to the recursive nature of object relationships, *Contexts* may continue to stack from below. Figure 6.2 shows a case of a *Context*. In design, a *Context* simply characterizes a set of possible sub-solutions of a sub-problem.

Figure 6.2 An instance of a Context

For any node generated from the expansion step of the CDH algorithm, it will be a terminal node, if it is either: (1) unable to produce any successor (its heuristic value will be assigned $-\infty$), or (2) if no further concept detailing is required (in other words, no successor node is necessary). In the second case, the terminal node shall be labeled ‘*Solved*’.

In the CDH algorithm, like other heuristic algorithms (Pearl, 1984), nodes that are expanded are called *closed*, while nodes that are generated and are awaiting expansion are called *open*. Two separate lists called **CLOSED** and **OPEN** are used to keep track of these two sets of nodes.

6.2.2 The sub-functions of the conceptual design heuristic algorithm

Several functions are prescribed in this section to support the CDH algorithm, namely the heuristic function h , function f_1 , function f_2 , and lastly the Solved-labeling function. Heuristic function h serves to hold the promises of the sub-solutions; function f_1 recommends the designers with solutions to the overall problem; function f_2 advises the direction to progress in the design space; and the Solved-labeling function keeps the designers informed of the status of the conceptual design process.

The principal aim of conceptual design is to generate *promising* concepts (Liu et al., 2003). In this design phase, when designs are abstract and information may be incomplete, the level of perceived *promise* a concept can affect the outcome of the selection processes. As such, the heuristic function $h(s_k^l)$ represents the *promise* that solution s_k^l holds for its parent, as shown in Equation 6.1.

$$h(s_k^l) : \begin{cases} h(s_k^l) > 1 & \text{If } s_k^l \text{ holds more promises than it is required.} \\ h(s_k^l) = 1 & \text{If } s_k^l \text{ holds promises as required.} \\ 0 < h(s_k^l) < 1 & \text{If } s_k^l \text{ holds less promises than it is required.} \\ h(s_k^l) = -\infty & \text{If } s_k^l \text{ holds no promise at all.} \end{cases} \quad (6.1)$$

$h(s_k^l)$ captures the design team's confidence level of the solution s_k^l , based on its next level of detailness. When the details or child nodes of s_k^l are yet to be explored, the value of $h(s_k^l)$ would be based on the team's *insight* – their tacit domain knowledge, experiences and judgment on s_k^l . This measurement, implicit in practice, motivates further exploration or termination of ideas. The value of $h(s_k^l)$ propagates and contributes to the collective worthiness of all its ancestors, from its direct parent to the graph root s_0^0 . Such a propagation is enabled by the Merit Ratio and expressed in Equation 6.2. In the case where s_k^l is considered for further exploration into details, its worthiness, i.e. Merit Ratio, beyond the concreteness of its initial heuristic h value, will be tuned and progressively affirmed by the heuristic values of its descendents. This work defines Merit Ratio (MR) of $s_{k_1}^l$ as the degree of promise $s_{k_1}^l$ hold for its parent. MR ($s_{k_1}^l$) measures the heuristic performances of the solution $s_{k_1}^l$ based on the proportional sum of merit ratios of its constituents. Mathematically,

$$\text{MR} (s_{k_1}^l) = \begin{cases} h(s_{k_1}^l) & \text{If } s_{k_1}^l \text{ is an OPEN node.} \\ h(s_{k_1}^l) \sum_i \Lambda(c_i) \sum_j \Lambda(p_j) \sum_k \max_l [\Lambda(s_k^l) \text{MR}(s_k^l)] & \text{If } s_{k_1}^l \text{ is a CLOSED node; } c_i \text{ is a child of } s_{k_1}^l; p_j \text{ is a child of } c_i; \text{ and } s_k^l \text{ is a child of } p_j. \end{cases} \quad (6.2)$$

where $\Lambda(n)$ is the contribution fraction of node n . It is the proportion of n 's contribution to its parents amongst its siblings along the X dimension of D , i.e. $0 < \Lambda(n) \leq 1$.

The merit ratio of any non-terminal node is influenced by its descendants' best alternatives (if any alternative is present) in the explicated graph G' . The best solution amongst the alternatives is defined as the one with the highest merit ratio. This form of mechanism originates from the fact that *promises* can be evaluated only retrospectively. As the design proceeds into more details, i.e. when additional information emerges, the initial perceived merit (or the demerit) of an abstract solution is likely to vary.

In this work, the root node of the graph - or the highest-level solution - has a definitive heuristic value of 1.0 (see Equation 6.3). This assignment states that the design starts off with an overall concept that promises to fully satisfy the given design problem.

$$h(s_0^0) = 1.0 \quad (6.3)$$

The selected solution and sub-solutions to a design problem can change – possibly frequently – during the conceptual design process. Such dynamic evolution of the perceived most promising concept can be tracked by function f_l . Function f_l provides the most promising solution graph G_0 , given the explicated graph G' and the merit ratios (MRs) of the solutions in graph G' (see Equation 6.4)

$$f_l : [G', \text{MR}(s_k^l)] \rightarrow G_0 \quad (6.4)$$

As G' varies with each algorithmic cycle, it follows that the values of G_0 may evolve and are updated cyclically.

It was argued that since each and every node in a solution base graph (AND graph) is relevant to the overall solution (whereby all its tip nodes on the OPEN list must eventually be expanded), the order of expansion is rendered immaterial (Pearl, 1984). However, it is sensible to first expand the node that has the highest probability of revealing an impasse, so as to possibly either declare the problem “unsolvable”, or to prompt seeking of alternative solutions at the earliest possible time. This argument is similar in the context of product conceptualization. The function of f_2 is to single out a node for the expansion exercise in every cycle of the CDH algorithm. The chosen node n^* should be taken from the OPEN list as well as being part of the ascertained

G_0 . For the arguments described above, probing the weakest element to possibly refute G_0 's superiority in the earliest time would be the rationale underlying the evaluation function f_2 . The role of Function f_2 is to identify an optimal node n^* for expansion in the CDH algorithm, as represented in Equation 6.5.

$$f_2(s_k^l \in G_0 \cap \text{OPEN}) = \min_k [h(s_k^l \in G_0 \cap \text{OPEN})] = n^* \quad (6.5)$$

During the conceptualization of designs, designers moderate the detailness or the depth of probe into the solutions. When designers deem that a sub-solution is adequately detailed, they may therefore - in the context of the CDH algorithm - label it as “solved” (i.e. *solve_status=1*). It signifies that further solution depth is not required for that particular solution node. It is in this instance when the CDH algorithm will invoke the Solved-labeling function, which is recursive. It is defined as:

1. Remove the operand, its siblings along dimension Y (its alternatives), and all their descendents if any from OPEN.
2. If all of the operand's siblings (if any) along dimension X have *solve_status=1*, update the parent of the operand with *solve_status=1*. Let this newly labeled parent be the operand. Go to Step 1. Else exit to Step 5 of the CDH algorithm.

6.2.3 The conceptual design heuristic algorithm

The conceptual design heuristic (CDH) algorithm is adapted from the GBF algorithm (Pearl, 1984) to operate on the DSF (established in Section 3.4). The algorithm is assumed to be embedded in a computer-aided conceptual design (CACD) system – hereby named as the Heuristic-Based Conceptual Design (HBCD) system.

Figure 6.3 Architecture of the Heuristic-Based Conceptual Design System

An HBCD system, as shown in Figure 6.3, is postulated to contain the following modules: design logic module, design database (long-term memory), working memory (short-term memory), and user-interface (UI) layer. The CDH algorithm embedded in the design logic module instructs the exchange of data amongst the rest of the three modules. The design database module allows the saving and retrieval of data while the UI facilitates the exchange of data with the system users. The working memory of the HBCD system on the other hand serves to hold the solutions of the respective design problems in the form of graph G .

The CDH algorithm is graphically depicted in Figure 6.4 and is prescribed as follows.

1. Put the start node s_0^0 on both OPEN and G_0 .
2. Using f_2 , select node n^* (if initial, just s_0^0). Remove n^* from OPEN and place it on CLOSED.
3. Expand node n^* - generating its immediate successive *Contexts* by eliciting data from the UI and/or the design database. Add all generated nodes as well as their relational pointers (leading back to n^*) to the search graph G' . Place all leaf nodes on OPEN.
4. For each new leaf node s_k^l , acquire from UI the heuristic information h that characterizes the set of solution graphs rooted at s_k^l . Let new leaf node s_k^l 's $solve_status(s_k^l) = 1$ if instructed by UI.
5. If any of the new leaf node s_k^l on OPEN has been marked $solve_status(s_k^l) = 1$ in Step 4, invoke the Solved-labeling function with s_k^l as the operand. Else go to next step.
6. Base on the explicit search graph G' constructed so far, compute the most promising solution base graph G_0 using function f_1 and the heuristics h provided in Step 4. Refresh G_0 .
7. If $solve_status(s_0^0) = 1$, exit with G_0 as the solution graph. Else if $MR(s_0^0) = -\infty$, exit with failure. Else go to Step 2.

Figure 6.4 The CDH Algorithm

6.3 System integration

In this section, the mechanisms of the HBCD system specified in Section 6.2 will be demonstrated to support conceptual design work. The proposed HBCD system (as with other CAD systems) has a common limitation - customer needs data fed to the system is static, which can be out-dated or at best, current. Within the period of product development (with reference to Figure 1.1), customer needs in the markets could vary. The degree of the variation is dependant on the length of development period and the volatility of market needs. By the time the products reach their respective

marketplaces, the designs may not be optimal due to the shift in customer needs. This is the issue that motivated the proposition of the CRAF system.

This chapter presents the approach by which the problem of dynamic customer requirements found within the span of product development cycles can be addressed using the CRAF system. In particular, the approach is demonstrated based on the HBCD system introduced in Section 6.2. Figure 6.5 shows the architecture of the overall system, with the CRAF system integrated to the HBCD system.

Due to the lag period depicted in Figure 1.1, the validity of the solutions produced by product developers at the respective development stages would not be clear to the product developers if no verification is performed; if solution verifications were performed based on initial (static) customer requirements, as commonly practiced, the integrity of the results would be uncertain in the context of dynamic markets. In that light, this study proposes a Dynamic Design Verification Module, as shown in Figure 6.5.

Figure 6.5 Architecture of the integrated system

The iDal algorithm embedded in the CRAF sub-system functions to dynamically learn and to forecast customer needs of products, as demonstrated in Chapter 5. With reference to an illustration in Figure 6.6, at time T_0 , the CRAF sub-system generated a set of customer needs which is forecasted to be relevant during the targeted time of product introduction to the market, i.e. T_2 . The forecast is made Γ_0 period ahead (i.e. $T_2 = T_0 + \Gamma_0$). The sub-system generated future customer

requirement data structured in the format of Requirement Space Framework (RSF) is fed to the design logic module of the HBCD sub-system, where the CDH algorithm is embedded (see Figure 6.5). RSF, being a reduced form of the Design Space Framework (DSF) (see Section 3.4), serves as the customer needs data objects $c_i \in C$ (see definition in Section 3.4) that are engaged by the HBCD sub-system. Based on the input RSF, the CDH algorithm installed in the Design Logic Module of the HBCD sub-system facilitates system users to generate design solutions (Chong et al., 2009b); the outputs of the HBCD sub-system are design concepts, in the format of DSF, as shown in Figure 6.5. Assuming that the design concepts are generated at time T_1 , where $T_1 < T_2$, verification of the solution can be performed at time T_1 as shown in Figure 6.6.

Figure 6.6 Design and verification forecasts

As depicted in Figure 6.5, customer needs data in the format of the RSF from the CRAF sub-system along with the results produced by the HBCD sub-system in the format of the DSF are employed for solution verification. The dynamic verification will not be based on the RSF originally generated during T_0 (see Figure 6.6), but will instead be performed based on the dynamically generated RSF during T_1 . The reason being that the shorter forecast period Γ_1 (relative to Γ_0) and the application of the most recent input dataset available between T_1 and T_0 would support forecast of higher accuracy.

The Dynamic Design Verification Module in the integrated architecture may additionally serve to reflect the degree of impact the varying customer needs has on the results produced by the respective product development functions (in this case, the conceptual design tasks). For instance, the degree of impact can be evaluated by comparing the verifications based on RSF generated at T_0 and T_1 respectively. Overall in this work, solution verification using datasets dynamically generated by the CRAF sub-system serves to further address the problem of dynamic customer needs.

6.4 Addressing a conceptual design problem

In this section, an example is presented to demonstrate the application of the proposed CRAF system in addressing a conceptual design problem, based on the integrated architecture shown in Figure 6.5.

A case of bicycle conceptualization (focused on the brake design) is adopted for the illustrations in this section (Chong et al., 2009b). A detailed introduction of the case problem is provided in Appendix D. It is assumed that the product is intended for introduction to market at time T_2 (see Figure 6.6). Based on the case employed here, the RSF generated at time T_0 by the CRAF sub-system (with procedures described and implemented in Chapters 3 and 5 respectively) is assumed and shown in Figure 6.7. The representations are m_0 : ideal bicycle, m_1 : safety, m_2 : comfort, m_3 : efficiency, m_4 : ease of use, m_5 : weather-proof, m_6 : brake modulation, m_7 : light weight, and m_8 : brake force. On the basis of the future customer needs, designers generated sets of solutions with the support of the HBCD sub-system. The following paragraphs describe the events. Detailed algorithmic and mathematical processes are provided in Appendix D for reference.

Figure 6.7 The generated RSF at time T_0

Although designers are free to choose the directions of nodes propagation in design space, the CDH algorithm (embedded in the Design Logic Module) at every step supports the process by strategically recommending the directions for further exploration. The recommended nodes can be from any level of abstraction (in dimension Z), any of the design options available (in dimension Y), and any of the solution components (along dimension X) in design space D . The node recommended (by function f_2) is defined as the most fallible solution node amongst the most promising set of solution graph G_0 , which in turn is selected from all the possible solution graphs G'' (by function f_1) within G' . In the beginning of the design case, s_0^0 (as shown in Figure 6.8) was selected and presented to the designers for expansion.

Customer needs datasets generated by the CRAF sub-system and the contexts are input to the working memory (i.e. G') of the HBCD sub-system through the Design Logic Module. The contexts may be contributed by designers via the user interface (UI) layer and/or queried from the design database (i.e. knowledge reuse). Two alternative sub-solutions of s_0^0 - the rim (s_{15}^1) and disc (s_{15}^2) braking systems – were generated in this case. The design team asserted that the rim type system was more promising for its higher braking power (longer moment arm for higher resistive torque) and also for its lower weight. As such, the heuristic value of the rim braking system was expected to be relatively high. Nevertheless, according to the team's knowledge and experiences, they noted that the alternative disc type system was known to provide better brake force modulation.

Figure 6.8 DSF generated by the HBCD sub-system

Of the generated sub-solutions, designers have the options to further clarify the concept or to stop generating details of sub-solutions when they are deemed adequately detailed for this phase of design. In the latter situation, the system users would declare the generated sub-solutions as *solved*. In this design case, designers deemed that more details of the bicycle brake system should be made explicit.

Having generated the contexts, the system reasoned and prompted the designers with the advice of expanding the rim brake concept (s_{15}^1). Sets of context under solution s_{15}^1 were therefore generated. With the next level of solutions made explicit, the designers proceeded to assign them with heuristic values and 'solved' status where applicable. In this design case, the system users deemed that the idea (s_{19}^1) of using aluminum as the material to reduce the weight of the braking system did not require further detail, and was therefore labeled as 'solved'. The 'solved' status was automatically propagated upwards the graph towards s_0^0 based on the Solve-labeling

function. In case where all solution components of the current most promising graph G_0 along the exploration boundary in the design space were labeled solved, s_0^0 will automatically be declared ‘solved’ by the CDH algorithm; that would therefore mark the completion of the conceptual design process.

As the process of conceptual development progressed, the system at every step prompted the designers with support on the direction of exploration (i.e. n^*). Having further explored the concept of rim braking concept (s_{15}^1), the system advised to divert their focus away from the detailed sub-solution of the rim braking system, such as the hydraulic transmission (s_{18}^1) and V-brake design (s_{21}^1). The system suggested that the designers could alternatively explore a design idea found on a higher abstraction level. In this case, the disc braking system (s_{15}^2) was recommended to the system users for further exploration. From a design viewpoint, recommendation of the integrated system (specifically the HBCD sub-system) was due to the recognized potential in the disc-type braking system. Furthermore, upon the explication of the details of the rim-type system, the design team discovered that the modulating capability of the braking system was poorer than they had earlier assumed. That is, the exploration of design details had revealed unanticipated weakness of the concept at a finer level. This led to the decrease of MR of the rim-type system, which had attributed to prompt for design backtracking (see Appendix D for the mathematical assertions).

As facilitated by a cycle of the CDH algorithm described in the preceding paragraphs, the process of conceptual design (i.e. the expansion of graph G') continued in such a fashion, to a point where the designers deem that the design solution is adequately clear. The output of the HBCD sub-system at time T_1 (see Figure 6.6) in the format of the DSF is shown in Figure 6.8.

In dynamic solution verification, the latest forecast of the customer needs at time T_1 is employed. A method to verify the design solution against the customer needs is to adopt a table as shown in Table 6.1. The rows represent the future customer needs elements from the RSF generated by the CRAF sub-system at time T_1 ; the columns represent the sub-parts of the solution extracted from the DSF generated by the HBCD sub-system at time T_1 . Each grid of the table can be marked with ‘+’, ‘-’, or ‘0’. That is to denote whether the sub-solutions satisfy the customer needs, otherwise, or neutral, respectively. The completed table would provide the designers with a concise expression of the degree of satisfaction the design solutions could provide to

the targeted customers, with respect to the individual customer requirements. The scores are summed up in the column on the right hand side of the table, where the positive scores show that the generated conceptual solution is in general able to satisfy the future customer needs. (*Note that three of the customer requirements shown in Table 6.1 are excluded in the case study, as described in Appendix D*).

Table 6.1 Solution verification table

	s_{15}^1	s_{16}^1	s_{17}^1	s_{18}^1	s_{19}^1	s_{20}^1	s_{21}^1	Total
m₁	+	+	+	+	+	+	+	7
m₅	0	+	+	0	0	0	0	2
m₆	-	+	+	+	0	0	0	2
m₇	+	+	-	-	+	+	-	1
m₈	+	+	-	+	0	0	+	3

While the dynamic verification process can be conducted manually by designers when the design problem is small, the process will be more demanding in cases of complex problems. Computational support for the dynamic verification task would be technically viable due to the common structures of the two data sources - RSF and DSF (recall that both RSF and DSF are mathematical graphs, and that the former is a reduced form of the latter). In further research and development of technologies in this area of work, graph-based operation methodologies based on graph theory can potentially computerize the process of dynamic solution verification.

6.5 Summary

The CDH algorithm embedded in the integrated system facilitated designers in navigating and managing the typically large spaces of design, which otherwise can be unsystematic and therefore less efficient when performed without aid. The study has shown the advantages of using DSF (formalized in Section 3.4), in contrast to other information models such as the well-known quality function deployment (QFD). The advantages of DSF can be attributed to the multi-level structure, and the representations of the considered but unemployed design sub-solutions. As a whole, the DSF data structure is robust in modeling complicated design information and the rationales of their existences. The characteristics and merits of the DSF are inherited

by the RSF, which is the customer need information model adopted in the proposed CRAF system.

Like other CAD systems and design methodologies, the HBCD system is limited in addressing the issue of dynamic customer needs (as highlighted in Sections 1.1 and 2.3). The common problem is that the existing methodologies do not consider the variation of customer needs across time (as reviewed in Section 2.1.5). To address the issue, this research proposed a CRAF system that aims to dynamically and autonomously learn the dynamism of customer needs. In this chapter, the approach by which the CRAF system can integrate with systems of downstream processes to address the problem of dynamic customer needs is demonstrated. The case presented in this chapter is based on the HBCD system. Figure 6.5 shows an architecture that integrates the CRAF and HBCD systems, as well as the exchanges of the data within. Section 6.4 demonstrated the application of the RSF data generated by the CRAF sub-system, in the process of design conceptualization work. In the dynamic verification of solution, the set of latest available future customer requirements (i.e. RSF) generated by the CRAF sub-system is tabled against the multi-level sub-solutions (i.e. DSF) derived by the HBCD sub-system. In effect, the CRAF sub-system provides the basis for both generating and verifying conceptual design solutions that are valid in satisfying customer needs at the time of product introduction, i.e., addressing the issue of dynamic customer needs.

In the paradigm of customer-oriented product development, phases in the development cycle take references from the needs of customers (Chong et al., 2009a). It is therefore expected that the literature has well-documented the implications of dynamic customer needs on functions such as design, manufacturing, marketing, and R&D (see Section 2.1.3). Accordingly, it is anticipated that the functions of the proposed CRAF system can, in the same approach demonstrated in this study, be applicable and beneficial to generating and dynamically verifying solutions in the scope of the product development activities.

Chapter 7 - Conclusion and Future Work

Rapidly evolving needs of customers represent the key drivers of market turbulence (Blocker and Flint, 2007). In a volatile market, strategic management based on (qualitative and quantitative) information of the market dynamism is an important basis of competitive advantage; management may apply the information to support decision-making processes, in a bid to minimize the uncertainty of success that is inherent in product development projects. Research in the dynamism of customer needs is therefore critical to producing solutions that can address the increasingly fast moving business environment. In the light of the problem, the emergence of the Internet as a solution facility indicates the potential of addressing the issue computationally. The objective of the research is to advance the body of knowledge that supports the computational approach of addressing the issue of dynamic customer needs¹.

Having introduced the position of the present research in the first chapter, stages of this work ranging from literature review to the application studies are documented from Chapters 2 to 6. Based on the discussions in the summary sections of the chapters, the conclusions arrived are summarized in Section 7.1. The limitations and the avenues of advancing the research are presented in Section 7.2

7.1 Conclusions

This research contributes to the body of knowledge in the area of product development by addressing the problem of dynamic customer needs; apart from that, the work has gained research mileage in the field of computational intelligence, specifically in the

¹ The issue of dynamic customer needs is expressed in Section 1.1.

AIS research. With respect to the discussions presented from Chapters 2 to 6, this section highlights the outcomes of the research that are original.

State of the art literature reviews

A review of the state of the art solutions and technologies that address the issue of dynamic customer needs was performed (Chong and Chen, 2010a). The literature review can be applied as a basis of future research that has interest in the dynamism of customer needs. A separate review of patents with regards to design technologies was also conducted (Chen et al., 2007). The review uncovered the concerns in the product development industry and highlighted efforts in addressing the practical problem of changing customer needs.

A robust customer requirement model – Requirement Space Framework

The robustness of models in representing information is a key premise in effective applications of the data. Literature review of this work identified the limitations of previous research and established that: (i) the qualitative and quantitative aspects, (ii) the alternatives and co-requirements, and (iii) the multiple abstraction levels of customer needs information should be modeled. In the investigations reported in Chapters 4 and 5, the Requirement Space Framework model was shown to satisfy the requirements and to robustly model customer requirement information (Chong and Chen, 2005; Chong and Chen, 2006; Chong et al., 2009a).

A dynamic architecture for handling changing customer needs

As reviewed in Chapter 2, customer needs data has traditionally been poorly represented in the temporal domain; typically, the information has been recorded in discrete points of time, with simple or no cross-reference made to time. In fast changing markets, sets of customer need information that are not tagged with temporal information can be misleading, if not inapplicable. The shortcoming of the currently available methodologies would therefore be detrimental to product developers if the customer requirements of their products are volatile.

This study proposed a prototype CRAF system based on the iDal (immunity-based dynamic and autonomous learning) technique. Chapter 4 illustrated the details of the dynamic CRAF system in rendering the parameters of analysis as time-based variables (see Figures 4.6 and 4.7); the result was forecasts with higher

accuracy, relative to static characterizations. In Chapter 5, the looping iDal algorithm implemented on the MATLAB platform (documented in Appendix C) demonstrated the ability of the system to dynamically generate solutions in the temporal dimension. By virtue of the dynamic framework, the CRAF system is applicable to intake streaming data, to learn the dynamism, and to generate continuous outputs for further downstream applications. The system is in contrast with traditional methodologies that treat singular temporal data in discrete approaches. Clearly, traditional methodologies are less suited for application in fast shifting markets. In this light, this research is a step forward in addressing the issue of dynamic customer needs (Chong and Chen, 2009; Chong and Chen, 2010b).

An autonomic learning mechanism for evolving environments

Changes in the importance of individual requirements along timeline are a common phenomenon. Further, new customer requirements can surface, while existing ones can fade as time passes. As reviewed in Chapter 2, existing methodologies proposed for customer needs analysis have a common limitation, i.e. human interventions are required to ensure that lists of customer needs are up to date and therefore applicable; users of the methodologies were known to manually learn and update sets of customer needs at regular intervals.

In the light of the increasingly fast moving market, an autonomic solution becomes necessary for product developers. In this work, the iDal technique was developed and applied in the CRAF system to independently learn customer requirement information, in the process of co-evolving with dynamic product markets. The system was demonstrated to train itself with input data of both the qualitative and quantitative aspects; as a result, the system possesses the ability to learn new customer needs, to discern the relative importance among customer requirements, and to distinguish between applicable (current) and inapplicable (premature or obsolete) customer needs (Chong and Chen, 2009; Chong and Chen, 2010b).

A customer requirement forecasting technique

Being sensitive to shifting customer requirements is a basic reactive strategy where volatile market is concerned. As an effective secondary strategy, (near) real-time data should be applied to forecast for future customer requirements. Forecasting reduces

uncertainty by providing figures that management can employ to manage risks and to support decisions.

This research proposed a technique that performs forecast of customer requirement with trend models not known in prior (including non-linear types). The forecast ability of the CRAF system demonstrated in Chapter 5 can be characterized as universal approximation (Park and Sandberg, 1991) - the ability to describe functions without the assumption of models in prior. The CRAF system was shown to generate forecasts of improving accuracies over the period (see Figure 5.8), reflecting the processes of machine learning over time. In general, the system learns the dynamics of pattern evolution to perform data forecast. Unlike previous research in the dynamism of customer needs, the CRAF system possesses the ability of universal approximators that can handle non-linear (and linear) problems (Chong and Chen, 2009; Chong and Chen, 2010b).

Application of the dynamic customer needs information on a downstream problem

Apart from studying the problem of dynamic customer needs, this research investigated both the implications of the problem as well as the application of the solution.

The problem of dynamic customer requirements bears implications on the functions of product development organizations, such as design, marketing, manufacturing and R&D (see Section 2.1.3 and Table 2.1). These implicated secondary problems form a sizable set of research problems (Chong and Chen, 2010a). As the set of problems can be approached via the investigation of the dynamism of customer needs (i.e. the root of the respective problems), the results of the present research can potentially be applied to the vast areas.

In the applications of dynamic customer needs information (as reviewed in Section 2.1.5), there has been previous research that assumed the availability of future customer needs data, in the respective bids to solve a range of research problems (McLaughlin and Stratman, 1997; Raharjo et al., 2006). The research documented in this thesis can therefore be instrumental in filling the gaps of such investigations. It is noted that such application research to date has been focused almost exclusively on supporting manufacturing (e.g. Adiano and Roth, 1994; Griffin and Hauser, 1992). Previous researchers have identified problems in the design of products that are due to

the dynamism of customer needs (Peeples and Boulton, 1995; Kärkkäinen and Elfvingren, 2001; 2002). In this light, an application of the CRAF system on a design problem was investigated as a part of this research.

Common to other systems and methodologies in product development phases, the proposed computer-aided conceptual design system (i.e. HBCD system) does not consider the variation of customer needs across time (Chong and Chen, 2010a; Chong et al., 2005; Chong et al., 2009b). To address the issue of the dynamic needs, the CRAF system is integrated to the HBCD system. For validation of the solutions produced, a dynamic verification methodology was proposed. As reported in Chapter 6, design solutions were generated and verified based on the sequential data generated by the integrated system. The study shows an application of dynamic customer needs information in generating design concepts, where the concepts were aimed to meet the needs of the market at the time of product introduction. In the words of Kusiak and Smith (2007), *better balance between customer needs and organization resources can bring about increase in overall profitability* – the basic motivation of this research.

Novel concepts in the research of AIS

The iDal technique is specified based on the AIS paradigm (de Castro and Timmis, 2002). In the definition of the technique, two novel concepts from the science of immunology were used to advance the AIS research.

- 1) While knowledge on the dynamism of antibody concentration (see Figure 3.4) has been considered important in the field of immunology, the dimension has not been referred to and applied in the studies of AIS. This research exploits useful information that can be extracted from the temporal dimension of B-cell concentration levels (which has been a common procedure performed in immunological studies (see Section 3.3.1 and Appendix A)). In this work, the information is found useful for the continuous characterization of the variables of interest over time domain (Chong and Chen, 2010b). Based on the continuous time-based datasets, forecast of variables can therefore be performed².

² Note that Nasraoui et al. (2008) recently proposed a novel dynamic algorithm that functions to learn web-users' profiles over time. The method is however limited to perform only discrete temporal characterization of profiles, i.e. the dichotomy of activeness status. As the method does not function to characterize continuous variables over the temporal dimension, quantitative forecasting functions are not applicable in the work.

- 2) *Specificity index* (SI) was devised in the studies of immunology (Cohn, 2005; Langman, 2000) to characterize cells' abilities to discern self from non-self. SI of zero denotes B-cells as universal glue, while SI of value one denotes infinite specificity. Customer needs information, like many other classes of information, can be represented in terms of abstraction levels. This work adopts the concept of SI to allow information (in this case customer needs) represented in the AIS (as B-cells and antigens) to be defined by a spectrum of abstraction levels. As a result, multi-tier structured information can be operated upon by the range of established AIS methodologies. More specifically, the notion of B-cells generality (describable by SI) that originally facilitates the discourses in biological pattern recognition is shown in this work to be applicable in the AIS paradigm to support information representation, recognition and therefore operations (Chong and Chen, 2010b).

Investigation of AIS in niche application

"To justify the usage of the AIS in any work, there should be clear benefits of using the AIS technology, which cannot be arrived at through other techniques", remarked Hart and Timmis (2008).

To move forward, AIS should be repositioned, developed and driven into niche areas, as suggested by the respective AIS proponents (Hart and Timmis, 2005; Aickelin and Dasgupa, 2005). Timmis (2006) pointed to the direction of looking for niche application of the AIS, where the benefits of adopting the AIS would be clear (see Section 2.2.7). As reviewed in Section 2.2.6, three of the advantages of AIS that are unique among the computational intelligence paradigms are as follows.

- 1) *The population as solution*. Aickelin and Dasgupa (2005) remarked that AIS are powerful when a population of solution is essential, in contrast to problems that require optimizations for single solutions. In the problem of dynamic customer requirements, a population of (instead of a single) B-cells as solutions (i.e. requirements) is relevant.
- 2) *The architecture for dynamic analysis of time-series data*. Proponents regard AIS as a tool that should be deployed in a dynamic environment in order to realize its potential (Aickelin and Dasgupa, 2005; Hart and Timmis, 2005).
- 3) *The mechanism for continuous learning/adaptation by autonomously co-evolving with the environment*. Hart and Timmis (2005; 2008) advocated the

application of AIS to problems that require continuous learning capability, as a way forward for the research area.

As the problem of dynamic customer needs (Chong and Chen, 2010a) aptly takes advantage of the above listed AIS unique capabilities (Chong and Chen, 2010b), this study possesses potential values to the research in AIS.

7.2 Limitations and future work

In this study, the iDal technique is developed with the aim of addressing the problem of dynamic customer needs. The iDal technique described in Section 3.3 is nonetheless a generic AIS method that can potentially be applied to a wide range of dynamic problems (see Section 2.2.7). The technique has however not been experimented and studied with respect to other problems (e.g. website users' profiling). The studies of immunology as part of this research include the functions of the immune system, cellular pattern recognition, and the dynamism of antibody concentration (as summarized in Appendix A); these studies were imperative in the advancement and deployment of the AIS theories. However, the scopes of investigations were limited to areas where solutions to the research problem (i.e. the dynamism of customer needs) can be found. As such, further research in immunology to address other problems can potentially further advances the paradigm of AIS. The dynamism of customer needs has impact on product development functions such as marketing, design and manufacturing (as reviewed in Section 2.1.3). This research is limited to investigating the application of the dynamic customer needs information in product concept development.

Research in the dynamism of customer needs is anticipated to grow due to the increasingly volatile markets (Raharjo et al., 2006). As the research problems identified in the literature review are fundamental to the issue of dynamic customer needs (Chong and Chen, 2010a), the results of this research (as concluded in Section 7.1) may serve as references and foundations for future studies. Five areas of future research are as listed below.

- 1) *Further theoretical development in AIS research.* The methodology of AIS has been identified by the research community as a unique machine learning technique for addressing temporal dynamic problems. Proponents have advocated future AIS research, especially on the level of theory development,

to work towards the niche area (see Sections 2.2.6 and 2.2.7). Accordingly, this work extended the theory of AIS in two ways (as described in Section 7.1), in the bid to address a dynamic problem. As future work, firstly, the extended theory can be specified and experimented to address a range of dynamic problems, other than the dynamic customer needs problem; for instance, the dynamic profiling of website users over the Internet. Secondly, at the current preliminary stage of the AIS research, the science of immunology should be further studied for applications in the AIS paradigm. These future investigations can be means to increase the robustness of the proposed theories, and to develop the overall AIS paradigm. By taking this prescribed direction of research, proponents envision that the AIS paradigm will be valuable for its unique usefulness.

- 2) *Product development companies as test bed.* This research can be advanced by putting various propositions (e.g. the iDal technique and Requirement Space Framework) to test in product development companies. In this line of inquiry, the prototype CRAF system should be further developed. Stakeholders of the companies can support to evaluate the usability, applicability, and efficacy of the system. Findings in the engineering and practical aspects can be used to support theoretical advancement in this area of research.
- 3) *Implications and applications of dynamic needs on product development functions.* Previous research has assumed the presence of future customer needs information in their proposed methodologies for R&D, design and manufacturing (McLaughlin and Stratman, 1997; Raharjo et al., 2006). These studies have however not clarified the derivation and the format of the dynamic customer needs data. The present research investigated the role of dynamic customer needs in one of the product development function - conceptual design. To this end, the implications and applications of the dynamic customer needs data on other phases of product development cycle (e.g. R&D and manufacturing) can be subjects of future studies.
- 4) *Dynamic verification.* Upon the applications of the dynamic customer needs data in phases of product development cycle (with examples given in the preceding point), solution verifications can be dynamically performed. Figure 7.1 shows the diminishing periods of forecast from Γ_1 to Γ_D , i.e. the respective periods from the time of verification (i.e. T_1 to T_D) to the time of product

introduction (i.e. T_M). Dynamic verification, a concept proposed in this research, facilitates the sensitivity of product development work to the dynamism of market needs. Along with the research topics recommended in the preceding point, the techniques of dynamic solution verification can be a component of the studies.

Figure 7.1 The diminishing forecast periods for verification

- 5) *Resource planning.* Customer requirement information is pivotal in resource planning of product development companies and supply chains (Reichwald et al., 2005; Kusiak and Smith, 2007). Future research may look into the applications of the dynamic data in the studies of resource allocation. For instance, on an implementation level, the dynamic analysis of customer needs data in enterprise resource planning (ERP) and manufacturing resource planning (MRP II) programs may be investigated.

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Appendix A – A Review of Immunology

A.1 The history of immunology

The science of immunology is relatively new. It originated from Edward Jenner who discovered the technique of vaccination in 1796 (Timmis, 2002). At that time, the mechanism of immune system was not known. In the 19th century, Robert Koch proved that pathogenic microorganism caused infectious diseases. Since then, various forms of diseases are countered by vaccinations discovered by a group of scientists. A landmark event is the design of a vaccine against chickenpox by Louis Pasteur in the 1880s. The mechanisms of vaccines on human body were not well understood until Emil von Behring and Shibasaburo Kitasato in 1890 demonstrated that protecting elements appeared in blood serum of inoculated individuals. These elements are agents – later named antibodies – that binds to other infectious agents. Emil von Behring received, in 1901, the first Nobel Prize in Medicine for his work on antibody production.

Elie Metchnikoff in 1882 demonstrated the presence of phagocytes, and suggested it as the main mechanism in the immune system. He further regarded antibodies as of little importance. This treatment was corrected when Almroth Wright and Joseph Denys showed in 1904 that antibodies were capable of binding with bacteria and promoted their elimination by phagocytes.

In the 1890s, Paul Ehrlich postulated the side-chain theory. He stated that surfaces of white blood cells are covered with side-chain, or receptors. These receptors form chemical links with the antigens encountered. It was shown that antibodies increase dramatically in numbers after exposure and binding with a given antigen. It was further shown that the receptors of white blood cells, such as B-cells, were instrumental in the selection and stimulation of the cells. Ehrlich and Metchnikoff shared the Nobel Prize in 1908.

The selectivist theory of Ehrlich was largely abandoned for the first half of the 20th century. This period saw the prominent work of Jules Bordet, Karl Landsteiner, Anton Breinl, Felix Haurowitz and Linus Pauling. Bordet received the 1919 Nobel Prize for the discovery of the complement system that participated in the attack of extra cellular pathogenic agents. Karl Landsteiner, who received the 1930 Nobel Prize for the identification of different blood type, made blood transfusion possible. During this period, the theory of template instruction was pioneered by Breinl and Haurowitz, and later defended by Nobel Prize winner Linus Pauling. This theory conflicted with Ehrlich's selective theory in the structure and formation of antibodies. Ehrlich suggested that different antibodies are constructed from a collection of genes, which are the subjects of selection for proliferation. On the other hand, Pauling theorized that all antibodies possess the same amino acid sequences, and synthesis involves the use of specific information provided by the encountered antigens.

The selective theories were revived in the early 1950s. Niels K. Jerne assumed that a diverse population of antibodies is circulated in human body, even without the intervention of antigens. And selection is based on the matching between antigens and antibodies. Frank M. Burnet formalized the clonal selection theory in 1959. He assumed that antibodies are randomly generated to create the diversity in our body. Stimulus given by antigens to the matched antibodies is responsible for the selection, secretion and proliferation of the antibodies. Peter Brian Medawar experimentally confirms Burnet's theory. Studies on how body reacts to pathogenic agents and how self-antigens are being tolerated resulted in a 1960 Nobel Prize for both Medawar and Burnet.

Jerne, in the 1970s, worked towards the immune network theory, which led to the award of the Nobel Prize in the 1984. More recently, the structure and diversity of antibody molecules is formalized by Susumo Tonegawa (1983). This work of Tonegawa gave him another immunology-related Nobel Prize in 1984.

To be able to better grasp and control the adaptive immune system is seen as one of the keys to battle certain virus such as the human immunodeficiency virus (HIV). Although the scientific development of immunology is seen as a pathway to improve our survival rate against diseases, it has also injected vitality into the field of computational intelligence. The association of these two fields is addressed in the next section

A.2 A review of immunological science

Immunology is the study of immune system and its responses to invading pathogens. Research in immunology has almost exclusively studied the vertebrate immune system. Concepts established and applied by immunologists are of interest to this study, as the basis of the work. They can be theories, models and/or empirically supported observations. Some of them, such as Jerne's Immune Network Theory (Jerne, 1974), have been controversial in the community. In fact, immunologists are till this day in disagreement on numerous theories (Langman and Cohn, 1986). It is however not an interest of this work to account for the validity of the immunological concepts. It is nor the interest in this work to extend the body of immunological knowledge.

The topics of review here is based on it relevancy to the work of this research (overview of the immune system can be found in textbooks, such as Kubi (2002)). As in many disciplines, the research of immunology is on-going, and many fronts of this inquiry still carry unanswered questions and hypotheses. Nonetheless, this section is devoted to review certain immunological facts and theories, with focus on ones that are the basis to this study.

A.2.1 The elements of immune system

The collection of cells, tissues, and molecules that mediate resistance to infections is called the immune system, and the coordinated reaction of these cells and molecules to the infectious pathogens is termed as immune response.

Our body defense system is in the form a layered architecture (see Figure A.1). The first layer is our skin. This layer acts as a physical barrier to protect us from disease causing microorganism, or pathogens - bacteria, virus, parasites and fungi. The second layer is the so-called biochemical barrier. For instance, fluid such as saliva and sweat contains destructive enzymes. The last two layers are the innate and adaptive immune systems, which is the focus of this work. Innate immune system is 'inborn', and it remains constant throughout lifetime. The final line of defense is the adaptive immune system. This system learns and memorizes the history of pathogenic invasion, so that it can swiftly and precisely eradicate the foreign pathogens. As such, the adaptive immune system constantly evolves to reflect the dynamic antigenic universe it

resides in. The two systems are further described in Sections A.2.3 and A.2.4 respectively.

Figure A.1 The layered architecture of human immune system

White blood cells or the leucocytes mediate both innate and adaptive immune systems. The specific agents mediating the innate immune system include granulocytes and macrophages (See Figure A.2). The former constitutes a special group of leucocytes with multilobule nuclei containing enzymes. These cells are instrumental in the innate immune system, for instance, eosinophils is capable of defending against parasites. Macrophage is another type of leucocytes that ingest and digest certain microorganism, i.e. a phagocyte type. Antigen-presenting cells (APC), is a class of agent, such as macrophages, that present antigens to other cells based on the pathogens they have digested.

Figure A.2 Immune lines of defense and their respective main mediators (de Castro and Timmis, 2002)

The adaptive immune system relies on a group of leukocytes to recognize and eliminate pathogenic agents. Two classes of these cells are B lymphocytes (B-cells) and T lymphocytes (T-cells). They are present only in vertebrate immune system. Their names originated from the organs where they differentiated – bone marrow and thymus respectively. Two sub-class of adaptive (and innate) immune system are the humoral and cellular systems. B-cells are responsible in releasing antibodies that opsonize foreign antigenic agent. Each B-cell can only produce one particular antibody. The general term used to describe the humors-mediated immune activity, primarily via the actions of antibody, is humoral immunity. On the other hand, there are three types of T-cells, namely the killer T-cells, the helper T-cells and the suppressor T-cells. The first kind is able to destroy virus-infected cells by injecting destructive chemical. The second type sends signals (cytokines) chemically upon recognition of proteins presented by APC. For the third kind, it inhibits the action of other immune cells thus preventing allergic reactions and autoimmune diseases. These T-cells are the agents of the cellular immunity.

There are numerous lymphoid organs (see Figure A.3) distributed throughout the body that make up the immune system. Primary lymphoid, i.e. bone marrow and thymus, are responsible for the production and maturation of lymphocytes. While secondary lymphoid organs are where the lymphocytes interacts with antigenic stimuli. Some examples are spleen, tonsil and the lymphatic vessels that run throughout the body.

Figure A.3 Physiology of the immune system (<http://healthcare.utah.edu/>)

A.2.2 The pattern recognition system of the immune system

The recognition of pathogens by the lymphocytes is based on the protein-based complementarity of the two agents. Both B-cells and T-cells have highly specific receptors on their surfaces, which identifies their respective cognate antigens. B-cell receptor (BCR) on B-cells and T-cells (TCR) on T-cells are the sensors that recognize the microorganisms (See Figure A.4). The signatures on the microorganisms can be expressed as antigen (Ag), which is a general term that points to any entity that can be recognised by the lymphocytes. BCR interacts with antigenic molecules free in solution while TCR recognizes antigens processed and bound to a surface molecule called major histocompatibility complex (MHC), as seen in Figure A.4 (labeled II and III). Upon recognition, the B-cells and T-cells will be activated. Though each lymphocyte has a specific type of receptor, a pathogen can have numerous types of epitopes. Consequently, a pathogen can attract more than a type of lymphocytes. The recognition process and functions of the T-cells will receive less coverage than the B-cells in this review. This is due to that the relevancy of B-cells in this study is higher. The events subsequent to the lymphocyte activation will be described in the sections of

adaptive and innate immune responses below (Sections A.2.3 and A.2.4). This section describes the pattern recognition between an antigen and an antibody, leading to the activation of the antigen.

Figure A.4 Simplified view of the immune recognition and activation mechanisms (de Castro and Timmis, 2002)

The B-cell receptor

Figure A.5 show a schematic construction of a BCR and a TCR. The review here will focus only on the BCR, which is most widely modeled in immunity-based computational systems. A BCR is in fact an antibody (Ab), or so-called immunoglobulin (Ig). It is bounded to the cell membrane, to be secreted upon cell activation. Made up of two pairs of proteins, the heavy chain and the light chain, it is mono-specific to a B-cell. It has two regions: the antigen binding region (Fab) and the tail (Fc) region. The Fab region that looks like a pair of hands is responsible for binding to antigens, while the Fc region is meant to bind to surface of cells such as macrophages.

Figure A.5 Lymphocytes and their surface receptor molecules (a) B-cell receptor (BCR) or antibody. (b) T-cell receptor (TCR) (De Castro and Timmis, 2003)

Immunologist estimated that 100 million types of Ab are needed to recognize all types of antigens (Sompayrac, 2003). Since an Ab is made up of a light chain and a heavy chain, 10,000 of each can be permuted to give 100 million types. However, given that human cells have only 40,000 genes in all, Sompayrac (2003) noted the problem of having half of that just for making Ab. Susumu Tonegawa (1983) tested his hypothesis that all B-cells started out the same, and matures into a wide diversity of possibly up to 100 million kinds. He was awarded a Nobel Prize as mentioned in the section above. In every B-cell, on the chromosomes that encode the Ab heavy chain, there are multiple copies of four types of DNA modules (gene segments) called V, D, J and C (See Figure A.6). In human gene library, there are about 50 different V segments, about 20 different D segments, 6 different J segments and about 10 C segments. B-cells randomly choose each of the four DNA modules to concatenate a heavy chain of the B-cell. Apart from such recombination of gene segments, high rate of genetic mutation (so-called somatic hypermutation) during clonal selection, too, contribute to millions of Ab types for diversity. The gene library and the concatenation of DNA sequences are two common metaphors applied in computational immunity system.

Figure A.6 DNA sequencing of B-cells

Affinity

Affinity is a measurement that reflects the strength of binding between two binding sites, such as a cell receptor and an epitope. Commonly used is the term Ag-Ab (antigen-antibody) affinity. Biologically, it is the bondage of complicated folded molecule. The interactions between the two protein-based surfaces of Ag and Ab can be explained by short-range non-covalent interactions based in electrostatic charge, hydrogen binding, van der Waals interaction etc. High affinity of certain degree will lead to the activation of the lymphocytes (coupled with cytokine signal). When adequate BCR of a B-cell cluster in an area to bind with epitopes on an antigen, the nucleus of the B-cells will be signaled for activation. Therefore, the degree of affinity (i.e. the degree of clustering) is a key to trip the release of the antibodies on the B-cells. An evolutionary process of somatic hypermutation is vital in increasing the Ag-Ab affinity. This evolution mechanism will be described in a later section.

The dual-signal requirement for cellular activation

The activation of naive B-cells requires a secondary signal, besides the clustering (or cross-linking) of the BCR (see Figure A.4 (IV)). This co-stimulatory signal is provided by the helper T-cells or the innate immune system. The signal is in the form of protein called cytokines. Lymphokines is cytokine secreted by lymphocytes such as T-cell. BCR clustering without the presence of co-stimulatory can result in the cell death – or anergy – of the B-cell. This type of dual-signal requirement helps to ensure that the destructive actions of the lymphocytes are not erroneously initiated.

A.2.3 The innate immune system

All multicellular organisms, including plants, invertebrate, and invertebrates, possess this intrinsic immune system. It is called 'innate' as it is within us since birth. The constituents and functions remain constant throughout the lifetime of an individual.

The three major interfaces between the external environment and our body are the skin, gastrointestinal tract, and the respiratory tract. Pathogens that breach these epithelial physical barriers and the biochemical system that lines them (see Figure A.1) are greeted by the innate immune system. Some immunologists consider the epithelial barrier as part of the innate immune system, while some do not.

Mediators of the innate immune system, macrophages and neutrophils, have surface receptors (called pattern recognition receptor or PRR) that recognize molecular patterns found only in pathogenic cells (called pathogen associated molecular patterns or PAMP). In this manner, the white blood cells are able to distinguish self-antigens to antigens that invade the body. Upon recognition, the involved leucocytes are activated to engulf and digest the pathogens. Cytokine is released during the process. A role of cytokine is to signal to the adaptive immune system informing the presence of the specific pathogen. Another function of cytokines in this case is the support of the inflammatory response - white blood cells are recruited to the site of infection. A rise in body temperature (i.e. fever), which is believed to be unfavorable to the activity of pathogens, is also activated by the protein-based signal.

The innate immune system performs a crucial role in the process of initiating and controlling of the adaptive immune system. It can control and eradicate the pathogens without having adaptive immune system activated. Innate immune system communicates with its co-system by sending signals (i.e. cytokines). In fact, bi-directional cross-talk happens between the two immune sub-systems. Innate immune system sends cytokines as second signal to activate B-cells of the adaptive system (as described in the previous section). These signals are called co-stimulator. A focus of the innate immune system, in terms of its role to initiate the adaptive immune system, is that its macrophages extract pathogenic information via MHC molecules to be presented to the T-cells of the adaptive immune system. These actions of the innate immune system exemplify its role in signaling and coordinating with the adaptive immune system, at the front line of defense.

A.2.4 The adaptive immune system

Vertebrate immune response has the functions to control and eradicate pathogens. More notably, the adaptive immune system has the ability to *learn*, *adapt* and *preempt* the future requirements of the defense system. Consequently, the defend strategy is both to cure and to prevent. Adaptive or acquired immunity, allows the immune system to launch an attack against any invader that the innate system cannot remove (Janeway and Travers, 1997). Further, innate (non-specific) immunity and adaptive (specific) immunity are inter-linked and influence each other (Abbas and Lichtman, 2000). They communicate via the schemes of immune diffusion (one-way) and immune dialogue (two-way). It is these exceptional characteristics that render vertebrates more effective in resisting infectious microorganisms. (Note that it is mostly the outstanding properties of the adaptive immune system, instead of the innate system, that proponents of computational intelligence have sought to employ.)

The adaptive immune system of organisms and individuals differ widely in terms of the memory. The memory status is defined by the repertoire of lymphocytes found within each individual body, according to the clonal selection theory (Burnet, 1959). The make-up of the repertoire is in turn based on the past immunity experiences or learning of each individual. And thus the term ‘memory’ is adopted for this context. The two classes of lymphocyte are B-cells and T-cells, as introduced above. (The review in this section is based on Burnet’s (1959) clonal selection theory, the widely accepted theory till date. An alternative definition of immune memory by Jerne (1974) will be separately discussed in an on-coming section.)

B-cells are the mediator of humoral immunity, also known as antibody mediated immune response. As described in Section A.2.2 above, B-cells are able to recognize specific antigen with their BCR (Figure A.4 – (V)). When the Ag-Ab affinity reaches certain threshold of clustering (which tolerates cross-reactivity), coupled with co-stimulation (Figure A.4 – (IV)), B-cells will be activated. Subsequently, the B-cell would proliferate (i.e. clone) and differentiate into plasma cells that secrete antibody molecules in high volume (See Figure A.4, VI). These Ab act on their targeted pathogens (Figure A.4 – (VII)) in several manners (de Castro and Timmis, 2002): (1) neutralization: the binding inhibits the toxicity of the pathogens, (2) opsonization: the Fc region of the BCRs (i.e. the soluble Ab) bounded to the pathogens stimulates the entrapment and digestion of phagocytes, and (3) complement

activation: the Ab activate the promotion of opsonization and cleavage of bacteria via the complement system (this system is not included in the scope of review here.). Some of the activated B-cells differentiate into memory cells. These cells remain to circulate in the lymphatic system, defining part of the immunity memory. When, in the future, the memory cells detect the same or similar types of antigens, adaptive immune system readily releases a relatively large quantity of the specific antibody to suppress the pathogens.

Immunity can be induced in an individual through infection or vaccination. In infection, the antigens of the pathogens invade the vertebrate's body system, and they are memorized by the adaptive immune system. This individual is said to be 'immune' to that pathogen type. In vaccination, attenuated or inactivated pathogens are voluntarily introduced to an individual's body as an immunization procedure.

Figure A.7 illustrates the two distinct properties of the adaptive immune system. They are the *specificity* and *memory* properties. The rise in concentration of an antibody type is a response of the adaptive immune system upon the detection of a pathogen. In Figure A.7, the concentration increases across time when antigens are introduced to a body system. A primary response is the first time the lymphocyte, which is naïve, encounter an antigen that match or closely match its receptors. Between primary and secondary response, lymphocytes undergo a process called affinity maturation. Basically, in this process, the receptors get mutated (genetically modified). Subsequent encounter with the antigen lead to responses, called secondary responses, that are usually faster and larger, and with improved effectiveness due to the affinity maturation process. This demonstrates the memory property of the adaptive immune system.

The second main property is the specificity. Introducing Ag_2 subsequent to Ag_1 does not induce a secondary response. This is because that the lymphocytes that recognized Ag_1 will not pick up Ag_2 , which is different. Having mentioned the specificity, it should be noted that the system tolerates cross-reaction. If Ag'_1 is similar to Ag_1 , introducing Ag'_1 subsequent to Ag_1 will result in cross-reactive response. The effect of this cross-reactive response will theoretically be weaker than the response to Ag_1 itself.

Figure A.7 The specificity and memory in adaptive immunity, illustrated by primary and secondary responses (de Castro and Timmis, 2002)

As related in the history of immunology (Section A.1), Burnet formalized the clonal expansion hypothesis in 1959. This is the most accepted theory till date, which explains most parts of the adaptive immune system. Textbooks on immunology generally use this theory to elucidate the adaptive immune system. This theory's implication to immune learning and memory is highly significant to this study. Jerne (1974) proposed another set of theory that has significant impact on computational intelligence research community in the recent years, called the immune network theory. The contribution of this theory in the CI field is high, despite of its highly debated validity from the immunology perspective. Both of these theories will be reviewed in the following sections.

A.2.5 The clonal selection principle

The clonal selection principle is proposed by Burnet (1959) to describe the basic functions and properties of the adaptive immune system. The general description of the adaptive immune system in the previous section is based on this theory. Burnet hypothesized that only lymphocytes that recognize antigenic stimulus get selected for proliferation (See Figure A.8). The rapidly cloning cells differentiate into plasma cells that secrete antibodies to bind to the type of antigen, or the like, that originally stimulated the lymphocyte activation. Simultaneously, the dividing cells undergo a

mutation process (i.e. somatic hypermutation) where cells with better quality (higher affinity to the target antigen) than the parent cell may be resulted. The high affinity cells are further selected and differentiate into memory cells. Mutated cells of low affinity as well as any cell that are reactive to self-antigen are clonally deleted through apoptosis. Apoptosis is ‘programmed cell-death’, an important process that supports the metadynamics of the system. The differentiated memory cells will circulate in the lymphatic system, awaiting the appearance of the relatively specific antigen that they are cloned to combat. Upon such reappearance, the memory cells differentiate into plasma cells that release a large number of antibodies. The principles of selection and genetic mutation underlie the clonal selection theory, which explains the evolutionary and adaptive characteristics exhibited by the adaptive immune system.

Figure A.8 The clonal selection principle (de Castro and Timmis, 2002)

It is clear that the types and sizes of the lymphocyte sub-populations define the memory of the immune system, under Burnet's clonal selection theory. The overall population size must be finite. Therefore, an increase of certain lymphocyte type (i.e. memorize) could be accompanied by a reduction of other lymphocyte type (i.e. forgetting). There are some regulations, as remarked by Perelson and Weisbuch (1997).

Repeated encounters of the same antigen send progressive signals to the immune system on the need for the specific lymphocytes. These acts constitute a reinforcement learning strategy. The system continuously senses and learns the dynamically changing antigenic environment, adapting the composition of its repertoire of lymphocytes to best defend the vertebrate from pathogens. From the system's decision to retain memory cells, one can say that it is biased towards the possibility that those are the cells needed in the future. It is thus a conjecture of this work that the rate of proliferation is *not random* (further elaborated in Chapter 3).

A.2.6 The immune network theory

The learning and memory phenomena of the immune system were alternatively explained by Jerne (1974) using his immune network theory. This theory is also referred to as idiotypic network theory. In the clonal selection theory, the lymphocytes interact with antigens in the process of self-organization. On the other hand, immune network theory assumes that within an immune system of a given individual, any antibody molecule could be recognized by a set of other antibody molecules. That is, apart from reacting to non-self antigens, lymphocytes also interact to self-antigen. The assertion on the inter-cellular interactions renders this theory in conflict with the clonal selection theory.

As seen in Figure A.9 (a), an antibody molecule has both paratope and idiotope. The former is a receptive interface that recognizes other epitope of antigens (either of pathogens or another antibody molecule), while the latter is a signature epitope that can be identified by paratopes of other antibody molecules. As the result, an antibody in the immune system can recognize a set of antigens and antibodies, and can also being recognized by a set of other antibodies (Figure A.9 (b)). Among the antibodies in the system therefore forms an enormous and complex network. The effects of recognition could either be positive (activation) or negative (suppression), as seen in Figure A.9 (b) too. Activation results in proliferation and antibody secretion (much like in clonal selection theory). On the flip side, suppression can lead to tolerance or cell death.

Figure A.9 Basic concept of immune network theory (de Castro and Timmis, 2002)

Two B-cells are connected if the affinities they share exceed a certain threshold, and the strength of connection is directly proportional to the affinity they share (Aickelin and Dasgupta, 2005). In a regulated network-like format, the antibodies continuously communicate among themselves in the process of self-organization, in seek of a dynamic steady state. Decay and cloning of the elements occur in a sort of eigen-behaviour, manifesting the autonomous emergent property of the immune system. In this vein, immune system was in fact theorized as a homeostatic system – a system capable of maintaining its own internal steady state in a varying environment.

Under this theory, *system learning* takes place via the compound *endogenous* and *exogenous* interactive behaviour of the biological system. It is suggested that perturbation not only comes from the external environment (i.e. non-self antigens), continuous production of novel elements in the system might be also present to enhance the immune capability. This continuous production of novel elements is referred to as *metadynamics*. The persistent network modulation dynamically tends the immune system to a steady state in response to these endogenous and exogenous perturbations. These are the high-level descriptions of the learning under this theory. And the memory under the immune network theory is, similar to the clonal selection theory, defined as the antigenic affinity and the composition of the lymphocyte repertoire. The immune network theory however has a corollary that adds to the immune memory defined by the clonal selection theory. That is, the relationships between the antibodies, or the network, constitute part of the immune system memory. The immune network theory therefore denies the immune memory as a simple arithmetic sum of single cells. The dynamic steady state of the immunological memory

is maintained by the emergent function. The learning mechanism and the memory constituents defined in the clonal selection theory and the immune network theory are hence different, as described in this paragraph.

Immune network theory is still a hypothesis till this day, as contrast to proven the clonal selection hypothesis. This theory has however been widely implemented in the field of CI.

Appendix B – Bass Model Experimental Data

Table B.1 ARB concentration levels

w=10						
Period, t	Non Cumulative, ck(t)			Cumulative, Ck(t)		
	ARB1	ARB2	ARB3	ARB1	ARB2	ARB3
Initial, 0	3	0	0	3	0	0
1	3	0	0	6	0	0
2	24	0	0	30	0	0
3	49	0	0	79	0	0
4	58	0	0	137	0	0
5	67	0	0	204	0	0
6	71	0	0	275	0	0
7	85	0	0	360	0	0
8	92	0	0	452	0	0
9	183	0	0	635	0	0
10	286	0	0	921	0	0
11	398	0	0	1319	0	0
12	550	0	0	1869	0	0
13	485	42	0	2354	42	0
14	599	75	0	2953	117	0
15	626	112	0	3579	229	0
16	526	121	0	4105	350	0
17	409	210	0	4514	560	0
18	752	274	0	5266	834	0
19	489	262	0	5755	1096	0
20	568	630	0	6323	1726	0
21	648	931	0	6971	2657	0
22	511	626	11	7482	3283	11
23	511	567	128	7993	3850	139
24	466	695	353	8459	4545	492
25	342	584	518	8801	5129	1010
26	392	857	386	9193	5986	1396
27	149	579	312	9342	6565	1708
28	89	471	319	9431	7036	2027
29	179	491	378	9610	7527	2405
30	129	536	420	9739	8063	2825
31	133	335	298	9872	8398	3123
32	92	235	291	9964	8633	3414
33	73	290	335	10037	8923	3749
34	60	151	178	10097	9074	3927
35	66	156	231	10163	9230	4158
36	56	183	215	10219	9413	4373
37	1	123	226	10220	9536	4599
38	0	68	77	10220	9604	4676
	10217	9604	4676			

Table B.2 Time varying estimated parameters ($\hat{a}_t$ and $\hat{b}_t$) and forecast results

Period, t	Est. a cap ARB1	Est. b cap ARB1	F/C Cumulative ARB1	F/C Error (ek to cul) % ARB1
Initial, 0				
1				
2				
3				
4				
5				
6				
7				
8				
9				
10	966.92864	-0.4849105		
11	473.06483	-0.3852494	1941.714	47.21107205
12	342.39837	-0.3483211	1947.908	4.221961417
13	313.08214	-0.3394942	2341.407	-0.534944827
14	315.44643	-0.3400305	2972.333	0.654691414
15	325.78055	-0.3415698	3764.137	5.172862452
16	312.80306	-0.3356809	4624.466	12.65447359
17	261.45893	-0.3186731	5392.766	19.46757259
18	194.59078	-0.2958906	5965.939	13.2916631
19	133.68592	-0.2694933	6455.519	12.17235629
20	93.123667	-0.2461624	6832.496	8.057826066
21	71.062293	-0.2302605	7191.044	3.156567666
22	61.201825	-0.2219432	7594.833	1.508063852
23	54.946922	-0.2164355	8021.091	0.351441017
24	53.717263	-0.2154841	8430.383	-0.33830313
25	54.573734	-0.2160667	8829.895	0.328310093
26	57.134611	-0.2181284	9179.985	-0.141572539
27	48.193768	-0.2101652	9497.706	1.666730708
28	37.788701	-0.1988667	9699.581	2.847857385
29	26.835087	-0.1842914	9836.977	2.361880411
30	17.601738	-0.1673606	9940.703	2.071080598
31	11.957687	-0.1525726	10015.88	1.457482525
32	7.8139434	-0.1370404	10085.9	1.223370997
33	5.1604297	-0.1224686	10139.3	1.019185921
34	3.5951623	-0.1101724	10183.06	0.852322886
35	2.6312116	-0.0999647	10222.63	0.586747166
36	2.3628985	-0.0963756	10261.33	0.414212818
37	1.8346056	-0.0882204	10311.18	0.892209395
38	1.1567885	-0.0741464	10336.27	1.137714972

Table B.3 RMSE of CRAF system and static forecast

Period, t	ek ²	ek ²
	CRAF	Static
Initial, 0		
1		
2		
3		
4		
5		
6		
7		
8		
9		
10		
11	387772.776	206542.513
12	6226.544884	632543.299
13	158.5736059	1055161.17
14	373.7663377	1750913.52
15	34275.61515	2532101.93
16	269845.0714	2892873.64
17	772230.0812	2670197.21
18	489914.5743	3435564.47
19	490727.0155	3097440.98
20	259586.5227	2911934.53
21	48419.50806	2920226.69
22	12731.36204	2457560.78
23	789.0863321	2067749.72
24	818.9362256	1668443.78
25	834.8962498	1131581.5
26	169.3840704	880075.03
27	24244.35307	393573.11
28	72135.98454	99859.5813
29	51518.42574	23218.9617
30	40683.91442	56.8025498
31	20702.22412	13254.5319
32	14858.80209	49017.9671
33	10464.40837	96345.5378
34	7406.15867	145790.03
35	3555.869819	177954.698
36	1791.694116	203383.158
37	8314.485408	268414.912
38	13519.7524	327656.757
	3044069.787	34109436.8
RMSE	329.7222742	1103.71834

Appendix C – CRAF System Program Code

Filename: iDal-Algorithm.m

```
%Immunity-based dynamic and autonomic learning (iDal) algorithm
%The algorithm takes time series data of products to generate
%preference comparisons and forecast trends of customer needs.

%Prior to running the algorithm, ensure presence of these input data
%files in same directory:
% 1) ProdAg.mat -> In a Prep Folder, run a prepared
%ProdAgAssignFunction.m. That is to assign Ag (in AgTypes.mat) to
%product-Ag list (i.e. ProdAg.mat).
% 2) TimeSeries.mat
% 3) InitialPara.mat
% 4) InitialARB.mat -> In a Prep Folder, run a prepared
%InitialARBAssignFunction.m. That is to assign Ag (in AgTypes.mat) to
%initial ARB list (i.e. InitialARB.mat).

%Loading the above first 3 data files
load('TimeSeries.mat');
load('ProdAg.mat');
load('InitialPara.mat');

%L=2 (therefore 0<D=<2)
L=2;

%Declare the delay and number of hidden neurons from the initial
%parameter mat file
delay = InitialPara.delay;

%Set the current real time, T, when the algorithm will stop to await
%Ag of T+1, and thereafter continue
T=38; %38 for full course of the given data

%Initialize time variable
t= 0;

%Declare an empty matrix as container for results
forecast_table =[];

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%iDal Algo Step 1 - Initialize ARB set%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%This step load the initializing ARB onto the system
load('InitialARB.mat');
t=1; %Initialize the ARBs into t=1
```

```

K=0; %K is global for ARB additions; k, k2 etc are local for sub-
steps
for k = 1: size(InitialARB,1);
    InitialARB(k,1).active = 1;
    InitialARB(k,1).conc = InitialPara.ARB;
    K=K+1; %convention is 'up' K then assign/add the new ARB
    ARB(K,t) = InitialARB(k,1);

    %Call Less-specific-ARB-Generator function (whenever any ARB
    %become active)
    %create dummy less specific ARB, check for any identical ones in
    %ARB list.
    dummyARB=ARB(K,t);
    dummyARB.att2='#';
    dummyARB.val2='#';

    for k2=1:K
        a=strcmpi(dummyARB.att1,ARB(k2,t).att1);
        b=strcmpi(dummyARB.val1,ARB(k2,t).val1);
        c=strcmpi(dummyARB.att2,ARB(k2,t).att2);
        d=strcmpi(dummyARB.val2,ARB(k2,t).val2);
        e = a & b & c & d;
        if e==1
            clear dummyARB a b c d;
            break
        end
    end
    clear k2;
    if e~=1
        K=K+1; %convention is 'up' K then assign/add the new ARB
        ARB(K,t)=dummyARB;
        clear dummyARB;
    end
    clear e;
end
clear k;

t=0; %Reset the time to t=0 prior to running the algorithm loop.

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%iDal Step 2 - Introduction of Ag%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% This is the point of starting the algorithm loop,
% When the Ag of't=t+1' are ready for introduction to the system.
% Note that at T= 38, the t=38 Ag data would be used here, &
% there is no t=39 data yet for use. Thus, to resume when data is
% available, resume from this same point.

while t < T
    t=t+1;

    %This step load the incoming Ag to the system
    I=0;p=1;q=1;%I is global total Ag, i is used as local counter
    while ~isempty(ProdAg(p,q).att1)
        while ~isempty(ProdAg(p,q).att1)
            ProdAg(p,q).active = 'NA';
            ProdAg(p,q).conc = TimeSeries(p,t);
            I=I+1;

```

```

        Ag(I,t)= ProdAg(p,q);
        q=q+1;
    end
    p=p+1;
    q=1;
    if p > size(ProdAg,1);
        break
    end
end
clear p q;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%iDal Step 3- Secondary Immune Response%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%Prior to stimulations and decay, the subjects(i.e. ARBs) are
%ported from previous 't-1' data to the current 't'.

if t~=1 %if t==1, the porting is done in step 1.
    for k=1:K
        ARB(k,t)=ARB(k,(t-1));
    end
end

% This step presents all the Ag to the active ARBs for
% stimulations (Only calculation, no data update).

for k = 1:size(ARB,1)
    S(k,t)= 0; %active or inactive, initialize as 0 first
    if ARB(k,t).active == 1
        for i=1:I
            Dist1= ~strcmpi(ARB(k,t).att1,Ag(i,t).att1);
            Dist2= ~strcmpi(ARB(k,t).val1,Ag(i,t).val1);
            Dist3= ~strcmpi(ARB(k,t).att2,Ag(i,t).att2);
            Dist4= ~strcmpi(ARB(k,t).val2,Ag(i,t).val2);
            if ARB(k,t).att2 == '#'
                Dist3 = 0;
            end
            if ARB(k,t).val2 == '#'
                Dist4 = 0;
            end
            Dist= or(Dist1,Dist2) + or(Dist3,Dist4);
            Affin= 1-(Dist*(1/L));
            S(k,t)= S(k,t)+ (Ag(i,t).conc * Affin);
            clear Dist1 Dist2 Dist3 Dist4 Dist Affin;
        end
        clear i;
    end
end
clear k;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%iDal Step 4- Primary Immune Response%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%This step presents all the Ag to the inactive ARBs for stimulations
%No cross-reaction here, i.e. need exact match. # still applicable to

```

```

%enable generalization representation(Only calculation, no data
%update)

    for k=1:size(ARB,1)
        if ARB(k,t).active == 0
            for i=1:I
                Affin1= strcmpi(ARB(k,t).att1,Ag(i,t).att1);
                Affin2= strcmpi(ARB(k,t).val1,Ag(i,t).val1);
                Affin3= strcmpi(ARB(k,t).att2,Ag(i,t).att2);
                Affin4= strcmpi(ARB(k,t).val2,Ag(i,t).val2);
                if ARB(k,t).att2 == '#'
                    Affin3 = 1;
                end
                if ARB(k,t).val2 == '#'
                    Affin4 = 1;
                end
                Affin= and(and(Affin1,Affin2),and(Affin3,Affin4));
                S(k,t)= S(k,t)+ (Ag(i,t).conc * Affin);
                clear Affin1 Affin2 Affin3 Affin4 Affin;
            end
            clear i;
        end
    end
    clear k;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%iDal Step 5- Apoptosis%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%Only calculation, no data update

    a=sum(S,1);
    decay(t)= InitialPara.d * (a(t)/size(S,1));
    clear a;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%iDal Step 6 - Concentration Updates%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%Final update of concentration attribute of ARBs, of the current
%time, t.

    for k=1:size(ARB,1)
        ARB(k,t).conc=ARB(k,t).conc + S(k,t) - decay(t);
        if ARB(k,t).conc < 0
            ARB(k,t).conc = 0;    %non-negativity of population size
        end

        %update a concentration table
        C(k,t)=ARB(k,t).conc;

        %update the total populations size table
        popsize(t)= sum(C(1:size(C,1),t),1);

    end
    clear k;

```

```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%iDal Step 7 – Antigenic Learning %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%This is a step that enables the system to learn exact Ag that has
%not been known to the system, to the threshold of epsilon r.
%(learn new ARB as inactive ones.)

    for i=1:I
        if Ag(i,t).conc > 0
            a=0; % Set up the counter for number of comparison
%between the i and all k
            KK = size(ARB,1);
            for k=1:KK
                Dist(1)= ~strcmpi(ARB(k,t).att1,Ag(i,t).att1); %0 if
%same
                Dist(2)= ~strcmpi(ARB(k,t).val1,Ag(i,t).val1);
                Dist(3)= ~strcmpi(ARB(k,t).att2,Ag(i,t).att2);
                Dist(4)= ~strcmpi(ARB(k,t).val2,Ag(i,t).val2);
                Dist(5)= or(Dist(1),Dist(2)); %1 if any one or both 1
                Dist(6)= or(Dist(3),Dist(4));
                Dist(7)= Dist(5)+Dist(6); %0 is exact case; 1 is one
dif;2 is two dif
                if Dist(7) >= InitialPara.epsilonr
                    a = a+1;
                end
            end
            if a == KK %if all k when compared with the i are further
than or equal to epsilon r
                K= size(ARB,1)+1;
                ARB(K,t)= Ag(i,t);
                ARB(K,t).active=0;%newly learnt are inactive
            end
            clear Dist KK k a;
        end
    end
    clear i;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%iDal Step 8 – Activeness Update%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%Activate and deactivate ARB based on PP and ARBT, as a result of
%Step 6, concentration changes in time t.

    KK=size(ARB,1); % declare a fixed KK since size(ARB,1) is
%variable inside the loop.

    if t >= InitialPara.PP
        for k=1:KK

            %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

            if ARB(k,t).active == 1 %check for deactivation
                for p=1:(InitialPara.PP)
                    if ~isempty(ARB(k,t-p+1).active) %ensure that it
%is not empty dataset, i.e. relatively new ARB

```

```

        a(p)= (ARB(k,t-p+1).conc < InitialPara.ARBt);
%1 is TRUE, 0 is FALSE or empty data
    end
end
if sum(a) == InitialPara.PP %check for consecutive PP
%all TRUE or not
    ARB(k,t).active = 0; % Deactivation
end
end

if ARB(k,t).active == 0 %check for activation
    for p=1:(InitialPara.PP)
        if ~isempty(ARB(k,t-p+1).active) %ensure that it
%is not empty dataset
            a(p)= (ARB(k,t-p+1).conc > InitialPara.ARBt);
%1 is for TRUE,0 is for FALSE or empty data
        end
    end
    if sum(a) == InitialPara.PP %check for consecutive PP
%all TRUE or not
        ARB(k,t).active = 1; % Activation

        %Calling the less-specific-ARB-generator
        dummyARB=ARB(k,t);
        dummyARB.att2='#';
        dummyARB.val2='#';

        for k2=1:size(ARB,1) %Check for any same ARB
            A1=strcmpi(dummyARB.att1,ARB(k2,t).att1);
            A2=strcmpi(dummyARB.val1,ARB(k2,t).val1);
            A3=strcmpi(dummyARB.att2,ARB(k2,t).att2);
            A4=strcmpi(dummyARB.val2,ARB(k2,t).val2);
            A = A1 & A2 & A3 & A4;
            if A==1 % True if exact match found
                clear dummyARB;
                break
            end
        end
        clear k2 A1 A2 A3 A4;
        if A==0
            K= size(ARB,1)+1; %convention is 'up' K then
%assign/add the new ARB
            ARB(K,t)=dummyARB;
            clear dummyARB;
        end
        clear A;
    end
end
clear a p;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

end
clear k KK ;
end

%Updating the number of active and inactive ARBs at t, and record
%the number of ARB in system at t
active=0;
inactive=0;

```

```

for k=1:size(ARB,1)
    switch ARB(k,t).active
        case 1
            active=active+1;
        case 0
            inactive=inactive+1;
        end
    end
end
ARBnumber(1,t)= active + inactive;
ARBnumber(2,t)= active;
ARBnumber(3,t)= inactive;

clear active inactive k;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%iDal Step 9 to 11- Learning, Forecast and Producing repertoire data%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%Training and forecast starts after delay+2
if t >= delay + 2
    forecast_table = ann(C,t,forecast_table); %Forecast_table at
%column t+1 for all k will be recorded
end

%Error evaluation at & after delay+3
if t>= delay + 3
    for k= 1:size(C,1)
        abs_error_percent(k,t)= ((abs(forecast_table(k,t)-
C(k,t))/C(k,t))*100);
    end
    clear k;
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% End of iDal Algorithm Loop %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

clear I;

end %Looping here

return

```

Filename: ANN.m

```

function [forecast_table]= ann(C,t,forecast_table)

load('InitialPara.mat');

%Declare ANN parameters
epoch_show = 800;
epoch = 800;
%Declare the delay and number of hidden neurons from the initial
parameter mat file
delay = InitialPara.delay;
hid_node = InitialPara.hid_node;

for k = 1:size(C,1);
    k % to show k & t values during runtime
    t

        if C(k,t)== 0
            forecast_table(k,t+1)= 0;
            continue;
        end
        %y is all the currently available data till the current time, t
        y = C(k,1:t);
        y = con2seq(y);

        net = newfftd(y,y,[1:delay],hid_node);

        net.trainParam.show = epoch_show;
        net.trainParam.epochs = epoch;

        initial_ip=y(1:delay);

        tip = y(delay+1:end-1);

        target = y(delay+2:end);

        net = train(net,tip,target,initial_ip);

        fip = y(delay+1:end);

        op = sim(net,fip,initial_ip);

        %Fill in the forecast table with results of each k at time t.
        op = cell2mat(op);
        forecast_table(k,t+1)= op(1,t-delay); % Only the last value of op

        clear y net tip fip initial_ip target op;

end % go to next ARB to predict

clear k hid_node epoch_show epoch;

return

```

Appendix D – The Conceptual Design Case Study

D.1 The conceptual design problem

Appendix D provides details for the case study presented in Chapter 6. In the case, a bicycle - codenamed Stallion - is required to satisfy a customer group X . The design case started with an abstract solution s_0^0 (Stallion), holding full promise to solve the design problem. Four highest-level needs of Stallion were established by the CRAF sub-system (in terms of RSF as correspondingly shown in Figure 6.7), namely: (1) safety, (2) comfort, (3) high efficiency and (4) ease of use. They were being assigned as c_1 , c_2 , c_3 and c_4 in the HBCD sub-system environment, and m_1 , m_2 , m_3 , m_4 respectively in the CRAF sub-system.

In accordance to the CDH algorithm, the integrated system¹ proceeded to establish the *Contexts* for each of the customer requirements. Under customers' desire for 'safety' (c_1), two product requirements (p_8 and p_9) were identified. They are respectively 'quality braking system' and 'high presence'. The latter demands *Stallion* to have obvious presences, and had further generated solutions such as having audio horn and flickering lightings. The other product requirement 'quality braking system' (denoted as p_8), awaits further exploration. The case study shall be focused from this point onwards as a detailed illustration of the design process, neglecting further propagations of nodes c_2 , c_3 , c_4 and p_9 (as seen in Figure 6.8). For the purpose of computing Stallion s_0^0 's merit ratio (MR), the *contribution fractions* of 'safety' (c_1) and 'quality brake system' (p_8) components are set to 1.0. On the other hand, their siblings' (c_2 , c_3 , c_4 , p_9) contribution ratios are set to 0.0. These assumptions render the siblings neglected in this case study, so as to allow focus on the bicycle brake sub-problem.

¹The integrated system (see Figure 6.5) is referred to as "the system" in Appendix D.

D.2 The algorithmic and quantitative perspective

While Section 6.4 presents the general descriptions of the case process, below presents the process in terms of the CDH algorithm steps. The data objects instantiated in the case study are documented in Tables D.1 to D.3.

- 1) CDH Algorithm Step 1: The design process started with the creation of s_0^0 , the *seed* of the entire conceptual solution. This instantiated S class object is illustrated in Figure 6.8.
- 2) CDH Algorithm Step 2: As only s_0^0 was in both OPEN and G_0 , by f_2 (Equation 6.5), *Stallion* (s_0^0) - the main solution - was selected for expansion by the CDH algorithm.
- 3) CDH Algorithm Step 3: Customer requirements (CRs) of *Stallion* were queried by the system. Four CRs were identified, viz. ‘safety’, ‘comfort’, ‘high efficiency’ and ‘ease of usage’. For each CR, the designers established the respective product requirements (PRs) that are capable of satisfying the parental CR. For the case of CR ‘safety’, two PRs were identified, namely: ‘quality braking system’ and ‘high presence’. The former PR is the focus of this case study. Therefore, the propagations of nodes ‘comfort’, ‘high efficiency’, ‘ease of usage’ and ‘high presence’ will be excluded in this case study. For the PR ‘quality braking system’, two alternative solutions were identified. They were the rim type (s_{15}^1) and disc type (s_{15}^2) braking systems.
- 4) CDH Algorithm Step 4: The users of the system assigned the heuristic values of 0.7 and 0.5 to the rim and disc type braking system respectively. As the team deemed that the conceptualized solution at that stage was not adequately detailed, they further explored into it.
- 5) CDH Algorithm Step 5: Since no new leave node was being labeled ‘solved’ by the designers, no action was taken in this step.
- 6) CDH Algorithm Step 6: The system computed the most promising solution base G_0 (as shown below) and the result was presented to the users. Of the two alternative braking systems, the rim type was included in the current solution base.

Using Equation 4.2, calculating MR from bottoms up,

Since s_{15}^1 and s_{15}^2 are in OPEN,

$$MR(s_{15}^1) = h(s_{15}^1) = 0.7$$

$$MR(s_{15}^2) = h(s_{15}^2) = 0.5$$

Since s_0^0 is in CLOSED,

$$\begin{aligned} MR(s_0^0) &= h(s_0^0) \sum_i \Lambda(c_i) \sum_j \Lambda(p_j) \sum_k \max_l [\Lambda(s_k^l) MR(s_k^l)] \\ &= h(s_0^0) \times \Lambda(c_1) \times \Lambda(p_8) \times \Lambda(s_{15}^1) \times MR(s_{15}^1) \\ &= 1.0 \times 1.0 \times 1.0 \times 1.0 \times 0.7 \\ &= 0.7 \end{aligned}$$

Solution s_{15}^1 (instead of s_{15}^2) was included in G_0 , as asserted by Equation 6.4 during the computation of G_0 's merit ratio (i.e. $MR(s_0^0)$). The working memory at this step records:

$$\text{OPEN} = \{ s_{15}^1, s_{15}^2 \}; \text{CLOSED} = \{ s_0^0 \}; G_0 = \{ s_0^0, c_1, p_8, s_{15}^1, w_{0,1}^0, u_{1,8}, v_{8,15}^1 \}$$

- 7) CDH Algorithm Step 7: No action was taken in this step, since *Stallion* (s_0^0) was neither 'solved' nor having $MR(s_0^0) = -\infty$. The CDH algorithm was looped.
- 8) CDH Algorithm Step 2: Amongst the current most promising solution base, the system identified the next logical node for expansion, as shown below. Using Equation 6.5, the value of n^* is evaluated:

$$f_2(s_k^l \in G_0 \cap \text{OPEN}) = \min_k [h(s_k^l \in G_0 \cap \text{OPEN})] = s_{15}^1$$

The rim braking system (s_{15}^1) was therefore recommended to the system users for further expansion.

- 9) CDH Algorithm Step 3: At this stage, the customer needs (in the form of RSF) of the rim braking system (s_{15}^1) were queried by the CDH algorithm. Four CRs arose (as shown in Figure 6.8): (1) robust performance in wet and muddy conditions (c_5), (2) good force modulation (c_6), (3) minimal weight (c_7), and (4) high force

leveraging ratio (c_8). PRs (p_{10} to p_{15}) that were capable of satisfying these CRs were generated from the design database and the users. Following that, the solutions (s_{16}^1 to s_{21}^1) for the respective PRs were generated (see Figure 6.8).

- 10) CDH Algorithm Step 4: The system prompted the users for the heuristic values of the generated solutions. As solutions s_{16}^1 (aluminum material to increase friction coefficient) and s_{21}^1 (V-brake design to increase the force ratio) promised to fully satisfy their respective PRs, they received the h values of 1.0. This was as anticipated by the team earlier (in Step 4 of CDH algorithm during the first loop) - the rim-type braking system was able to provide high force leveraging ratio and lightweight components. The team however discovered that the force modulation capability of the rim brake system was less adequate than they had assumed, which would be demanded by racing and cross-terrain cyclists. Albeit using hydraulic transmission (s_{18}^1) to replace the traditional cable type (s_{18}^2) in a bid to alleviate the problem, the heuristic value assigned was still low at 0.4 (it was noted that hydraulic transmission would increase the maintenance of the braking system). This low value reflected the low confidence of the designers in the capability of the rim brake system in satisfying the “force modulation” product requirement. In this step, the system users labeled solution s_{19}^1 as ‘solved’.

- 11) CDH Algorithm Step 5: As the design team had declared solution s_{19}^1 ‘solved’ in the previous step, the system propagated this status upwards in graph G , as accordance to the Solve-labeling function.

- 12) CDH Algorithm Step 6: The system computed the most promising solution base G_0 , which was presented to the system users via the user interface layer. Within this cycle of CDH algorithm, the merit ratio of the rim brake system had fallen below that of the disc brake system (computations as shown below). Due to this trigger, the latter system replaces the former in the solution base G_0 .

Using Equation 6.2, calculating MR upwards from bottom,

Since s_{15}^1 is in CLOSED,

$$\begin{aligned} MR(s_{15}^1) &= h(s_{15}^1) \sum_i \Lambda(c_i) \sum_j \Lambda(p_j) \sum_k \max_l [\Lambda(s_k^l) MR(s_k^l)] \\ &= 0.7 \{ 0.3[0.6(1.0) + 0.4(0.2)] + 0.4[0.4(1.0)] + 0.1[0.5(1.0) + 0.5(1.0)] + 0.2[1.0(1.0)] \} \\ &= 0.465 \end{aligned}$$

Since s_0^0 is in CLOSED,

$$\begin{aligned} MR(s_0^0) &= h(s_0^0) \sum_i \Lambda(c_i) \sum_j \Lambda(p_j) \sum_k \max_l [\Lambda(s_k^l) MR(s_k^l)] \\ &= h(s_0^0) \times \Lambda(c_1) \times \Lambda(p_8) \times \Lambda(s_{15}^2) \times MR(s_{15}^2) \\ &= 1.0 \times 1.0 \times 1.0 \times 1.0 \times 0.5 \\ &= 0.5 \end{aligned}$$

Note that at this stage, $MR(s_{15}^1) < MR(s_{15}^2)$. Since $\Lambda(s_{15}^1) = \Lambda(s_{15}^2)$, in the computation of $MR(s_0^0)$, i.e. G_0 's merit ratio, $MR(s_{15}^2)$ was used instead of $MR(s_{15}^1)$. Solution s_{15}^2 was therefore included in G_0 , instead of s_{15}^1 and its descendents as shown below.

$$\begin{aligned} \text{OPEN} &= \{ s_{15}^2, s_{16}^1, s_{17}^1, s_{18}^1, s_{18}^2, s_{20}^1, s_{21}^1 \}; \quad \text{CLOSED} = \{ s_0^0, s_{15}^1, s_{19}^1 \}; \quad G_0 = \{ s_0^0, \\ & \quad c_1, p_8, s_{15}^2, w_{0,1}^0, u_{1,8}, v_{8,15}^2 \} \end{aligned}$$

13) CDH Algorithm Step 7: Since *Stallion* (s_0^0) was neither 'solved' nor having $MR(s_0^0) = -\infty$, no action was taken in this step. The CDH algorithm was looped.

14) CDH Algorithm Step 2: Amongst the current most promising solution base identified in the last cycle of the algorithm (Step 6), the system identified the next logical node for expansion. Using Equation 6.5, the value of n^* was evaluated:

$$f_2(s_k^l \in G_0 \cap \text{OPEN}) = \min_k [h(s_k^l \in G_0 \cap \text{OPEN})] = s_{15}^2$$

As the result, the disc braking system (s_{15}^2) was recommended to the system users for expansion.

- 15) The CDH algorithm continued with Step 3 from here, guiding the conceptual development process until the satisfaction of the algorithm termination criteria, as depicted in Figure 6.4.

Appendix D

Table D.1 Object class S in G'

name	Stallion	...	Rim Brake	Disc Brake	Ai Alloy Rim	Dirt Scraper
superclass	N		N	N	N	N
class	S		S	S	S	S
id	0		15	15	16	17
l_id	0		1	2	1	1
contribution_fraction	1.0		1.0	1.0	1.0	1.0
description			Adequate brake power; Light; Non-weather resistance	Low braking power; Heavy; Good brake force modulation	Ai alloy stop bicycle 4 times faster than steel	A scraper on pad mounted on spring. More parts.
MR	0.5		0.465	0.5	1.0	0.2
heuristics_h	1.0		0.7	0.5	1.0	0.2
solve_status	0		0	0	0	0

name	Hydraulic	Cable	Ai material	Minimize vol.	V-system
superclass	N	N	N	N	N
class	S	S	S	S	S
id	18	18	19	20	21
l_id	1	2	1	1	1
contribution_fraction	1.0	1.0	1.0	1.0	1.0
description	Good modulation. But high maintenance	Bad modulation when dirty.	Light and high strength	Minimal part volume	V-brake system provides leverage for force
MR	0.4	0.2	1.0	1.0	1.0
heuristics_h	0.4	0.2	1.0	1.0	1.0
solve_status	0	0	1	0	0

Appendix D

Table D.2 Object classes C and P in G'

name	Safety	Comfort	Efficiency	Easy Use	...
superclass	N	N	N	N	
class	C	C	C	C	
id	1	2	3	4	
contribution_fraction	1.0	0.0	0.0	0.0	
solve_status	0	0	0	0	
description		<i>Excluded in the case</i>	<i>Excluded in the case</i>	<i>Excluded in the case</i>	

name	Brake	Presence	Weather	Modulate	Light	Brake Force
superclass	N	N	N	N	N	N
class	P	P	C	C	C	C
id	8	9	5	6	7	8
contribution_fraction	1.0	0.0	0.3	0.4	0.1	0.2
solve_status	0	0	0	0	0	0
description	Quality braking system	<i>Excluded in case</i>	Robust in rain and muddy track	Good control	Minimal weight	Low force required to brake

name	Wet resistance	Dirt	Modulation	Density	Volume	Force ratio
superclass	N	N	N	N	N	N
class	P	P	P	P	P	P
id	10	11	12	13	14	15
contribution_fraction	0.6	0.4	1.0	0.5	0.5	1.0
solve_status	0	0	0	0	0	0
description	High coefficient of friction in wet condition	Prevent dirt between pad and rim	Linear relationship between applied force and braking force	Low overall density	Low overall volume	Low applied vs braking force ratio

Table D.3 Relational object classes U , V and W in G'

superclass	E	E	E	E		E	E	...	E
class	W	W	W	W		U	U		V
parent_id	0	0	0	0		1	1		8
child_id	1	2	3	4		8	9		15
l_id	0	0	0	0		NA	NA		1

superclass	E	E	E	E	E	E	E	E	E
class	V	W	W	W	W	U	U	U	U
parent_id	8	15	15	15	15	5	5	6	7
child_id	15	5	6	7	8	10	11	12	13
l_id	2	1	1	1	1	NA	NA	NA	NA

superclass	E	E	E	E	E	E	E	E	E
class	U	U	V	V	V	V	V	V	V
parent_id	7	8	10	11	12	12	13	14	15
child_id	14	15	16	17	18	18	19	20	21
l_id	NA	NA	1	1	1	2	1	1	1